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Determinants of Farmers' Willingness to Pay for IoT Adoption in Rice Farming: Evidence from Malaysia

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ABSTRACT

Rice farming faces persistent challenges that constrain productivity and sustainability, underscoring the urgent need for digital innovations such as the Internet of Things (IoT). While IoT technologies offer the potential for efficiency and resilience, their adoption depends on farmers' willingness to pay (WTP), which remains poorly understood in resource-constrained contexts. This study aimed to identify the determinants of WTP for IoT adoption by integrating farmer-related, technological, and institutional factors. A structured survey was conducted among 229 rice farmers in the Integrated Agricultural Development Area, Barat Laut Selangor, Malaysia. The findings revealed that most farmers demonstrated moderate IoT awareness, with the awareness index highlighting gaps in technical knowledge and training. The IoT readiness index recorded relatively high scores for shared infrastructure (71.8) and Internet connectivity (71.6) but lower levels for technical support (60.0) and energy supply (54.4), reflecting uneven preparedness. Logistic regression results indicated that higher-income farmers were significantly more likely to invest, with middle- and high-income groups showing 20.13% and 22.45% higher probabilities, respectively. Secure land tenure increased WTP by 3.18%, while each additional year of age reduced WTP by 0.61%. IoT infrastructural readiness raised WTP by 10.53%, and perceived ease of use increased WTP by 8.27%. However, perceived usefulness exhibited a negative marginal effect, suggesting that recognising IoT's benefits does not necessarily translate into WTP when financial or institutional barriers persist. The findings indicate that financial support, reliable IoT infrastructure, and practical training are crucial to fostering inclusive IoT adoption and enhancing resilience in rice farming.

Keywords: Internet of Things, willingness to pay, rice farming, technology adoption, digital agriculture.

INTRODUCTION

Rice remains the main food source for billions of people worldwide. Asia dominates the sector, producing and consuming more than 90% of the world's rice supply (Omar et al., 2019; Fahad et al., 2018). In Malaysia, rice plays a critical role not only as a food security crop but also as an economic lifeline for rural households. Around 40% of farmers rely heavily on paddy cultivation for their livelihoods (Dorairaj & Govender, 2023). Yet, the sector continues to grapple with long-standing structural and environmental challenges. Rice yields have shown minimal improvement for decades, and the ageing farmer population raises critical concerns regarding generational continuity and labour availability. Challenges such as pest outbreaks, crop diseases, unpredictable weather, and resource inefficiency have compounded these issues. In 2023, the national rice self-sufficiency level (SSL) declined to 56.2%, far below the target of 75–80% outlined in the National Agrofood Policy 2021–2030 (NAP 2.0). This decline has increased dependence on imports and exposed the country to fluctuations in global grain markets. Collectively, these realities highlight the need for technology-driven solutions that can boost productivity and strengthen resilience in rice farming.

The Fourth Industrial Revolution (4IR) has introduced a range of digital tools capable of transforming the agricultural industry, with the Internet of Things (IoT) recognised as a leading driver of "smart farming." According to Patil and Kale (2016) and Sicari et al. (2015), IoT systems are defined as integrated sensors, devices, communication networks, and data platforms. These systems allow farmers to monitor farm conditions in real-time, automate processes, and make precise as well as evidence-based decisions. The adoption of IoT technologies provides measurable benefits that can enhance rice farming practices. For example, smart irrigation systems deliver water more efficiently by matching crop needs, while soil and climate monitoring improve the accuracy of fertiliser application. Additionally, IoT-based monitoring enables early detection of pests and diseases, allowing timely interventions to minimise yield losses (Alfred et al., 2021). Predictive analytics further enhances decision-making by providing accurate yield estimates that support rice farmers and policymakers in planning for food security (Phupattanasilp & Tong, 2019). These innovations demonstrate how IoT can modernise rice production to ensure greater resilience, efficiency, and long-term sustainability.

Malaysia has made notable progress in integrating IoT technologies into rice farming as part of efforts to modernise the agricultural sector. These innovations aim to boost productivity, optimise resource use, and promote data-driven decision-making. A recent IoT application involves soil sensors that monitor moisture, temperature, and pH levels in real time. The data generated allows for precise irrigation scheduling and nutrient management, conserving resources while maintaining crop health (Bamurigire et al., 2020). Additionally, the integration of wireless sensor and actuator networks (WSAN) with cloud computing platforms in automated irrigation systems enables watering schedules based on soil conditions and weather forecasts. This method reduces uncertainty, improves water-use efficiency, and reduces reliance on manual labour (Zhang et al., 2025; Ali et al., 2025). Remote sensing and drone-assisted monitoring equipped with multispectral imaging support quick field assessments. These tools detect early signs of crop stress, nutrient deficiencies, and pest outbreaks to prevent rice yield loss (Tripicchio et al., 2014; Athirah et al., 2020). Furthermore, IoT-enabled pest-surveillance systems that utilise digital traps and image-recognition technologies enhance crop protection (Najib & Mustika, 2022). Finally, integrating cloud-based platforms with mobile applications streams data to a dashboard that offers agronomic insights and supports timely interventions (Navarro et al., 2020; Sambas et al., 2023).

Despite these advancements, the adoption of IoT technologies among rice farmers remains relatively low. Several barriers continue to hinder widespread adoption, including inadequate energy infrastructure, weak Internet connectivity in rural areas, high initial and maintenance costs, and limited technical expertise among smallholder farmers (Saili et al., 2024). Moreover, the economic dimension of adoption, specifically farmers' willingness to pay (WTP) for IoT technology, remains underexplored, even though it represents a critical indicator of whether farmers perceive IoT as a viable and sustainable investment. Perceptions of usefulness, ease of use, and compatibility with traditional practices, along with socioeconomic factors such as income, land tenure security, and access to credit, further influence farmers' WTP to adopt IoT technologies in rice farming (Ruslan et al., 2024). The adoption of IoT technologies in rice farming is likely to remain uneven unless these structural, financial, and perceptual barriers are systematically addressed. This unevenness risks widening the digital divide, favouring large producers and leaving smallholders behind. Consequently, the potential of digital agriculture to effect meaningful change is constrained by disparities in IoT adoption, reflecting the limitations of existing technology adoption models in fully explaining the complex and context-specific patterns of technology diffusion in resource-limited farming systems.

Given these challenges, there is an urgent need to understand the conditions under which rice farmers are willing to invest in IoT technologies. While IoT promises to enhance farm efficiency, productivity, and resilience, adoption is still constrained by financial, infrastructural, and perceptual barriers that remain insufficiently addressed in existing research, particularly in developing countries such as Malaysia. Specifically, WTP for IoT reflects not only farmers' perceptions of its potential benefits but also their capacity to allocate resources and manage risk. Therefore, this study seeks to investigate the determinants influencing farmers' WTP for IoT adoption in rice farming by integrating farmer-related, technological, and institutional dimensions within a unified framework. The findings aim to provide empirical evidence to inform policy and practice, promoting inclusive and sustainable digital transformation in Malaysia's rice sector.

RELATED WORKS

The empirical literature on WTP for the adoption of agricultural IoT technologies offers valuable insights into the complex and context-specific factors shaping farmers' decision-making processes. This section provides a comprehensive discussion by drawing on prior studies across various agricultural technologies.

Empirical Review on WTP for IoT Technology Adoption in Agriculture

Technology adoption in agriculture is influenced by social, economic, and perceptual factors (Feder et al., 1985; Knowler & Bradshaw, 2007; Minh et al., 2022). These three concepts are central to this study. Technology adoption refers to the process by which farmers decide whether to adopt or reject new practices or technological innovations (Rogers, 1995; Tao et al., 2023). Meanwhile, Shamshiri et al. (2024) defined digital agriculture as the use of advanced technologies such as sensors, robotics, and data analysis to improve the environmental and economic sustainability of farming, as well as increasing crop yield and quality. The WTP is the maximum amount of money farmers are willing to invest in technologies and innovations that reflect how they balance costs against perceived benefits (Hanemann, 1991). These concepts offer insight into how rice farmers assess agricultural technologies in their paddy fields.

Research indicates that the farmer-related factor is the key determinant of WTP. Factors such as farm size and income significantly impact WTP across various empirical studies (Paudel et al., 2019; Anugwa et al., 2022; Kahwai et al., 2021). Evidence from Luangchosiri et al. (2025) highlighted that education, land ownership, and debt shape farmers' investment decisions, while cultivation area influences the amount they are willing to invest in solar water pumping (SWP) systems. Larger farms enable producers to spread production risks and distribute costs over greater output. This scalability reduces the marginal cost of technology adoption and enhances the feasibility of implementing IoT-based irrigation and monitoring systems. Moreover, farmers' income is an important determinant, as higher earnings provide financial flexibility to meet the upfront and recurring costs associated with digital agriculture, such as internet services, repairs, maintenance, and infrastructure upgrades. Wealthier farmers are generally more resilient to financial uncertainty, which strengthens their confidence in adopting new technologies. In contrast, smallholders often face narrow profit margins and limited access to credit, constraining their ability to invest in costly or untested technologies. Consequently, resource disparities function not only as enablers but also as barriers to adoption, determining who can capture the benefits of technological change in agriculture (Munthali et al., 2025; Adam & Abdulai, 2023)

Demographic characteristics such as age and farming experience are identified as key determinants of farmers' WTP to adopt IoT technology in agriculture. Younger farmers were usually more open to innovation, as their adaptability and willingness to experiment with new practices (Anugwa et al., 2022; Kahwai et al., 2021). Yet, in some studies, age is not a key predictor, suggesting that broader socioeconomic factors and access to resources may play a greater role (Alhassan, 2012; Onugo & Onyeneke, 2022). Next, farming experience shows mixed effects on farmers' WTP for IoT adoption. Studies such as Minh et al. (2022) and Tao et al. (2023) found that experience enhances awareness and decision-making but may also lead to caution toward unfamiliar technologies. Its influence largely depends on contextual factors, including technology type, farm size, and access to training or support services. Besides, awareness is frequently highlighted as a key influence on technology adoption, as it improves farmers' understanding of both the potential benefits and risks of new technologies (Minh et al., 2022; Onugo & Onyeneke, 2022). Greater awareness not only stimulates interest but also reduces uncertainty and makes farmers more open to experimenting with innovations.

Next, institutional support is widely recognised as a critical factor influencing farmers' WTP for IoT technology adoption in agriculture across various empirical studies. Access to credit is particularly important as it reduces financial barriers and provides farmers with the resources needed to cover initial as well as maintenance costs of digital innovations. Studies show that when farmers have reliable access to credit, they are more confident in making investments that may otherwise seem too risky or expensive (Paudel et al., 2019; Anugwa et al., 2022). Farmer-to-farmer extension, including peer sharing, farmer networks, and group learning, also plays a crucial role by building trust and reducing uncertainty. It lets farmers seek advice, observe demonstrations, and learn from peers' practical experience. These interactions drive technology appraisal and informed decision-making by providing context-rich evidence and success stories that reduce perceived adoption barriers (Kahwai et al., 2021; Onugo & Onyeneke, 2022). In addition, access to accurate and timely information further enhances farmers' awareness and promotes technology adoption. Minh et al. (2022) showed that better access to information increases farmers' confidence and willingness to invest. Diallo & Ronald Dossou-Yovo (2024) found that male rice farmers' WTP for climate information services was influenced mainly by access to training and radio, whereas rice farming experience and social organisation membership were the key determinants of WTP among female rice farmers in Mali. Likewise, Mangole et al. (2026) reported that institutional variables and digital literacy particularly shape farmers' WTP for a mobile app-based extension platform. Overall, credit, extension, training, and information create an enabling environment that lowers barriers as well as supports the sustained integration of IoT technology in rice farming. These institutional supports bridge the gap between willingness and actual adoption, making them essential for digital transformation in agriculture.

Besides, technological factors are increasingly recognised as important drivers in measuring WTP for the adoption of IoT technology. In technology adoption studies, perceived usefulness and ease of use remain the central predictors of behavioural intention and WTP (Li et al., 2023). When farmers view IoT systems as practical, reliable, and easy to apply, they are more likely to invest. Moreover, IoT facilities and infrastructure readiness also play a critical role. Stable electricity, reliable internet connectivity, as well as accessible technical support are essential conditions for IoT adoption, yet these infrastructural elements remain underexplored in much of the literature. A recent empirical study indicates that training and access to reliable information further strengthen farmers' decisions to adopt and pay for IoT technology. Jabbari et al. (2023) found that targeted awareness programmes and farmer training significantly enhanced IoT adoption. This finding highlights the importance of integrating perceptual and infrastructural readiness with demographic, economic, and institutional determinants to comprehensively explain farmers' WTP to adopt IoT technology in rice farming. Table 1 presents a comparative review of selected empirical studies, summarising key determinants and highlighting research gaps with broader implications across different agricultural technologies.

Table 1

Review of Related Literature

Author(s)	Type of technology studied	Objectives of the study	Key determinants measured	Research gap
Alhassan (2012)	Improved irrigation service (Bontanga scheme, Ghana)	To estimate farmers' WTP for an improved irrigation scheme	Age, education, farming experience, land ownership, plot size, and access to credit	Perceptual factors (ease of use, risk) and informational access were not examined; single scheme context
Masud et al. (2015)	Conservation farming and pollution-control measures (Bangladesh)	To access WTP for environmentally friendly farm practices	Education, farm income, and environmental awareness	Institutional enablers (credit, extension) omitted; awareness treated only as a binary dummy
Paudel et al. (2019)	Scale-appropriate mechanisation (mid-hills, Nepal)	To analyse smallholders' WTP for two-wheel tractors and attachments	Farm size, household income, land ownership, access to credit	No perceptual or infrastructural variables; restricted to mechanisation tools
Shee et al. (2020)	Mobile phone-based digital extension platform (Kenya and Tanzania)	To examine how interactive SMS advice affects the adoption of good agronomic practices	Education, participation in extension groups, and frequency of SMS use	Income, farm size, and liquidity constraints are not modelled; short evaluation horizon

(continued)

Author(s)	Type of technology studied	Objectives of the study	Key determinants measured	Research gap
Anugwa et al. (2022)	Climate-smart rice technologies (Nigeria)	To elicit farmers' preferences and WTP for alternate wetting and drying (AWD)	Age, education, climate-change awareness, farm size, income, extension contact, and credit access	Grid electricity and Internet coverage were ignored; technology-use perceptions were not captured
Kahwai et al. (2021)	Hexanal spray for banana shelf-life extension (Meru Country, Kenya)	To measure WTP for hexanal formulation technology among banana farmers	Age, household income, prior awareness of hexanal, and farm size	Institutional variables (credit, extension) and infrastructure readiness were not included
Minh et al. (2022)	IoT sensors in the swiflet-house environment control (Vietnam)	To identify factors driving WTP for IoT packages in niche farming	Education, farming experience, awareness, off-farm income, and access to information	Highly context-specific; electricity/internet reliability not measured
Onugo and Onyeneke (2022)	Climate-smart rice varieties (Nigeria)	To analyse the determinants of WTP for drought-tolerant varieties	Age, education, awareness level, farm size, income, extension visits, information access	Physical infrastructure and potential scepticism despite awareness have not been analysed
Jabbari et al. (2023)	Smart IoT technologies (Jizan, Saudi Arabia)	To assess how awareness, training and information influence technology adoption	Awareness, hands-on training hours, and information access	Credit, land size, and other structural constraints were excluded; the study was based on stated intention
Tao et al. (2023)	Smart irrigation (drip and sensor package) (Hebei, China)	To estimate farmers' WTP and adoption drivers for sensor-controlled drip systems	Age, education, farming experience, farm size, land-tenure security	Ease of use perceptions and social influence variables were missing; the irrigation-specific focus
Diallo and Ronald Dossou-Yovo (2024)	Climate information services (CIS) (Mali)	To identify the main barriers and factors influencing farmers' uptake of CIS from a gender perspective	Training access, radio access, experience, social organisation membership, irrigation access, remittances, stored seeds, household food stress	Broader farmer-related, technological, and institutional determinants of farm-level IoT adoption were not analysed

(continued)

Author(s)	Type of technology studied	Objectives of the study	Key determinants measured	Research gap
Idris and Zulkifli (2024)	Smart farming technology (Melaka, Malaysia)	To assess farmers' knowledge, attitude, and practices regarding smart farming technologies in paddy production	Knowledge, attitude, practice, age, education level, exposure to smart farming tools	Did not examine how infrastructural readiness, institutional support, and technology perceptions jointly shape investment decisions
Saili et al. (2024)	Smart farming technology (IADA BLS, Malaysia)	To explore the challenges and adoption factors of smart farming among paddy farmers	Awareness, engagement, perceived usefulness, attitudes, and limited exposure to technology	Did not test an integrated empirical model linking farmer, technological, and institutional components
Luangchosiri et al. (2025)	Solar water pumping (SWP) system (Thailand)	To identify factors affecting farmers'willingness to invest in SWP systems and estimate WTP	Gender, education, source of income, debt amount, land ownership, knowledge, cultivation area	Infrastructural readiness, information access, and technological perceptions were not assessed
Osrof et al. (2025)	Smart farming technologies (Malaysia)	To examine farmers' readiness and intention to adopt smart farming technologies	Perceived efficiency, facilitating conditions, financial incentives, perceived cost, complexity, uncertainty	Did not integrate institutional variables such as credit access, information access, and peer extension into a unified valuation framework
Omar et al. (2025)	Smart farming technologies (Malaysia)	To identify factors influencing the adoption of smart farming technologies	Labour shortage, cost savings, time flexibility, awareness and education campaigns, government support	Did not quantify WTP and test the combined effects of socioeconomic, technological, and institutional determinants
Mangole et al. (2026)	Farmbetter mobile app-based digital agricultural extension (Tanzania and Burkina Faso)	To estimate farmers' WTP for a mobile app-based system and identify its main drivers	Socioeconomic characteristics, institutional variables, farm-related stress, digital literacy, smartphone access, and use of digital tools	Gender-specific differences were not analysed in depth, and infrastructural readiness and Technology Acceptance Model (TAM)-related perception were not central to the model

Across the reviewed studies, diverse technologies were investigated, including irrigation services (Alhassan, 2012; Tao et al., 2023; Luangchosiri et al., 2025), mechanisation (Paudel et al., 2019), and IoT applications (Shee et al., 2020; Minh et al., 2022; Jabbari et al., 2023; Mangole et al., 2026). The majority of studies investigated demographic and socioeconomic variables such as age, education, farm size, farming experience, land ownership, and household income. Education, farm size, and income consistently emerged as key determinants across the reviewed literature. In contrast, perceptual factors such as ease of use, perceived risk, and social influence received limited attention. Similarly, infrastructural readiness, particularly the availability of electricity and internet connectivity, was rarely addressed, despite being critical for the effective adoption of digital and IoT technologies. The research gaps identified in these studies highlight an uneven focus in the existing literature, where institutional support, perceptual considerations, and infrastructural readiness remain underexplored dimensions when assessing farmers' WTP for IoT technology adoption in agriculture.

Evidence from comparative studies suggests that demographic and socioeconomic variables alone provide only a partial explanation of farmers' WTP for IoT adoption. Although factors such as education level, age, and farm size were found to be associated with WTP, their explanatory power diminishes when perceptions, awareness, and enabling conditions are excluded. Shee et al. (2020) emphasised the significance of participation in extension groups and the dissemination of information, while Jabbari et al. (2023) identified training and access to information as crucial drivers. However, both studies overlooked structural barriers, such as limited access to credit and insecure land tenure. Similarly, Minh et al. (2022) and Tao et al. (2023) demonstrated the potential of IoT and sensor technologies, but their limited study contexts failed to address how infrastructural weaknesses and trust in agricultural digital innovations affect broader scalability. Overall, this body of empirical evidence reveals a consistent tendency to prioritise measurable variables, while technological components and institutional conditions remain underexplored.

This literature review identified three critical gaps. First, while digital innovations in agriculture have grown rapidly, the adoption of IoT technology in rice farming remains insufficiently explored, despite rice being vital to Malaysia's food security agenda. This gap is especially evident in Malaysia, where the majority of studies have focused more on smart farming technologies and have examined knowledge, attitudes, practices, and adoption challenges rather than on farmers' monetary valuation or WTP for IoT-based technologies (Idris & Zulkifli, 2024; Saili et al., 2024; Osrof et al., 2025; Omar et al., 2025). Second, there has been limited attention given to the IoT infrastructural readiness, encompassing internet connectivity, reliable electricity, as well as technical support. These elements are particularly crucial for the effective integration of IoT technology (Wolfert et al., 2017). Third, factors like IoT awareness, perceived usefulness, and ease of use were often underexplored in WTP studies. It is important to recognise that IoT awareness alone does not ensure farmers' WTP, especially when they have concerns regarding cost, risk, and technological complexity (Venkatesh et al., 2012; Rezaei-Moghaddam & Salehi, 2010).

Accordingly, this study seeks to bridge these gaps by integrating farmer-related, technological, and institutional determinants into a unified framework to measure farmers' WTP to adopt IoT technology in rice farming. Unlike previous studies that examined these factors separately, this study adopts a holistic approach, considering how resources, institutional support, and technological readiness collectively influence WTP. The focus is on rice farmers in the Integrated Agricultural Development Area, Barat Laut Selangor (IADA BLS), one of Malaysia's key granary regions. This research provides context-specific empirical evidence in a field where data remain limited. The findings are expected to inform policy and practice aimed at promoting inclusive and sustainable IoT adoption, enabling both smallholders and resource-rich farmers to benefit from the transformative potential of digital agriculture (Carolan, 2020).

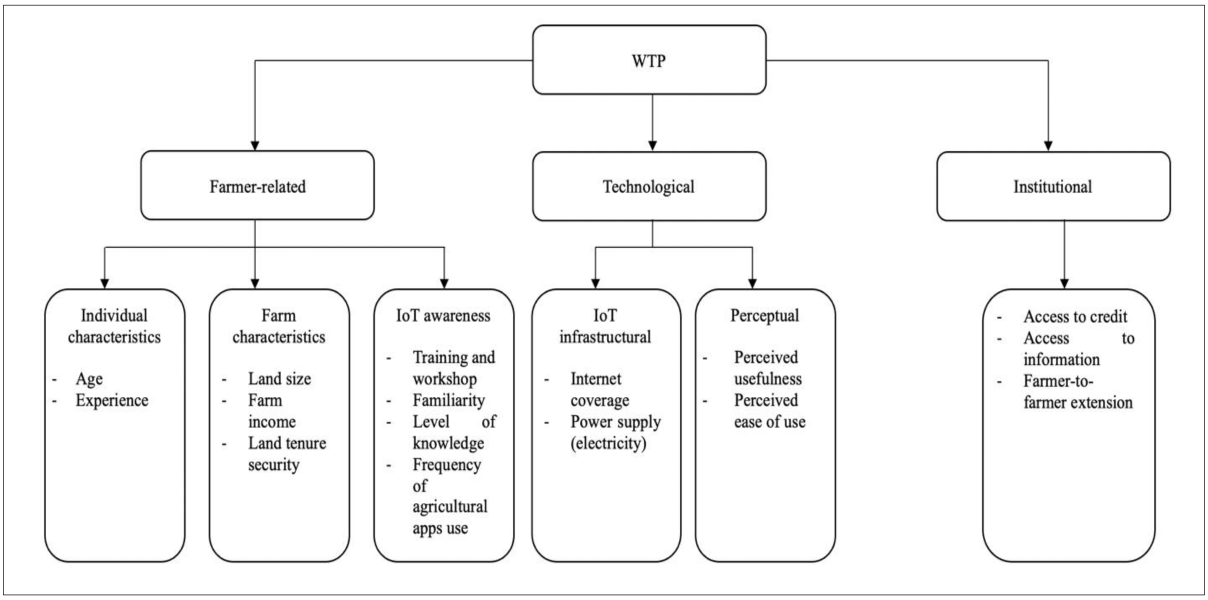
THE METHODOLOGY

Conceptual and Methodological Framework

The framework and empirical model, illustrated in Figure 1, were developed in response to gaps identified in previous literature, particularly the underrepresentation of farmer-related, infrastructural, and institutional dimensions in prior studies on WTP for agricultural technology adoption (Shee et al., 2020; Minh et al., 2022; Tao et al., 2023). This integrated structure enables the model to capture the combined effects of farmers' demographic and socioeconomic characteristics, technological readiness and perceptions, as well as institutional support systems in shaping WTP decisions. The farmer-related dimension includes individual and farm-level characteristics that influence farmers' decision-making behaviour and capacity to invest in new technologies. Variables such as age, farming experience, farm size, income, and land tenure security represent the socioeconomic and resource-based factors shaping WTP for IoT adoption. Previous research has shown that these attributes play a significant role in determining farmers' attitudes and responsiveness to agricultural innovations (Paudel et al., 2019). However, demographic and economic factors alone do not sufficiently explain technology adoption behaviour when cognitive elements are excluded. To address this, IoT awareness measured through participation in training programmes, familiarity with IoT, level of knowledge, and frequency of agricultural application use was incorporated to reflect farmers' cognitive readiness and exposure to digital technologies (Onugo & Onyeneke, 2022; Jabbari et al., 2023).

Figure 1

The Research Framework



Next, the technological dimension encompasses both infrastructural and perceptual factors that influence farmers' ability and WTP for IoT adoption. Infrastructural readiness captures the physical and technical resources that enable IoT integration in rice farming, including internet accessibility, reliable electricity supply, and availability of technical support. These elements are essential for ensuring the functionality and sustainability of IoT systems (Wolfert et al., 2017; Minh et al., 2022). Without adequate IoT infrastructure, even farmers with high awareness and positive attitudes toward technology may face adoption barriers. On the other hand, the perceptual component draws from the Technology Acceptance Model (TAM) developed by Davis (1989) and later extended by Venkatesh et al. (2012), which posits that perceived usefulness and perceived ease of use shape users' acceptance and behavioural intention to adopt and invest in technology. Integrating infrastructural and perceptual components allows the framework to account for both the practical feasibility and psychological readiness necessary for effective IoT adoption.

Finally, the institutional dimension encompasses the structural and social support mechanisms that enable farmers to engage effectively with IoT-based agricultural technologies. This dimension reflects the broader enabling environment influencing farmers' decision-making capacity through key variables such as access to credit, access to information, and participation in farmer-to-farmer extension activities. Empirical evidence indicates that institutional enablers play a crucial role in mitigating risk perceptions, improving knowledge sharing, and fostering collective learning, all of which enhance farmers' WTP for adopting agricultural technologies (Shee et al., 2020; Anugwa et al., 2022). The inclusion of institutional factors acknowledges that IoT adoption is influenced not only by individual preferences and technological attributes but also by external support systems and social structures that empower farmers to make well-informed and confident investment decisions. All variables identified under these three dimensions were operationalised through the survey instrument, which is discussed in the following section. A binary logistic regression model was employed to estimate the probability of farmers' WTP for IoT adoption across the identified determinants. This analytical approach directly corresponds to the relationships specified in the research framework, translating theoretical constructs into measurable variables for empirical analysis.

Research Design

This study employed a quantitative survey design to investigate the determinants of farmers' WTP to adopt IoT technologies in rice farming. Data were collected using a structured questionnaire adapted from validated constructs in prior studies on WTP for agricultural technology adoption (Tao et al., 2023; Blasch et al., 2022; Anugwa et al., 2022; Venkatesh et al., 2003). The instrument comprised four sections. Section A captured farmer-related characteristics, including age, farming experience, income, farm size, and IoT awareness. Section B focused on technological factors, particularly infrastructural readiness, including internet access, device reliability, and electricity supply, as well as perceptual attributes. Section C assessed the institutional environment, focusing on access to credit, access to information, and peer influence. Section D measured farmers' WTP for IoT adoption using binary (Yes/No) options. Constructs were rated on five-point Likert scales, while demographic information was obtained through open-ended questions. A pilot test involving 30 farmers demonstrated strong reliability, with Cronbach's alpha values exceeding the 0.70 threshold, confirming the instrument's internal consistency and contextual suitability.

Study Area and Sampling

The study was conducted among rice farmers in the IADA BLS, one of Malaysia's principal granary regions located on the northwestern coast of Selangor. The area makes a substantial contribution to national rice self-sufficiency and food security, covering 18,800 hectares of irrigated land divided into nine irrigation blocks. There are 23,614 registered land lots cultivated by 7,366 rice farmers. IADA BLS operates under an integrated irrigation system managed by the Department of Irrigation and Drainage (JPS), in collaboration with the Department of Agriculture (DOA) and IADA authorities (Dorairaj & Govender, 2023). The strong institutional framework and infrastructural support make this area ideal for examining WTP for IoT adoption in rice farming. Data were collected between December 2024 and March 2025, coinciding with the main harvest and off-season preparation periods, when farmers typically make key decisions regarding technology integration. A total of 229 rice farmers were selected using proportionate sampling, ensuring balanced representation across the irrigation blocks.

Data Analysis

The collected data were analysed using Stata version 17, a statistical software commonly used in agricultural economics. Descriptive statistics were employed to profile farmers' socioeconomic characteristics, IoT awareness, and infrastructural readiness, thereby identifying variations across the sample. Understanding these variations is critical for explaining disparities in WTP for IoT technology adoption in rice farming. Subsequently, a binary logistic regression model was used to identify the factors influencing farmers' WTP for IoT adoption, as the dependent variable was dichotomous. The probability that a farmer is willing to pay for IoT technology adoption is given by Equation 1.

$$P_i = \Pr(WTP_i = 1 | X_i) = \frac{\exp(\eta_i)}{1+\exp(\eta_i)} \tag{1}$$

$$\text{where } \eta_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki}$$

where:
P_i = probability of farmer *i* is willing to pay for IoT adoption (WTP = 1)
η_i = linear predictor combining explanatory variables for farmer *i*
β_0 = constant (intercept term)
$\beta_1, \beta_2, \ldots, \beta_k$ = estimated coefficients for explanatory variables
$X_{1i}, X_{2i}, \ldots, X_{ki}$ = explanatory variables representing socioeconomic, technological, and institutional factors

This functional form shows how the likelihood of WTP depends on a combination of explanatory variables. Equation 2 shows the full estimation model for this study.

$$\text{logit}(P_i) = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 AGE_i + \beta_2 EXP_i + \beta_3 LSIZE_i + \beta_4 INC_{Mi} + \beta_5 INC_{Hi} + \beta_6 LANDTEN_i + \beta_7 APPS_i + \beta_8 CREDIT_i + \beta_9 INFO_i + \beta_{10} EXT_i + \beta_{11} AWARE_i + \beta_{12} READY_i + \beta_{13} PU_i + \beta_{14} PEOU_i + \varepsilon_i \tag{2}$$

where:
$\text{logit}(P_i) = \ln\left(\frac{P_i}{1-P_i}\right)$ = log-odds of WTP for the adoption of IoT technology
P_i = probability that farmer *i* is willing to pay for IoT technology adoption (Yes = 1, No = 0)
β_0 = constant (intercept term)
$\beta_1, \ldots, \beta_{14}$ = estimated coefficients for explanatory variables

Table 2 presents the definitions, measurements, and hypothesised relationships of the variables used in the study.

Table 2

Definition, Measurement, and Hypothesised Relationship of Variables

Variables	Definition and unit of measurement	Expected sign	Literature
Dependent variable			
WTP	WTP for the adoption of IoT technologies in rice cultivation (Yes = 1, No = 0)		
Socio-demographic factors			
Age	Farmers' age (years)	-	Alhassan (2012)
Experience	Farmers' experience in rice farming (years)	+	Tao et al. (2023), Alhassan (2012)
Land size	Farmers' area of paddy field (hectares)	+	Onugo and Onyeneke (2022), Kahwai et al. (2021)
Farm income	Farmers' annual farm income (RM)	+	Anugwa et al. (2022), Masud et al. (2015)
Land tenure security	If the land is owned by the farmer (Yes = 1, No = 0)	+	Paudel et al. (2019)
Applications usage	Frequency of agricultural apps use (Likert scale)	+	Tao et al. (2023)
IoT awareness	Farmers' awareness of the availability of IoT technology in rice farming (Likert scale)	+	Paudel et al. (2019)
Technological factors			
IoT infrastructural readiness	Current access to IoT facilities and infrastructures in paddy fields (Likert scale)	+	Minh et al. (2022)
Perceived usefulness	Farmers perceive IoT technology as useful (Yes = 1, No = 0)	+	Davis (1989)
Perceived ease of use	Farmers perceive IoT technology as user-friendly (Yes = 1, No = 0)	+	Venkatesh et al. (2003)
Institutional factors			
Access to credit	If the farmer has access to credit (Yes = 1, No = 0)	+	Anugwa et al. (2022), Kahwai et al. (2021)
Access to information	If the farmer has access to information (Yes = 1, No = 0)	+	Onugo and Onyeneke (2022)
Farmer-to-farmer extension	Involvement in the farmer-to-farmer extension services (Yes = 1, No = 0)	+	Kahwai et al. (2021)

Additionally, marginal effects were calculated to convert the estimated coefficients into percentage changes in predicted probabilities, thereby enhancing the interpretability of the results. The marginal effects at the mean (MEM) were computed after estimating the binary logistic regression model to quantify the magnitude of change in the probability of farmers' WTP for IoT adoption associated with a one-unit change in each explanatory variable, while holding other variables constant at their mean values. This approach allows for a more intuitive interpretation of how each determinant influences the likelihood of WTP (Greene, 2012; Long & Freese, 2001). The MEM values were generated using the *margins* command in Stata, which derives partial derivatives of predicted probabilities from the logistic function evaluated at sample means. Furthermore, to ensure the reliability and stability of the model estimates, multicollinearity diagnostics were conducted prior to the regression analysis. The Variance Inflation Factor (VIF) was applied to detect potential correlations among the explanatory variables.

ANALYSIS AND RESULTS

This section presents the study's findings on farmers' awareness, the readiness of IoT facilities and infrastructure, and the determinants of farmers' WTP to adopt IoT technology in rice farming.

IoT Technology Awareness, Index, and Level

Table 3 presents the descriptive analysis of farmers' awareness of IoT technology in rice farming. Mean values were used to illustrate the overall response patterns, consistent with previous research practices in which Likert scale items are treated as interval data when response categories are evenly spaced (Norman, 2010; Boone Jr & Boone, 2012). The results indicate that rice farmers in IADA BLS generally demonstrate a strong awareness of the potential benefits of IoT technologies; however, notable gaps persist in their technical knowledge and training needs. The highest mean scores were recorded for statements relating to IoT's role in improving rice farm efficiency (M = 3.83, SD = 0.83), supporting farm-level decision-making (M = 3.75, SD = 0.84), and increasing rice yields (M = 3.70, SD = 0.94). These results suggest that farmers conceptually recognise the potential value of IoT for enhancing productivity and efficiency in rice farming. These findings are consistent with prior studies that highlight farmers' positive perceptions of digital tools in agriculture (Klerkx et al., 2019; Rose & Chilvers, 2018).

Table 3

Descriptive Statistics of Farmers' IoT Awareness in Rice Farming (N=229)

Statement	Strongly disagree (%)	Disagree (%)	Neutral (%)	Agree (%)	Strongly agree (%)	Mean	Median	SD
I am aware that IoT can enhance rice farm efficiency	2.2	5.7	14.0	62.9	15.3	3.83	4	0.83
I am confident that IoT data supports rice farm decision-making	1.3	7.0	21.8	55.0	14.8	3.75	4	0.84
I know that IoT can assist in improving farm rice yield	3.1	10.0	14.4	58.5	14.0	3.70	4	0.94

(continued)

Statement	Strongly disagree (%)	Disagree (%)	Neutral (%)	Agree (%)	Strongly agree (%)	Mean	Median	SD
I know the basic steps to operate IoT devices/apps in rice farming	1.7	10.5	20.5	55.9	11.4	3.65	4	0.88
I know IoT tools for monitoring rice field operations	3.1	16.2	15.3	47.2	18.3	3.62	4	1.06
I am aware of IoT devices exist specifically in farm rice operation	1.7	15.3	16.2	55.5	11.4	3.59	4	0.94
I am confident that my knowledge about IoT in rice farming is sufficient	1.3	18.3	15.3	52.8	12.2	3.56	4	0.97
I am aware of IoT-based mobile apps for rice farm advice	1.3	19.2	19.7	43.7	16.2	3.54	4	1.02
I can name at least one IoT device/app in rice farming	12.7	19.2	16.6	39.3	12.2	3.19	4	1.25
I am aware that training is needed to integrate IoT effectively in rice farming	9.6	36.2	19.2	29.3	5.7	2.85	3	1.12

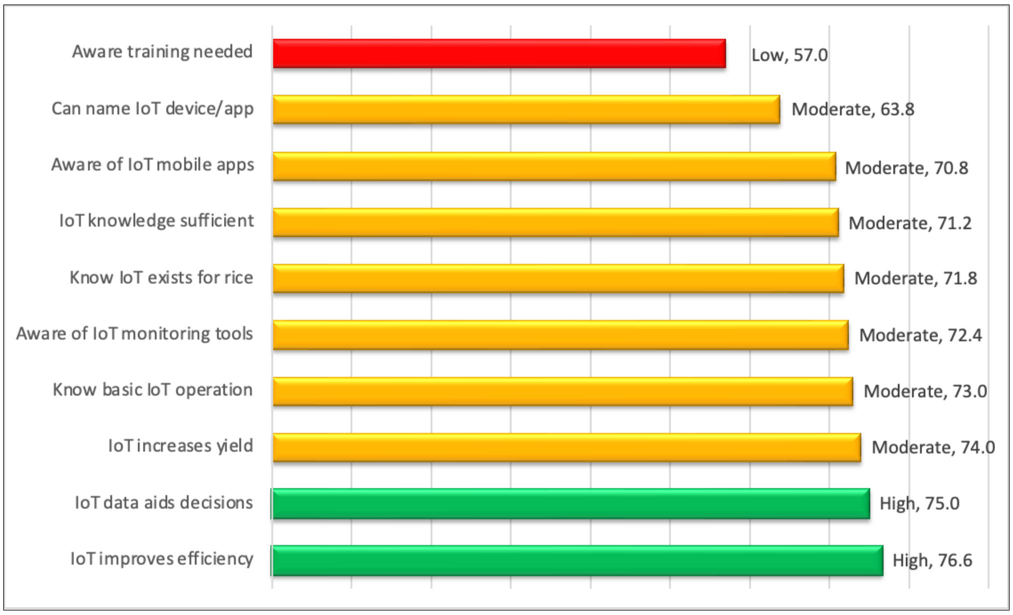
In contrast, indicators reflecting practical knowledge and confidence in operating IoT systems scored comparatively lower. Awareness of the basic steps to operate IoT devices (M = 3.65, SD = 0.88) and knowledge of IoT tools for monitoring rice field operations (M = 3.62, SD = 1.06) reflect moderate familiarity but limited competence in hands-on application. The lowest awareness level was found in the ability to name at least one IoT device or application specific to rice farming (M = 3.19, SD = 1.25), with a wide variation in responses. This variability demonstrates uneven exposure among farmers, with some showing familiarity while others remain largely uninformed. This finding aligns with earlier studies indicating that the transition from awareness to willingness to adopt and pay is often hindered by limited technical knowledge and exposure to digital innovations (Rezaei-Moghaddam & Salehi, 2010; Shepherd et al., 2020).

Likewise, farmers expressed low agreement on the need for training in the effective utilisation of IoT in the rice field (M = 2.85, SD = 1.12). More than one-third of the farmers disagreed with the statement, indicating that the perceived need for training was relatively low among respondents. This finding is important because the effective adoption of digital and precision agriculture technologies depends not only on awareness of their potential benefits, but also on technical competence, practical skills, and appropriate training support (Michailidis et al., 2024; Nakano et al., 2018; Xue et al., 2022). This result suggests that some farmers viewed training mainly as a basic introductory activity rather than as the practical and continuous support needed to operate, maintain, and troubleshoot IoT systems under actual field conditions. Moreover, it indicates that farming experience and general awareness led some respondents to believe that additional training was unnecessary. The descriptive results are consistent with the interpretation, as farmers reported generally positive awareness of IoT benefits, yet lower scores for naming specific IoT devices and apps, and only moderate confidence in their operational knowledge. The finding suggests that the low level of agreement on training does not imply that training is unimportant. Rather, it reflects limited recognition of the technical and practical support required for sustained IoT adoption among farmers. Additionally, the median values predominantly indicate an *Agree* response, confirming that most farmers consistently expressed positive awareness of IoT technology. However, the lower median value of *Neutral* for the training-related statement indicates uncertainty about the need for technical training, reflecting a gap between conceptual understanding and practical readiness.

Figure 2 illustrates the distribution of IoT awareness among rice farmers, represented through an awareness index categorised into three levels. The majority of farmers fall within the *moderate awareness* category, as indicated by the yellow bar. This finding suggests that while many rice farmers possess a reasonable understanding of IoT and its basic concepts, their knowledge may not yet be sufficient to translate into adoption or investment decisions. A smaller proportion of farmers demonstrated *high awareness* (green bar), indicating a more comprehensive, in-depth understanding of IoT's potential and benefits. Conversely, a limited segment of the farming community remains in the low-awareness category (red bar), highlighting persistent information and exposure gaps. Bridging the gap between moderate and high awareness levels is therefore essential to strengthen farmers' readiness to adopt IoT technologies. Enhancing awareness and technical competence through targeted training, extension programmes, and demonstration projects may play a crucial role in increasing farmers' WTP and accelerating the digital transformation of rice farming.

Figure 2

IoT Awareness Index and Level (N=229)



Overall, the results point to a dual reality in which farmers are generally optimistic about the potential benefits of IoT technologies but lack sufficient technical knowledge and training to translate this awareness into adoption and WTP. Bridging this gap requires strengthening institutional capacity, scaling up extension services, including peer-led models, and redesigning IoT training programmes to prioritise practical competencies over mere general awareness. Enhancing these areas will better position farmers to adopt and invest in IoT technologies, thereby improving productivity and ensuring the sustainability of rice cultivation.

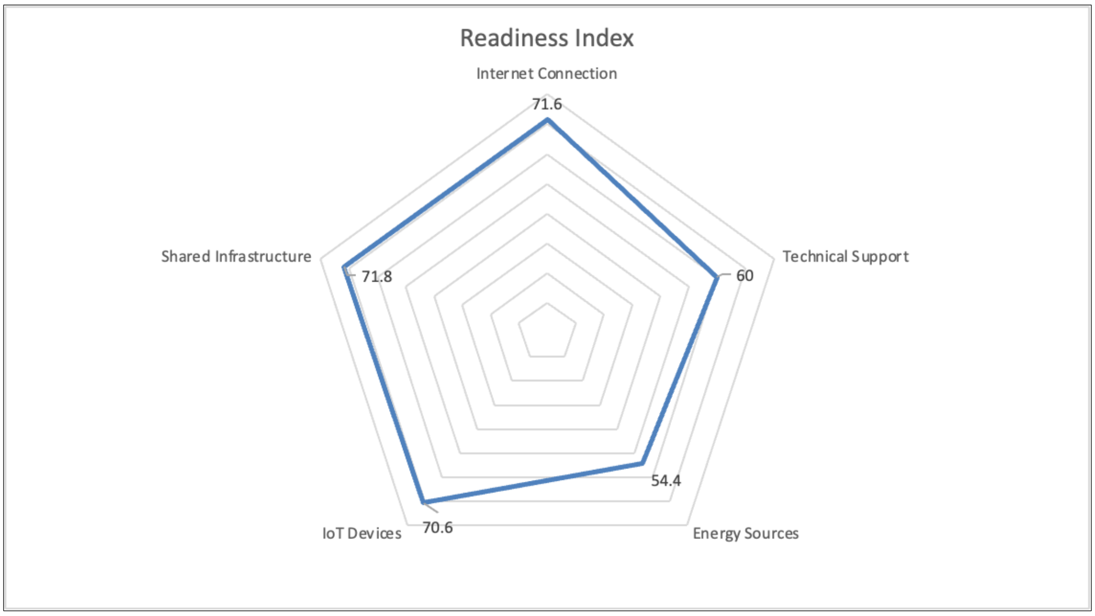
IoT Facilities and Infrastructure Readiness

The availability and reliability of IoT facilities and infrastructure critically determine the extent to which rice farmers' WTP and the effective adoption of IoT technologies. Previous studies highlight that important components, namely internet connectivity, energy supply, technical support services, and access to reliable devices, form the foundation of digital agriculture technology, especially in resource-limited farming conditions (El Bilali & Allahyari, 2018; Wolfert et al., 2017). The IoT infrastructural conditions significantly influence farmers' WTP for IoT technologies and impact their adoption behaviour, as these factors affect both the perceived ease of use and the practical feasibility of implementation (Rose & Chilvers, 2018).

The IoT readiness index across five infrastructural dimensions is illustrated in Figure 3. The highest levels of readiness were observed for shared infrastructure (71.8), internet connectivity (71.6), and IoT device availability (70.6). In contrast, technical support scored considerably lower at 60.0, while energy supply recorded the lowest readiness level (54.4). This index highlights potential vulnerabilities in sustaining the integration and utilisation of IoT technologies in rice farming.

Figure 3

IoT Readiness Index

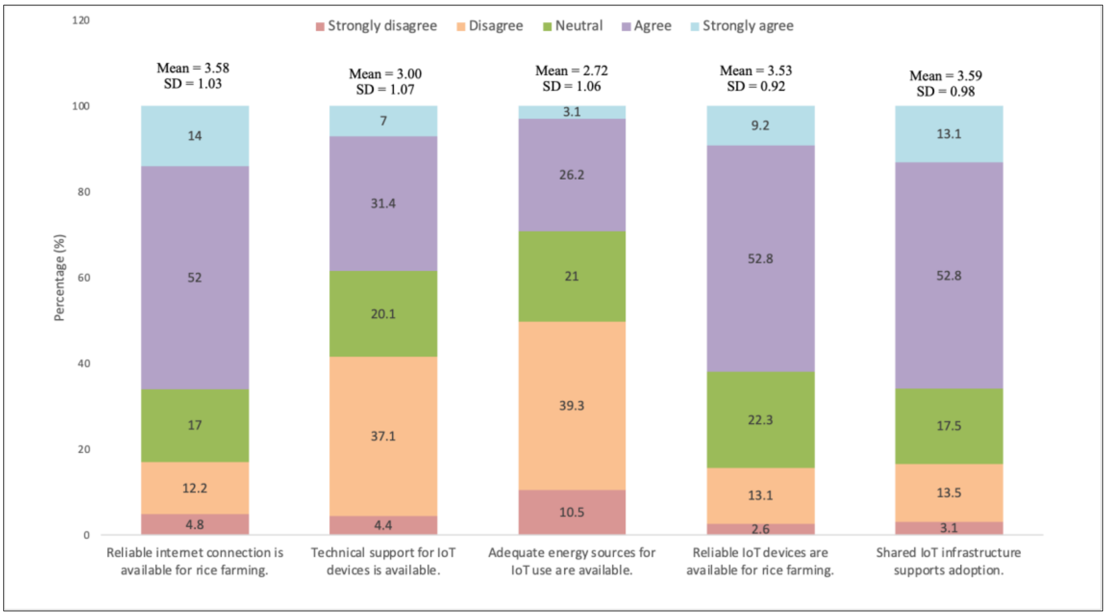


Furthermore, Figure 4 presents farmers' perceptions of IoT infrastructure readiness. Reliable internet connectivity and IoT device availability were perceived relatively positively, with mean scores of 3.58 and 3.53, respectively; over half of the respondents rated these items at level 4. This finding suggests that the basic IoT infrastructure is already present within the study area. Shared infrastructure was also viewed favourably (M = 3.59, SD = 0.98). In contrast, technical support (M = 3.00, SD = 1.07) and energy supply (M = 2.72, SD = 1.06) received lower ratings, reflecting farmers' concerns about the availability of timely assistance with troubleshooting and uncertainty about the reliability of the energy required to operate IoT devices.

The results highlight a contrast between infrastructural strengths and weaknesses within the study area. Internet connectivity, IoT device availability, and shared facilities are relatively well established, reflecting positive progress towards Malaysia's digital agriculture agenda. However, deficiencies in energy supply and technical support remain significant barriers to both farmers' WTP and effective IoT adoption. The consistency between the readiness index and farmers' perceptions reinforces the robustness of these findings; while access to hardware and connectivity is no longer a major obstacle, sustained usage and technical troubleshooting capacity remain uncertain (Klerkx & Rose, 2020; Jabbari et al., 2023).

Figure 4

Perceived IoT Infrastructure Readiness (N=229)



Marginal Effects of Key Predictors

The binary logistic regression results presented in Table 4 identify the determinants of WTP for IoT technology adoption among rice farmers in IADA BLS. The model demonstrated a good fit, with a log-likelihood of -100.59 and a significant likelihood ratio chi-square ($\chi^2(14) = 89.88$, $p < 0.001$), confirming the joint relevance of the predictors. The pseudo R^2 of 0.3088 indicates that approximately 31% of the variation in farmers' WTP was explained by the model. This reflects strong explanatory power in economic and behavioural studies (McFadden, 1974; Hosmer et al., 2013). All VIF values were below 5.0, with a total mean of 1.65, confirming the absence of multicollinearity among the explanatory variables.

Among the farmer-related factors, age showed a negative and significant relationship with WTP (p = 0.048; MEM = -0.61%), indicating that each additional year of age reduced the likelihood of willingness to pay for IoT adoption by 0.61%. This supports evidence that younger farmers are more open to digital agricultural innovations (Ruzzante et al., 2021). Income had a strong positive effect, with middle- and high-income farmers willing to pay up to 20.13% and 22.45% more, respectively, for IoT adoption than low-income farmers. This emphasises the important role of financial capacity in facilitating technological investment (Gulzar et al., 2025). Land tenure security also had a significant positive impact (p = 0.003; MEM = +3.18%), suggesting that secure ownership boosts confidence and long-term commitment for the integration of technology, consistent with Paltasingh (2018). Conversely, awareness of IoT technology showed a marginally negative effect (p = 0.054; MEM = -8.22%), indicating that awareness alone, without trust, demonstration, or practical evidence, may increase scepticism rather than encourage WTP for IoT adoption (Jayashankar et al., 2018).

Next, the technological dimension was a central factor that influenced WTP for IoT adoption in rice farming. IoT infrastructure readiness had a highly significant effect (p = 0.007; MEM = +10.53%). Improved access to reliable internet, electricity, and device functionality increases farmers' WTP by 10.53%. Islam et al. (2024), Masoomi et al. (2024), and Munasser & Golshan (2024) discovered that improved infrastructure, particularly electricity, energy, and internet coverage, was a prerequisite condition for IoT adoption. This evidence was consistent with the present research finding. Moreover, perceptual attributes also played an important role. The perceived usefulness of IoT was statistically significant, with a negative marginal effect of -2.06%. In contrast, perceived ease of use was marginally significant and increased farmers' WTP for IoT adoption by 8.27%. These research findings align with prior technology adoption studies, which emphasise usefulness and ease of use as the primary drivers of technology adoption (Davis, 1989; Venkatesh et al., 2003).

Lastly, the impact of the institutional dimension was relatively limited. Among the factors examined, only access to agricultural IoT information showed a marginal significance (p = 0.066; MEM = +1.80). The marginal effect indicated that great access to information increased the probability of farmers' WTP by 1.8%. Similarly, Davis et al. (2025) discovered that effective extension and advisory services fostered a greater readiness for technology adoption. On the other hand, access to credit and farmer-to-farmer extension were found to be insignificant predictors in this study.

Table 4

Binary Logistics Regression (N=229)

Variable	OR (Exp(β))	Std. error	p-value	MEM (%)	95% conf. interval		VIF
Age	0.965	0.018	0.048**	-0.61	0.931	0.999	1.22
Experience (years)	1.028	0.019	0.143	+0.10	0.991	1.067	2.24
Land size (ha)	0.945	0.056	0.339	-0.30	0.841	1.062	2.12
Income (middle)	2.971	1.384	0.019**	+20.13	1.193	7.403	1.32
Income (high)	3.569	2.056	0.027**	+22.45	1.154	11.039	2.05
Owner-operated land tenure	1.979	0.460	0.003***	+3.18	1.256	3.122	1.29
Frequency of agricultural apps use	1.141	0.080	0.061*	+2.22	0.994	1.309	1.36
Credit access	1.086	0.506	0.859	+0.40	0.436	2.708	1.46
Information access	1.445	0.289	0.066*	+1.80	0.976	2.141	1.93
Farmer -to-farmer extension	0.494	0.262	0.184	-3.40	0.175	1.399	1.61
Awareness of IoT technology	0.614	0.155	0.054*	-8.22	0.374	1.008	1.89
Readiness of IoT facilities and infrastructure	1.868	0.433	0.007***	+10.53	1.185	2.945	1.66
Perceived usefulness	1.634	0.365	0.028**	-2.06	1.054	2.531	1.89
PERCEIVED EASE OF USE	1.573	0.382	0.062*	+8.27	0.978	2.532	1.64

Notes. *p < 0.10; **p < 0.05 and ***p < 0.01

Discussions

This study provides empirical evidence on the multifactorial nature of farmers' WTP for IoT-based technologies in rice farming. The analysis demonstrates that WTP is shaped by the interaction of economic capacity, technological readiness, and institutional support mechanisms. These findings address the research objectives by identifying the key drivers influencing farmers' investment decisions and answering the broader question of *why* some farmers are more willing to pay for IoT adoption than others. The results confirm that farmers' WTP decisions are not purely attitudinal but are embedded within their socioeconomic realities and the structural conditions that either facilitate or constrain technological uptake (Wolfert et al., 2017; Venkatesh et al., 2003).

From a theoretical standpoint, this study refines the TAM by illustrating that perceived usefulness and perceived ease of use function differently under contextual constraints such as facilitating conditions, perceived risk, and social influence (Ghozali et al., 2025). The negative marginal effect of perceived usefulness reveals a behavioural paradox, where, although rice farmers recognise IoT's potential benefits, their willingness to invest declines when perceived costs or uncertain institutional support outweigh expected gains (Shi et al., 2022). Conversely, perceived ease of use has a positive and significant effect, underscoring the importance of intuitive, locally adaptable, and reliable IoT systems that minimise complexity and enhance user confidence. These outcomes extend existing adoption frameworks by demonstrating that perceptual constructs must be supported by affordability and infrastructural readiness to transform into WTP decision and behaviour.

In practical terms, the results highlight that infrastructural reliability as well as institutional facilitation are essential for bridging the gap between awareness and WTP for IoT adoption in rice farming. A stable energy supply, internet connectivity, and timely technical assistance form the foundation for effective digital engagement in agriculture (Prinsloo & Smuts, 2025). Without these enabling conditions, even well-promoted technologies may fail to sustain farmer participation. Mohsin et al. (2025) further emphasised that digital and ICT-based innovations, including mobile applications for rice yield prediction, can significantly enhance farmers' decision-making and adaptive capacity under changing climatic and production conditions. Moreover, the limited role of credit access and peer-to-peer extension observed in this study reinforces evidence that financial instruments alone are insufficient without trust, demonstration-based learning, and consistent service support (Hidrobo et al., 2022; Bontsa et al., 2023).

CONCLUSION

The findings indicate that the IoT technology interventions must go beyond awareness campaigns or equipment distribution. Structural and institutional barriers strongly influence rice farmers' willingness to invest in digital IoT technologies. Strengthening technical support services is necessary because poor knowledge dissemination among farmers often limits the effective integration of innovation and new technologies on farms (Gutiérrez Cano et al., 2023). Reliable energy access is also critical. An unstable power supply reduces the functionality of the IoT system as well as discourages farmers' WTP for IoT adoption in rice farming (Chanchaichuji et al., 2024). Next, training programs that were tailored to farmers' needs can build their confidence, improve perceived usefulness, and reduce uncertainty among them (Ren & Zhong, 2022). Additionally, financing mechanisms such as subsidies, microcredit, or leasing models can help bridge financial gaps that limit the adoption of IoT technology among farmers (Hu et al., 2023; Huang et al., 2023). Policies that combine infrastructure, institutional support, and access to financial resources will create a stronger facilitating environment for IoT adoption, as well as foster farm productivity and resilience in Malaysia's rice sector.

Several limitations should be acknowledged to provide context for the research findings. The cross-sectional survey design restricts the ability to establish a causal relationship. The dynamics in WTP and adoption behaviour may change over time due to several factors, including seasonal causes, policy reforms, or external shocks such as climate variability (Kumar et al., 2024; Saad et al., 2024). Another limitation lies in the reliance on stated WTP, which may not always reflect actual behaviour. This difference can result from hypothetical bias or from external constraints such as volatile markets, unstable input prices, as well as shifting government policies that directly influence farmers' investment decisions (Mgale et al., 2022). Future research could employ longitudinal or experimental designs to capture temporal changes in farmers' WTP for IoT adoption more accurately. Comparative studies across diverse farming systems would enhance external validity and provide deeper insights into contextual drivers of IoT adoption. Additionally, exploring collective approaches, such as cooperatives, farmer associations, and public–private partnerships, could provide practical avenues to reduce costs, share risks, and promote broader, more sustainable IoT adoption in Malaysia's rice sector.

Finally, policy should prioritise building trust and demonstrating value by showcasing the tangible benefits of IoT technology through pilot projects, farmer field schools, and peer-to-peer learning platforms. Demonstrations that clearly evidence improved yields, enhanced operational efficiency, reduced input costs, and better risk management are more likely to convince hesitant farmers than awareness campaigns alone. These initiatives align with the NAP 2.0, which prioritises productivity growth, resilience, and food security. They also reflect Malaysia's broader commitment to the 4IR, which emphasises the integration of advanced digital technologies, namely IoT, automation, and data analytics, to modernise the agricultural sector and enhance national competitiveness.

Integrating technological promotion with affordability, usability, and institutional support is therefore crucial. Targeted credit schemes, micro-leasing models, and outcome-based subsidies can help lower financial barriers, while farmer-focused training and practical IoT demonstrations can build skills and trust. These strategies aim to ensure that digital transformation does not widen the gap between large-scale and smallholder farmers, thereby promoting inclusivity in Malaysia's agricultural modernisation. Overall, the findings support Malaysia's national agricultural digitalisation agenda and provide a replicable framework for similar initiatives in other developing regions.

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