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Assessing the Readiness of Implementing Internet of Things (IoT) Systems among Malaysian Agricultural Graduates

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Abstract: The Internet of Things (IoT) has emerged as a transformative technology in agriculture, offering innovative solutions to enhance productivity and sustainability. This study examines the readiness of agricultural graduates from four Malaysian universities to adopt IoT technologies, addressing challenges in the agricultural sector. The research assesses graduates' understanding, attitudes, and perceived usefulness of IoT, identifying factors influencing their preparedness for IoT integration. Data collected from 204 respondents through a structured questionnaire revealed that perceived usefulness is the strongest predictor of IoT readiness, followed by perceived behavioral control and social influences. Attitude, though positively correlated, was not a significant predictor. The study extends the Technology Acceptance Model (TAM) by incorporating perceived behavioral control and social influences, offering theoretical and practical insights. It recommends integrating IoT-related subjects and hands-on training in educational programs to enhance readiness. Future research should explore external factors like IoT infrastructure and government policies to understand barriers and facilitators of IoT adoption in agriculture.

Keywords: Internet of Things (IoT), Theory Acceptance Model (TAM), Agricultural Graduate, Precision Agriculture, Smart Farming.

1. Introduction

Over the past two decades, the rapid expansion of the Internet has transformed various sectors, providing real-time services and enhancing connectivity (Kraus et al., 2021; Kez et al., 2022). One of the most significant technological advancements is the Internet of Things (IoT), which has revolutionized industries such as education, commerce, transportation, and particularly, agriculture (Dhanaraju et al., 2022). In the agricultural sector, IoT plays a pivotal role in automating processes, improving resource management, and boosting productivity. In Malaysia, the agricultural landscape is facing growing challenges, including labor shortages, inefficient resource use, and the need for increased sustainability (Othman et al., 2024; De Sousa et al., 2024). These issues underscore the necessity for IoT-based smart farming solutions to drive a digital transformation in agriculture (Dhanaraju et al., 2022). To realize this transformation, future agricultural professionals must be equipped with the knowledge and skills to effectively implement IoT technologies.

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This study assesses the readiness of agricultural first degree (bachelor) program graduates to adopt IoT technologies by evaluating their understanding, attitudes, and perceived usefulness of these innovations (Farooq et al., 2019). The insights gained from this research will inform educational programs, helping to better prepare both current students and graduates for IoT integration in agricultural practices, thereby fostering a workforce capable of leveraging these advanced technologies (Ghashim & Arshad, 2023; Rashid & Kausik, 2024). Specifically, the study investigates the key variables influencing the readiness of agricultural graduates for IoT implementation (Pillai & Sivathanu, 2020). It explores the relationship between these factors such as perceived usefulness, behavioral control, social influences and the graduates' overall preparedness to integrate IoT into their agricultural practices, identifying the dominant drivers of IoT adoption.

1.1 Theoretical Framework and Hypotheses.

The study modifies the Technology Acceptance Model (TAM) to assess the readiness of agricultural graduates for IoT implementation. The inclusion of perceived behavioral control and social influences in the TAM framework addresses the unique context of agricultural technology adoption, where confidence in using technology and peer influence play critical roles. This adaptation ensures a more comprehensive understanding of the factors driving IoT readiness among agricultural graduates. The framework includes four independent variables from literature that are hypothesized to influence IoT readiness as shown in Table 1 below.

Table 1: Hypothesis Approaches

Hypothesis (*H*)	Approach
H1: Attitude positively affects IoT readiness.	This hypothesis posits that the attitude of the graduates towards IoT will significantly influence their readiness to adopt IoT systems in agricultural practices.
H2: Perceived behaviour positively affects IoT readiness.	This hypothesis suggests that the graduates' perceptions of their behavior, including their confidence and control over using IoT, will have a significant positive impact on their readiness to implement IoT technologies
H3: Social influences positively affect IoT readiness.	This hypothesis asserts that the social environment, including peers, mentors, and societal norms, will positively influence the readiness of graduates to adopt IoT systems.
H4: Perceived usefulness positively affects IoT readiness.	This hypothesis indicates that the perceived benefits and utility of IoT systems in improving agricultural outcomes will significantly enhance the readiness of the graduates to adopt these technologies.

2. Literature Review

2.1 IoT in Agriculture

The next century of Smart Computing is expected to focus significantly on the Internet of Things (IoT). IoT transforms traditional technology into "New Century Anywhere Computing," connecting various devices and systems to the internet (Atzori et al., 2017; Farooq et al., 2019). IoT technologies enable easy control of devices over the internet, data collection through distributed sensors, and data analysis for better decision-making (Farooq et al., 2019). Recent agricultural IoT studies have highlighted barriers to large-scale adoption in the agri-food supply chain, such as the need for innovative operating models, security, safety, and data management (Villa-Henriksen et al., 2020). Wireless sensor networks (WSN) are commonly used in smart agriculture to enhance crop yields and reduce costs by providing real-time data for informed decision-making (Kiani & Seyyedabbasi, 2018; En & Hui, 2023)

WSNs increase productivity and efficiency by monitoring field variables like soil quality, temperature, and biomass, and they can also be used during transport to monitor conditions like temperature and humidity (Kodali et al., 2014; Muangprathub et al., 2019). IoT applications in agriculture assist farmers with decision-making, improve crop growth, and optimize harvesting periods (Muangprathub et al., 2019; Ismail et al., 2023). Integrated Information Systems (IIS) based on IoT, such as the one proposed by Ismail et al., 2023, combine IoT, cloud computing, and geoinformatics to enhance environmental monitoring and management. These systems improve decision-making and monitoring efficiency (Muangprathub et al., 2019). In the agro-industrial supply chain, IoT has been used to develop knowledge systems, track food production, and ensure product traceability (Sa'ari et al., 2017). IoT applications in agriculture support farmers with tools and automated systems for increased production, efficiency, and profit (Atzori et al., 2017). Malaysian agricultural graduates face significant challenges in adopting IoT technologies due to a lack of practical training, limited access to IoT infrastructure, and insufficient awareness of the benefits and applications of IoT in agriculture.

2.2 Technology Readiness

The effective implementation of Internet of Things (IoT) systems hinges on technological readiness, encompassing resource availability and organizational knowledge (Duang-Ek-Anong et al., 2019). The Technology Readiness Index (TRI) measures an individual's propensity to adopt new technologies by evaluating optimism, innovativeness, discomfort, and insecurity (Kiani & Seyyedabbasi, 2018). The Technology Acceptance Model (TAM) as shown in Figure 1, complements TRI by explaining technology acceptance through perceived usefulness (PU) and perceived ease of use (PEOU) (Abu et al., 2015). Integrating TRI and TAM provides a comprehensive framework for understanding technology adoption, addressing readiness and psychological predispositions (TRI) alongside acceptance and usage behavior (TAM) (Hallikainen et al., 2016; Zaidi et al., 2019). This integration enables organizations to formulate strategies enhancing technology adoption by assessing and addressing both readiness and acceptance factors, ensuring smoother transitions and higher adoption rates.

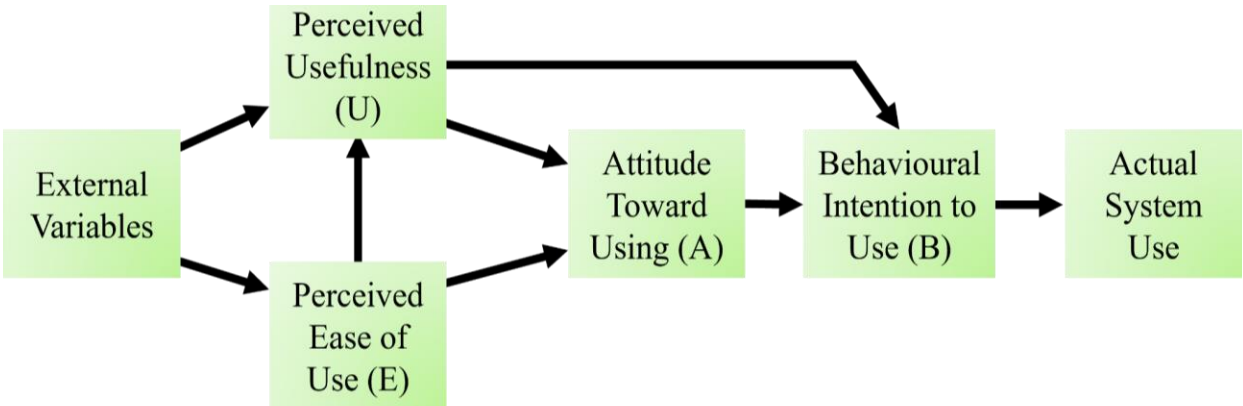

Figure 1. Technology Acceptance Model (Limani et al., 2019)

2.3 Digital Transformation Trends in Higher Education

Traditional education, based on static learning environments, is being transformed by digital technologies and online tools. These innovations enhance teaching and learning processes, making education more cost-effective and accessible (Peña-López et al., 2016; Limani et al., 2019). Higher education institutions are increasingly adopting digital technologies to improve educational outcomes and maintain competitiveness. These technologies enable personalized learning, better access to resources, and more efficient administrative processes (Lawrence et al., 2019). The digital transformation in higher education supports excellence in teaching and learning, adapting to the changing needs of students and educators (Kiani & Seyyedabbasi, 2018).

2.3 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was introduced by Davis et al. (1989) as an extension of the Theory of Reasoned Action (TRA) (Venkatesh & Davis, 2000), which posits that behavior is determined by intention, influenced by attitude and subjective norms. TAM specifically focuses on technology adoption, identifying perceived usefulness (the belief that using a system will improve performance) and perceived ease of use (the belief that using a system will be effortless) as the key determinants of user acceptance (Venkatesh & Davis, 2000). For this study, TAM was selected because of its proven robustness and simplicity in explaining technology adoption behaviors across diverse contexts, particularly in agriculture and education. Unlike broader models such as the Unified Theory of Acceptance and Use of Technology (UTAUT) or the Theory of Planned Behavior (TPB), TAM provides a focused approach to understanding core acceptance drivers directly tied to technology (Cheng, 2018; Marikyan & Papagiannidis. 2023). While UTAUT and TPB incorporate a broader range of factors, including organizational and societal influences, these models can be overly complex for the specific objective of this study, which is to assess individual readiness for IoT systems among agricultural graduates.

Additionally, TAM has been widely validated in similar domains, such as IoT adoption in agriculture (Muangprathub et al., 2019; Villa-Henriksen et al., 2020) and offers adaptability to integrate additional constructs relevant to this study especially on perceived behavioral control and social influence. By incorporating these variables, TAM is refined to capture the unique context of IoT technology adoption, where confidence in usage and peer influence are critical factors (Alzahrani, 2023). This integration ensures a more tailored and efficient framework for analyzing the readiness of Malaysian agricultural graduates to embrace IoT technologies, providing actionable insights for educational and policy interventions.

3.0 Methodology

3.1 Population and Sample Design

This study employs a quantitative research design, focusing on a descriptive and explanatory approach to assess the readiness of agricultural graduates to adopt Internet of Things (IoT) technologies. The population comprises 430 graduates from four Malaysian universities, each holding at least a bachelor's degree in an agricultural-related program.

A simple random sampling technique was utilized to select 204 participants, ensuring every individual in the population had an equal chance of selection. This approach minimizes bias and enhances the generalizability of the results. The sample size was narrowed based on the Krejcie & Morgan (1970) sample size determiner with a 5% margin of error and a 95% confidence level to achieve statistical significance (Bukhari, 2021). Data collection was conducted through a structured questionnaire administered online via Google Forms. Participants received an email, phone messages and social media invitation containing a link to the questionnaire. The whole questionnaire took approximately 10–15 minutes to complete. Follow-up reminders were sent to ensure a high response rate, and the anonymity of responses was maintained to encourage honest feedback.

The questionnaire underwent pre-testing with a pilot group of 30 graduates to ensure clarity, reliability, and validity. Feedback from the pilot phase led to minor adjustments, enhancing the quality of the final instrument. The finalized questionnaire consisted of sections on demographic information, IoT readiness, and factors influencing IoT adoption, aligning with the objectives of the study.

3.2 Data Collection Method

Data is collected through a questionnaire filled out by 204 randomly selected graduates from four universities. The survey includes questions on demographics, IoT readiness, and factors influencing IoT adoption. The questionnaire was developed based on existing validated scales and pre-tested with a pilot group of 30 graduates to ensure clarity and relevance. Adjustments were made based on the pilot feedback to enhance the reliability and validity of the instrument. Descriptive and frequency analyses determine respondent characteristics using SPSS to identify factors affecting IoT readiness. Data for this study was collected through a structured questionnaire distributed via Google Forms to 204 randomly selected graduates from four Malaysian universities. The questionnaire was designed based on validated scales from previous studies, with modifications to suit the context of IoT adoption in agriculture as shown in Table 2. .

Table 2: The elements and sections of questionnaires' development.

Section	Elements and Predictors	References
Demographic Information	*Age, gender, marital status, educational background, and IoT budget*	Hallikainen et al. (2022); Ismail et al. (2023)
IoT Readiness	*General readiness, confidence in IoT usage, intention to adopt IoT*	Atzori et al. (2017); Farooq et al. (2019); En & Hui. (2023)
Perceived Factors	*Perceived usefulness, perceived ease of use, perceived behavioural control, and social influences*	Sa'ari et al. (2017); Kiani & Seyyedabbasi. (2018); Villa-Henriksen et al. (2020)

The reliability of the questionnaire was assessed using Cronbach's alpha as shown in Table 3, which yielded values exceeding 0.7 for all constructs, indicating acceptable internal consistency. The validity was ensured through content validation by two experts in the field of technology adoption and agriculture. Feedback from these experts helped refine the phrasing and relevance of the items to align with the study objectives.

Table 3: The Cronbach's Alpha Reliability

Construct	Number of Items	Cronbach's Alpha	Interpretation
IoT Readiness	5	0.85	Good
Perceived Usefulness	6	0.88	Excellent
Perceived Behavioural Control	5	0.82	Good
Social Influence	4	0.79	Acceptable
Attitude	5	0.83	Good

Responses were analyzed using statistical techniques, including descriptive analysis and multiple linear regression, to explore the relationships between the variables and IoT readiness. The structured design of the questionnaire and rigorous testing ensured the accuracy and applicability of the data collected for this research.

4. Results and Discussion

4.1 Demography of the Graduates

Many respondents are female (66.7%) and unmarried (96.6%). Most are aged 23 or older (53.9%) and predominantly Malay (90.2%). All hold a bachelor's degree. Graduates are from various university backgrounds, with the highest numbers from Universiti Teknologi MARA (38.2%) and Universiti Putra Malaysia (35.8%). Most of the graduates primarily major in plantation and management (50.5%) as shown below in Table 4.

Table 4: Demographic information of respondents.

Profile		Frequency (n)	Percentage (%)
Gender	Male	68	33.3
	Female	136	66.7
Marital Status	Single (unmarried)	197	96.6
	Married	7	3.4
Race	Malay	184	90.2
	Bumiputera Sabah & Sarawak	20	9.8
Age Group (years)	21	32	15.7
	22	62	30.4
	> 23	110	53.9
University Name	Universiti Teknologi MARA[a]	78	38.2
	Universiti Putra Malaysia[b]	73	35.8
	Universiti Pendidikan Sultan Idris[c]	28	13.7
	Universiti Sultan Zainal Abidin[a]	25	12.3

Notes: **a**, focuses on plantation and management; **b**, focuses on agricultural engineering; **c**, focuses on agricultural education.

The results in Table 5 indicate that most graduates (38.2%) are willing to invest RM 2000–RM 4000 in IoT implementation for agriculture, with fewer ready to allocate higher budgets. This suggests a moderate level of affordability, highlighting the need for cost-effective IoT solutions. Financial constraints may limit adoption for some, emphasizing the importance of subsidies, affordable technologies, and education on the benefits and returns of IoT to encourage broader implementation (Abiog, 2022).

Table 5: Expected budget to involve the implementation of IoT system in agriculture.

Profile	Frequency (n)	Percentage (%)
< RM 2000	36	17.6
RM 2000 – RM 4000	78	38.2
RM 4000 – RM 6000	41	20.1
RM 6000 – RM 8000	23	11.3
> RM 8000	26	12.7

4.2 Pearson Correlation Analysis

Table 6 reveals the strength and significance of relationships between the dependent variable and four independent variables: attitude, perceived behavioral control, social influences, and perceived usefulness. All correlations are statistically significant at the 0.01 level (2-tailed), indicating a very low probability that the observed relationships occurred by chance. Among the variables, perceived usefulness exhibits the strongest positive relationship with the dependent variable ($r = 0.780$), suggesting it plays a crucial role in influencing the outcome. Meanwhile, social influences show a moderate, yet relatively strong correlation ($r = 0.668$) followed by Perceived Behavioral Control ($r = 0.607$) and Attitude ($r = 0.568$), both of which also demonstrate moderate positive relationships. These findings highlight that as these independent variables increase, the dependent variable tends to increase correspondingly, with "perceived usefulness" having the most substantial impact.

Table 6: Correlation coefficient analysis

Variable *(x)*		**r**	**Relationship *(y)***
Attitude	Pearson Correlation	**.568**	Moderate
	Sig. (2-tailed)	.000	
Perceived of Behaviour Control	Pearson Correlation	**.607**	Moderate
	Sig. (2-tailed)	.000	
Social Influences	Pearson Correlation	**.668**	Moderate
	Sig. (2-tailed)	.000	
Perceived of Usefulness	Pearson Correlation	**.780**	Strong
	Sig. (2-tailed)	.000	

Notes: Correlation is significant at the 0.01 level of significant (2-tailed); ***x***: IoT Predictors; ***y***: Readiness of Implementing Internet of Things (IoT).780

4.3 Multiple Linear Regression Analysis

The model explains 65% of the variance in IoT readiness using MLR as shown in Table 7. Significant predictors include perceived behavioural control (*β* = 0.132, *p* = .034), social influences (β = 0.193, *p* = .004), and perceived usefulness (β = 0.532, *p* = .000). Attitude is not a significant predictor (β = 0.023, *p* = .691) as shown in Table 8.

Table 7: Multiple linear regression analysis results.

Model	**R**	**R–square**	**Adjusted R-square**	**Std. Error of the Estimate**
1	0.806	**0.650**	0.643	0.45671

Table 8: Regression coefficients analysis results.

Model	Unstandardized Coefficients		Standardized Coefficients	t	*p-value*	Status
	β	Std. Error	Beta			
(Constant)	0.526	0.181		2.906	0.004	
Attitude	0.023	0.059	0.24	0.399	0.691	Rejected
Perceived of Behaviour Control	0.132	0.062	0.132	2.139	0.034	Accepted
Social Influences	0.193	0.067	0.183	2.884	0.004	Accepted
Perceived of Usefulness	0.532	0.061	0.556	8.698	0.000	Accepted

The analysis shows that perceived usefulness is the strongest factor influencing graduates' readiness to adopt IoT technologies, followed by social influences and perceived behavioral control. While a positive attitude toward IoT was expected to be significant, it was not a strong predictor. Together, these factors explain 65% of the variation in IoT readiness, highlighting the importance of showcasing IoT benefits, building confidence, and fostering a supportive environment for adoption.

4.1 Attitude Towards IoT and Readiness

Based on the analysis shown in Table 8, contrary to expectations which posited that attitude towards IoT would positively influence IoT readiness, was rejected. This finding suggests that having a positive attitude towards IoT does not necessarily translate into graduates feeling prepared or motivated to adopt the technology in practice. This outcome is consistent with the Technology Acceptance Model (TAM) literature, which indicates that while attitudes toward technology are important, they may not be as influential as other factors like perceived usefulness or behavioural control in determining technology adoption (Venkatesh et al., 2003).

Graduates may have favourable views of IoT, but this does not automatically translate into readiness, likely due to practical barriers such as inadequate training or limited access to IoT systems (Rashid & Kausik, 2024). As such, positive attitudes alone are insufficient to drive actual implementation, reinforcing the need for targeted educational programs that go beyond changing attitudes and focus on improving technical skills and confidence in using IoT. Educational institutions should not rely solely on fostering positive attitudes toward IoT but should also focus on providing practical tools and experiences that build ongoing students and graduates' confidence and competence with IoT technologies.

4.2 Perceived Usefulness as a Strong Predictor of IoT Readiness

The results clearly show that perceived usefulness (PU) is the strongest predictor of IoT readiness among graduates, consistent with previous studies based on the Technology Acceptance Model (TAM) (Davis, 1989). PU refers to the extent to which individuals believe that using IoT technologies will enhance their performance or productivity. In this case, graduates who understand the practical benefits of IoT, such as improving efficiency in resource management, automating processes, and boosting agricultural yields are more likely to be ready for IoT adoption. This result aligns with the findings of Muangprathub et al. (2019), who demonstrated that farmers are more likely to embrace IoT when they recognize its value in optimizing agricultural processes. Similarly, Villa-Henriksen et al. (2020) emphasize the critical role of PU in driving IoT adoption in agriculture, as it directly relates to improving decision-making, monitoring, and productivity.

Educational programs should prioritize enhancing graduates' understanding of the tangible benefits of IoT. Case studies, field demonstrations, and exposure to successful IoT applications in agriculture would likely increase the perceived usefulness of IoT among graduates, motivating them to adopt these technologies in their future careers.

4.3 The Role of Perceived Behavioral Control

Another significant factor identified in this study is perceived behavioral control (PBC), which reflects the graduates' confidence in their ability to use IoT technologies. Those who feel more capable of controlling and using IoT devices are more likely to adopt them. This finding is consistent with Ajzen's (1991) Theory of Planned Behavior, which posits that PBC is crucial in determining whether individuals engage in a particular behavior, especially in technology adoption.

The results indicate that while graduates may understand the value of IoT, there is a notable gap in their confidence and perceived control over the technology. This could be due to the lack of practical exposure and hands-on experience with IoT systems during their education. A previous study by Kiani & Seyyedabbasi (2018) also noted that practical barriers, such as a lack of training and infrastructure, could hinder the readiness of individuals to implement IoT. To enhance PBC, agricultural education programs should integrate more practical IoT training, including workshops, internships, and real-world projects. Universities can collaborate with industry partners to offer hands-on experiences, allowing graduates to work directly with IoT devices and systems. This would help graduates develop the confidence and skills needed to successfully implement IoT in their future careers.

4.4 Social Influence as a Key Driver

The study also highlights the importance of social influence in shaping graduates' readiness for IoT adoption. Social influence refers to the impact of peers, mentors, and societal norms on individuals' decisions. Graduates are more likely to adopt IoT technologies if they perceive that their social environment, whether through peer support, guidance from educators, or societal trends, encourages it. This finding is consistent with research from Venkatesh et al. (2003), which demonstrates that social influence significantly affects technology adoption, especially in educational and professional settings. In agriculture, social norms and peer recommendations play a critical role in influencing the adoption of new technologies. For instance, farmers and graduates often look to successful peers or mentors for guidance on whether adopting new technologies like IoT is worth the investment (Sa'ari et al., 2017). Universities and agricultural programs can leverage social influence by fostering a collaborative learning environment where graduates can share experiences and knowledge about IoT. Peer mentoring programs, IoT-focused clubs, and industry-education partnerships can help create a culture that encourages the adoption of these technologies.

4.5 Practical and Policy Recommendations

Based on the findings, several practical recommendations emerge. First, educational institutions should integrate IoT-related subjects into their curricula, ensuring that graduates receive both theoretical knowledge and practical training. This can be achieved through partnerships with industry leaders and hands-on projects that allow graduates to apply IoT in real-world agricultural settings. Second, policymakers should support the development of IoT infrastructure in rural areas to facilitate adoption (Doyduk et al., 2019; Sa'ari et al., 2017). Graduates entering the workforce in rural settings often face limited access to the technologies they are expected to use. Government initiatives can provide grants and financial incentives to universities and farmers to invest in IoT technologies, making them more accessible.

Lastly, industry collaboration is key. Universities should collaborate with agricultural businesses and IoT providers to offer internships, workshops, and job placements. This would not only give graduates practical experience but also help close the gap between industry expectations and educational preparation.

5. Conclusion

This research utilized the Technology Acceptance Model (TAM) to explore the relationships between perceived usefulness, ease of use, social influence, and user acceptance of IoT technology. The study confirms that IoT applications' adoption is influenced by their perceived usefulness and ease of use, demonstrating the applicability of TAM to modern technologies like IoT. The findings indicate that all variables such as attitude, perceived behavioral control, social influence, and perceived usefulness have moderate to strong relationships with the readiness of agricultural graduates to implement IoT systems. While attitude showed a positive correlation, it was not a significant predictor. In contrast, perceived behavioral control, social influence, and perceived usefulness were significant predictors, with perceived usefulness being the dominant factor. This suggests that if IoT technology significantly improves task efficiency and success in farming activities, students are more likely to adopt it.

Based on the findings, several recommendations are proposed for education and training to help graduates and young farmers understand and effectively use IoT, workshops and seminars should be conducted. These educational initiatives will reduce discomfort associated with new technology by providing hands-on experience and practical knowledge. Additionally, it's important to implement long-term plans that balance the use of IoT with preserving essential human interactions, ensuring technology enhances rather than replaces personal engagement. To improve the response rate, future studies could implement multiple follow-up reminders, offer incentives for completing the survey, or streamline the questionnaire to reduce the time required for completion.

A special body should be established to develop, supervise, and evaluate comprehensive plans at federal, state, and local levels to enhance readiness and acceptance of agricultural technologies among farmers in Malaysia. This body would focus on improving awareness of IoT through targeted programs and training, aiming to transition small-scale and government-dependent agri-entrepreneurs into large-scale operators. Furthermore, offering loans to coastal agri-entrepreneurs would facilitate the purchase of IoT technologies, making these advanced tools more accessible and affordable. Increasing farmer awareness of IoT benefits is crucial. Awareness campaigns should provide detailed explanations of the advantages of sustainable farming technologies. This study confirms that perceived usefulness, perceived behavioral control, and social influence significantly impact IoT readiness among agricultural graduates. Educational programs should focus on enhancing these factors through targeted training and curriculum development. Future research should explore the role of external factors and develop strategies to overcome practical barriers to IoT adoption.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the author(s) used CHATGPT to refine the text's readability and language. After utilizing this tool, the author(s) carefully reviewed and edited the content as required, taking full responsibility for the final publication.

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