Economic and Technology Management Review, Vol. 25(2026): 77 – 94

Assessing smart farming technology usage among paddy farmers using a Fuzzy Logic index: Evidence from major granary areas in Malaysia

(Penilaian tahap penggunaan teknologi pertanian pintar dalam kalangan pesawah padi. Pendekatan indeks Logic Kabur di kawasan jelapang utama Malaysia)

Rosnani Harun[1], Engku Elini Engku Ariff[1], Hairazi Rahim[1], Nuruddin Mohamad Isa[1] and Nor Azlina Saari[1]

Keywords: smart farming technology, agricultural digitalisation, paddy farming, Fuzzy Logic index, technology usage gap and granary areas

Abstract

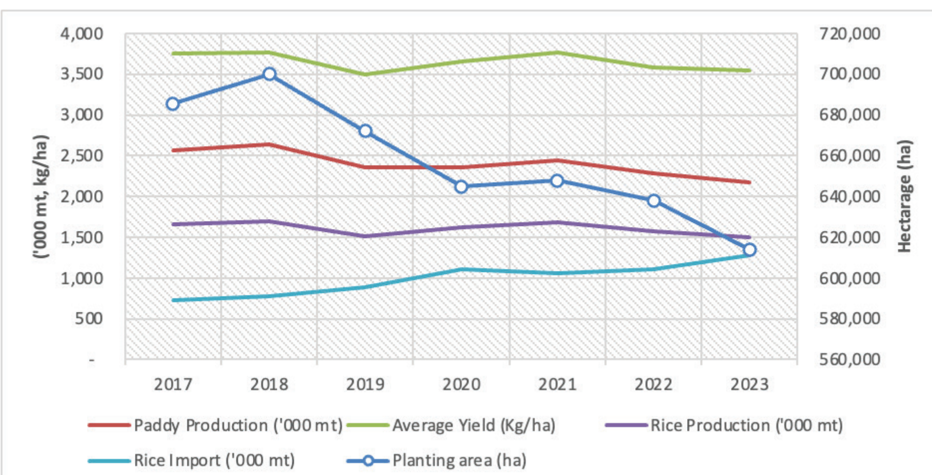
The smart farming technologies mark a transformative era in global rice cultivation. In Malaysia, despite the development of these technologies, including Internet of Things (IoT) applications, their usage and impact among paddy farmers remain limited. This transition toward Smart Farming Technology (SFT) is critical for strengthening national food security and improving the sustainability of Malaysia's rice production sector. Correspondingly, this study assesses the level of the SFT Usage Index among paddy farmers across six major granary areas. Primary data were collected through a structured questionnaire and face-to-face interviews with 982 respondents. A Fuzzy Logic approach was used to measure the SFT Usage Index, classifying technology usage into three levels: low, moderate and high. Results indicate that Integrated Agricultural Development Area (IADA) Rompin exhibited the highest average index score (0.629), followed by IADA Pulau Pinang (0.533). At the same time, Muda Agricultural Development Authotity (MADA) recorded the lowest (0.325). Statistical analysis confirmed a significant difference in mean index scores among the granary areas (p <0.001). Meanwhile, Tukey post hoc tests revealed that IADA Rompin significantly outperformed all other granaries, whereas MADA consistently lagged. Despite a national mean index of 0.499 (moderate), the findings highlight substantial inter-and intra-regional gaps. Further, the study found that farm size, financial support, and training had a significant positive influence on the SFT Usage Index. Conversely, farmers' age was reported to have a significant negative influence on the SFT Usage Index. These disparities suggest the need for targeted interventions, enhanced training and inclusive financial support strategies to bridge the technology divide. Overall, the study provides actionable insights for policymakers and stakeholders to formulate region-specific strategies to boost the transfer and application of SFT among paddy farmers, ultimately contributing to sustainable national food security.

[1]Socio-Economy, Market Intelligence and Agribusiness Research Centre, MARDI Headquarters, Persiaran MARDI-UPM, 43400 Serdang, Selangor
e-mail: rosnani@mardi.gov.my

Introduction

The advent of Smart Farming Technology (SFT) has ushered in a new era of digitalisation in rice cultivation globally. Notably, the integration of SFT into paddy production is expected to reduce field management time and production costs. Accordingly, the Twelfth Malaysia Plan (12MP, 2021 – 2025) places significant emphasis on modernising the agricultural sector through the adoption of SFT. Consequently, the efficient utilisation of resources, coupled with the rapid advancement of digital technologies, is critically needed to ensure optimal and sustainable food production.

The paddy and rice industry is an important sector that receives primary attention in national food security policies. In line with the government's target to improve the national paddy and rice industry, the current policy has focused on addressing issues related to paddy crops and the country's rice sufficiency. However, the country's paddy and rice industry has experienced a decline in planted area, with a negative annual growth rate of 1.56% (*Figure 1*). This lack of significant yield improvement is a critical issue. As such, the flat trend indicates that technological improvements and modern farming practices are not being adopted at a rate that can offset the shrinking agricultural land base. The impact on paddy production also presents a negative trend, with a value of 2.36% per year. Moreover, this trend affected the domestic rice supply, with total rice imports increasing at an annual growth rate of 8.47%. The combined effects of a shrinking planted area, declining production, and rising imports result in a significant drop in the country's Self-Sufficiency Level (SSL) for rice. In fact, SSL decreased by about 17.4% from 68% in 2018 to 56.2% in 2024 (MOA 2024). This figure encapsulates the overall negative trend presented in *Figure 1*. The country is producing a smaller percentage of its own rice, making it more vulnerable to global market fluctuations, supply chain disruptions and price volatility. This, in turn, poses a serious threat to national food security and highlights the urgent need for a strategic intervention to reverse these trends.



Source: Ministry of Agriculture and Food Security Malaysia, 2024

Figure 1. Current status of Malaysia's paddy and rice industry

In response to these challenges, the agricultural sector is undergoing a digital transformation, with growing interest in SFT (Baharin et al. 2025). SFT has become a central focus in efforts to modernise the agricultural sector, aligning with the goals of the National Agrofood Policy (NAP 2.0) for 2021 to 2030. In addition, the NAP 2.0 explicitly supports the modernisation and application of smart farming in the paddy and rice subsector. In response, a primary strategy is to enhance efficiency and productivity by widely disseminating modern technology applications. Various programmes have been implemented to increase the adoption rate of modern technologies across the agri-food sector. These efforts include strengthening farmers' technological literacy and developing affordable technology packages.

Furthermore, the 12MP emphasises increasing agricultural productivity through the adoption of modern and digital technologies. In the paddy sector, SFTs are expected to improve field management, optimise input use and increase harvest efficiency (Hashim et al. 2024), thereby contributing to long-term sustainability and food self-sufficiency. Still, the availability of smart farming technologies in the market and their level of adoption among paddy farmers continue to raise concerns. Smart farming technologies for paddy production, including the Internet of Things (IoT), Decision Support System (DSS), Geographical Information System (GIS) and drones (Kamal and Amin 2020; Abdul Aziz et al. 2008). Additionally, the Malaysian Agricultural Research and Development Institute (MARDI), as a research institution, has developed several smart farming technologies. This includes land levelling systems and Variable Rate Technology (VRT) for precision farming (Rahim et al. 2018).

Digital literacy plays a crucial role in shaping the uptake of smart farming technologies among smallholder paddy farmers (Kamarul Zaman et al. 2023), particularly in developing countries. In Malaysia, while the digital transformation of agriculture is gaining attention, the readiness and adoption among rural farmers remain uneven (Baharin et al. 2025). Correspondingly, the successful integration of smart technologies, particularly IoT, drones and Artificial Intelligence (AI), is envisioned to catalyse a more resilient and self-reliant paddy production ecosystem in Malaysia. At the same time, the application of drone technology on paddy farms will have a positive impact on society by enabling the production of products from the field in a limited time. As a result, farmers will be better informed about technology, able to meet society's overall demand and help create a better future for Malaysian food security (Abdul Latiff and Zulkifli 2020).

Despite significant efforts in Malaysia to develop rice production technologies, including innovative technologies and the IoT, their impact on improving overall rice productivity remains limited. The availability of these technologies in the market and their level of adoption among farmers continue to raise concerns, suggesting a gap between technological innovation and practical application in the field. This situation highlights the need for a systematic assessment of SFT adoption among rice farmers in Malaysia. Such an evaluation is crucial to strengthening the competitiveness and sustainability of the rice industry by leveraging technologies developed by MARDI. It also ensures that these innovations effectively contribute to national food security. Nonetheless, questions persist regarding the availability of these technologies in the market and their use among farmers. Therefore, the objectives of this study are to measure the level of the SFT Usage Index and identify the factors influencing the index among paddy farmers in Malaysia.

Measuring the level of smart agriculture technology usage among rice farmers will offer valuable insights for government agencies and policymakers. It will serve as a guideline for designing effective policies and interventions that can enhance productivity and competitiveness in the rice industry. Hence, this study will contribute to the paddy and rice industry by providing evidence-based guidelines for policymakers and relevant agencies to enhance the productivity, efficiency and resilience of Malaysia's rice sector.

Literature review

Definition of smart farming technology

Smart farming, often referred to as precision or digital agriculture, is a technology-driven approach that integrates advanced information and communication systems, decision-making and efficiency to enhance sustainability in agricultural production (FAO 2019). The foundation of smart farming lies in the integration of Industry 4.0 technologies. It shifts from traditional intuition-based practices to data-driven agriculture supported by real-time data analytics.

Commonly, five core technological domains are highlighted in the literature. Sensors are utilised for monitoring soil moisture, temperature, crop health and water levels (Saili et al. 2024; Bujang et al. 2019). Second, communication systems enable seamless transmission of field data (Saili et al. 2024). Meanwhile, big data processing is used to manage large and heterogeneous agricultural datasets (Garg and Alam 2023). Actuators, including drones and automated machinery, are employed for irrigation, fertilisation and pest control. Lastly, AI and machine learning for predictive analytics, yield forecasting and automated decision-making (Wolfert et al. 2017).

Smart farming technology usage in paddy farming

Smart farming technologies are increasingly applied in paddy systems globally, especially in China, Japan, South Korea, Thailand and Malaysia. Key applications include IoT-based automated water management (Mat Lazim et al., 2020; Liakos et al., 2018), drone-assisted monitoring and input application and AI-driven yield forecasting (Chen et al. 2021). These technologies improve yields, reduce input costs, save labour and time and enhance environmental sustainability (Harun et al. 2024; Kamarul Zaman et al. 2023; Gabriel and Haritharan 2020; Balafoutis et al. 2020). However, constraints such as high investment costs, low digital literacy among older farmers, limited technical support and inadequate financing remain as major barriers (Kamarul Zaman et al. 2023).

Internationally, SFT adoption is shaped by socioeconomic characteristics, farm attributes, technology awareness and institutional support (Baharin et al. 2025; Saili et al. 2024; Fragomeli et al. 2024; Idris and Zulkifli 2024; Saili et al. 2024; Kamarul Zaman et al. 2023; FAO 2021). Key barriers consistently identified include high upfront costs, interoperability issues, data privacy concerns and farmer resistance to change (Fragomeli et al. 2024; Kamarul Zaman et al. 2023). Building on this, individual and farm-related factors, such as social trust and influence, serve as crucial drivers of adoption, while economic constraints and infrastructure limitations, particularly internet access, pose significant barriers (Fragomeli et al. 2024). Note that success requires addressing infrastructure gaps, enhancing farmer training, strengthening policy frameworks, ensuring stakeholder collaboration and maintaining continuous research and development (Ahmed et al. 2024). Furthermore, previous studies have used a qualitative approach (Baharin et al. 2025; Saili et al. 2024; Kamarul Zaman et al. 2023) to explore factors influencing farmers' adoption of smart farming technologies.

In Malaysia, empirical studies remain limited and are typically focused on specific technologies rather than providing a comprehensive assessment of overall SFT usage. Existing studies have explored adoption qualitatively (Kamarul Zaman et al. 2023), assessed Knowledge, Attitude and Practice (KAP) (Idris and Zulkifli 2024) and examined digital tool usage patterns (Baharin et al. 2025). In addition, findings suggest widespread smartphone use and low adoption of advanced technologies such as drones, IoT sensors and Global Positioning System (GPS) enabled applications. Key adoption drivers include peer demonstration and perceived usefulness, while barriers include limited digital confidence and high technology costs. Meanwhile, informal peer networks and intergenerational learning emerged as significant pathways for knowledge dissemination. Although smart farming presents significant potential, adoption faces challenges such as infrastructure gaps, limited digital literacy, data privacy concerns, limited collaboration and insufficient policy support (Ahmed et al. 2024). Thus, overcoming these hurdles is essential to ensure that the digital transformation of agriculture is both effective and equitable. Given these gaps, there is a need for a more comprehensive, quantitative measurement of SFT usage among paddy farmers in Malaysia. Correspondingly, this study addresses that gap by developing a Fuzzy Logic model based on a quantitative method to capture varying degrees of adoption rather than relying on binary measures (Zadeh 1965; Abdullah et al. 2022).

Fuzzy Logic approach

Fuzzy Logic provides a robust methodological framework for assessing technology usage and innovation performance, especially when addressing subjective, uncertain or linguistic data. Introduced by Zadeh (1965), Fuzzy set theory allows variables to take values between 0 and 1, enabling a more flexible representation of human judgments than traditional crisp classification. The systems provide a means of representing human expert knowledge of the process as Fuzzy (IF-THEN) rules (Alavi 2013). Likewise, previous studies have demonstrated Fuzzy Logic's strengths in overseeing ambiguity within decision-making processes. It has also been applied to qualitative innovation assessments (García et al. 2015), performance measurement under uncertainty (Gurrea et al. 2014) and technology choice modeling using expert-based fuzzy hierarchical methods (Prabhu and Vizaya Kumar 2014). In line with this, its theoretical grounding in modeling imprecision (Klir and Yuan 1995) makes it well-suited for evaluating multidimensional agricultural technologies. In essence, these studies collectively demonstrate that Fuzzy Logic provides greater generality and expressive power for technology evaluation frameworks compared to traditional crisp measurement approaches.

In agriculture, Fuzzy Logic is widely employed for soil assessment, irrigation control, crop growth modeling and expert advisory systems (Devarajan et al. 2020; Sinha and Tiwari 2024). Recent reviews (Widayat et al. 2024) highlight its growing importance in smart farming, as it enables the management of imprecise field data and supports more reliable decision-making. As such, this study adopts Fuzzy Logic to construct an SFT Usage Index that accommodates varying degrees of technology adoption across farmers and regions, providing a more nuanced assessment than qualitative or Likert-scale measures.

Methodology

Study area and sampling

This study utilized primary data collected through face-to-face surveys conducted in six selected rice granary areas in Malaysia. The six granary areas are MADA, IADA Pulau Pinang, IADA Barat Laut Selangor (IADA BLS), IADA Rompin, IADA Kemasin Semerak in Peninsular Malaysia, and IADA Kota Belud in East Malaysia. Respondents were selected using stratified random sampling by granary area. A total of 982 paddy farmers were surveyed during the Main Season in 2023.

Following this, data were collected via structured questionnaires, through in-person interviews conducted by enumerators and focus group discussions. The questionnaire was then divided into seven sections: farmer profile, field information, machinery and capital, farm management activities, yield data and farmers' perceptions and views on smart agriculture technologies.

Statistical analysis

The data were analysed using descriptive and Fuzzy Logic methods. Descriptive analysis was conducted to summarise respondents' profiles on demographic characteristics, farm size and yield, presented as frequencies and proportions. This analysis was applied to farmer profiles and field output data. A one-way ANOVA test was conducted to assess whether the mean SFT Usage Index differs significantly across the six granary areas. Furthermore, a Tukey's Honestly Significant Difference (HSD) post hoc test was performed to identify which specific pairs of granary areas had significant differences. Subsequently, correlation analysis was conducted to explore the relationships between the dependent variable (SFT Usage Index) and the independent variables (farmers' age, education, farm size, paddy yield, financial support and training).

Fuzzy Logic analysis

The development of the SFT Usage Index using Fuzzy Logic is grounded in the selection of eight key parameters derived from the Rice Check guidelines from the Department of Agriculture (DOA), a nationally recognised best-practice framework for paddy cultivation. These parameters, including seed preparation, planting method, land preparation, ploughing, water management, fertilisation, Integrated Pest Management (IPM) and harvesting were selected. This is mainly due to the fact that they represent the core stages of the rice production cycle and are directly influenced by farmers' decisions on adopting smart technologies. Fuzzy Logic is a simulation-based approach that operates across these eight parameters. The Fuzzy set is defined following Chen and Roger (1994):

$$D = \{(x, \mu D(x)) \mid x \in X\},$$

where:

D is a fuzzy subset of X.

$\mu D(x)$ is the membership function of fuzzy set D.

The degree of membership $\mu D(x)$ is within the range [0,1].

Index measurement

The SFT Usage Index in rice production is measured using eight input variables, representing a distinct and critical dimension of smart technology utilisation in paddy production. Each parameter is assessed based on the assigned weightage for the implementation of activities and the use of smart agricultural technologies by farmers. For analytical consistency, each parameter was qualitatively evaluated and categorised into three linguistic levels as low, moderate and best based on farmers' reported practices and alignment with recommended smart farming standards. The Fuzzy inference system then converted these qualitative assessments into numerical membership values ranging from 0 to 1, where 1 represents full smart technology usage (100%) and 0 indicates no technology usage. Concurrently, the final SFT Usage Index was computed through defuzzification, producing a continuous score that reflects each farmer's overall level of technology adoption. The classification of smart agricultural technology usage levels in paddy production is defined as follows:

i. High: If the index value is $X \geq 0.66$
ii. Moderate: If $0.33 \leq X < 0.66$
iii. Low: If $X < 0.33$

In addition, a smart technology usage gap analysis was conducted by comparing adoption scores between farmers in the high-and low-adoption groups for each parameter. In particular, larger gap values indicate substantial disparities in technology uptake, while smaller values reflect more uniform adoption across farmers. Additionally, descriptive statistics and correlation analyses were performed using IBM Statistical Package for Social Sciences (SPSS) Statistics Version 22. Meanwhile, the Fuzzy Logic modelling and simulation procedures were executed in MATLAB. These analytical steps ensure methodological rigor and strengthen the index's measurement.

Results and discussion

Respondent profile

A total of 982 paddy farmers were interviewed across the six selected granary areas. *Table 1* presents a summary of respondent demographics, while detailed profiles by region are included in *Appendix 1*. The majority of respondents (30.2%) were aged 50 – 59, while 5.6% were under 29, indicating some youth participation in paddy farming. Notably, about 30.5% of farmers in all sampling areas were aged 60 years or older, indicating that Malaysia is facing an ageing farming population, which would be a barrier to technology adoption and use. In essence, there are serious issues the government must address to ensure smart technology has a positive impact on the paddy industry.

Regarding gender distribution, 87.2% of respondents were male. The ethnic composition was predominantly Malay (87.2%), except for IADA Kota Belud, which featured a mix of ethnicities, including Dusun, Bajau, Irranun and Kadazan. Regarding education levels, the majority (52.3%) held secondary school qualifications (SPM). In comparison, a smaller segment (11.9%) had attained a diploma or tertiary education, notably among respondents from IADA Pulau Pinang and IADA Kota Belud. Note that the presence of more highly educated farmers is increasingly important given the technical requirements of smart agriculture technologies such as IoT. Most respondents (73.1%) had over 10 years of experience in paddy cultivation, indicating a seasoned farming population with valuable insights into traditional and evolving agricultural practices.

Based on *Table 1*, the majority of respondents (40.8%) across all study areas cultivated less than 1 hectare of paddy land. This reflects the general trend of small-scale farming practices within Malaysia's rice production system. Notably, in IADA BLS, a significant portion (15%) of respondents reported owning more than 5 hectares, indicating the presence of larger-scale operators in that region. Among the surveyed regions, IADA Rompin recorded the highest proportion (67%) of respondents with landholdings of less than 1 hectare, followed by MADA (52%) and IADA Kota Belud (49%). These figures highlight the prevalence of smallholder farming, particularly in certain regions.

In terms of yield performance, 43.7% of respondents achieved an average yield of 4 – 6 tonnes per hectare, which is considered moderate under Malaysian paddy production standards. The highest performing region was IADA BLS, where 34% of farmers reported average yields of 6 – 8 tonnes per hectare, followed by MADA (20%) and IADA Pulau Pinang (16%). These results suggest regional variation in productivity, possibly due to differences in agroecological conditions, infrastructure and technology adoption.

Table 1. Farm size and paddy yield by granary areas

Granary areas	IADA BLS		IADA Rompin		MADA		IADA Kota Belud		IADA Kemasin Semerak		IADA Pulau Pinang	
	n	%	n	%	n	%	n	%	n	%	n	%
Farm size (ha)												
<1.0	16	8	67	67	199	52	60	49	29	29	29	36
1 – 2.0	78	39	19	19	134	35	28	23	27	27	23	29
2.01 – 3.0	41	21	1	1	39	10	9	7	14	14	12	15
3.01 – 4.0	20	10	2	2	3	1	7	6	12	12	9	11
4.01 – 5.0	13	7	2	2	3	1	4	3	4	4	1	1
> 5.0	30	15	9	9	2	1	14	11	14	14	6	8
Total (n)	198	100	100	100	380	100	122	100	100	100	80	100
Paddy yield (Tonne/ha)												
< 2.0	6	3	8	8	16	4	46	38	6	6	5	6
2.01 – 4.0	37	19	36	36	75	20	57	47	39	39	28	35
4.01 – 6.0	81	41	49	49	207	55	14	12	46	46	32	40
6.01 – 8.0	68	34	3	3	77	20	5	4	7	7	13	16
> 8.0	8	4	4	4	5	1	0	0	2	2	2	3
Total (n)	200	100	100	100	380	100	122	100	100	100	80	100

Source: Survey Data, 2023

Level of smart farming technology usage indexes

A spider chart was used to compare the level of smart agricultural technology usage among farmers across the six granary areas. *Figure 1* presents a spider chart illustrating the index scores for smart agricultural technology usage across parameters and granary areas. Parameters related to ploughing and harvesting recorded high usage scores in most granary areas, whereas fertilisation, land preparation and IPM consistently reported lower scores across all regions. IADA Rompin recorded the highest technology usage score for water management, with an average of 0.682. Conversely, MADA recorded the lowest at 0.317, compared to other granaries. Moreover, IADA Pulau Pinang demonstrated a high average index for technology usage in ploughing. In contrast, for the IPM parameter, MADA recorded a lower index than the other granary areas.

The stacked bar chart in *Figure 2* displays the distribution of farmers across three levels of smart agriculture technology usage. The classification is based on Fuzzy Logic index thresholds: low (< 0.33), moderate (0.33 – 0.66) and high (> 0.66). The results reveal that IADA Rompin leads with 55.0% of farmers in the high-usage category, followed by IADA Pulau Pinang and IADA BLS. On the other hand, MADA recorded 64.2% of its respondents in the low-usage category, with only 0.3% in the high-usage category. IADA Kota Belud also reported 40.2% of respondents in the low-usage category. These disparities highlight the need for targeted interventions and capacity-building programmes in underperforming regions.

Figure 3 visualises the level of the SFT Usage Index gap, the difference between the highest and lowest Fuzzy Logic index scores among respondents in each granary. Larger gaps suggest greater disparity in technology adoption. Fuzzy Logic analysis indicates that IADA Rompin had the highest mean index (0.629), followed by IADA Pulau Pinang (0.533) and IADA BLS (0.490). In particular, MADA recorded the lowest average index (0.325), though it also had the smallest gap (0.454), indicating low yet relatively consistent adoption. The widest gap was observed in IADA BLS (0.589), suggesting significant variability in technology use among its farmers. The national mean index across all granaries was 0.499, indicating a moderate level.

The ANOVA results present an F-statistic of 73.13 (p <0.001), indicating a statistically significant difference in index scores across the six granary areas. Subsequently, a Tukey HSD post hoc test was performed to identify which specific pairs of regions exhibited significant differences (*Appendix 2*). The Tukey HSD post-hoc test revealed that IADA Rompin differs significantly from all other regions, while MADA lags far behind. Overall, the national mean index (0.499) places the country in the moderate SFT usage, indicating a promising yet uneven adoption of smart agriculture technologies.

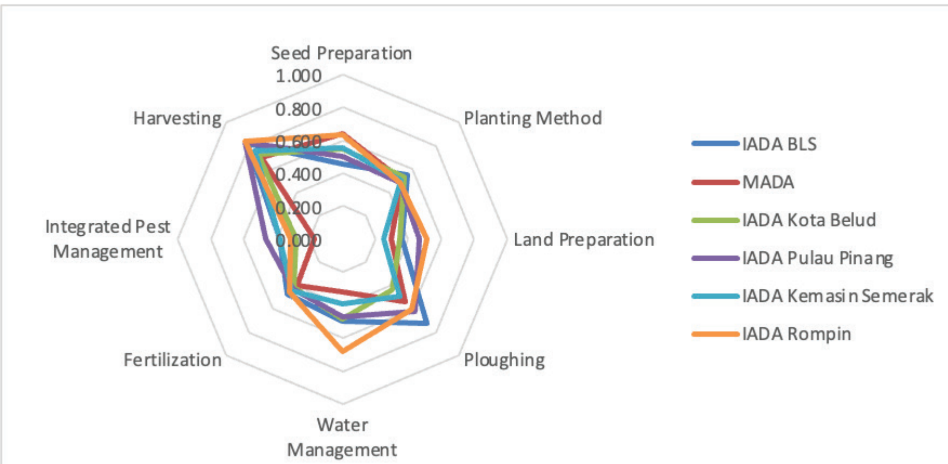
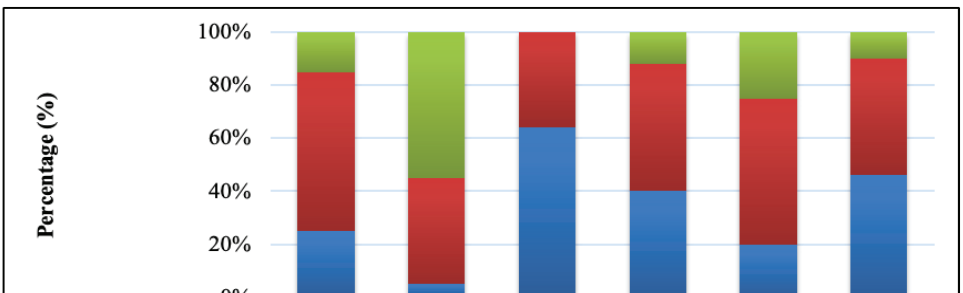


Figure 1. *The index of smart agriculture technology usage by parameters and granaries*



	IADA BLS	IADA Rompin	MADA	IADA Kota Belud	IADA Pulau Pinang	IADA Kemasin Semerak
High (>0.66)	15%	55%	0%	12%	25%	10%
Moderate (0.33-0.66)	60%	40%	36%	48%	55%	44%
Low (<0.33)	25%	5%	64%	40%	20%	46%

Figure 2. *Classification of smart farming technology usage index by granary areas*

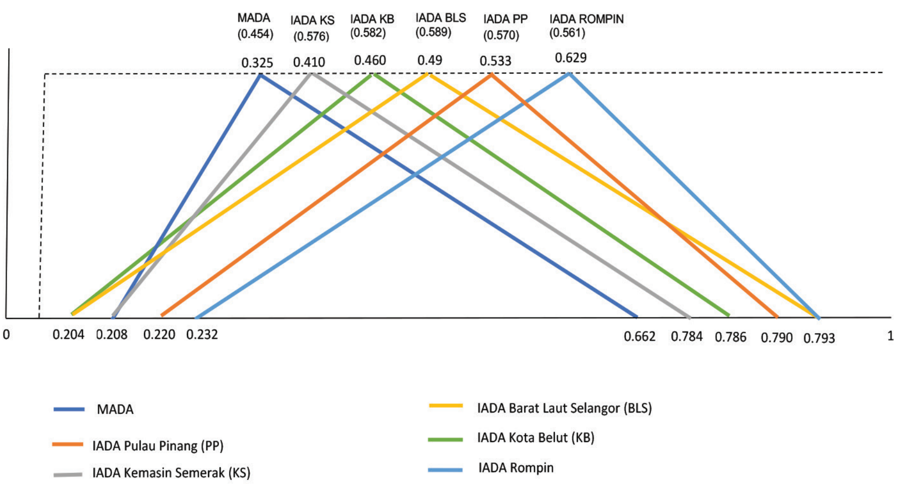


Figure 3. SFT usage index gap by granary areas

Factors influencing the level of smart farming technology index

Table 2 presents a Spearman's rho correlation matrix, which measures the strength and direction of the monotonic relationship between factor variables. The analysis is based on a sample size of 982. The farm area presented a positive, statistically significant correlation ($r = 0.255$, $p < 0.0001$). This, in turn, suggests that farmers with larger land areas are more likely to have a higher SFT Usage Index. Notably, this is logical, as the initial capital investment in technology such as drones or machinery is often more cost-effective for larger-scale operations. Financial support had a positive correlation and was significant ($r = 0.147$, $p < 0.0001$). This finding is critical as it implies that access to financing is a key enabler for adopting technology. Additionally, farmers who secure financial support, such as loans or credit, are better positioned to overcome the high upfront costs associated with smart farming. Training demonstrated a positive, statistically significant correlation ($r = 0.078$, $p < 0.05$). This indicates that participation in courses or training programmes is linked to higher technology adoption. In general, this underscores the significance of knowledge transfer and skill development in encouraging farmers to use new technologies.

Table 2. Factors influencing SFT Usage Index

Variables	Correlation Coefficient	Sig. (2-tailed)
Farm area (ha)	0.255**	0.000
Paddy yield (Tonnes/ha)	-0.026	0.423
Farmer age	-0.177**	0.000
Education level	0.056	0.080
Financial support	0.147**	0.000
Training	0.078*	0.014

Note: (* and **) denote significance levels ($p < 0.05$ and $p < 0.01$, respectively)

The analysis reveals a negative, statistically significant correlation ($r = -0.177$, $p < 0.000$). This is a common finding in technology adoption studies, suggesting that older farmers, who may be less digitally literate or more resistant to change, tend to have lower SFT usage indices. Specifically, the most striking and critical finding is the lack of a statistically significant correlation between the SFT Usage Index and Average Yield ($p = 0.423$). This suggests that, at present, simply using smart technology does not directly translate into a higher average yield for these farmers. This could be due to several factors, such as the technologies being in their early stages of application and the full benefits not yet being realised. Likewise, many technologies (e.g., smart irrigation, pest monitoring) are aimed at reducing costs and managing resources more efficiently, rather than boosting output in the short term. Other variables, such as soil quality, climate and pest outbreaks, may have a stronger influence on yield than technology use.

However, the relationship between the SFT Usage Index and education is not statistically significant. This is quite a surprising result, as one might expect higher education to correlate with a greater inclination to use smart technology. Nonetheless, the findings on training suggest that practical, targeted training is more influential than formal academic education in the context of agricultural technology.

Discussion

The results reveal substantial variability in the adoption of smart agriculture technologies across the six granary areas. Our study discovered that IADA Rompin had the highest index (0.629), suggesting that a combination of enabling infrastructure, farmer engagement and institutional support plays a critical role in accelerating adoption. Conversely, MADA, despite being a major rice-producing region, lags significantly (index of 0.325), with 64.2% of its farmers in the "low usage" category. Remarkably, this finding aligns with previous work by Baharin et al. (2025), who identified infrastructural constraints and limited farmer readiness as key barriers to smart farming in Malaysia.

Across all regions, low scores in fertilisation, IPM and land preparation indicate that these parameters have yet to benefit from smart solutions. This suggests a disconnect between Research and Development (R&D) output and field-level adoption. A study by Idris et al. (2024) observed that farmers expressed limited familiarity with technologies such as GIS, sensors, IoT, drones and satellite imagery. While MARDI and other agencies have developed relevant technologies (e.g., IoT-based fertiliser recommendations and pest sensors), uptake remains limited, possibly due to affordability, complexity, or a lack of technical support (Saili et al. 2024; Kamarul Zaman et al. 2023).

One of the clearest issues from this study is the internal adoption gap within regions like IADA BLS (index gap = 0.589) and Kota Belud (0.582). This reflects a two-speed system in which progressive farmers are advancing while others are left behind. This digital divide mirrors what FAO (2020) reported across Southeast Asia, that smart agriculture risks increasing inequality if it is not made accessible to smallholders. These wide gaps may be attributed to constraints such as limited access to financial resources, inadequate technical support, and insufficient digital infrastructure. These collectively hinder farmers from fully exploiting available technologies (Saili et al. 2024; Idris and Zulkifli 2024; Kamarul Zaman et al. 2023). In comparison, MADA and IADA Rompin demonstrate smaller technology gaps, suggesting that existing institutional support, farmer awareness and resource allocation in these regions are comparatively more effective in narrowing the divide between potential and actual adoption. Thus, the observed variation implies that a one-size-fits-all approach is unlikely to succeed. Instead, targeted interventions tailored to the socioeconomic and institutional contexts of each granary area are required. Therefore, bridging these gaps is critical, as effective integration of smart farming technologies enhances production efficiency and contributes to long-term sustainability and resilience of Malaysia's rice sector.

The results of the one-way ANOVA provide strong evidence that the usage of smart agriculture technologies is not uniform across Malaysia's major granary areas. The highly significant F-statistic ($F = 73.13$, $p < 0.0001$) confirms that substantial regional variation exists in the mean usage index. Hence, this finding underscores the uneven pace of technological integration within the paddy sector, reflecting potential disparities in institutional support, resource allocation, and farmer readiness across different granaries. The subsequent Tukey HSD post hoc test provides deeper insights into these variations. Notably, IADA Rompin emerged as a clear outlier, with significantly higher usage levels than in all other regions. This suggests that Rompin may have benefited from more effective extension services, stronger institutional interventions, or a farmer profile that is comparatively more receptive to technological innovation. By contrast, MADA registered significantly lower usage levels, despite being one of the country's most established granary schemes. This paradox may highlight an entrenched reliance on conventional practices, structural barriers to innovation, or insufficiently tailored technology-dissemination strategies within MADA.

Among the intermediate-performing granaries, such as IADA BLS, IADA Pulau Pinang and IADA Kemasin Semerak, the lack of statistically significant differences suggests a more homogeneous pattern of usage. These regions may share similar socioeconomic characteristics, infrastructural conditions, or policy environments that yield comparable usage outcomes. Despite this, the clustering of these regions in the mid-range also highlights the risk of stagnation if usage barriers are not strategically addressed. Overall, the distribution of the usage index highlights the need for differentiated policy responses. Rather than applying uniform strategies nationwide, interventions should be more granular, targeting the unique institutional, infrastructural and socio-cultural factors that shape usage outcomes in each granary. In line with this, the findings particularly stress the importance of leveraging high-performing regions, such as IADA Rompin, as models for peer learning and diffusion. It simultaneously addresses systemic barriers that appear to constrain adoption in lagging regions, such as MADA.

The results of the correlation analysis provide crucial insights into the drivers and barriers to SFT use among paddy farmers. The finding clearly suggests that economic capacity (farm size and financial support, e.g., access to loans) and practical knowledge (Training) are significant enablers of technology adoption. This finding is in line with international studies, such as Wolfert et al. (2017) and Zhang et al. (2012), which asserted that in countries such as the Netherlands and Japan, the success of smart farming was contingent on technology availability, coordinated implementation frameworks, continuous farmer education and economic incentives to de-risk adoption. In contrast, age is a major barrier. Past studies frequently link technology adoption to farmers' age, education and financial capacity (Baharin et al. 2025; Saili et al. 2024; Kamarul Zaman et al. 2023). The lower scores in MADA could be linked to an older farming demographic that is more resistant to change, less digitally literate and less willing to make large initial investments. On the other hand, the higher scores in IADA Rompin may indicate a younger, more educated, or more financially stable farming community, or a population that has been specifically targeted by government initiatives to embrace new technologies. Thus, younger, more educated farmers were more likely to use technology, underscoring the importance of education as a predictor of adoption. This finding is supported by past studies, which indicate that peer influence and informal learning are potent forces in the adoption of SFT (Baharin et al. 2025; Kamarul Zaman et al. 2023; Nguyen et al. 2022).

Conclusion and policy implications

The transition toward smart farming is critical for strengthening national food security and improving the sustainability of Malaysia's rice production sector. This study evaluated the level of the SFT Usage Index among paddy farmers across six major granary areas using a Fuzzy Logic approach. The findings also revealed significant regional variation in both the mean index scores and the distribution of technology usage. IADA Rompin, IADA Pulau Pinang, and IADA BLS emerged as leading adopters, with IADA Rompin recording the highest average index score. By contrast, MADA recorded the lowest average score, with the majority of its respondents falling into the low adoption category. The findings clearly highlight that economic capacity, as measured by farm size and financial support, is a significant enabler of SFT usage. In addition, practical knowledge gained from training and courses on rice cultivation technology also had a significant positive influence on adoption. Meanwhile, farmer age was identified as a major barrier, a critical issue given that almost all rice planting in Malaysia is carried out by an ageing farming population.

The analysis provides a clear roadmap for policy intervention in Malaysia's rice sector. Thus, policy implications should focus on addressing these identified drivers and barriers to technology usage rather than simply promoting technology for its own sake. This nuanced understanding of regional differences in SFT usage is essential for Malaysia to achieve its goal of food security and modernise its rice sector. Furthermore, the government and stakeholders should use this finding to develop region-specific strategies. Regions such as MADA and IADA Kota Belud require immediate, focused interventions that combine financial incentives, infrastructural upgrades and capacity-building programs to overcome adoption barriers. For IADA Rompin, a different approach is needed, positioning it as an innovation hub for pilot projects. Hence, these projects should deploy advanced technologies, such as AI-driven decision support and autonomous field monitoring, to encourage spillover learning effects for surrounding regions.

The findings suggest that the high initial cost of SFT is a significant barrier. Incentives should be offered for specific technologies, such as low-interest loans or grants tied to technology purchases. For example, providing technology bundles that include the hardware (e.g., drones, sensors), installation, training and maintenance, financed through a single, manageable package, moves the policy from simply offering inputs to enabling a complete technological transition. On a similar note, hands-on practical training is far more effective than general knowledge in influencing adoption. In line with this, policy should expand and standardise agricultural extension services to deliver practical, field-based training on smart technologies. Additionally, farmers in regions like IADA Rompin can serve as role models for "farmer-to-farmer" knowledge transfer. It is also essential to develop user-friendly interfaces and applications that do not require high levels of digital literacy, making them accessible to all farmers regardless of their formal education.

Finally, policy interventions should introduce small-scale, attractive smart farming models for young farmers. This involves government or private-sector entities owning the technology and offering the service to smallholders on a pay-per-use basis. This model by passes the high upfront cost and technical expertise barriers. Additionally, policymakers should implement land consolidation programmes or promote cooperative farming to create larger, more economically viable plots that can better leverage smart technologies. Targeted programmes should also be created to attract and train young Agri-entrepreneurs to ensure the long-term sustainability and modernisation of the sector.

The potential of smart agriculture to revolutionise paddy cultivation in Malaysia is significant. However, its realisation depends on effective dissemination, capacity-building and policy support. This study underscores the importance of assessing technology adoption and aligning innovation efforts with farmers' practical needs to ensure that digital transformation benefits the national rice industry in a meaningful and sustainable way. In response, by implementing these targeted, multi-faceted policies, Malaysia can effectively bridge the gap between technology potential and practical adoption, leading to a more productive, efficient and sustainable agricultural sector.

References

Abang Ahmad, D. S. N., Abdul Fatah, F., Saili, A. R. Saili, J., Hamzah, N. M., Che Mat Nor, R., Omar, Z., & Ghali, M. (2025). Exploration of the challenges in adoption smart farming among smallholder farmers: A qualitative study. *Journal of Advanced Research in Applied Sciences and Engineering Technology*. 45, Issue 1, 17–27.

Abdul Aziz, A., Hashim, N., & Ahmad, D. (2008). Precision agriculture applications in Malaysia: A review. *Journal of Tropical Agriculture and Food Science,* 36(1), 1–10.

Abdul, L., & Zulkifli (2020). Farmers Intentions Towards Drone Based Technology in Paddy Cultivation. *International Network for Innovation, Research & Education*. Vol. 8, 74–80.

Abdullah, N., Hassan, M., & Rahman, A. (2022). Measuring smart farming technology adoption using fuzzy logic: Evidence from Malaysian paddy farmers. *Journal of Smart Agriculture and Technology*, 4(2), 55–70.

Ahmed, S., Khan, R., & Bakar, A. (2024). Policy frameworks and stakeholder collaboration for smart agriculture adoption: A global perspective. *Journal of Agricultural Policy and Innovation*, 12(1), 45–63.

Alvari, N. (2013). Quality determination of mozafati dates using mamdani fuzzy inference system. *Journal of the Saudi Society of Agricultural Science*, 12, 137–142.

Baharin, N., Ahmad, R., & Hamid, S. (2025). Adoption of smart farming technologies among paddy farmers in Malaysia: Opportunities and challenges. *Asian Journal of Agricultural Research,* 17(2), 115–128.

Balafoutis, A. T., van Evert, F. K., & Fountas, S. (2020). Smart farming technology trends: Economic and environmental effects, labor impact, and adoption readiness. *Agronomy*, 10(5), 743. https://doi.org/10.3390/agronomy10050743.

Bujang, A. S., & Bakar, B. A. (2019). Precision agriculture in Malaysia. *Proceedings of International Workshop on ICTs for Precision Agriculture*, 6–8 August 2019, 91–104. MARDI Headquarters, Selangor, Malaysia.

Chen, S., & Roger, E. G. (1994). Evaluation of cabbage seedling quality by fuzzy logic. ASAE Paper No. 943028, St. Joseph, MI.

Devarajan, M., Somasundaram, S., & Kannan, R. (2020). Applications of fuzzy logic in agriculture: From soil analysis to plant production systems. *International Journal of Agricultural Science and Technology*, 8(2), 45–56.

Food and Agriculture Organization (FAO). (2021). The state of food and agriculture 2021: Making agrifood systems more resilient to shocks and stresses. Rome: FAO. https://doi.org/10.4060/cb4476en.

Food and Agriculture Organization (FAO). (2020). Digital Agriculture Report: Rural E-commerce Development Experience from China. *Food and Agriculture Organization of the United Nations*. https://www.fao.org/documents/card/en/c/ca9456en.

Fragomeli, M., Rossi, F., & Conti, G. (2024). Barriers and drivers of digital agriculture: Insights from European farms. *Computers and Electronics in Agriculture*, 210, 107084.

Gabriel, W. W. E., & Haritharan, D. (2020). The Development of Smart Farming Technologies and Its Application in Malaysia. *International Journal of Scientific & Technology Research*, 9(08).

Garg, D., & Alam, M. (2023). Smart agriculture: a literature review. *Journal of Management Analytics*, DOI: 10.1080/23270012.2023.2207184.

García, J., Pérez, M., & Alfaro, J. (2015). Measuring innovation using fuzzy logic methodologies. *Journal of Business Research*, 68(7), 1480–1487. https://doi.org/10.1016/j.jbusres.2015.01.049.

Gurrea, A., Calvo-Mora, A., & Criado, F. (2014). Fuzzy logic applications in performance management systems. *Total Quality Management & Business Excellence*, 25(3–4), 199–212. https://doi.org/10.1080/14783363.2013.776763.

Hashim, N., Rahman, A. A., & Abdullah, S. (2024). Advancing sustainable rice production through smart farming technologies in Malaysia. *Asian Journal of Agriculture and Development*, 21(2), 55–72.

Harun, R., Engku Ariff, E. E., Suhaimee, S., & Wan Mat, K. (2024). Farmers' perception towards the effectiveness use of drones in selected rice farming areas in Malaysia. *International Journal of Agriculture, Forestry and Plantation*, Vol. 14 (Sept).

Idris, M., & Zulkifli, H. (2024). Knowledge, attitudes, and practices (KAP) of smart farming technologies among paddy farmers in Melaka, Malaysia. *Malaysian Journal of Agricultural Economics*, 41(1), 55–72.

Kamal, R. M., & Amin, M. S. M. (2010). GIS-based irrigation water management for precision farming of rice. *International Journal of Agricultural and Biological Engineering*, 3(3), 27–35.

Kamarul Zaman, N., Rahman, A., & Abdullah, M. (2023). Exploring the adoption of smart farming technologies among paddy farmers: Evidence from IADA Barat Laut Selangor. *Journal of Rural Studies*, 98, 44–56.

Klir, G. J., & Yuan, B. (1995). *Fuzzy sets and fuzzy logic: Theory and applications*. Upper Saddle River, NJ: Prentice Hall.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674. https://doi.org/10.3390/s18082674.

MAFS (2021). National Agrofood Policy NAP 2.0 (2021–2030). Putrajaya: Ministry of Agriculture and Food Security (MAFS), Malaysia.

MAFS (2021). National Food Security Policy Action Plan, 2021–2025. Putrajaya: Ministry of Agriculture and Food Security (MAFS), Malaysia.

Mat Lazim, R., Mat Nawi, N., Masroon, M. H., Abdullah, N., & Mohammad Iskandar, M. (2020). Adoption of IR4.0 in the Agricultural Sector in Malaysia. Potential and Challenges. *Advances in Agricultural and Food Research Journal*, 1(2).

Nguyen, T. L., Tran. D. M., & H. A. Le, H.A. (2022). Adoption of digital agriculture in Vietnam: Evidence from smallholder rice farmers. *Vietnam Journal of Agricultural Development*, Vol. 24, No. 1, 29–43.

Prabhu, V., & Vizaya Kumar, V. (2014). A fuzzy hierarchical decision-making methodology for technology choice. *Expert Systems with Applications*, 41(4), 2238–2246. https://doi.org/10.1016/j.eswa.2013.09.002.

Rahim, H., Abdul Wahab, M. A. M., Mat Amin, M.Z., Harun, A., & Haimid, M. T. (2018). Perception and Acceptance of Farmers on Precision Farming Technology in Selected Granary Area. *Economic and Technology Management Review*, Vol. 13, 97–110.

Saili, A. R., Kamarul Zaman, N. B., Wan Mohd. Noor, W.N., Abdul Fatah, F., & Abdullah, F. A. (2024). Smart Farming: Challenges and Adoption Factors among Paddy Farmers in IADA Barat Laut Selangor. *Information Management and Business Review,* Vol. 16, No. 4(S), 394–400.

Sinha, R., & Tiwari, P. (2024). Fuzzy logic in agricultural expert systems: Applications and challenges. *Journal of Smart Agriculture and Sustainability*, 12(1), 88–102.

Widayat, W., Raharjo, B., & Santosa, A. (2024). The role of fuzzy logic in precision agriculture: A systematic review (2017–2024). *Computers and Electronics in Agriculture*, 214, 107002. https://doi.org/10.1016/j.compag.2023.107002.

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big Data in Smart Farming – A Review. *Agricultural Systems*, 153, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353.

Zhang, C., & Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: A review. *Precision Agriculture*, 13(6), 693–712. https://doi.org/10.1007/s11119-013-9334-7.

Abstrak

Teknologi pertanian pintar merupakan era transformatif dalam penanaman padi global. Perkembangan teknologi ini termasuk aplikasi *Internet of Things* (IoT) semakin meningkat di Malaysia, namun penggunaan dan impaknya dalam kalangan pesawah masih terhad. Peralihan ke arah teknologi pertanian pintar ini adalah penting untuk mengukuhkan keselamatan makanan negara dan meningkatkan kemampanan sektor padi dan beras Malaysia. Kajian ini menilai Indeks Tahap Penggunaan Teknologi Pertanian Pintar (SFT) dalam kalangan pesawah di enam kawasan jelapang terpilih. Data primer dikumpul melalui survei secara bersemuka dengan menggunakan borang soal selidik berstruktur terhadap 982 responden. Pendekatan Logik Fuzzy digunakan untuk mengukur Indeks Tahap Penggunaan SFT dengan mengklasifikasikan penggunaan teknologi kepada tiga tahap iaitu rendah, sederhana dan tinggi. Keputusan analisis menunjukkan bahawa IADA Rompin menunjukkan skor indeks purata tertinggi (0.629), diikuti oleh IADA Pulau Pinang (0.533), manakala MADA mencatatkan indeks yang terendah (0.325). Analisis statistik mengesahkan perbezaan ketara dalam skor purata indeks antara kawasan jelapang (p <0.001). Ujian *post-hoc* Tukey mendedahkan bahawa IADA Rompin mengatasi semua jelapang lain dengan ketara, manakala MADA secara agak ketinggalan. Walaupun indeks purata nasional 0.499 (sederhana), penemuan tersebut menunjukkan wujud jurang yang besar antara dan dalam wilayah. Kajian mendapati bahawa saiz sawah, sokongan kewangan dan latihan mempunyai pengaruh positif yang signifikan terhadap Indeks Penggunaan SFT. Sebaliknya, umur didapati mempunyai pengaruh negatif yang signifikan terhadap Indeks Penggunaan SFT. Dapatan ini mencadangkan keperluan campur tangan secara bersasar, peningkatan aktiviti perkhidmatan pengembangan dan strategi sokongan kewangan yang inklusif untuk merapatkan jurang teknologi. Kajian ini memberikan panduan kepada penggubal dasar dan pihak berkepentingan untuk merangka strategi khusus berdasarkan jelapang bagi meningkatkan pemindahan dan aplikasi teknologi pertanian pintar dalam kalangan pesawah, seterusnya menyumbang kepada keselamatan makanan negara yang mampan.

Appendix 1. Respondents profile

Profile	Frequency (N)	Percent (%)
Age		
<29 year	55	5.6
30 – 39 year	158	16.1
40 – 49 year	173	17.6
50 – 59 year	297	30.2
60 – 69 year	214	21.8
>70 year	85	8.7
Total (N)	982	100.0
Gender		
Male	856	87.2
Female	126	12.8
Total (N)	982	100.0
Race		
Malay	859	87.5
Chinese	1	0.1
Bajau	30	3.1
Dusun	77	7.8
Irranun	8	0.8
Kadazan	5	0.5
Others	2	0.2
Total (N)	982	100.0
Education		
Primary school	139	14.2
Secondary school (PMR)	207	21.1
Secondary school (SPM)	514	52.3
STPM/Certificate/Diploma	91	9.3
Degree	26	2.6
Others	5	0.5
Total (N)	982	100.0
Experience		
< 5 years	133	13.8
5 – 10 years	127	13.1
> 10 years	706	73.1
Total (N)	966	100.0

Source: Survey Data, 2023

Appendix 2. Summary of Tukey HSD Post-Hoc Test Results

Group 1	Group 2	Mean Diff	*p*-value	Significant
IADA BLS	IADA Kemasin Semerak	0.0213	0.9097	No
IADA BLS	IADA Kota Belud	–0.0503	0.1506	No
IADA BLS	IADA Pulau Pinang	–0.0035	1.0000	No
IADA BLS	IADA Rompin	0.2338	0.0000	Yes
IADA BLS	MADA	–0.1668	0.0000	Yes
IADA Kemasin Semerak	IADA Kota Belud	–0.0715	0.0214	Yes
IADA Kemasin Semerak	IADA Pulau Pinang	–0.0247	0.9094	No
IADA Kemasin Semerak	IADA Rompin	0.2125	0.0000	Yes
IADA Kemasin Semerak	MADA	–0.1881	0.0000	Yes
IADA Kota Belud	IADA Pulau Pinang	0.0468	0.3788	No
IADA Kota Belud	IADA Rompin	0.2840	0.0000	Yes
IADA Kota Belud	MADA	–0.1165	0.0000	Yes
IADA Pulau Pinang	IADA Rompin	0.2372	0.0000	Yes
IADA Pulau Pinang	MADA	–0.1633	0.0000	Yes
IADA Rompin	MADA	–0.4006	0.0000	Yes

Source: Survey Data, 2023