Pak. j. life soc. Sci. (2024), 22(2): 18294-18302 E-ISSN: 2221-7630;P-ISSN: 1727-4915

Pakistan Journal of Life and Social Sciences

www.pjlss.edu.pk

https://doi.org/10.57239/PJLSS-2024-22.2.001335

RESEARCH ARTICLE

Determinants of IoT Technology Adoption in Rice Farming: An Empirical Analysis

Nur Aziera Ruslan[1, 2*], Roslina Kamaruddin[1], & Rozana Samah[1]

[1]School Of Economics, Finance and Banking, College Of Business, Universiti Utara Malaysia, Kedah, Malaysia
[2]Faculty of Plantation and Agrotechnology, Universiti Teknologi MARA, Malaysia

ARTICLE INFO

Received: Oct 17, 2024

Accepted: Dec 3, 2024

Keywords

IoT adoption
Variable rate technology
I-paddy applications
Rice farming

***Corresponding Author**

nurazieruslan@gmail.com

ABSTRACT

Integrating Internet of Things (IoT) technologies in rice farming offers significant potential to improve productivity, enhance resource efficiency, and promote precision agriculture. Yet, the uptake among rice farmers is hindered by financial limitations, inadequate infrastructure, and a lack of technical expertise. This study explores the main factors affecting IoT adoption in rice farming, specifically examining variables such as farm income, yield, working hours, and resource accessibility. A cross-sectional survey of 150 rice farmers from major granary areas was conducted using stratified random sampling to ensure a representative sample. Binary logistic regression was used to assess the impact of various factors on IoT adoption. The findings reveal that while increased farm yields and longer working hours positively influence adoption, farm income negatively correlates with IoT usage. Additionally, access to credit and regular extension visits are strong predictors of IoT adoption, emphasizing the importance of financial and institutional support in encouraging technological advancements. In contrast, age, education, and land ownership have little impact on adoption choices. This study presents empirical insights regarding the determinants of IoT adoption in rice farming and offers actionable recommendations for policymakers to overcome barriers and harness critical factors, thus promoting productivity and sustainability in agriculture.

1. INTRODUCTION

The incorporation of IoT technology in agriculture, particularly in rice farming, marks a significant advancement in modern farming practices. IoT adoption has the potential to revolutionize rice production by optimizing resource management, enhancing productivity, and enabling precision farming techniques (Jayashankar et al., 2018; Dlodlo & Kalezhi, 2015). These innovations provide farmers with real-time insights into soil conditions, weather, and crop health, allowing for informed decision-making and improved overall farm management (Patil & Kale, 2016; Wolfert et al., 2017). As global food demand rises, the integration of IoT in agriculture is increasingly viewed as essential for sustainable farming and food security. In Malaysia, there is a growing trend to adopt cutting-edge technologies in rice farming, particularly IoT, which drives improvements in agricultural efficiency, sustainability, and productivity despite challenges like the aging farmer population, limited resources, and small farm sizes. However, farmers' awareness of IoT technologies in Malaysia is moderate at best. A significant obstacle they face when implementing these technologies is the lack of resources, including financial support and access to technology (Tarmizi et al., 2020). Additionally, inadequate infrastructure and connectivity present major challenges in rural areas where rice farming is widespread. Poor network coverage and unreliable internet access hinder the effective transfer of data from IoT devices to centralized systems for analysis and decision-making. Without reliable resources and connections, farmers may find it difficult to acquire timely information and insights essential for improving farming practices, monitoring crop health, and managing risk efficiently. Moreover, the high costs of implementing IoT, including purchasing devices, maintenance, and data management, place extra financial strain on small-scale farmers, who often have limited capital. These problems are worsened by a lack of technical expertise among farmers, which limits their ability to fully exploit IoT technologies and integrate them into their existing practices. This study aims to enrich the existing literature by investigating how factors like farm income, crop yield, working hours, and resource accessibility influence rice farmers' decisions to adopt IoT technologies. Ultimately, the research intends to guide the formulation of policies and interventions that can facilitate the widespread implementation of IoT technologies, thus enhancing the productivity, sustainability, and profitability of rice farming.

LITERATURE REVIEW

Economists, researchers, and agricultural technology experts are keen to understand adoption behaviors. Loevinsohn et al. (2013) found that adopting new technology is shaped by a dynamic interplay between the technology itself and the contextual factors affecting its acceptance. To assess the elements that spur growth and to assist those engaged in technology development and dissemination, economists need to understand the variables that influence the adoption of agricultural technology.

In Ethiopia, research by Melesse (2018) identified three main drivers of advanced technology adoption in agriculture: (1) Demographic characteristics, such as gender preferences among farmers; older individuals with traditional experience and younger farmers employ different methods for integrating new technology into farming; (2) Socio-economic factors encompass the farmers' education level, land ownership types, access to inputs, labor resources, and farm size; (3) Institutional elements refer to services enhancing agricultural efficiency, including financial services, insurance, information dissemination, infrastructure, market access, and agricultural extension programs.

Moreover, previous studies have primarily focused on understanding technology adoption through individual traits and capabilities, limited information, perceived risks and uncertainties, institutional challenges, input accessibility, and infrastructure (Mwangi & Kariuki, 2015; Ruttan, 2010; Uaiene & Arndt, 2009). A recent analysis also explored how social networks and educational background influence technology adoption (Uaiene & Arndt, 2009). Different studies categorize the factors affecting technology adoption variably. For instance, Akudugu et al. (2012) categorized the factors into institutional, social, and economic aspects, whereas Kebede et al. (1990) identified them as economic, physiological, and social elements. Additionally, McNamara et al. (1991) structured components in terms of farmer-related, farm structure, organizational, and leadership aspects, while Wu and Babcock (1998) analyzed them as human capital and productivity.

Furthermore, Kinyangi (2014) identified critical factors affecting advanced technology adoption and agricultural productivity among small-scale farmers in Kakamega district, Kenya. These factors include credit access, human resource training programs, agricultural extension policies, market size, education level, gender, and age. In Nerica, Ghana, factors positively influencing the adoption of advanced technology in rice farming were identified as farm size, credit access, farm training, ownership of machines, tools, equipment, and household labor. Conversely, age and profit orientation were found to hinder advanced technology adoption in rice cultivation (Udimal et al., 2017).

The factors influencing technology acceptance may vary depending on the geographical context, researcher perspectives, and customer needs (Bonabana-Wabbi, 2002). For instance, while some scholars might classify educational background as human capital, others may regard it as a personal trait. Accordingly, this study seeks to examine the various determinants, including individual, farm, institutional, and technology-related attributes, that influence the adoption of IoT technology in rice production. Through a thorough investigation of each element, this study aims to deepen understanding of the impact these factors have on the incorporation of IoT technology in rice farming.

METHODS

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).

RESULT

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 an 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 an 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 an 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 2 = secondary 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 2 = 1-2 times per season 3 = 3-4 times per season 4 = 4-5 times per season 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)

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 four categories, namely (1) individual characteristics; (2) farm factors; (3) institutional factors; and (4) technology attributes.

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.

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.

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% with 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, other more significant factors influence the adoption of IoT technologies in rice farming.

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

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, suggesting 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 (Kendall et al., 2022).

Based on the findings, the frequencies of extension workers' visits significantly influence IoT technology adoption in rice farming. 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 even though 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.

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.

ACKNOWLEDGMENTS

This research was supported by the Ministry of Higher Education (MoHE) Malaysia through the Long Run Research Grant Scheme (LRGS/1/2019/UPM/01/2/4).

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