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ARTICLE

Technology Attributes and Preference Heterogeneity in IoT Adoption among Rice Farmers in IADA Barat Laut Selangor, Malaysia

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ABSTRACT

Rice is central to Malaysia's food security and rural economy, yet stagnant yields and rising import reliance signal an urgent need for productivity-improving upgrading in the sector. This study examined how rice farmers value key attributes of Internet of Things (IoT) technologies and how preferences vary across farm sizes. A choice experiment (CE) was administered to 229 farmers in the Integrated Agricultural Development Area of Barat Laut Selangor (IADA BLS). Five attributes were evaluated, namely yield improvement, real-time data access, technical support, IoT system reliability, and subscription cost. The willingness to pay (WTP) was derived using a random parameters logit (RPL) model. Yield improvement emerged as the strongest driver of choice, indicating that productivity gains remain the primary motivation for WTP for IoT adoption. Farmers were willing to pay up to Malaysian ringgit (RM) 1,657 per hectare for high yield potential, RM 786 for moderate real-time information, RM 500 for advanced technical support, and RM 671 for a reliable no-risk IoT system. Preference heterogeneity was evident, since larger farms placed greater weight on productivity-related features and showed lower sensitivity to subscription costs. In contrast, smaller farms displayed stronger cost constraints. Policies that offer financial incentives,

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affordable subscription packages, and practical training are essential to encourage wider IoT adoption, improve rice self-sufficiency and support Malaysia's digital transformation in agriculture.

Keywords: Choice Experiment; Internet of Things; Willingness to Pay; Preference Heterogeneity; Digital Technology; Rice Farming

1. Introduction

Agriculture continues to be one of Malaysia's primary economic pillars, alongside industry and services. It sustains rural subsistence, contributes to national food security, and offers employment to a significant portion of the rural workforce. Although its contribution to gross domestic product (GDP) has diminished due to industrialization and broader structural transformation, the sector remains politically significant and socially important. It underpins rural development, sustains household income stability, and mitigates vulnerability to fluctuations in domestic and international food prices. Rice constitutes a significant element of the Malaysian diet, with the average Malaysian consuming approximately 87.9 kg of rice annually [1]. Malaysia's per capita rice consumption exceeds the global average of 54.6 kg per person. This figure surpasses India's per capita consumption of 69.0 kg and China's per capita consumption of 77.9 kg [1]. Government support to the rice sector continues to be substantial. It encompasses fertilizer and input subsidies, assured minimum prices, extensive irrigation projects, and incentives for mechanization and infrastructure upgrading for technology integration. These interventions underscore the socio-economic significance of rice, as well as demonstrate an ongoing commitment to the domestic production, subsistence livelihood, and national stability [2]. Paddy production continues to be a key focus of policy initiatives, yet the sector persists in encountering challenges in enhancing productivity and, at the same time, decreasing dependence on imports. In 2023, Malaysia documented 506.4 thousand hectares dedicated to paddy cultivation, predominantly concentrated in key granary regions. Non-granary regions constitute a smaller proportion and frequently operate with limited irrigation coverage and insufficient supporting infrastructure. The 2024 Agriculture Census reported that paddy sales amounted to 1.7 million tons, with a total sales value of RM 2.4 billion in 2023.

Despite its strategic role, Malaysia continues to experience a persistent gap in rice self-sufficiency. The national self-sufficiency ratio stood at 56.2% in 2024, with domestic production meeting only about half of the annual consumption of around three million metric tons. The imports were mainly from Thailand, Vietnam, Pakistan, and India to satisfy the local demand. This reliance increases Malaysia's exposure to price volatility and global supply chain disruptions. The COVID-19 pandemic and India's export restrictions in 2023 highlighted this vulnerability when local retail prices spiked sharply. Moreover, the paddy cultivation area fell from 700,000 ha in 2018 to 506,400 ha in 2023 due to urbanization and land conversion [3]. These pressures are reflected in national policy priorities. The National Agrofood Policy (NAP 2.0) 2021–2030 identifies rice as a strategic crop that requires digital transformation, mechanization, and innovation to improve farm productivity as well as to reduce import dependence. Nevertheless, climate variability, erratic rainfall, and extreme weather events increasingly disrupt planting schedules and reduce yield stability in Malaysia's rice sector [4]. Hence, digital agriculture, particularly IoT applications, has emerged as a transformative tool for improving productivity, efficiency, and resilience. IoT systems provide real-time data on soil, water, and weather conditions, which can help farmers make timely farm management decisions. Additionally, global evidence shows that IoT can increase farm productivity by 15–25% while reducing input costs and resource use [5, 6]. Studies in China and Vietnam have reported that IoT-supported irrigation and alternate wetting and drying practices can improve the efficiency of water use while also increasing yields [7].

The adoption of IoT in Malaysia's rice sector is still limited and uneven. Many smallholders are unfamiliar with the availability of applications that can assist them in managing the farm operation. Farmers are also uncertain about the practical benefits, since initiatives are often restricted to pilots and trial projects. The broader digital agriculture ecosystem also lags behind regional leaders, including China and Vietnam. Smallholders have limited access to IoT-enabled systems, even though the system can improve input efficiency, lower the costs of production, and strengthen climate resilience [8, 9]. The reliance on conventional practices has contributed to yield stagnation, and it has slowed the transition toward precision and climate-smart rice farming [6, 10]. Several barriers continue to limit wider IoT uptake. Affordability is a key issue because many farmers lack the financial capacity to invest in devices, systems, sensors, and other supporting infrastructure [4]. Technical literacy also differs across farmers, which influences the ability to operate, interpret, and maintain the IoT systems [11]. Extension and advisory support are often limited, which narrows access to training and reduces ongoing guidance [12]. Infrastructure challenges add further constraints, particularly weak rural connectivity and uneven internet access [13]. Concern about system reliability and weak local support networks can reinforce skepticism and reduce willingness to adopt digital innovations and IoT technologies in agriculture [14–16]. These constraints slow the wider integration of IoT and keep farmers reliant on conventional practices that offer lower efficiency [10]. Digitalization is emphasized under Malaysia's Industry 4.0 agenda and NAP 2.0 as a key pathway for agricultural modernization, yet current progress has not fully shifted the rice sector toward a more technology-oriented and higher productivity system. This situation highlights the importance of understanding farmers' preferences for specific IoT attributes to guide the design of IoT system packages that are affordable, practical, and aligned with smallholder needs.

Existing studies on IoT adoption in Malaysia have mainly examined conventional innovations, such as mechanization, fertilizer use, and irrigation practices. Only a limited number of studies have assessed IoT adoption decisions and WTP for agricultural technologies. Literature also indicates that farmers assess technologies as bundles of attributes rather than as single and uniform products. Choices often involve trade-offs across expected benefits, perceived risks, and costs [17, 18]. Conventional adoption surveys and contingent valuation methods (CVM) often do not capture these attribute-level trade-offs or the way preferences differ across farmers. Discrete choice experiments (DCE) address this limitation as they allow valuation of specific attributes and support analysis of preference heterogeneity across farmer groups [19, 20]. Moreover, recent work on IoT and digital agriculture has also focused largely on system development and field deployment. Studies commonly describe sensor-based monitoring, data transmission, and decision-support functions designed to improve farm management [21]. Review evidence suggests that innovation in digital agriculture often progresses faster than adoption in practice, since farmers' decisions depend on factors beyond technical capability [22]. IoT uptake is less likely when services involve recurring fees, when performance is uncertain, or when after-sales support is weak. These concerns align with the barriers reported consistently in the technology adoption literature, namely, cost, skills, and access to support for installation, use, and troubleshooting [22]. Empirical evidence from paid agricultural service models also suggests that pricing structures and service design shape demand, which makes affordability part of the technology offering rather than an external constraint [23]. Nevertheless, studies remain limited on how rice farmers value individual IoT technology attributes and at what price trade-offs they accept, especially in Malaysian granary areas where production conditions and support systems vary. Furthermore, the empirical applications of CE in Malaysia's rice sector also remain scarce, which limits evidence on attribute-level valuation and WTP.

Hence, this study responds to these gaps by quantifying marginal WTP for key IoT attributes and examining whether preferences differ systematically across rice farmers. This study employed a DCE in the IADA BLS to elicit farmers' preferences for specific IoT attributes and to generate evidence that can support demand-driven and farmer-centred digital agriculture strategies. A RPL specification was used to capture unobserved preference heterogeneity and to estimate marginal WTP for each attribute level [24]. This approach extends beyond binary adoption survey studies, as it evaluates choices under realistic attribute bundles and price levels. It also identifies which package features farmers' priorities and whether these priorities vary across farmer groups. This study addresses the following research questions:

RQ (Research Question) 1: Which IoT technology attributes significantly influence rice farmers' choices of IoT bundle packages in IADA BLS?

RQ2: How do farm size and selected socio-demographic characteristics influence the differences in rice farmers' preferences and WTP for IoT bundle packages in IADA BLS?

RQ3: How do preferences vary across rice farmers in IADA BLS?

RQ4: What is the marginal WTP for each IoT attribute level?

Therefore, the general objective of this study is to examine rice farmers' preferences for IoT technology attributes in IADA BLS. The findings contribute to the literature on digital agriculture adoption and provide empirical guidance for practical and inclusive policy design. The results also support Malaysia's efforts to strengthen food security and resilience in the rice sector, consistent with sustainability frameworks that emphasize agricultural innovation and digital technologies.

2. Materials and Methods

2.1. Theoretical Framework

This study adopted a CE approach grounded in random utility theory (RUT). The theory assumes that each farmer selects the alternative that provides them with the highest utility, given both observable and unobservable factors [24, 25]. In this framework, utility is associated with the attributes of a product or service rather than the product itself. This allows preferences to be expressed as attribute-specific utilities that can be estimated from observed choices [26]. This aligns with Lancaster's characteristics approach, which treats goods and services as bundles of characteristics that generate utility [27]. This theoretical basis supports the use of a CE to estimate WTP and to assess farmers' preference heterogeneity for IoT technology adoption in rice farming.

A CE is particularly suitable for this study because the decision problem involves choosing among IoT technology bundle packages, not valuing IoT technology in general. The IoT packages offered differ in yield potential, real-time data access, technical support, reliability, and subscription cost. The method applied repeated choice tasks and required respondents to make trade-offs across multiple attributes and cost levels. This scenario aligns with how farmers compare competing options under budget constraints [28, 29]. Meanwhile, the methods of CVM often elicit a single WTP amount for one defined situation. These estimates can be useful for overall valuation; however, they do not directly identify the implicit value for each package feature. It also fails to assess the substitutions farmers make across different IoT attributes at different subscription costs [19, 30].

Under RUT, the utility that farmer *i* obtains from alternative *j* is expressed as a systematic component and a random error term:

$$U_{ij} = V_{ij}(A_j, X_i) + \varepsilon_{ij} \tag{1}$$

where V_{ij} is the systematic component of utility, A_j is the vector of attribute levels describing alternative *j*, X_i represents observed farmer characteristics, and ε_{ij} is a random error term. For another alternative *m*:

$$U_{im} = V_{im}(A_m, X_i) + \varepsilon_{im} \tag{2}$$

Farmer *i* chooses alternative *m* over *j* when $U_{im} > U_{ij}$. The associated choice probability can be written as:

$$P(m|A_m) = P[U_{im}(A_m, X_i) - U_{ij}(A_j, X_i) > \varepsilon_{ij} - \varepsilon_{im}] \tag{3}$$

Preference heterogeneity was modelled using the RPL model. This specification allows taste parameters to vary across individuals and relaxes the restrictive substitution patterns implied by the standard conditional logit (CL) [19, 24]. This flexibility is important as farmers may value yield gains, data access, technical support, reliability, as well as subscription costs differently. The utility specification is:

$$U_{im} = (\beta + \mathit{\Gamma} X_i)^T A_{im} + \varepsilon_{im} \tag{4}$$

where A_{im} denotes the vector of IoT attribute levels for alternative *m*, β is the vector of mean preference parameters, X_i is the vector of farmer socioeconomic characteristics, $\mathit{\Gamma}$

captures systematic taste shifts associated with X_i, and ε_{im} is the random error term. This structure supports the estimation of attribute-level preferences while allowing both observed and unobserved heterogeneity in tastes.

Model estimation was conducted using simulated maximum likelihood. Simulation employed 100 draws from standard Halton sequences, which improve efficiency relative to purely random draws [24, 31]. All estimations were performed in Stata 17.

Stated preference (SP) data can be subject to hypothetical bias because choices were made in a survey rather than under actual market conditions. This risk is reduced when scenarios are realistic, payment mechanisms are clearly described, and choice tasks are carefully designed, and these elements were incorporated into the survey instrument [30, 32]. Attribute descriptions were presented in clear operational terms, and follow-up questions were used to verify farmers' understanding. Additionally, robustness checks were also conducted to evaluate the sensitivity of results to alternative response patterns, including the potential attribute of non-attendance [19, 33].

2.2. Implicit Price of Attributes

The coefficients estimated from the CE are expressed in utility units. Hence, they are not directly interpretable in monetary terms. To obtain monetary values, this study derived the implicit price, also termed as marginal WTP, for each IoT attribute. Marginal willingness to pay (MWTP) is defined as the marginal rate of substitution between a non-monetary attribute and the cost attribute. It represents the additional amount a farmer is willing to pay for a marginal improvement in a given attribute, holding other attributes constant [34]. Accordingly, MWTP is calculated as the negative ratio of the estimated coefficient of the IoT attribute to the estimated coefficient of the price attribute [35]:

$$\text{MWTP}_k = -\beta_k/\beta_{price} \tag{5}$$

2.3. Description of Study Area

This study was conducted in the IADA BLS, a major rice-producing region on the northwestern coast of Selangor, Peninsular Malaysia (**Figure 1**). IADA BLS is one of Malaysia's designated granary areas and supports national rice self-sufficiency and food security [2]. Paddy cultivation operates under a centralised irrigation system that is coordinated by the Department of Irrigation and Drainage (JPS) in collaboration with the Department of Agriculture (DOA) and the IADA authority. This governance arrangement enables planned water distribution, coordinated production management, and routine technical monitoring of paddy farming activities.

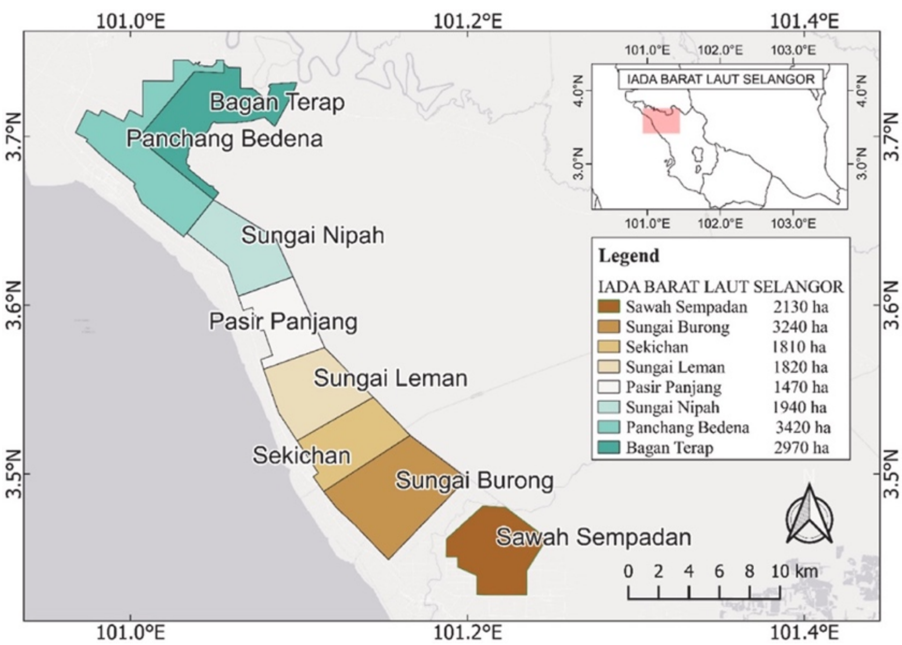

Figure 1. Maps of IADA BLS.

These conditions make IADA BLS a suitable setting for examining farmers' preferences and WTP for IoT technology adoption. The area combines favourable agroecological conditions with established infrastructure, relatively widespread mechanisation, and an operating environment where technology integration is already present. Average yields are about 5.7 t per hectare per season, which ranks among the highest in Malaysia, and the area contributes roughly 7% of national rice output[36].

The scheme covers approximately 18,800 ha of irrigated paddy land and is organized into nine irrigation blocks, namely Sawah Sempadan, Sungai Burong, Sekinchan, Sungai Leman, Pasir Panjang, Sungai Nipah, Pancang Bedena, Bagan Terap, and Sungai Panjang. These blocks include 23,614 registered paddy lots managed by 7,366 rice farmers. Reliable integration, practice of double cropping, and mechanized field operations highlight a relatively advanced rice production environment. This context enables an assessment of IoT-enabled technology packages that reflect conditions in the major granary production system in Malaysia.

2.4. Sampling and Determination of Sample Size

A proportional stratified sampling design was implemented across the nine irrigation blocks in IADA BLS to ensure a representative sample of rice farmers. Farmers were first stratified using block-level population and cultivated area information obtained from the IADA BLS office. Respondents were then randomly selected within each block in proportion to the number of registered paddy farmers. This design supports balanced coverage across locations and farm-size groups, reduces sampling bias, and strengthens the generalizability of findings to the IADA BLS farmer population.

An adequate sample size is crucial for reliable estimation in CE studies. Following Orme[37], the minimum required sample size was assessed using the widely used rule-of-thumb formula:

$$n \geq 500 \times \frac{c}{t \times a} \tag{6}$$

where n denotes the minimum required sample size, t is the number of choice tasks completed by each respondent, a is the number of alternatives presented in each choice set, and c is the largest number of levels among the attributes in the design. In this study, the highest number of levels for any attribute was four ($c = 4$). Each respondent completed six choice tasks ($t = 6$), and each task presented three designed IoT alternatives ($a = 3$) plus an opt-out option:

$$n \geq 500 \times \frac{4}{6 \times 3} = 111.11 \tag{7}$$

Hence, a minimum sample size of 112 respondents was required to estimate the main effects with acceptable precision. Since this study estimated an RPL model to account for preference heterogeneity, the target sample was increased by 50% to improve estimation precision and model stability. In total, 229 valid responses were obtained from rice farmers in IADA BLS. The sample reflects variation in farm size, irrigation conditions, and exposure to IoT technology initiatives across the study area.

2.5. Experimental Design and Attribute Selection

Existing research on digital agriculture and IoT has expanded rapidly, with recent empirical work moving beyond prototype demonstrations to report field performance and service delivery arrangements. Evidence from multi-sensor IoT applications indicates that connected monitoring can support day-to-day decisions and resource management in agri-food systems[38]. Studies on crop protection that combine sensing with advanced analytics also point to earlier detection and more timely intervention, which can reduce yield losses and improve targeting of responses[39]. Even so, adoption evidence consistently shows that uptake depends not only on technical capability but also on farmers' perceptions of usefulness, ease of use, and facilitating conditions. This aligns with technology adoption frameworks such as the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology[40, 41]. Together, this literature supports an evaluation approach that can quantify attribute-level trade-offs under realistic service configurations and cost levels.

A CE was applied to elicit rice farmers' preferences for IoT technology bundle packages. Attribute selection and level specification were informed by the literature, stakeholder consultation, and pilot testing to ensure local relevance and clear interpretation. Agricultural officers, IoT service providers, and farmers reviewed the proposed attributes and confirmed that each level represented a feasible service configuration in IADA BLS. Pilot testing with selected rice farmers was used to verify comprehension of the tasks and the realism of the alternatives. The final design included five attributes, including a monetary cost attribute, and each attribute was specified with three to four levels that captured stepwise changes in functionality and service quality from basic to more advanced packages. A status quo option was included in every choice set to allow respondents to retain current practices, which strengthens behavioural realism and follows established guidance for stated choice methods [19, 42, 43].

Table 1 summarises the attributes and levels used in the choice tasks. All levels were described in operational terms during the survey so that respondents valued comparable bundle offers when making trade-offs. Yield improvement was framed as an expected percentage gain relative to current practice, ranging from no change to higher gains. Real-time data access captured the availability and timeliness of field information, moving from no access to faster updates that support timely decisions. Technical support was specified as a service arrangement covering installation, operation, maintenance, and troubleshooting. The no support level reflected prevailing practice where formal assistance is not provided. Low support referred to remote assistance on request during working hours with limited follow-up. Moderate support added structured guidance and troubleshooting with a stated response time and escalation when needed. Advanced support represented a comprehensive package that included hands-on training, responsive troubleshooting, and on-site visits when problems could not be resolved remotely, alongside ongoing guidance to help farmers interpret system outputs and maintain functionality. Perceived risk and reliability reflected expected consistency of system performance and the likelihood of failure, with lower risk indicating more stable operation and higher risk indicating greater uncertainty and potential disruption. Subscription cost was defined as an annual fee per hectare to reflect the recurring payment structure typical of IoT service provision.

Table 1. Attribute and level.

Attribute	Description	Level	Relevant Studies
Potential increase in rice yield	Represents the expected gain in rice productivity compared to current practices, reflecting the IoT technology's contribution to higher yields.	No change Low (5%) Medium (10%) High (15%)	Tao et al. [42], Osuafor and Ude [44], Paudel et al. [45]
Real-time data access	Indicates the availability and speed of live farm data for farmers to make timely and informed decisions.	None Basic Moderate Fast	Blasch et al. [43], Obaideen et al. [46]
Technical support	Captures the extent and quality of assistance provided to farmers for operating, maintaining, and troubleshooting the IoT system.	None Low Moderate Advanced	Saifan et al. [12], Bakang et al. [23]
Perceived risk and reliability	Reflects farmers' level of uncertainty about potential failures and their confidence in the consistency of IoT performance.	No risk Low Medium High	Liesivaara and Myyrä [34], Li et al. [47]
Subscription cost (RM/ha)	Denotes the financial requirement for farmers to access the service, expressed as annual subscription fees.	0 300 500 700	Tao et al. [42], Blasch et al. [43], Hidrobo et al. [48], Selvaggi et al. [49]

Socioeconomic characteristics were also considered, as IoT technology valuation is shaped by farmer resources and enabling conditions, not only by package attributes offered. The variables in **Table 2** were included to test observable heterogeneity in preferences and WTP among rice farmers in IADA BLS. This is consistent with technology adoption research that links intention and uptake to individual characteristics and facilitating conditions alongside perceived technology benefits [40, 41].

Table 2. Socioeconomic variables.

Variable	Measurement	Expected Effect	Actual Effect	Supported Literature	Evidence from Literature
Age (years)	Categorical variable that is grouped into age ranges, measured in years of age.	–	Positive across all yield levels, and not significant.	Ambali et al. [50]; Olum et al. [51]	Reviews and empirical studies show age effects are often inconsistent or insignificant in WTP contexts.
Experience (year)	Categorical variable, grouped by years of experience.	+	Negative across all yield levels, and not significant.	Yue et al. [52]; Dao et al. [53]	Experience can assist adoption, but studies report mixed or insignificant effects on WTP. Experienced farmers may be reluctant to innovation due to risk aversion.
Education	Categorical variable, classified by rice farmers' level of formal education.	+	Negative across all yield levels, and not significant.	Selvaggi et al. [49]; Shee et al. [54]	Education may increase awareness but does not consistently affect WTP; several studies report it insignificant once structural variables were considered.
Farm income (RM)	Categorical variable, divided into income brackets.	+	Mixed effects and not significant.	Lawi et al. [55]; Anugwa et al. [56]	Income shows mixed results. While higher income may increase WTP in some cases, studies often report it insignificant once structural variables were included.
Farm size (ha)	Categorical variable, grouped into farm size categories.	+	Strong positive and significant effect for large vs. small farms across all yield levels.	Paudel et al. [45]; Anugwa et al. [56]; Onugo and Onyeneke [57]	Studies show that farm size is a robust predictor of WTP and adoption, with larger farms more willing and able to pay for agricultural innovations.

2.6. Nature and Source of Data

A cross-sectional survey design was used, and primary data were collected using a systematically structured questionnaire. Face-to-face interviews were conducted with rice farmers to reduce response error associated with differences in digital literacy and uneven familiarity with IoT-related terminology. The questionnaire comprised five sections, progressing from general awareness items to the DCE tasks and ending with sociodemographic information. Likert scale statements were combined with open-ended and closed-ended items to capture both measured perceptions and contextual explanations.

Section A assessed farmers' awareness and prior experience with IoT applications in rice cultivation, including familiarity with relevant tools, participation in training activities, and current use of digital technologies. Section B examined the perceived importance of enabling conditions for digital readiness, focusing on internet connectivity, stability of electricity supply, access to credit, and access to information.

Section C contained the DCE and served as the core component of the instrument. Attribute information was communicated using pictograms supported with short explanatory captions to improve comprehension and reduce literacy-related bias [58–60]. Debriefing questions were administered after the choice tasks to confirm understanding and to identify the main factors guiding decisions, with special attention given to respondents who repeatedly selected the status quo option [20]. Items on WTP, preferred payment methods, and subsidy preferences were included to support monetary valuation and policy interpretation [61, 62]. Data collection was carried out by three trained enumerators. The questionnaire was translated into Bahasa Malaysia and assessed for content validity by agricultural specialists and academic examiners. Interview length was maintained at about 25 to 30 min to sustain engagement while limiting respondent burden.

Choice tasks were generated in Ngene using a D Bayesian efficient design. Statistical efficiency was improved for a fixed sample size since the expected variance of parameter estimates was minimised under the assumed utility specification and prior information [20, 63]. The design produced 30 choice sets, and these were blocked into five questionnaire versions to reduce fatigue. Each version contained six choice sets, which were found manageable during pilot testing.

Blocking ensured that each respondent completed only one questionnaire version. Respondents were randomly assigned to one of the five versions to secure full coverage of the design while keeping cognitive demands low. Each choice set presented three IoT technology alternatives and a status quo option. This structure reflected the study context where farmers compare feasible technology bundles at specified price points while retaining the option to continue existing practices.

A total sample of 229 respondents yielded an expected 5,496 alternative evaluations (6 × 4 × 229). After validation and data cleaning, 5,308 evaluations were retained. Incomplete or inconsistent responses were removed to strengthen reliability and internal consistency, consistent with established guidance for SP studies [28]. Six choice sets were completed per farmer, producing 24 alternative assessments per respondent. **Figure 2** presents an example of the choice task used in the survey.

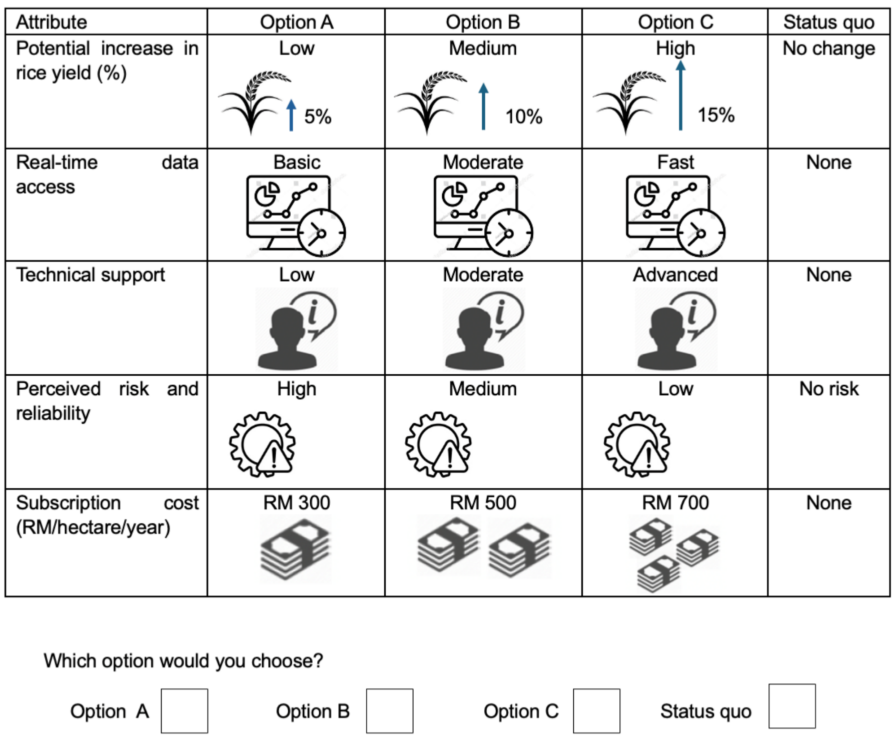

Figure 2. Example of a choice task.

3. Results

Descriptive analysis of the choice outcomes indicated that farmers selected the IoT-enhanced alternatives more often than the status quo. **Table 3** shows that the status quo accounted for only 9.34% of choices, while Alternative I (28.18%), Alternative II (29.77%), and Alternative III (32.71%) were selected more frequently. Overall, the distribution suggests a general preference among IADA BLS rice farmers for IoT technology-based packages that offer perceived productivity and operational benefits. This finding is consistent with evidence from prior CE studies on agricultural technologies [64].

Table 3. Survey over alternatives.

Choice	Alternative I (%)	Alternative II (%)	Alternative III (%)	Status Quo (%)	Total (%)
Selected	374 or 28.18	395 or 29.77	434 or 32.71	124 or 9.34	1,327 or 25.00
Not selected	953 or 71.82	932 or 70.23	893 or 67.29	1,203 or 90.66	3,981 or 75.00
Total	1,327 or 100.00	1,327 or 100.00	1,327 or 100.00	1,327 or 100.00	5,308 or 100.00

Table 4 summarizes the demographic profile of the 229 respondents. Most respondents were male (89.1%), which reflects the male-dominated structure of paddy farm management and field operations in Malaysia. The mean age was 47.68 years, with most farmers being between 31 and 60 years old, indicating a largely middle-aged sample. Average farming experience was 18.67 years, and nearly two-thirds reported having less than 20 years of experience. This reflects that the sample was dominated by established and mid-career farmers rather than new entrants. Moreover, the farmer's background of education was moderate. About 70.7% of farmers had completed their secondary education, while 18.8% attained tertiary education. This profile may support comprehension of technical information and engagement with IoT-based technologies among farmers. Farm income showed wide dispersion, with 39.3% earning below RM 5,249 per season and 36.2% earning more than RM 11,820. Farm size was predominantly small, as 81.7% of rice farmers cultivated less than five hectares. The findings were consistent with the dominance of smallholders in the sector. Mean paddy yield was 19.09 t, indicating substantial variation in farm performance. Overall, respondents in IADA BLS can be characterized as small to medium-scale rice farmers with moderate education and experience. Farmers were operating under resource constraints that are likely to shape their WTP behavior for IoT technology adoption in rice farming.

Table 4. Respondents' profile (N = 229).

Variable	Category	Frequency	Percentage (%)	Mean (Standard Deviation or S.D)
Gender	Male	204	89.1	
	Female	25	10.9	
Age (years)	Below 30	39	17.0	47.68 (14.52)
	31–40	39	17.0	
	41–50	38	16.6	
	51–60	66	28.8	
	Above 61	47	20.5	
Experience (years)	Less than 10	85	37.1	18.67 (12.87)
	11–20	66	28.8	
	21–30	41	17.9	
	31–40	32	14.0	
	More than 41	5	2.20	
Level of education	Primary	24	10.5	
	Secondary	162	70.7	
	Tertiary	43	18.8	
Farm income (RM)	Below 5,249	90	39.3	13,266.62 (15,533.32)
	5,250–11,819	56	24.5	
	Above 11,820	83	36.2	
Farm size (ha)	Less than 5.00	187	81.7	3.83 (4.372)
	5.01–20.00	39	17.0	
	More than 20.01	3	1.30	

Table 4. *Cont.*

Variable	Category	Frequency	Percentage (%)	Mean (Standard Deviation or S.D)
Total paddy yield (t)	Below 20	152	66.4	19.09 (20.18)
	20.01–40.00	52	22.7	
	40.01–60.00	17	7.40	
	60.01–80.00	4	1.70	
	Above 80.01	4	1.70	

3.1. Random Parameter Logit Model

The RPL model relaxes the assumption of homogeneous preferences across respondents. It allows taste parameters to vary across farmers and captures unobserved heterogeneity in how IoT attributes were valued. Estimation was conducted in two steps. First, preference heterogeneity was assessed by testing whether the estimated standard deviations of the random parameters differ from zero. Statistically significant standard deviations indicate dispersion in tastes around the population mean. Second, observed farmer and farm characteristics were introduced to examine systematic differences and WTP across groups.

Model fit improved markedly relative to the homogeneous CL benchmark. The log-likelihood increased from −934.92 in the basic CL model to −806.99 in the RPL model. This gain indicates that heterogeneous tastes describe the observed choice patterns more accurately than a single-parameter specification [19, 24].

3.1.1. An Investigation of the Presence of Heterogeneity in Taste Parameters

Table 5 reports the estimation results of the RPL model used to evaluate farmers' preferences for IoT technology attributes in rice farming. The fit statistics indicate strong explanatory power, with a Pseudo-R^2 of 0.534 and an adjusted Pseudo-R^2 of 0.513. This suggests that the model explains more than half of the observed variation in choices. The results show that all main attributes were statistically significant. The results highlight that farmers consider each attribute when making their choices. This indicates that every attribute plays an important role in shaping farmers' utility and influencing the selected alternatives.

Table 5. Estimation results of the random parameter logit model.

Variable	Coefficient
Random Coefficients (Mean)	
Yield—5% (Low)	7.9682*** (1.5352)
Yield—10% (Medium)	11.4485*** (1.6607)
Yield—15% (High)	11.7473*** (1.9084)
Support—Low	1.4645** (0.5788)
Support—Moderate	1.6678*** (0.4272)
Support—Advanced	3.2370*** (0.6812)
Access—Basic	3.2120*** (0.6185)
Access—Moderate	4.4491*** (0.4936)
Access—Fast	4.3751*** (0.7586)
Risk—Low	3.8758*** (0.5361)
Risk—Medium	2.4914*** (0.5310)
Risk—No risk	3.9806*** (0.5939)
Non-Random Coefficient	
Price	−0.0789*** (0.0116)
Std. Deviations	
Yield—5% (Low)	0.0227 (0.2667)
Yield—10% (Medium)	1.8849* (1.0180)
Yield—15% (High)	0.9379* (0.4859)
Support— Low	0.3080 (0.4052)
Support—Moderate	1.4196 (1.1067)
Support—Advanced	0.1587 (0.2982)

Table 5. *Cont.*

Variable	Coefficient
Std. Deviations	
Access—Basic	0.4130 (0.5658)
Access—Moderate	3.8226*** (1.4537)
Access—Fast	0.0902 (0.3103)
Risk—Low	0.5121 (0.6946)
Risk—Medium	0.2011 (0.6581)
Risk—No risk	5.5960*** (1.0929)
Summary Statistics	
Number of observations	5308
Wald chi-square	303.20
Prob > chi-square	0.0000
Log-likelihood function: L(β)	−806.99
Log-likelihood: L (0)	−1731.28
Pseudo-R^2	0.534
Adjusted Pseudo-R^2	0.513
AIC	1685.99
BIC	1872.85
Chi-squared	1848.57

Note: *** significant at 1%, ** significant at 5%, and * significant at 10%; standard errors are in brackets.

A potential increase in rice yield is strongly valued by farmers in IADA BLS and shows the highest coefficient magnitudes among the IoT attributes. This pattern is consistent with DCE evidence from Malawi, where smallholders reported the highest WTP for options that improved maize yields under climate-smart practices [65]. Similarly, Miriti et al. [66] reported that Tanzanian farmers were willing to pay substantial premiums for higher-yielding sorghum varieties. Access to real-time data also emerges as a key determinant of farmers' preferences. All access levels were positive and statistically significant. This shows that farmers place value on timely information to support farm management decisions, improve operational efficiency, and enhance productivity [6, 67].

Next, system reliability and risk management further shape preferences for IoT adoption. The "no-risk" level exhibits one of the largest coefficients (3.9806, p < 0.01). This indicates a strong preference for dependable performance and reduces the risk of IoT system failure. Abdul-Majid et al. [68] likewise identified perceived operational risk as a major barrier to digital technology adoption among smallholders. Singh et al. [69] also found that reliability and advanced technical support increase WTP for smart farming tools in Bangladesh. Finally, subscription cost has a negative coefficient and is significant at the 1% level, which clearly shows price sensitivity among rice farmers. Higher subscription fees reduce the probability of choosing an IoT package. This implies that affordability remains a central condition for uptake and WTP for IoT adoption in rice farming.

The estimated standard deviations highlight meaningful preference heterogeneity across respondents. The standard deviations for medium yield and high yield were significant at the 10% level, while moderate access and no risk were significant at the 1% level. These results indicate substantial variation in how farmers value key IoT attributes, beyond what is captured by the mean coefficients. This unobserved heterogeneity particularly supports the need for differentiated IoT technology bundle packages that account for variation in farm scale, constraints, and resource capacity [70].

3.1.2. Possible Source of Heterogeneity in Mean Parameters

Table 6 reports the RPL results, with farm size included to capture systematic preference heterogeneity in the yield attributes. The model is jointly significant and shows a greater improvement over the null specification. The log likelihood increases from −1731.28 to −903.54. The Pseudo-R^2 of 0.478 and the adjusted Pseudo-R^2 of 0.453 indicate that the model explains a substantial share of observed choices. This improvement is consistent with the mixed logit framework that allows taste to vary across farmers and relaxes restrictive substitution patterns assumed under a homogeneous logit model [19, 24].

Table 6. Random parameter logit model with the effects of farm size.

Variable	Coefficient
Random Coefficients (Mean)	
Yield—5% (Low)	3.71*** (0.87)
Yield—10% (Medium)	6.52*** (1.23)
Yield—15% (High)	6.42***(1.07)
Non-Random Coefficient	
Support—Low	1.4438*** (0.4145)
Support—Moderate	1.2085*** (0.2817)
Support—Advanced	1.9701*** (0.3464)
Access—Basic	1.8663*** (0.2120)
Access—Moderate	3.0976*** (0.3684)
Access—Fast	2.2505*** (0.2163)
Risk—Low	1.9960*** (0.2354)
Risk—Medium	1.3032*** (0.2399)
Risk—No risk	2.6445*** (0.2486)
Price	−0.0394*** (0.0036)
Heterogeneity in the Mean of Parameter	
Farm size (5–20 ha): Yield—5% (Low)	0.7465 (0.6728)
Farm size (5–20 ha): Yield—10% (Medium)	0.5147 (0.8956)
Farm size (5–20 ha): Yield—15% (High)	0.9729 (0.8120)
Farm size (>20 ha): Yield—5% (Low)	20.7773*** (1.8351)
Farm size (>20 ha): Yield—10% (Medium)	20.6506*** (2.1993)
Farm size (>20 ha): Yield—15% (High)	19.6064*** (2.028)
Std. Deviations	
Yield—5% (Low)	0.0285 (0.1141)
Yield—10% (Medium)	1.9904*** (0.7344)
Yield—15% (High)	1.4179** (0.6882)
Summary Statistics	
Number of observations	5308
Wald chi-square	1810.18
Prob > chi-square	0.0000
Log-likelihood function: L(β)	−903.54
Log-likelihood: L (0)	−1731.28
Pseudo-R^2	0.478
Adjusted Pseudo-R^2	0.453
AIC	1893.07
BIC	2175.88

Note: *** significant at 1%; ** significant at 5%; standard errors are in brackets.

Yield improvement remains the main driver of WTP for IoT adoption across groups. The effect is strongest among larger farms (>20 ha), where the yield coefficients were very high at β = 20.78, 20.65, and 19.61 for the low, medium, and high levels, respectively. Nguyen et al. [71] and Day et al. [72] highlighted that larger farms place a higher value on productivity-enhancing technologies. This suggests that scale-related gains and stronger profitability prospects increase the WTP for technology adoption. Advanced technical support (β = 1.97), moderate data access (β = 3.10), and no risk (β = 2.64) were all significant at the 1% level. This indicates that farmers value guidance, timely information, and dependable IoT system performance.

The price coefficient is negative and significant at 1%, confirming cost sensitivity. Its relatively small magnitude suggests that larger farms were less constrained by price increases because they have stronger financial capacity and can absorb recurring costs [73, 74]. Overall, the results indicate that farm size moderates WTP for IoT technology adoption in rice farming. Larger farmers respond more strongly to productivity and data-driven features, while smaller farmers may need targeted financial, technical, or institutional support to participate effectively in Malaysia's digital agricultural transformation.

3.1.3. Marginal Willingness to Pay

Table 7 shows the MWTP estimates that transform the preference parameters into monetary values. All MWTP estimates were significant at the 1% level. This reflects that farmers place a clear economic value on each IoT technology attribute. Yield improvement records the largest MWTP. Farmers were willing to pay RM 941 per hectare for low yield potential, RM 1,630 for medium yield potential, and RM 1,657 for high yield potential. Nguyen et al. [71] and Miriti et al. [66] reported similar research findings, where the highest expected yield gains were associated with greater WTP for digital farming technologies.

The MWTP dispersion estimates indicate heterogeneity in the valuation of yield gains. The standard deviations were significant for medium yield (RM 360, $p < 0.05$) and high yield (RM 505, $p < 0.01$). The finding suggests that farmers differ most in their valuation of larger productivity improvements. This variation is in line with differences in farm scale and resource capacity. Larger operators can justify higher investment in yield-enhancing technologies, as the expected returns are greater at scale. In contrast, smaller farms tend to value these gains more cautiously under tighter budget constraints. Substantial MWTP values were also observed for moderate data access (RM 786), no risk (RM 671), and advanced technical support (RM 500). This indicates that information access, reliability, and operational support strengthen the attractiveness of IoT packages. Overall, the results confirm that yield improvement is the primary driver of WTP, while service quality and IoT system reliability add further value and help to explain variation in adoption preferences across rice farmers.

Table 7. MWTP of RPL models with the effects of farm size.

Variable	MWTP (RM)	Lower Limit (LL)	Upper Limit (UL)
Random Coefficients			
Yield—5% (Low)	941.00*** (231.40)	487.47	1394.53
Yield—10% (Medium)	1629.68*** (303.15)	1035.52	2223.85
Yield—15% (High)	1656.60*** (322.04)	1025.41	2287.79
Non-Random Coefficient			
Support—Low	366.59*** (86.88)	196.30	536.87
Support—Moderate	306.82*** (64.41)	180.59	433.06
Support—Advanced	500.20*** (70.78)	361.47	638.94
Access—Basic	473.85*** (46.09)	383.51	564.19
Access—Moderate	786.46*** (58.35)	672.09	900.84
Access—Fast	571.39*** (53.17)	467.18	675.59
Risk—Low	506.78*** (39.32)	429.71	583.84
Risk—Medium	330.88*** (38.03)	256.34	405.42
Risk—No risk	671.44*** (41.24)	590.61	752.26
Std. Deviations			
Yield—5% (Low)	7.23 (2.88)	−49.22	63.68
Yield—10% (Medium)	360.00** (14.98)	66.46	653.54
Yield—15% (High)	505.35***(15.22)	206.98	803.71

Note: *** significant at 1%; ** significant at 5%; standard errors are in brackets.

4. Discussion

Rice farmers in IADA BLS place substantial economic value on IoT bundle packages when these packages can deliver measurable improvements in rice productivity. Preferences also underscore the importance of reliable IoT system performance and service support that reduces effort and disruption during routine farm operations. The relatively low frequency of status quo choices indicates that farmers were willing to consider technology-based services when the offered packages are practical and the benefits are clear.

Yield improvement dominates both preference and monetary valuation in both RPL specifications. Large yield coefficients indicate that expected output gains provide the primary basis for accepting subscription payments. This is reflected in the MWTP estimates, which range from RM 941 per hectare for a low yield improvement to RM 1,657 per hectare for a high yield improvement. These magnitudes confirm that productivity gains form the core economic rationale for IoT adoption. Farmers appear to evaluate bundles first on expected output performance, then assess whether complementary features make the service dependable and workable under field conditions.

Farm size strengthens this pattern and points to segmented demand. Larger farms value yield-related gains more strongly and show weaker sensitivity to subscription costs, since a given percentage yield increase produces larger absolute output gains at scale and raises expected returns. Larger farms also have greater capacity to absorb trial costs and recurring payments. Smallholders, in contrast, face tighter liquidity and stronger affordability constraints that can restrict IoT adoption even when expected gains are attractive. This indicates that adoption potential exists across farm types, while affordability thresholds differ across scales, making a single pricing approach unlikely to suit all farmers.

Service attributes also add meaningful value and help explain choice beyond yield effects. Farmers reported sizeable MWTP for data access, IoT system reliability, and technical support. The MWTP of RM 786 per hectare for moderate real-time data access suggests that information services are treated as productive inputs when they support timely operational decisions, including irrigation scheduling, input timing, and early responses to field problems. The MWTP of RM 671 per hectare for a no-risk IoT system highlights the importance of reliability, since system failure can disrupt farm operations and weaken confidence in subscription-based services. Concerns about performance risk and system failure are frequently reported as barriers to digital technology uptake, particularly among smallholders [68]. The MWTP of RM 500 per hectare for advanced technical support indicates WTP for guidance and troubleshooting that reduces learning costs and downtime, consistent with evidence that support services strengthen adoption and continued use in smart farming integration [69].

Preference heterogeneity is also indicated by the dispersion estimates, which remain significant for data access and reliability even after accounting for farm size. This suggests that farmers differ in how they value information services and performance assurance. This variation is likely shaped by unobserved factors, including risk preferences, digital literacy and confidence in using data, tenure security, and access to credit, all of which can influence willingness to commit to recurring payments. Therefore, adoption barriers extend beyond price and include capability and resource conditions that determine whether IoT benefits translate into improved farm outcomes.

Overall, the results reveal a stable preference structure. Yield improvement provides the main economic motivation for IoT adoption, while service quality, reliability, and technical support increase value by lowering uncertainty and enabling practical use. Farm size shapes both attribute valuation and affordability of subscription costs, supporting differentiated IoT bundle packages and targeted policy support that reflect differences in capacity and constraints.

5. Conclusions and Recommendations

This study provides empirical evidence on rice farmers' preferences and WTP for IoT technology bundles in IADA BLS, using a CE and RPL estimation. The results show a clear ordering of what farmers value in an IoT package. Potential yield improvement dominates adoption preferences, followed by access to real-time data, system reliability, and technical support. This pattern indicates that IoT is evaluated as a paid productivity-enhancing service that must also operate reliably and fit routine farm management. The dominance of yield-related benefits is consistent with prior evidence that farmers attach the highest monetary value to productivity gains. A sorghum trait valuation study in Tanzania reports a mean WTP of TSh 3,150 for a higher yield option of 2.5 t/ha, compared with TSh 1,790 for a lower yield option of 1.5 t/ha [66].

The MWTP estimates also provide a direct basis for financial recommendations. Yield gains represent the main benefit farmers are prepared to internalise, while adoption-enabling features define a defensible envelope for public support. Farmers were willing to pay up to RM 1,657 per hectare for high yield potential, RM 786 for moderate real-time information, RM 500 for advanced technical support, and RM 671 for a reliable no-risk IoT technology system. These values suggest that policy support can be structured to subsidise the reliability and support components at roughly RM 700 to RM 800 per hectare, while farmers absorb the remaining cost that corresponds to their primary motivation, measurable yield improvement. This approach improves fiscal discipline since support is tied to the attributes that reduce adoption barriers rather than substituting for the productivity value that farmers already prioritise.

Product and service design should reflect this valuation structure. Potential increase in rice yield should be positioned as the core value proposition, supported by service features that lower perceived risk and reduce learning costs. Reliability should be treated as a contractual service commitment rather than a technical add-on, with minimum standards for uptime, sensor checks, data update frequency, and time-bound fault resolution. Real-time services should emphasise actionable decision support for irrigation timing, input application, and risk alerts, since information is valued when it enables timely operational action. Technical support should be embedded as a core service feature, supported by a shared delivery model in which agricultural authorities certify local digital facilitators at the irrigation block level, while providers retain responsibility for advanced troubleshooting, calibration, and maintenance protocols.

Policy design should be segmented across farm sizes because affordability and implementation capacity differ. Smallholders are likely to respond to affordability instruments that reduce upfront burden, including time-limited co-financing or matching grants for the first one to two seasons, instalment plans aligned with cropping cycles, and cooperative subscription arrangements that lower per-farm costs. Larger farms tend to be less price-constrained and more output-oriented, so adoption can be supported using concessional loans, partial guarantee credit lines, and performance-linked agreements that reward verified yield gains and sustained service use. These instruments protect public budgets while preserving strong incentives for providers and farmers to focus on outcomes.

Performance assurance should be treated as a central governance mechanism, since IoT system failure during real farm use can undermine confidence in subscription-based services. Provider participation can be conditioned on warranty requirements and season-level service guarantees. Public support can be linked to verified delivery, using recorded uptime, documented sensor checks, consistent data updates, and response time logs for fault resolution. Accountability becomes stronger when monitoring indicators are standardised and auditable, and uncertainty is reduced when minimum service thresholds are enforced.

Capacity building remains essential because farmers differ in how they value data access and reliability, which signals differences in skills and ability to act on digital information. Training should prioritise practical use of dashboards for routine decisions rather than technical features alone. Short follow-up sessions after installation and support during key production periods can reduce early problems and limit discontinuation after trial. Enabling infrastructure also shapes realised benefits, since real-time functions carry limited value when connectivity is unstable. Targeted improvements, including shared gateways and strengthened network access at the irrigation block level, can improve service continuity and increase the practical value of data services.

Several limitations should be acknowledged. The study relies on SP data, so estimated choices may differ from actual purchasing behaviour under binding financial constraints and realised service performance, particularly when farmers have limited experience with IoT systems. The focus on IADA BLS limits generalisability to settings with similar irrigation infrastructure, institutional support, and production conditions. Future research can strengthen external validity using field pilots, revealed preference evidence where feasible, and sampling across multiple granary regions. Future work should also measure enabling constraints, including digital literacy, risk preferences, and credit access, since these factors are likely to explain remaining preference heterogeneity beyond farm size. Structured pilots at the irrigation block level can support learning and accountability, using indicators such as uptime records, response times, training participation, and user-reported operational issues, while testing whether SP translates into continued subscription under real payment conditions.

Overall, three policy implications emerge. Yield improvement underpins farmers' economic viability, so adoption strategies should prioritise IoT bundles that deliver measurable productivity gains. Service quality determines continued use, so reliability standards and embedded technical support should be treated as minimum requirements rather than optional upgrades. Policy instruments should be tailored to farm size, with stronger entry support and risk sharing for smallholders, and performance-linked contracts and scale-appropriate financing for larger farms.

Author Contributions

Conceptualization, N.A.R. and R.K.; methodology, N.A.R. and R.S.; formal analysis, N.A.R.; data curation, N.A.R.; writing—original draft preparation, N.A.R.; writing—review and editing, R.K. and R.S.; supervision, R.K. and R.S.; project administration, N.A.R. All authors have read and agreed to the final version of the manuscript.

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Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki and was approved by the Institutional Review Board of Universiti Utara Malaysia, Othman Yeop Abdullah Graduate School of Business (Ref. No. UUM/OYAGSB/R-4/4/1; approved on 8 December 2024).

Informed Consent Statement

Informed consent was obtained from all subjects involved in this study.

Data Availability Statement

The data presented in this study are available upon request.

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Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

AI Use Statement

The authors used [ChatGPT-5.2 Thinking] solely for grammar checking, sentence structure refinement, and improving the readability of the English text in this manuscript. The authors take full responsibility for all academic content, including all ideas, data, analyses, and conclusions presented herein. The use of AI was thoroughly reviewed and supervised by the authors.

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