# Determinants of Iot Technology Adoption in Rice Farming: An Empirical Analysis

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## Abstract

The integration of Internet of Things (IoT) technologies in rice farming represents a transformative approach to modern agriculture, offering significant potential to enhance productivity, optimize resource use, and enable precision farming. Despite the evident benefits, the adoption of IoT technologies among rice farmers remains limited, particularly in developing regions where financial constraints, infrastructural challenges, and limited technical knowledge prevail. This study aims to explore the determinants influencing the adoption of IoT technologies in rice farming, with a focus on key variables such as farm income, yield, working hours, and access to resources. A quantitative cross-sectional survey was conducted among 150 rice farmers in Peninsular Malaysia, using stratified random sampling to ensure representativeness across different socioeconomic and demographic groups. The data were analyzed using binary logistic regression to assess the relative influence of various factors on the likelihood of IoT adoption. The findings reveal that farm income negatively influences IoT adoption, suggesting that wealthier farmers may perceive less need for technological innovation due to their reliance on established traditional practices. Conversely, higher farm yields and extended working hours are positively associated with IoT adoption, indicating that productivity-driven and labor-intensive farming practices motivate farmers to embrace IoT technologies. Additionally, access to credit and the frequency of extension visits emerged as significant predictors of IoT adoption, underscoring the importance of financial support and institutional engagement in promoting technological uptake. However, factors such as age, education, and land ownership were found to have minimal impact on IoT adoption decisions. The study contributes to the existing literature by providing empirical evidence on the determinants of IoT adoption in rice farming and offers practical recommendations for policymakers and stakeholders to enhance the adoption of IoT technologies. By addressing the identified barriers and leveraging the significant predictors, it is possible to foster the widespread adoption of IoT technologies, ultimately improving the productivity, sustainability, and profitability of rice farming.

**Keywords:** IoT adoption, variable rate technology, I-paddy applications, rice farming, technology adoption determinants.

## 1.0 Introduction

The integration of Internet of Things (IoT) technology in agriculture, specifically in rice farming, signifies a noteworthy progression towards modern agricultural approaches. The adoption of IoT technology has the capacity to transform rice production via the optimization of resource allocation, the improvement of productivity, and the facilitation of precision farming practices (Jayashankar et al., 2018; Dlodlo & Kalezhi, 2015). These technologies offer farmers real-time data on soil conditions, weather patterns, and crop health, facilitating informed decision-making and improving overall farm management (Patil & Kale, 2016; Wolfert et al., 2017). As the global demand for food continues to rise, the adoption of IoT in agriculture is increasingly seen as a critical strategy for achieving sustainable agricultural practices and ensuring food security. There is an emerging tendency in Malaysia to incorporate state-of-the-art technologies in the production of rice, with an emphasis on the adoption of IoT technology. The occurrence is propelled by the imperative to improve agricultural efficiency, sustainability, and productivity in the midst of obstacles including the aging of the farmer demographic, limited resources, and small farm sizes. Despite the manifold benefits associated with the application of IoT in rice farming, farmers' awareness of IoT technologies in Malaysia has been considered moderate. A critical challenge that farmers encounter when implementing IoT technologies is the scarcity of resources, which includes financial capital and technological accessibility (Tarmizi et al., 2020). Additionally, insufficient infrastructure and connectivity pose substantial obstacles in isolated or rural regions where rice cultivation is prominent. The lack of adequate network coverage and inconsistent internet access create significant barriers to the seamless transfer of data from IoT devices to centralized platforms for analysis and decision-making. In the absence of reliable facilities and connections, farmers may struggle to obtain up-to-date information and valuable insights necessary for enhancing farming methods, monitoring crop conditions, and efficiently managing risks.

Furthermore, the high costs associated with IoT implementation, including the acquisition of devices, maintenance, and data management, exacerbate the financial burden on small-scale farmers, who often operate with limited capital. These challenges are compounded by a lack of technical expertise among farmers, which hinders their ability to fully utilize IoT technologies and integrate them into existing farming practices. The present study seeks to contribute to the existing body of knowledge by exploring how variables such as farm income, yield, working hours, and access to resources impact the decision to adopt IoT technologies among rice farmers. Ultimately, this research aims to inform the development of more effective policies and interventions that can support the widespread adoption of IoT technologies, thereby improving the productivity, sustainability, and profitability of rice farming.

## 2.0 Literature Review

Considerable interest has been devoted by economists, researchers, and specialists in the field of agricultural technology to measure adoption behavior. As per the findings of Loevinsohn et al. (2013), the decision to adopt new technology is influenced by a dynamic interplay between the technology itself and the surrounding situations and circumstances throughout its adoption. An in-depth understanding of the variables that impact the adoption of agricultural technology is crucial for economists in evaluating factors that drive growth, as well as for those involved in the development and dissemination of the technology.

Research conducted by Melesse (2018) in Ethiopia has shown that the adoption of new advanced technology in agricultural production is driven by three primary factors: (1) Demographic characteristics, such as male or female farmers have preferences in the adoption of technology. Additionally, older individuals with extensive experience in traditional agricultural practices and younger individuals exhibit different ways of incorporating new technology into farm practices; (2) Socio-economic factors include farmer's education level, types of land ownership, access to input, as well as labor resources availability and size of farm; (3) Institutional components include services that support agricultural and farm efficiency, including financial services, insurance, information dissemination, infrastructure and facilities, accessibility of markets as well as agricultural extension programs.

Moreover, past research has mostly concentrated on comprehending technology adoption by examining individual characteristics and abilities, limited information, potential risks and uncertainties, institutional limitations, input availability, and infrastructure (Mwangi & Kariuki, 2015; Ruttan, 2010; Uaiene & Arndt, 2009). A recent study has also examined the influence of social networks and education on the adoption of technology (Uaiene & Arndt, 2009). Various studies classify the characteristics that impact technology adoption in different ways. For instance, in a study conducted by Akudugu et al. (2012), the variables were categorized into institutional, social, and economic aspects. On the other hand, Kebede et al. in 1990 defined the components as economic, physiological, and social elements. McNamara et al. (1991) classified the components into categories such as farmer, farm structure, organizational, and leadership structure aspects, while Wu and Babcock (1998) grouped them as human capital and productivity.

Furthermore, a study carried out by Kinyangi (2014) has identified the key factors that influence the adoption of advanced technology and agricultural productivity among small-scale farmers in the northern region of Kakamega district, Kenya. These factors include access to credit facilities, training development programs for human resources, agricultural extension policies, market size, level of education, gender, and age. The study has identified several factors that have a positive impact on the adoption of new high technology in rice cultivation by farmers in Nerica, Ghana namely size of the farm, access to credit, farm training, machine ownership, tools and equipment as well as household labor. Age and profit orientation negatively impact the adoption of new advanced technology in rice cultivation in Nerica, Ghana (Udimal et al., 2017).

The classification of factors that influence technology acceptance may differ based on geographical context, the inclinations of researchers, and the requirements of the customer (Bonabana-Wabbi, 2002). For example, certain academicians may categorize the educational background as human capital, while others may consider it as an attribute of an individual. Hence, this study aims to analyze the several determinants, including individual, farm, institutional as well as technology attributes aspects, that affect the adoption of IoT technology in the production of rice. This study can provide a more profound comprehension through an in-depth investigation of each component and its impact on the adoption of IoT technology in rice farming.

## 3.0 Methodology

This study utilized a quantitative approach to identify factors influencing the adoption of IoT technologies in the production of rice. The study employed a cross-sectional survey approach to gather data from a wide and varied sample of rice farmers at a certain point in time. The stratified random sampling technique was employed to guarantee the sample's representativeness across various socioeconomic and demographic groups. A total sample of 150 farmers was selected from the target population, which included rice farmers from MADA (Kedah), KADA (Kelantan), and IADA (Selangor). To obtain a comprehensive understanding of the agricultural community, the stratification was determined by critical variables including income levels, farm size, and geographic location. A structured questionnaire that was specifically designed for this study was employed to collect data. The questionnaire was developed to collect quantitative data on a variety of variables, such as the extent of IoT adoption, agricultural income, yield, and working hours. Face-to-face interviews were employed to administer the survey instrument, which guaranteed a high level of response accuracy and reduced the likelihood of misunderstandings.

Given the dichotomous nature of the dependent variable, binary logistic regression models were utilized to assess the relative influence of various covariates on the decision to adopt IoT technology. The dependent variable in this context represents whether or not rice farmers adopt IoT technologies, with a value of 1 indicating adoption and 0 indicating non-adoption. The binary logistic regression model is therefore employed to estimate the probability of IoT technology adoption in rice production, allowing for the identification and quantification of key factors that influence this decision. This methodological approach is appropriate for analyzing dichotomous outcomes and provides robust insights into the determinants of IoT adoption among rice farmers in Peninsular Malaysia. The expressions of the model were formulated as follows:

$$\mathrm{logit}(\mathrm{p_i}) = \ln\left(\frac{\mathrm{p_i}}{1-\mathrm{p_i}}\right) = \sum_{k=0}^{n} \beta \kappa \varkappa i \kappa$$

where $p_i$ = 1 if the farmers adopt IoT, and 0 otherwise, $x_{ik}$ represents the independent variables (e.g., socio-demographic, farm, institutional factors, and technology attributes).

## 4.0 Result

### 4.1 Descriptive Statistics

The descriptive statistics for the dependent and independent variables offer valuable insights into the characteristics of the sample and the potential factors that may affect the adoption of technology in rice farming. The average adoption rate for Variable Rate Technology (VRT) is 0.480 with a standard deviation of 0.501. This suggests that 48% of the farmers included in the sample have adopted VRT. On the other hand, the I-paddy application exhibits a lower adoption rate, with a mean of 0.253 (SD = 0.436), indicating that only 25.3% of the farmers have embraced this technology.

Table 1 presents a concise overview of the descriptive statistical data for the determinants employed in the adoption decision framework. The farmers' demographic profile reveals an average age of 49.85 years, with the ages ranging from 21 to 86 years. The wide range of ages represented here encompasses a diverse array of viewpoints on the adoption of technology. The classification of educational background is divided into three categories: primary education and below (with a mean of 1.793), secondary education, and tertiary education. The relatively low mean value indicates a prevalence of rice farmers with lower levels of education, which may impact their willingness to adopt new technologies. Next, the average rice farming experience is 18.507 years, with a SD of 12.154. The range of farming experience among the respondents is from 1 to 51 years, indicating a significant variation in agricultural expertise. The level of awareness among farmers regarding IoT technology, as measured on a Likert scale ranging from 1 to 5, has a mean score of 3.958, indicating a relatively high level of awareness. The mean number of weekly working hours is 18.673, with a range of 1 to 56 hours, which indicates the diverse levels of labor intensity involved in rice farming activities.

Furthermore, farm income exhibits considerable variation, with a mean of RM 14,916.67 and a range from -3,000 to 236,000. This wide range underscores the economic disparities among the sampled farmers. The average farm size is 3.830 hectares, ranging from 0.29 to 63.60 hectares, which indicates a substantial difference in farm scale. The majority of farmers have off-farm employment (mean = 0.873) and own their land (mean = 0.587) suggesting a degree of financial stability and security that could facilitate investment and adoption of new technologies. The yield per season per hectare averages 10.819 tonnes, with a range from 0 to 424 tonnes, indicating significant variability in productivity. This variance may be attributed to differences in farming practices, soil fertility, and access to resources.

Credit accessibility is assessed using a Likert scale ranging from 1 to 5, with an average score of 3.340, indicating a moderate level of access to financial services for farmers. The access to information among farmers is measured as a binary variable, with 44.7% of farmers reporting that they have access. The mean value for access is 0.447, with a SD of 0.499. The frequency of extension visits is classified into five levels, with an average of 2.473, indicating different degrees of institutional support and advisory services provided to the farmers. Moreover, a significant proportion of farmers, specifically 60.7%, actively participate in farmer-to-farmer extension activities, indicating a robust network of peer support and knowledge sharing within the farming community. This is supported by a mean value of 0.607 and a SD of 0.490.

Lastly, a Likert scale from 1 to 5, with a mean score of 3.813, is used to measure subjective norms, which are indicative of the perceived social pressure to adopt technology. In general, this suggests that the social environment is conducive to the adoption of IoT technology. The technology's PU and PEOU are further evaluated on a Likert scale from 1 to 5, with mean scores of 3.840 and 3.700 respectively. This score indicates that the majority of farmers recognize the potential benefits and perceive the technology as easy to use in the context of rice farming.

Table 1: Descriptive statistics (N=150)

| Dependent variables | | | | |
|---|---|---|---|---|
| | | Min | Max | Mean (SD) |
| VRT | If adopted = 1, 0 otherwise | 0 | 1 | 0.480 (0.501) |
| I – paddy apps | | 0 | 1 | 0.253 (0.436) |
| Independent variables | | | | |
| Individual characteristics | | | | |
| Age | Continuous: in years | 21 | 86 | 49.85 (14.077) |
| Education | 1 = primary and below<br>2 = secondary<br>3 = tertiary | 1 | 3 | 1.793 (0.422) |
| Experience | Continuous: in years | 1 | 51 | 18.507 (12.154) |
| Awareness | Likert scale | 1 | 5 | 3.958 (0.759) |
| Average working per week | Continuous: in hours | 1 | 56 | 18.673 (17.254) |
| Farm factors | | | | |
| Farm income | Continuous: in RM | -3,000 | 236,000 | 14,916.67 (27,298.72) |
| Farm size | Continuous: in hectare | 0.29 | 63.60 | 3.830 (6.133) |
| Off-farm | Binary | 0 | 1 | 0.873 (0.334) |
| Land ownership | Binary | 0 | 1 | 0.587 (0.494) |
| Yield (season/ha) | Continuous: in tonnes | 0 | 424 | 10.819 (35.018) |
| Institutional factors | | | | |
| Access to credit | Likert scale | 1 | 5 | 3.340 (1.073) |
| Access to information | Binary | 0 | 1 | 0.447 (0.499) |

| | | | | |
|---|---|---|---|---|
| Frequencies of extension visits | 1 = none<br>2 = 1-2 times per season<br>3 = 3-4 times per season<br>4 = 4-5 times per season<br>5 = more than 5 times per season | 1 | 5 | 2.473 (1.180) |
| Farmer-to-farmer extension | Binary | 0 | 1 | 0.607 (0.490) |
| Subjective norms | Likert scale | 1 | 5 | 3.813 (0.774) |
| Attributes of technology | | | | |
| PU | Likert scale | 1 | 5 | 3.840 (0.969) |
| PEOU | Likert scale | 1 | 5 | 3.700 (1.002) |

### 4.2 Determinants of IoT Technologies Adoption

Table 2 provides the findings of binary logistic regression analysis on the variables that influence the adoption of IoT technology in rice farming. The Nagelkerke $R^2$ value of 0.440 suggests that the model accounts for 44% of the variability in the adoption of VRT. Furthermore, the Nagelkerke $R^2$ value of 0.481 signifies that the model accounts for 48.1% of the variance in the adoption of the I-paddy application. This study classified the adoption determinants into 4 categories, namely (1) individual characteristics; (2) farm factors; (3) institutional factors; and (4) technology attributes.

#### *4.2.1 Individual Characteristics*

The age, educational background, and years of experience in rice farming do not exert a substantial influence on farmers' decisions to adopt VRT and I-paddy applications. This finding suggests that these demographic factors have a minimal impact on the adoption of IoT technologies in rice farming. In contrast, farmers' awareness of VRT exhibits a positive but marginally significant relationship at the 10% level. This result implies that a higher level of knowledge about VRT has a small positive effect on the probability of its acceptance. Farmers with greater awareness of VRT are slightly more inclined to embrace its implementation, as they possess a deeper understanding of its potential advantages and relevance to their farming methods. Conversely, the level of awareness does not significantly impact the adoption of I-paddy applications among rice farmers.

#### *4.2.2 Farm Factors*

As for farm factors, farm size was not a significant predictor for the adoption of the VRT and I-paddy applications, indicating that the likelihood of IoT technologies adoption is not influenced by the scale of the farming operations. Additionally, variables such as off-farm employment and land ownership did not show significant effects on the adoption of both IoT technologies. This suggests that additional sources of income and land ownership status do not play a major role in influencing farmers' decisions to adopt this specific technology.

The findings reveal a negative correlation at a significance level of 5%, indicating that higher farm income is associated with a lower probability of adopting VRT. This counterintuitive result suggests that wealthier farmers may rely less on precision technology or employ alternative methods to optimize their inputs. Furthermore, the data indicates a positive correlation between yield per season and the likelihood of adopting the I-paddy application, with this correlation being marginally significant at the 10% level. This suggests that higher yields are linked to a greater probability of adopting the I-paddy application, possibly due to the convenience of managing and monitoring agricultural productivity via smartphones.

Moreover, there is a strong and statistically significant correlation between the average working hours of rice farmers and the adoption of both VRT and I-paddy applications. This finding implies that farmers who dedicate more hours per week to their work are more inclined to embrace IoT technologies in rice farming. This inclination is likely driven by their higher level of involvement and commitment to enhancing their farming practices.

*4.2.3. Institutional Factors*

Access to credit demonstrates a significant positive relationship at the 5% level, indicating that improved credit accessibility increases the likelihood of adopting the I-paddy application. In contrast, the availability of credit exhibits a notable inverse correlation at a significance level of 5% in relation to the adoption of VRT. This implies that greater credit accessibility is linked to a reduced probability of adopting VRT. Therefore, it is necessary to conduct further research to comprehend the underlying causes of this unexpected discovery. Next, the frequency of extension visits shows a statistically significant positive correlation at the 5% significance level. Regular extension visits seem to promote the adoption of VRT by equipping farmers with essential information and assistance. The interactions between farmers in the extension program demonstrate a positive and slightly significant correlation at the 10% level. This indicates that peer interactions can have a positive impact on the adoption of the I-paddy application. Furthermore, subjective norms demonstrate a slightly significant positive correlation at the 10% level, suggesting that social pressures or norms have a positive impact on the adoption of the I-paddy application.

However, it was determined that access to information did not have a significant impact on the adoption of both VRT and I-paddy applications. This suggests that although having access to information is generally significant, there are other more significant factors that influence the adoption of IoT technologies in rice farming.

*4.2.4. Attributes of Technology*

The statistical analysis reveals that there is a positive correlation between the PU of VRT and its adoption, although the relationship is only marginally significant at the 10% level. On the other hand, PEOU shows a negative correlation at a significance level of 5%. This suggests that when users perceive VRT as difficult to use, they are less likely to adopt it. However, the results suggest that both PU and PEOU do not have a significant impact on the adoption of the I-paddy application among rice farmers in this study. Consequently, neither PU nor PEOU plays a crucial role in the decision-making process for adopting the I-paddy application.

Table 2: The Antecedents of IoT Technologies Adoption

| Variables | VRT | I – paddy apps |
|---|---|---|
| Age | -0.008 (0.972) | 0.079 (0.778) |
| Education | 0.092 (0.872) | -0.063 (0.929) |
| Experience | -0.105 (0.678) | .0041 (0.897) |
| Awareness | 0.926 (0.074)* | -0.745 (0.174) |
| Farm size (ha) | 0.344 (0.609) | -0.047 (0.941) |
| Farm income (RM) | -0.844 (0.023)** | -0.334 (0.405) |
| Off-farm employment | 0.259 (0.720) | 0.154 (0.905) |
| Land ownership | -0.300 (0.496) | -0.671 (0.186) |
| Yield (per season) | 0.940 (0.341) | 1.415 (0.098)* |
| Average working hour | 0.443 (0.012)** | 0.834 (<0.001)*** |
| Frequencies of extension visits | 0.426 (0.032)** | 0.059 (0.805) |
| Farmer-to-farmer extension | 0.477 (0.219) | 0.497 (0.088)* |
| Access to credit | -0.540 (0.018)** | 0.692 (0.010)*** |
| Access to information | 0.090 (0.864) | 0.577 (0.337) |
| Subjective norms | 0.222 (0.583) | 0.742 (0.074)* |
| PU | 0.542 (0.071)* | -0.248 (0.487) |
| PEOU | -0.690 (0.019)** | -0.334 (0.282) |
| Constant | -4.953 (0.027)** | -5.594 (0.022)** |
| -2 Log likelihood | 147.686 | 110.610 |
| Nagelkerke-$R^2$ | 0.440 | 0.481 |

**5.0 Discussion**

This study identifies several key determinants that significantly influence the adoption of specific IoT technologies in rice farming. These determinants include farmers' awareness, farm income, yield per season per hectare, average working hours, frequency of extension visits, farmer-to-farmer extension, access to credit, subjective norms, PU, and PEOU. Conversely, the adoption of IoT technology in this context appears unaffected by variables such as age, education, farming experience, farm scale, off-farm employment, land ownership, or access to information.

The awareness of farmers regarding the availability and potential benefits of IoT plays a crucial role in influencing technology adoption. This finding aligns with a study conducted in Bahrain, where the implementation of ICT in agriculture, including IoT technologies, was found to be closely linked to the level of awareness and ICT literacy among farmers. The study emphasized that raising awareness and providing education on modern agricultural technologies could significantly increase adoption rates, particularly in regions with lower technological infrastructure (Al-Ammary & Ghanem, 2024). Similarly, Arjune and Kumar (2023) demonstrated that increasing awareness through targeted educational programs can substantially boost the adoption rates of IoT in agriculture highlighting well-informed farmers are more likely to embrace IoT innovations. Interestingly, this study discovered that farm income negatively influences the adoption of IoT technology in rice farming. Farmers with higher incomes often rely on established traditional methods they perceive as effective, thus viewing IoT investments as unnecessary. This resistance to change is supported by Feder et al. (1985), who noted that wealthier farmers might avoid disrupting profitable operations. Additionally, higher incomes can lead to complacency, reducing the urgency to innovate or improve practices, resulting in slower adoption rates for new technologies, including IoT

(Mariano et al., 2012). Furthermore, Nwokoye et al. (2019) suggest that while higher income provides the means to invest in new technologies, it also increases the opportunity cost of experimenting with unproven methods, contributing to reluctance in adopting IoT innovations. the complex dynamics between income levels and technology adoption in agriculture.

Next, the present study shows that higher farm yields significantly influence the adoption of IoT technologies, consistent with the existing body of literature. Farmers with higher farm yields were more likely to adopt IoT to maintain or enhance productivity. For example, a study conducted in Vietnam revealed that smallholder rice farmers with higher seasonal yields were more intent to adopt cleaner production practices to sustain their production levels (Nguyen et al., 2024). Furthermore, the amount of time farmers spend in their fields significantly influences their openness in adopting IoT technologies. This study suggests that farmers with longer working hours are more likely to adopt IoT in rice farming, as the technology can optimize their workload. Consistent with this, a study in China found that farmers who worked more than eight hours a day showed a higher propensity to adopt IoT-enabled precision farming tools to reduce their manual labor (Li et al., 2018).

Based on the findings, the frequencies of extension workers' visits influence the adoption of IoT technology in rice farming significantly. This aligns with the insights drawn from prior studies on the adoption of contemporary rice technologies in the Philippines and the adoption of improved rice technology in Niger State, Nigeria, as reported by Mariano et al. (2012) and Ahmad et al. (2020) respectively. In addition, the results showed that farmer-to-farmer extension had a positive correlation with technology adoption and was considered an efficient approach for technology dissemination, despite the fact that it was not universally measured across studies. The current study also demonstrated that credit accessibility and the adoption of IoT were positively associated. The significance of these economic factors is shown by the research conducted by Day et al. (2022) and Mariano et al. (2012) in investigating modern technology adoption by rice farmers in Bangladesh and the Philippines respectively. Better access to credit facilities empowers farmers to meet the early expenses of adopting new advanced technology and effectively handle financial uncertainties. Moreover, it was shown that social pressure had a crucial role in positively and significantly influencing the adoption of IoT. Empirical evidence shows that farmers who perceived a positive attitude towards IoT adoption within their community were more likely to adopt Green Fertiliser Technology (GFT) in rice cultivation (Adnan et al., 2020).

Finally, the cost of technology and its perceived features, such as its ease of use and comparative benefits, have a substantial influence on decisions about its adoption. Nwokoye et al. (2019) and Sondakh et al. (2023) have observed that the perceived advantages of technology, such as enhanced efficiency and production, are the main factors that encourage its adoption. Nevertheless, the exorbitant expenses might be a significant obstacle, particularly for small-scale farmers who have limited financial capabilities.

## 6.0 Conclusion

The findings of this study provide significant insights into the determinants of IoT technology adoption in rice farming. The study reveals that key factors such as farm income, yield, working hours, and access to resources play crucial roles in influencing farmers' decisions to adopt IoT technologies. Interestingly, while higher farm income might be expected to facilitate technology adoption, this study identifies a negative correlation, suggesting that wealthier farmers may resist adopting IoT due to reliance on established traditional methods. Conversely, higher yields and longer working hours are positively associated with IoT adoption, indicating that productivity concerns and labor intensity drive the need for technological solutions.

Furthermore, the study underscores the importance of institutional support, particularly the frequency of extension visits and farmer-to-farmer interactions, in promoting IoT adoption. Access to credit also emerges as a critical enabler, highlighting the necessity of financial mechanisms that support farmers in overcoming the initial costs of technology adoption. However, variables such as age, education, and farm size do not significantly impact adoption decisions, suggesting that demographic factors may be less influential in this context.

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