Applied Quantitative Analysis, Vol. 6 No. 1 (2026) https://doi.org/10.31098/quant.4115

Research Paper

Agriculture IoT Adoption: Linking Technology Readiness, Acceptance and Entrepreneurial Ambidexterity Among Sabah Smallholders

Nurul Alam Mohd Yaakub, Viduriati Sumin*, Ung Ling Ling
Universiti Teknologi MARA Sabah Branch, Malaysia

Received : January 8, 2026	Revised : June 26, 2026	Accepted : June 29, 2026	Online : June 30, 2026

Abstract

Internet of Things (IoT) adoption in agriculture potentially enhances operational efficiency and sustainability. However, smallholding farmers, such as in Sabah, often face barriers in terms of technological literacy, acceptance, and resources. Sabah food security could be sustained through IoT-based technological interventions; therefore, it is important to investigate farmers' readiness and acceptance towards IoT adoption. The objectives of this study are (i) to examine the influence of technology readiness on acceptance within a technology readiness-acceptance (TRAM) framework; (ii) to investigate the effects of perceived usefulness and ease of use on IoT adoption intention; and (iii) to analyze the mediating effect of entrepreneurial ambidexterity in the relationship of technology acceptance towards adoption intention among Sabahan smallholders. Quantitative research was conducted, using 385 datasets, which were analyzed using partial least squares structural equation modeling (PLS-SEM) to test the research conceptual framework. Results demonstrated that (i) technology readiness motivators influence acceptance significantly, (ii) perceived usefulness emerges as the strongest predictor of adoption intention, and (iii) entrepreneurial ambidexterity is a significant mediator, specifically through perceived ease of use. This study provides a novel theoretical extension of TRAM by establishing entrepreneurial ambidexterity as a mediator of IoT adoption intention. Practical directions are proposed for agricultural policymakers, technology providers, and stakeholders in formulating strategies that align with farmers' predispositions towards supporting the transformation of Sabah's agricultural sector.

Keywords: *Technology Acceptance, Technology Readiness, Technology Adoption Intention, Entrepreneurial Ambidexterity*

INTRODUCTION

Sabah, as one of the key agricultural states, remains an important contributor to Malaysia's gross domestic product (GDP), particularly through agricultural trade in commodities such as oil palm (DOSM, 2023). Despite this significance, the other agricultural sector – the agrifood sector in the state – faces persistent setbacks, including low food productivity, limited digital integration, gaps in institutional facilities, manpower shortages, and inefficient policy frameworks (EPU, 2021; Jabatan Pertanian Sabah, 2022; Suffian & Suffian, 2022; Yapp et al., 1999). Insufficient domestic food production leads to import dependence and threatens the sustainability of food security (Jabatan Pertanian Sabah, 2022; Malay Mail, 2022). Smallholding farmers are the core players in Sabah's agriculture, yet they are among the most exposed to systemic obstacles. Limited resources and small landholdings leave them with low incomes, constrained market access, and minimal output growth (Yusof & Annuar, 2023). The declining self-sufficiency ratio (SSR) of Sabah's food production intensifies vulnerabilities, underscoring the need for agricultural modernization. Technology-driven agriculture, particularly through Internet of Things (IoT) adoption, is viewed as a potential solution to enhance productivity and sustainability. However, adoption among smallholders remains low, primarily due to institutional and behavioral constraints (Aris et al., 2021; Mat Lazim et al., 2020; Sinha & Dhanalakshmi, 2022). Globally, Agriculture 4.0 initiatives such as precision farming, livestock monitoring, and supply chain digitalization have demonstrated the transformative potential of IoT. Programs such as the European Union's SmartAgriHubs

Corresponding author's email: vidur595@uitm.edu.my

(SmartAgriHubs, 2023) and Australia's Sustainable Agriculture Facilitators (DAFF, 2026) highlight its role in enhancing efficiency and food security. In Malaysia, digitalization is actively promoted through government incentives and entrepreneurship schemes, yet adoption remains slow (MAFS, 2023; Mat Lazim et al., 2020; Sinha & Dhanalakshmi, 2022). High costs, knowledge gaps, and entrenched reliance on traditional practices continue to hinder smallholding farmers, while generational differences further exacerbate resistance to change (Bujang & Bakar, 2019; Mat Lazim et al., 2020; Sinha & Dhanalakshmi, 2022).

In the Malaysian context, studies to date largely focus on systemic and institutional constraints, overlooking behavioral factors such as technology readiness, acceptance, and farmers' entrepreneurial innovation-related tasks or ambidexterity (Aris et al., 2021; Mohd Yaakub et al., 2024). This highlights a notable gap in the Malaysian context, where research has, by and large, focused more on external and structural factors such as infrastructure, policy support, and resource constraints, while comparatively little attention has been given to interpersonal behavioral factors that may influence farmers' intention to adopt IoT technologies. This quantitative research aims to address these issues or gaps by answering research questions that explore (i) how technology readiness influences acceptance, (ii) how acceptance influences adoption intention, and (iii) how entrepreneurial ambidexterity mediates this relationship toward IoT adoption intention among smallholders in Sabah. The research findings contribute novel theoretical perspectives by presenting evidence for the conceptual framework that explains IoT adoption intention through the consolidation of the Technology Readiness and Acceptance Model (TRAM) (Lin et al., 2007) with the ambidexterity concept from organizational behavior research (March, 1991). Practically, the study provides strategic recommendations to guide future actions among agricultural stakeholders.

LITERATURE REVIEW

Background of Malaysian Agriculture and IoT Adoption

Agriculture is a vital sector in Sabah, providing income and employment for much of its rural population. Through initiatives such as the National Agrofood Policy (2021–2030) and the Sabah Maju Jaya plan, the Malaysian government has prioritized agricultural modernization to address labor shortages, enhance productivity, and reduce regional imbalances in food production (MAFI, 2021; Sabah State Government, 2021). These initiatives emphasize entrepreneurial engagement and technology adoption, particularly the Internet of Things (IoT), as essential tools for improving efficiency and food security. However, despite policy support and institutional assistance, adoption of smart agriculture technologies remains low among smallholding farmers (Abu Dardak et al., 2022; Ahmad et al., 2025; Hashim, 2022; Ministry of Digital, 2025). Socioeconomic factors such as education and access to resources, coupled with demographic challenges like an aging farming population, influence farmers' readiness and openness to embrace technological innovations (Aris et al., 2021; Bujang & Bakar, 2019; Harun et al., 2015; Mat Lazim et al., 2020; Mohd Yaakub et al., 2024; Yusof & Annuar, 2023). Given these challenges, it is inevitable that researchers study the internal human factors or traits that could increase farmers' willingness to adopt IoT technologies and help resolve the discrepancy between policy initiatives and actual technology diffusion by farmers (Bahari et al., 2024).

Successful adoption of IoT depends not only on external infrastructure and support but also on farmers' individual predispositions and attitudes toward technology (Adnan et al., 2019; Ahmad et al., 2025; Ahmad Tarmizi et al., 2020; Shariff et al., 2022; Zaman et al., 2023). Defined as the capability to pursue new opportunities while utilizing current resources, entrepreneurial ambidexterity could further boost farmers' willingness and capacity to adopt new innovations (Cegarra-Sánchez et al., 2020; Chen & Yu, 2022; March, 1991). Because farmers are often entrepreneurs at a small scale, the propensity to grow through ambidextrous activities could be used or measured to predict their adoption intention for new technologies.

Although studies have examined agricultural digitalization, technology readiness, technology acceptance, and entrepreneurial behavior separately, limited research has integrated these perspectives to explain IoT adoption intention among smallholding farmers, particularly within the Sabah context; therefore, this presents an empirical and theoretical gap for this demographic and area of research. Notably, the ways in which technology readiness interacts with acceptance, how acceptance shapes adoption intention, and whether entrepreneurial ambidexterity strengthens these relationships remain uncertain. Addressing these gaps is important to support evidence-based policy formulation and to develop more effective intervention strategies aimed at accelerating agricultural digitalization among smallholders. Accordingly, this study operationalizes these influences through hypotheses that examine: (i) the relationship between technology readiness and acceptance, (ii) the effect of acceptance on farmers' adoption intention, and (iii) the mediating mechanism of entrepreneurial ambidexterity in affecting these relationships among smallholding farmers in Sabah.

Theoretical Background

Understanding farmers' decisions to embrace or reject new technologies remains a challenge in technology adoption research. While adoption refers to the actual use of technology, acceptance reflects an individual's behavioral intention and attitude prior to use. In agricultural settings, acceptance before adoption is important because farmers may recognize the potential benefits of technology yet still hesitate to adopt it due to acceptance issues. Among available frameworks, the Technology Acceptance Model (TAM) (Davis, 1989) is widely used in agricultural research, particularly in studies involving smallholder farmers (King & He, 2006; Mohd Yaakub et al., 2024). TAM suggests that intention to adopt is mainly influenced by perceived usefulness and ease of use, a proposition that has been consistently supported in rural contexts, where acceptance may be influenced by limited technical literacy and access to infrastructure, as documented in the literature by Mohd Yaakub et al. (2024). The demographic similarity of such studies to Sabahan farmers indicates that the TAM framework is suitable for this research. These studies also demonstrate that pragmatic evaluations of whether technology improves efficiency often outweigh broader social or environmental considerations.

Although TAM has been criticized for its parsimony and limited capacity to address contextual factors, as admitted by Davis (1989), it can be enhanced when integrated with complementary frameworks such as the Technology Readiness Index (TRI) by Parasuraman (2000; 2015) (Chiu & Cho, 2021; Mohr & Kühl, 2021; Montes de Oca Munguia et al., 2021; Sorce & Issa, 2021; Taherdoost, 2018). Technology readiness extends acceptance analysis by incorporating farmers' psychological predispositions - optimism, innovativeness, discomfort, and insecurity; thereby, capturing motivational drivers and barriers that TAM alone cannot adequately explain. TRI complements TAM by explaining not only how farmers evaluate technology, but also why they may be willing or reluctant to engage with it in the first place. This justifies using TAM and TRI as a stronger theoretical foundation for this research.

Beyond technology readiness and acceptance, entrepreneurial ambidexterity adds depth to understanding farmers' responses to new technology. Integration of technology readiness and acceptance on its own does not guarantee adoption, as Venkatesh et al. (2003) note. Following Vroom's Expectancy Theory (1964), farmers need to perceive the overall benefits or rewards to increase their motivation toward adoption. To make sense of the benefits of new innovations, farmers need to understand the context or the basic know-how of a technology and be able to visualize its integration with their existing operations. Ambidexterity refers to the capacity to balance exploring new opportunities with exploiting current knowledge and farming practices (Duncan, 1976; March, 1991). In agriculture, farmers often must maintain productive operations while simultaneously evaluating and integrating innovations that can enhance future performance. Earlier studies have shown that stronger ambidextrous capability is associated with individuals who are more adaptive, proactive, and innovative (He & Wong, 2004; Snehvrat et al., 2022). This capability enables farmers to translate favorable perceptions of usefulness and ease of use into stronger IoT adoption intentions by balancing experimentation with innovative technologies alongside the implementation of existing farming practices. Therefore, entrepreneurial ambidexterity is proposed as a mediating mechanism linking technology readiness and acceptance with IoT adoption intention among smallholding farmers.

Hypothesis development and research framework

Grounded in the Technology Readiness and Acceptance Model (TRAM), this study combines the Technology Readiness Index (TRI) dimensions (optimism, innovativeness, discomfort, and insecurity) with the Technology Acceptance Model (TAM) dimensions of perceived usefulness and perceived ease of use to explain adoption intention (Lin et al., 2007). TRI motivators, optimism and innovativeness, are expected to positively influence perceived usefulness and ease of use, reflecting proactive attitudes and openness to experimentation (Negm, 2023a; Parasuraman, 2000; Parasuraman & Colby, 2015; Rogers, 2003). By contrast, discomfort and insecurity (as inhibitors) are anticipated to have negative effects due to fear or resistance toward unfamiliar technology (Buyle et al., 2018; Chiu & Cho, 2021; Kim & Chiu, 2019; Lin et al., 2007; Negm, 2023a). The hypotheses linking individual TRI dimensions to TAM constructs are listed as follows:

(*Technology readiness with perceived usefulness*)

H_{1a}: Optimism positively influences perceived usefulness
H_{1b}: Innovativeness positively influences perceived usefulness
H_{1c}: Discomfort negatively influences perceived usefulness
H_{1d}: Insecurity negatively influences perceived usefulness

(*Technology readiness with perceived ease of use*)

H_{2a}: Optimism positively influences perceived ease of use
H_{2b}: Innovativeness positively influences perceived ease of use
H_{2c}: Discomfort negatively influences perceived ease of use
H_{2d}: Insecurity negatively influences perceived ease of use

Perceived usefulness and ease of use are theorized in TAM to shape adoption intentions both directly and indirectly. Perceived usefulness is posited as the main determinant of adoption intention, while perceived ease of use may indirectly influence intention by enhancing perceived usefulness (Davis, 1989; Dillon & Morris, 1996). This distinction acknowledges that smallholding farmers, particularly in resource-constrained settings, prioritize performance-related benefits over usability alone. However, system simplicity could facilitate learning and experimentation and may later influence perceived usefulness of an IoT system (Blut & Wang, 2020; Buyle et al., 2018; Michels et al., 2021; Negm, 2023b; Venkatesh & Davis, 2000). The hypotheses representing these assumptions are as follows:

(*Technology acceptance with intention to adopt IoT*)

H_{3a}: Perceived usefulness positively influences adoption intention
H_{3b}: Perceived ease of use positively influences adoption intention
H_{3c}: Perceived usefulness positively mediates the influence of perceived ease of use on adoption intention

The framework is further extended by incorporating entrepreneurial ambidexterity as a mediator, capturing farmers' capacity to balance exploratory activities (experimenting with new technologies) and exploitative activities (optimizing existing practices) (March, 1991). Perceived usefulness and ease of use are hypothesized to boost both propensities to explore and exploit, on the premise that individuals are more willing to experiment and apply new technology in novel ways if it is perceived as beneficial, rewarding, and user-friendly (Benner & Tushman, 2003; Gupta et al., 2006; Jansen et al., 2006; March, 1991; Mishra et al., 2024; Venkatesh, 1999; Vroom, 1964). In turn, these propensities mediate the relationship between acceptance and adoption intention.

(*Technology acceptance with entrepreneurial ambidexterity*)

H_{4a}: Perceived usefulness positively influences exploration propensity
H_{4b}: Perceived usefulness positively influences exploitation propensity
H_{4c}: Perceived ease of use positively influences exploration propensity
H_{4d}: Perceived ease of use positively influences exploitation propensity

(*Entrepreneurial ambidexterity mediation with technology acceptance and adoption intention*)

H_{5a}: Exploration propensity positively mediates the influence of perceived usefulness on adoption intention
H_{5b}: Exploitation propensity positively mediates the influence of perceived usefulness on adoption intention
H_{5c}: Exploration propensity positively mediates the influence of perceived ease of use on adoption intention
H_{5d}: Exploitation propensity positively mediates the influence of perceived ease of use on adoption intention

Finally, entrepreneurial ambidexterity is predicted to directly influence the intention to adopt technology, reflecting how it enables farmers to leverage new technologies effectively for operational improvements and innovative experimentation, as they are equipped with the resilience and agility to face risks and setbacks (Asif & de Vries, 2015; Drucker, 1985; Hashem et al., 2024; March, 1991; Schumpeter, 1934; Teece et al., 1997).

(*Entrepreneurial ambidexterity with intention to adopt IoT)*

H_{6a}: Exploration propensity positively influences adoption intention
H_{6b}: Exploitation propensity positively influences adoption intention

This integrated model illustrates a dynamic process in which technology readiness shapes Perceptions influence ambidextrous behaviors, and these behaviors ultimately determine adoption intention, all of which are represented in Figure 1.

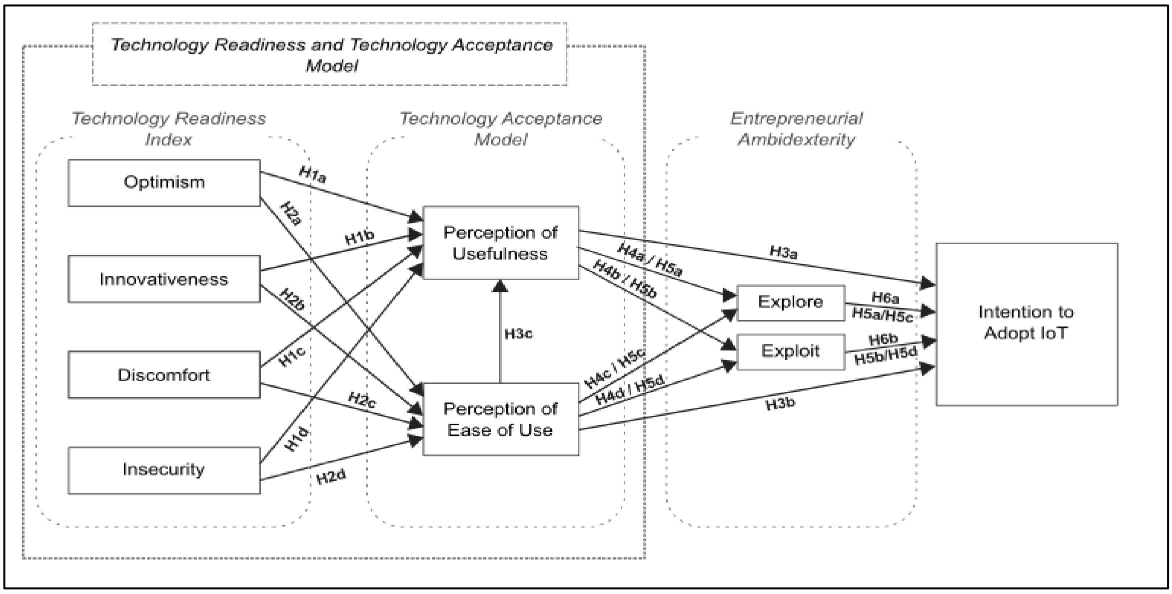

Figure 1. Conceptual model of the study

RESEARCH METHOD

Research Design

Adopting a positivist paradigm, this study emphasizes objectivity, empirical evidence, and the identification of causal relationships through systematic measurement (Creswell & Creswell, 2017; Park et al., 2020; Ryan, 2018). Farmers' technology readiness, acceptance, and entrepreneurial ambidexterity are treated as observable constructs that influence IoT adoption intentions. A deductive, cross-sectional quantitative design is employed, using survey data from smallholding farmers in Sabah engaged in non-commodity food agriculture to test hypotheses about the effects of technology readiness on acceptance, the role of acceptance in predicting adoption intention, and the mediating influence of entrepreneurial ambidexterity (Ray, 2020; Wang & Cheng, 2020). Data are collected through a structured questionnaire that incorporates demographic profiling and validated measurement items adapted from the Technology Readiness Index, the Technology Acceptance Model, and the Entrepreneurial Ambidexterity frameworks, assessing optimism, innovativeness, discomfort, insecurity, perceived usefulness, perceived ease of use, and exploration and exploitation activities. An open-ended question supplements these measures by capturing qualitative insights on IoT adoption, thereby enriching the interpretation of responses. This methodological alignment ensures rigor while enabling a comprehensive assessment of the determinants shaping IoT adoption among smallholding farmers in Sabah (Setia, 2016; Wang & Cheng, 2020). Collected data are then cleansed and analyzed using SPSS and SmartPLS for PLS-SEM analyses.

Research Instrument

The study employed a structured questionnaire to quantitatively assess factors influencing IoT adoption among smallholding farmers in Sabah. A 5-point Likert scale was used to measure respondents' standpoints on the prescribed statements or items. The scale ranged from 1 ("Strongly Disagree") to 5 ("Strongly Agree").

Measurement items were adapted from earlier research on the Technology Readiness Index (TRI) (Parasuraman, 2000; Parasuraman & Colby, 2015; Walczuch et al., 2007), the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 2000; Walczuch et al., 2007), and

Entrepreneurial Ambidexterity (EA) (Gibson & Birkinshaw, 2004; Good & Michel, 2013; He & Wong, 2004; Kauppila & Tempelaar, 2016; March, 1991; Raisch & Birkinshaw, 2008; Raisch et al., 2009; Tushman & O'Reilly, 1996), assessing TRI and TAM dimensions and exploration/exploitation activities reflecting entrepreneurial tendencies. Definitions of constructs are provided in Table 1. An open-ended item requesting respondents' views on barriers to adopting IoT technology was added to conclude the questionnaire.

Prior to distribution, the instrument was pre-screened for ethical clearance and evaluated by linguistic panels and panels from academia and the agricultural industry to test for contextual validity and ensure that comprehensive technical terms were included. The questionnaire was then distributed in printed form to encourage engagement, complemented by instructional videos demonstrating IoT applications. This design ensured reliable, valid, and comprehensive data on farmers' attitudes, readiness, and intentions to adopt IoT technologies.

Research Sampling Method

Smallholding farmers in Sabah are the focus of the study. They are registered with agricultural agencies and primarily cultivate fruits, vegetables, and food crops, as classified by the Ministry of Agriculture and Food Industries (MAFI). These crops are significant contributors to Malaysia's food security, making the group highly relevant to the study objectives (DOA, 2022; MAFI, 2021). In this research, smallholding farmers are defined as smallholders who manage farm operations of approximately 10 acres or less, directly monitored and operated by the farmers or family members, as outlined by the Ministry of Agriculture and Food Security (KRI, 2024; MAFI, 2021). A monthly income threshold of RM10,000 or below is used as an operational criterion – not an official classification of smallholders' income, but rather a contextual delimiter for sampling inclusion/exclusion and an indicator of a farming operation's economic size (Keung et al., 2020; Khalil et al., 2017). This threshold is considered adequate to indicate that respondents' technology adoption resources might be constrained. Farmers with higher incomes are excluded to avoid bias caused by differences in capital, scale, and investment capacity. A similar method was previously employed in research on Sabah smallholding farmers by Yusof and Annuar (2023). Respondent details were sought from the Sabah State Department of Agriculture (RISDA) and the Farmers' Organisation Authority, or Lembaga Pertubuhan Peladang (LPP), with most participants registered under LPP and a smaller proportion under RISDA Kota Belud. The exact size of the target population is uncertain, as many farmers operate across multiple agricultural sectors (e.g., oil palm, food crops, livestock), leading to possible duplication in reported numbers (DOA, 2022). This issue has been acknowledged by the Department of Agriculture in its official reporting (DOA, 2022). To address this, proportional stratified random sampling (Glasgow, 2005; Lee & Park, 2015; Stephan, 1941) was adopted to ensure representation across Sabah's five main administrative divisions: Kudat, West Coast, Interior, Sandakan, and Tawau. As public data on farming population density are unavailable, the study relied on non-industrial cultivation land use in Sabah (MAMPU, 2016), covering fruits, vegetables, herbs, and cash crops, to approximate the percentage of farmers across Sabah divisions, as organized in Table 2.

Table 1. Definition of Constructs

Constructs	Definition	Reference
Optimism (OPT)	Favorable view of technology and an assumption that it serves better control, efficiency, and flexibility in their lives.	Parasuraman (2000), Parasuraman & Cobly (2015), Walczuch et al. (2007)
Innovativeness (INN)	An inclination toward pioneering technology and thought leadership.	
Discomfort (DIS)	Feeling limited in user control and being strained by its demands.	
Insecurity (INS)	Lack of trust in technology, caused by doubts about its performance and concerns about adverse outcomes.	
Perceived Usefulness (PoU)	A farmer's impression that utilizing a particular system will improve farm performance.	Davis (1989), Venkatesh & Davis (2000), Walczuch et al. (2007)
Perceived Ease of Use (PEoU)	A farmer's impression that utilizing a particular system involves low effort in carrying out a task.	
Exploration Propensity (EXP)	Inclination to innovate, experiment, and take risks to improve farm performance.	Gibson & Birkinshaw (2004), Good & Michel (2013), He & Wong (2004), Kauppila & Tempelaar (2016), March (1991), Raisch & Birkinshaw (2008), Raisch et al. (2009), Tushman & O'Reilly (1996)
Exploitation Propensity (EXPL)	Inclination to apply and refine existing knowledge to improve farm performance.	
Intention to Adopt IoT (INT)	Farmer's adoption intention to use for farm management.	Venkatesh & Davis (2000)

Table 2. Non-industrial Cultivation Land Size per Division in Sabah

Division	Districts	Non-industrial Cultivation Land (ha)
Kudat	Kudat, Kota Marudu, Pitas	2,158.0
West Coast	Kota Kinabalu, Penampang, Putatan, Papar, Tuaran, Kota Belud, Ranau	11,151.6
Interior	Beaufort, Sipitang, Keningau, Tenom, Tambunan, Kuala Penyu, Nabawan	5,291.4
Sandakan	Sandakan, Kinabatangan, Beluran, Telupid, Tongod	1,891.2
Tawau	Tawau, Kalabakan, Lahad Datu, Kunak, Semporna	3,204.8
	TOTAL	23,697.0

To determine the required sample size, Cochran's (1977) formula was used, which is appropriate when the overall population size is large but unknown. At a 95% confidence level (Z-value = 1.96), with a 5% margin of error and a presumed population proportion of 0.5 to maximize variability, the formula yielded a recommended sample size of 385 respondents. This figure is consistent with guidelines for quantitative studies employing regression analysis, where excessively large samples may not necessarily increase accuracy or significance (Hair et al., 2018). The proportional distribution of this sample across the identified divisions was calculated according to the relative size of non-industrial farming land, as organized in Table 3. Eligible respondents were then filtered based on the defined study criteria, including location, farm size, crop type, and IoT exposure, before being randomly selected for inclusion. This stratified approach ensures methodological rigor and enhances the sample's proportional representation of the overall smallholder population in Sabah.

Table 3. Sample Size of Each Stratum Based on Land Cultivation Size Proportion

Stratum	Cultivation Size (ha)	Stratum Proportion	Sample Size
Kudat	2,158.0	0.091	35
West Coast	11,151.6	0.471	181
Interior	5,291.4	0.223	86
Sandakan	1,891.2	0.080	31
Tawau	3,204.8	0.135	52
TOTAL	23,697.0	1	385

Data Collection

The data collection process began after receiving ethical clearance and final approval of the research instruments, with relevant authorities approached to access databases of registered farmers. Respondents were identified through three main groups: randomly selected agropreneur exhibitors at agricultural events, members of the RISDA Agrofood Program in Kota Belud, and members of PPK from 16 administrative areas across Sabah. Data were collected over four months (April-August 2024) using printed questionnaires administered primarily in person at gatherings such as meetings and exhibitions, with enumerators assisting across districts. Before the survey was administered, respondents were introduced to IoT applications through knowledge-sharing activities, demonstration videos, and access to a live IoT system available online, ensuring adequate understanding before completing the questionnaires. Translation or reading assistance was provided when necessary to enhance inclusivity. Completed questionnaires were collected, screened for validity (discarding incomplete or empty responses), and digitized using Google Forms and Microsoft Excel for subsequent analysis.

506 cases were collected through in-person questionnaire distribution, yielding a response rate of 76.3%. Following the recommended practice of omitting surveys with more than 25% missing data (Hair et al., 2018; Tabachnick & Fidell, 2007), 34 incomplete or empty responses were removed, leaving 472 raw cases for screening. The responses were then assessed against the study's smallholders sampling criteria: profiles with monthly incomes above RM10,000; those cultivating solely non-food industrial crops; respondents already adopting IoT; and farmers operating outside Sabah were excluded, resulting in 446 valid cases. Data cleaning involved translating and standardizing responses, correcting spelling and syntax, and identifying straight-lined responses, with some retained to preserve divisional quotas (Guenther et al., 2023). Missing values were treated using series mean imputation in SPSS (Saidu et al., 2023). To align with Cochran's (1977) size formula and maintain proportional representation across Sabah's five administrative divisions, 385 cases were selected from 446 using simple random sampling, following the stratum proportions specified in Table 3, for final analysis (Tables 4 and 5).

Analysis Method

Descriptive statistics were computed in SPSS to summarize the datasets by calculating mean scores and standard deviations for the variables before conducting further analyses (IBM Corp., 2022; Pallant, 2020). The descriptive statistics are presented in Table 6. The study's objectives extend beyond examining direct relationships to understanding how technology readiness influences technology acceptance and how entrepreneurial ambidexterity mediates the relationships between these perceptions and IoT adoption intention among smallholders. Subsequently, Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to scrutinize complex causal associations among latent variables, indicators, and structural paths, providing robust estimates of indirect effects through bootstrapping (Hair et al., 2022; Ramayah et al., 2018). Its suitability for research with non-normal data distributions, limited sample sizes, and models that connect theoretical constructs to real-world applications makes it an appropriate analytical tool in this context (Guenther et al., 2023). Furthermore, it is widely recommended for behavioral and technology adoption research because it emphasizes prediction-oriented analysis and theory development, particularly in emerging research contexts where theoretical integration is still evolving (Hair et al., 2022; Sarstedt et al., 2022). Following the protocol suggested by Anderson and Gerbing (1988), the measurement model was initially evaluated to confirm construct reliability and validity, consistent with the guidelines proposed by Hair et al. (2022) and Ramayah et al. (2018). Subsequently, the hypothesized relationships were examined, followed by mediation analysis to estimate the extent of indirect effects. Predictive relevance analysis was conducted to evaluate the model's applicability across various samples.

Table 4. Demography Profile

Demography	Category	Frequency	%
Gender	Male	192	49.9
	Female	193	50.1
Education Level	Primary school	45	11.7
	Secondary school	241	62.6
	College/University	99	25.7
Age Group	18-28 years old	34	8.8
	29-39 years old	65	16.9
	40-50 years old	109	28.3
	51-61 years old	111	28.8
	62 years old and above	66	17.1
Years of Farming	5 years and below	191	49.6
	6-11 years	77	20.0
	12-20 years	55	14.3
	21 years and above	62	16.1
Monthly Income	RM4,000 and below	338	87.8
	RM4,001-RM8,000	46	11.9
	RM8,001-RM10,000	1	0.3
Cultivation Land Size	5 acres and below	342	88.8
	6-10 acres	43	11.2

Table 5. Respondents Distribution According to Divisional Strata

Division	District	Frequency	%
Kudat Division	Kota Marudu	10	2.6
	Kudat	25	6.5

Division	District	Frequency	%
	Subtotal	*35*	*9.1*
West Coast Division	Kota Belud	12	3.1
	Kota Kinabalu	24	6.2
	Papar	18	4.7
	Penampang	44	11.4
	Ranau	41	10.6
	Tuaran	42	10.9
	Subtotal	*181*	*46.9*
Interior Division	Keningau	32	8.3
	Beaufort	23	6.0
	Nabawan	13	3.4
	Tenom	11	2.9
	Sipitang	4	1.0
	Tambunan	2	0.5
	Membakut	1	0.3
	Subtotal	*86*	*22.4*
Sandakan Division	Kinabatangan	19	4.9
	Tongod	10	2.6
	Sandakan	2	0.3
	Subtotal	*31*	*7.8*
Tawau Division	Kunak	12	3.1
	Lahad Datu	27	7.0
	Semporna	2	0.5
	Tawau	11	2.9
	Subtotal	*52*	*13.5*

Table 6. Descriptive Statistics of Constructs

Construct	Mean	SD
Technology Readiness Index (TRI)		
Optimism	3.9140	0.8315
Innovativeness	3.5599	0.8118
Discomfort	2.8930	0.8409
Insecurity	3.1844	0.8974
Technology Acceptance Model (TAM)		
Perceived Usefulness	3.9570	0.8104
Perceived Ease of Use	3.5753	0.8481
Entrepreneurial Ambidexterity (EA)		
Exploration Propensity	3.7603	0.7687
Exploitation Propensity	3.6746	0.7759
Intention		
Intention to Adopt IoT	3.9527	0.7802

SD – Standard Deviation

Measurement Model

Correlations among constructs were estimated using the PLS-SEM algorithm. Before testing the structural model, the measurement model was evaluated to ensure reliability and validity. Reliability was assessed through outer loadings, composite reliability (CR), and average variance extracted (AVE), while discriminant validity was examined using the heterotrait-monotrait (HTMT) ratio (Hair et al., 2022; Ringle et al., 2024). Items with low factor loadings, high variance inflation factor (VIF) values, or limited theoretical relevance (DIS4, OPT2, PoU5, PoU6, PEoU1, PEoU3, INT2, INT3, INT7) were excluded from the analysis to enhance construct precision and minimize redundancy bias. The retained items demonstrated satisfactory loadings (0.744-0.941), with all CR values over 0.7 and AVE values exceeding 0.5, thereby satisfying the recommended threshold criteria (Hair et al., 2022). HTMT values across constructs remained below 0.85, establishing discriminant validity (Franke & Sarstedt, 2019; Henseler et al., 2015), affirming that survey participants treated constructs as distinct from one another. Analyses showed that satisfactory reliability and validity were established, and the final set of indicators was retained for subsequent structural model analysis. The results of both assessments are presented in Table 7 and Table 8.

Table 7. Reliability and Validity Assessment

Constructs		Loadings	Items	Reference
Technology Readiness Index (TRI)				
Optimism AVE=0.870 CR=0.953	OPT1	0.921	I like that IoT application makes me more productive at my work.	Parasuraman & Colby (2015), Walczuch et al. (2007)
	OPT3	0.941	I feel confident that IoT application will follow through with what I instruct them to do.	
	OPT4	0.937	I like that IoT application gives me more freedom of mobility.	
Innovativeness AVE=0.665 CR=0.887	INN1	0.744	Other people come to me for advice on new technologies.	
	INN2	0.876	I find new technologies to be mentally stimulating.	
	INN3	0.754	I can usually figure out new high-tech products and services without help from others.	
	INN4	0.877	Learning about technology can be as rewarding as technology itself.	
Discomfort AVE=0.677 CR=0.863	DIS1	0.872	Technology always seems to fail at the worst possible time.	
	DIS2	0.776	It is embarrassing when I have trouble with a high-tech gadget while people are watching.	
	DIS3	0.818	Technical support lines are not helpful because they do not explain things in terms I understand.	
Insecurity AVE=0.667 CR=0.888	INS1	0.901	I worry that information I make available over the Internet may be misused by others.	
	INS2	0.766	Technology lowers the quality of relationships by reducing personal interaction.	
	INS3	0.802	People are too dependent on technology to do things for them.	
	INS4	0.790	Too much technology distracts people to a point that is harmful.	

Technology Acceptance Model (TAM)				
Perceived Usefulness AVE=0.812 CR=0.945	PoU1	0.912	The IoT application could enable me to complete tasks on my farm faster.	Davis (1989), Mohr & Kuhl (2021)
	PoU2	0.924	The IoT application could increase the productivity of my farm.	
	PoU3	0.896	The IoT application could make work easier for all the workers on my farm.	
	PoU4	0.871	The IoT application is suitable for my farm operation.	
Perceived Ease of Use AVE=0.800 CR=0.941	PEoU2	0.872	Working with IoT applications is possible without any problems.	
	PEoU4	0.890	The use of IoT application allows for more flexibility in my farming processes.	
	PEoU5	0.900	It is easy to skillfully operate the IoT application.	
	PEoU6	0.915	My interaction with the IoT application would be clear and understandable.	
Entrepreneurial Ambidexterity (EA)				
			Within the last 3 years,	
Exploration Propensity AVE=0.770 CR=0.944	EXP1	0.898	I search for new possibilities with respect to new products, processes or markets.	Kauppila and Tempelaar (2016), Mom et al. (2007, 2009), Tushman and O'Reilly (1996)
	EXP2	0.911	I evaluate diverse options with respect to products, processes or markets.	
	EXP3	0.893	I focus on strong renewal of products/services or markets.	
	EXP4	0.804	I perform activities requiring quite some adaptability to me.	
	EXP5	0.877	I perform activities requiring me to learn new skills or knowledge.	
			Within the last 3 years, I have been engaged in activities,	
Exploitation Propensity AVE=0.743 CR=0.935	EXPL1	0.812	which a lot of experience has accumulated by myself.	
	EXPL2	0.884	which serve existing (internal) customers with existing services/products.	
	EXPL3	0.903	It is clear to me how to conduct them.	
	EXPL4	0.811	which primarily focuses on achieving short-term goals.	
	EXPL5	0.895	which I can properly conduct by using my present knowledge.	
Intention to Adopt (Dependant Variable)				
Intention to Adopt AVE=0.771 CR=0.944	INT1	0.871	I intend to adopt IoT for my farming activities.	Kim et al. (2017)
			Given my financial access, I predict I would use it.	
			I intend to adopt IoT for farming activities despite potential risks.	
			I understand that the benefits of IoT outweigh the risks.	
			I intend to encourage others to adopt IoT for farming activities in the future.	

Table 8. Discriminant Validity (HTMT) Model

Consruct	1	2	3	4	5	6	7	8	9
1									
2	0.653								
3	0.103	0.195							
4	0.095	0.164	0.746						
5	0.786	0.623	0.081	0.066					
6	0.662	0.673	0.136	0.097	0.706				
7	0.607	0.598	0.113	0.103	0.599	0.717			
8	0.575	0.521	0.266	0.294	0.557	0.557	0.713		
9	0.757	0.707	0.077	0.084	0.851	0.641	0.668	0.655	

1 Optimism	4 Insecurity	7 Exploration
2 Innovativeness	5 Perceived Usefulness	8 Exploitation
3 Discomfort	6 Perceived Ease of Use	9 Intention to Adopt

Structural Model Analysis

The assessment of the structural model's validity and reliability involved a full collinearity test, to investigate if the model is contaminated with common method bias via evaluation of variance inflation factors (VIF) values between latent constructs. Bootstrap results showed that all VIF values ranged from 1.547 to 2.377, which fall within the acceptable threshold range (1.0–3.0). This indicates that multicollinearity was not a concern and that the model was free from common method bias (Becker et al., 2015; Hair et al., 2022; Kock, 2017). Subsequently, the 21 proposed hypotheses were tested using PLS-SEM algorithm with bootstrapping, of which results are discussed in the next section.

Mediation Analysis

The mediating role of entrepreneurial ambidexterity, represented by exploration and exploitation, in the association between the technology acceptance dimension (perceived usefulness and perceived ease of use) and the intention to adopt was examined. First, the direct and indirect effects were tested for significance using bootstrapped procedures with 5,000 iterations at the 5% level. The p-values, along with the lower (2.5%) and upper (97.5%) bias-corrected confidence intervals, were assessed (Preacher & Hayes, 2004). The mediating effects were then evaluated by comparing path coefficients to determine whether exploration and exploitation strengthened or weakened the direct effects. Given that entrepreneurial ambidexterity comprises two constructs, parallel mediation was tested using a multi-mediation approach, as recommended by Hair et al. (2014), and total indirect effects were computed by combining the indirect paths of exploration and exploitation. Finally, the type and magnitude of mediation were analyzed by performing a variance accounted for (VAF) analysis.

FINDINGS AND DISCUSSION

The 21 hypothesized relationships were empirically tested using PLS-SEM and bootstrapping. Analyses indicated that optimism ($\beta=0.602$, $p<0.01$) and innovativeness ($\beta=0.214$, $p<0.01$) significantly predicted perceived usefulness, whereas discomfort and insecurity were non-significant, providing partial support for H1. Similarly, optimism (β=0.401, p<0.01) and innovativeness (β=0.356, p<0.01) significantly influenced perceived ease of use, whereas discomfort and insecurity were again non-significant, providing partial support for H2. Within TAM, perceived usefulness positively influenced adoption intention (β=0.599, p<0.01), supporting H3a, whereas perceived ease of use was non-significant (β=-0.002, p=0.967), leading to rejection of H3b. Hypothesis test results are tabulated in Table 9.

Mediation analysis (Table 10) indicates that the mediation effect of entrepreneurial ambidexterity on the link between perceived usefulness and IoT adoption intention is significant, though with little impact (VAF=13.8%). A higher VAF is observed for the indirect effect through perceived ease of use (VAF=49.4%), suggesting partial mediation. Exploration behaviors exert a stronger mediating effect (VAF=26.7%) than exploitation on the perceived ease of use. In addition, it reduces the direct effect of perceived usefulness (β decreases from 0.599 to 0.096). These findings suggest that IoT adoption among smallholding farmers is more strongly reinforced when ease of use is coupled with entrepreneurial behaviors that drive more exploration than exploitation.

Table 9. Results from Hypothesis Test

	β	**Std Error**	**t-value**	**p-value**	**LL 0.025**	**UL 0.975**	**Decision**
Influence of technology readiness dimensions towards perceived usefulness							
$H1_a$ OPT → PoU	0.602	0.056	10.772	p<0.01	0.489	0.705	Accept
$H1_b$ INN → PoU	0.214	0.054	3.953	p<0.01	0.111	0.327	Accept
$H1_c$ DIS → PoU	-0.024	0.048	0.494	0.621	-0.127	0.063	Reject
$H1_d$ INS → PoU	0.013	0.057	0.226	0.822	-0.109	0.115	Reject
Influence of technology readiness dimensions towards perceived ease of use							
$H2_a$ OPT → PEoU	0.401	0.065	7.462	p<0.01	0.287	0.525	Accept
$H2_b$ INN → PEoU	0.356	0.069	5.162	p<0.01	0.215	0.486	Accept
$H2_c$ DIS → PEoU	-0.003	0.057	0.044	0.965	-0.129	0.099	Reject
$H2_d$ INS → PEoU	0.040	0.054	0.729	0.466	-0.066	0.144	Reject
Influence of technology acceptance dimensions towards adoption intention							
$H3_a$ PoU → INT	0.599	0.046	13.038	p<0.01	0.505	0.684	Accept
$H3_b$ PEoU → INT	-0.002	0.056	0.042	0.967	-0.113	0.105	Reject
$H3_c$ PEoU → PoU → INT	0.179	0.036	4.952	p<0.01	0.107	0.249	Accept
Entrepreneurial ambidexterity dimensions mediation effect between technology acceptance adoption intention							
$H4_a$ PoU	0.214	0.068	3.162	p<0.01	0.080	0.346	Accept

→ EXP							
$H4_b$ PoU → EXPL	0.317	0.070	4.522	p<0.01	0.175	0.447	Accept
$H4_c$ PEoU → EXP	0.520	0.059	8.849	p<0.01	0.401	0.632	Accept
$H4_d$ PEoU → EXPL	0.309	0.065	4.761	p<0.01	0.182	0.435	Accept
$H5_a$ PoU → EXP → INT	0.034	0.016	2.081	0.037	0.001	0.065	Accept
$H5_b$ PoU → EXPL → INT	0.062	0.021	2.951	p<0.01	0.020	0.103	Accept
$H5_c$ PEoU → EXP → INT	0.093	0.032	2.938	p<0.01	0.030	0.154	Accept
$H5_d$ PEoU →EXPL→ INT	0.079	0.020	3.862	p<0.01	0.039	0.119	Accept
Influence of entrepreneurial ambidexterity dimensions towards adoption intention							
$H6_a$ EXP → INT	0.159	0.051	3.106	p<0.01	0.059	0.257	Accept
$H6_b$ EXPL → INT	0.196	0.046	4.288	p<0.01	0.101	0.278	Accept

OPT – Optimism　INS – Insecurity　EXP – Explore
INN – Innovativeness　PoU – Perceived Usefulness　EXPL – Exploit
DIS - Discomfort　PeoU – Perceived Ease Of Use　INT – Intention to Adopt IoT

Table 10. Summary of Analysis on Entrepreneurial Ambidexterity Mediation Effect

Inderect Path	β	Total Effect	p-value	Inderect Effect Significance	VAF (%)	
					EXP	EXPL
Perceived Usefulness	0.096	0.694	p<0.01	Yes	4.9	8.9
Perceived Ease of Use	0.172	0.348	p<0.01	Yes	26.7	22.7

Optimism contributed most on perceived usefulness (f^2=0.319), while innovativeness contributed a smaller effect (f^2=0.016), jointly explaining 55.8% of variance in perceived usefulness. As for perceived ease of use, optimism (f^2=0.194) and innovativeness (f^2=0.151) exerted medium effects, explaining 46.2% of variance. Within entrepreneurial ambidexterity, perceived usefulness imposed more effect on exploration (f^2=0.286) compared with ease of use (f^2=0.080), together explaining 46.3% of variance, while both acceptance constructs accounted for 32.5% of variance in exploitation, albeit with small effect. Perceived usefulness had the most effect (f^2=0.597) on adoption intention, trailed by exploration (f^2=0.034) and exploitation (f^2=0.065), whereas perceived ease of use contributed negligible impact. Summing up, the model explained 68.7% of variance of adoption intention, indicating medium-to-high predictive capability. According to Hair et al. (2014), R^2 values confirmed medium-to-high in-sample predictive power, with adoption intention (R^2=0.687) and perceived usefulness (R^2=0.606) showing the strongest predictive validity, while exploitation had the lowest (R^2=0.325). Model predictive assessment results are as tabulated in Table 11 and Table 12. Summary of results from structural model assessment are described in Figure 2.

Table 11. Level of Coefficient Determination, R^2

Construct	R^{2*}	Std Error	t-value	p-value	LL 0.025	UL 0.975
Perceived Usefulness	0.606	0.041	14.817	p<0.01	0.509	0.674
Perceived Ease of Use	0.463	0.046	10.051	p<0.01	0.366	0.542
Exploration Propensity	0.462	0.048	9.593	p<0.01	0.361	0.549
Exploitation Propensity	0.325	0.053	6.162	p<0.01	0.216	0.424
Intention to Adopt IoT	0.687	0.045	15.189	p<0.01	0.573	0.759

* Benchmark threshold – 0.25 low, 0.50 medium, 0.75 high (Hair et al., 2014)

Table 12. Latent Variable Assessment PLS-Predict

	Q^2 Predict	Predictive Power	RMSE
Perceived Usefulness	0.544	Strong	0.679
Perceived Ease of Use	0.444	Strong	0.751
Exploration Propensity	0.357	Strong	0.808
Exploitation Propensity	0.298	Moderate	0.844
Intention to Adopt IoT	0.538	Strong	0.685

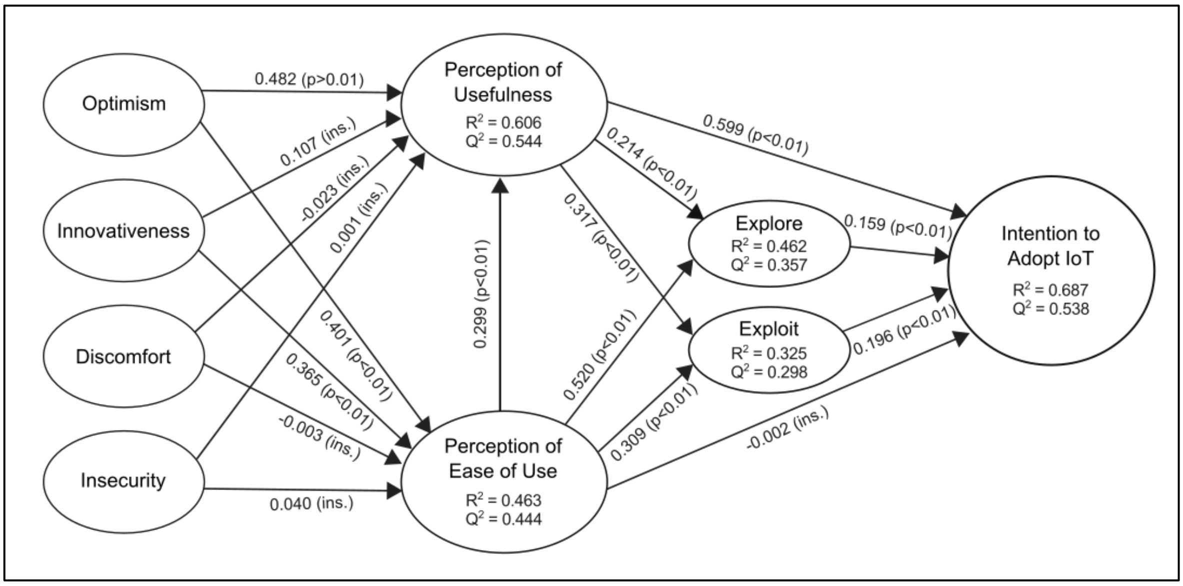

Figure 2. Summary of structural model assessment

This study highlights how technology readiness, acceptance, and entrepreneurial ambidexterity jointly shape smallholding farmers' IoT adoption intention in Sabah. Optimism and innovativeness, the motivators of technology readiness, emerged as strong predictors of technology acceptance, with optimism showing the most consistent effect on both perceived usefulness and ease of use. Farmers who expect positive outcomes are more inclined to perceive IoT as both useful and manageable, consistent with previous research identifying optimism as an important determinant of technology readiness (Lin et al., 2007; Parasuraman, 2000). By contrast, discomfort and insecurity showed no significant influence, indicating that enabling factors outweigh inhibiting ones in this context (Castiblanco Jimenez et al., 2021; Godoe & Johansen, 2012). Prior findings suggest that inhibitors may be less salient among Sabah farmers due to their limited exposure to IoT technologies, resulting in relatively unclear or undeveloped concerns about discomfort and security risks (Blut & Wang, 2020).

Consistent with the TAM, perceived usefulness emerged as the dominant predictor of adoption intention, whereas perceived ease of use had an insignificant direct effect on adoption intention (Davis, 1989). Perceived ease of use only supported adoption by enhancing perceived usefulness, reinforcing the idea that performance benefits outweigh usability concerns for Sabahan farmers. The observed insignificant direct effect is similar to earlier studies, particularly in the context of complex and task-specific technologies such as IoT (Muk & Chung, 2015; Negm, 2023b). In practical terms, Sabah farmers appear willing to accept system complexity if they strongly perceive that IoT technologies provide substantial benefits to their agricultural operations. This finding underscores the practical importance of intuitive IoT usability design and experiential training to strengthen perceptions of ease of use (Gefen et al., 2003; Venkatesh, 2000).

The mediation effect of entrepreneurial ambidexterity on the relationship between technology acceptance and adoption intention was significant. Perceived usefulness and ease of use both promoted explorative and exploitative inclinations, though ease of use exerted the greater impact, indicating that high effort expectancy is a stronger driver of ambidextrous activities in resource-constrained, low-digital-maturity environments, as in the study (Benner & Tushman, 2003; Jansen et al., 2006; Li et al., 2020; Liu et al., 2025). Propensity to explore displayed a stronger mediating pathway through perceived ease of use, enabling farmers to experiment with IoT applications, while exploitation exerted a stronger direct effect, anchoring IoT within existing routines. These dynamics reflect established ambidexterity theory (Benner & Tushman, 2003; March, 1991), where exploration opens pathways for innovation while exploitation reinforces the belief in incremental performance gains from knowledge application.

Theoretical and Empirical Implications

The research extends TRAM (Lin et al., 2007) to the under-researched context of smallholders in Sabah, offering novel theoretical and empirical contributions to technology adoption research. While TRAM has been widely applied in domains such as marketing (Jin, 2019), healthcare (Kuo et al., 2013), and tourism (Lestari et al., 2023), its integration into agriculture highlights that individual dimensions of TRI and TAM influence IoT adoption intentions differently rather than uniformly. The novelty of incorporating entrepreneurial ambidexterity (Drucker, 1985; Lidow, 2022; March, 1991), which stems from technology readiness and acceptance (Davis, 1989; Lin et al., 2007; Parasuraman, 2000; Parasuraman & Colby, 2015), further demonstrates the interplay of farmers' explorative and exploitative measures, an essential capability when facing the dual pressures of innovation and operational constraints when deciding to implement new technology. Empirically, the study provides rare, structured evidence from Sabahan smallholders, revealing that the common assumption that the 'perceived ease of use' indicator predicts adoption may not inherently drive adoption across cultural and social groups (Muk & Chung, 2015; Negm, 2023b; Venkatesh, 2000), thereby underscoring the importance of context in shaping technology acceptance. These findings enrich the literature on agricultural technology adoption and inform policymakers and practitioners in developing culturally sensitive and practically relevant strategies to enhance IoT adoption toward sustainable farming and food security.

Practical Implications

This study provides significant insights into the behavioral drivers and barriers influencing IoT adoption among Sabahan smallholders. Findings reveal that optimism, perceived usefulness, and entrepreneurial ambidexterity, particularly exploration propensity, significantly shape adoption intentions, whereas perceived ease of use exerts an insignificant direct influence. Farmers with stronger exploratory tendencies and a positive outlook toward technology are more likely to adopt IoT when it is perceived as useful. This indicator could help agencies profile and filter recipients of initiatives, distinguishing productive from nonproductive ones and indirectly avoiding wasteful resource spending on farmers' developments (Hindrawati et al., 2025). Results show that adoption intentions are most effectively strengthened through user-friendly system design, comprehensive introductory and ongoing training programs for IoT familiarization, and policy measures that promote experimentation while enabling gradual integration. For example, technology providers could leverage widely used applications such as ChatGPT to interact with the system or use simple multilingual interfaces suitable for older farmers (Arman & Lamiyar, 2023). The government could introduce IoT demonstration plots in each district or region for hands-on training and experience, as well as advisory and support centers for smallholders.

Divisional variations in readiness and acceptance, as well as entrepreneurial ambidexterity (Table 13), further highlight the need for region-specific interventions. Overall, the key observations presented inform policymakers and practitioners in designing targeted strategies to address specific weak points that enhance IoT technology adoption, improve farm productivity, and align with Sabah's agricultural and economic transformation goals.

Table 13. Mean Scores of Variables According to Sabah Divisions

Construct	Kudat	West Coast	Interior	Sandakan	Tawau
Technology Readiness Index (TRI)					
Optimism	4.0286	4.0632	3.7436	3.8306	3.649
Innovativeness	3.8599	3.6256	3.4085	3.629	3.3413
Discomfort	2.7643	2.8958	2.9843	2.7742	2.8894
Insecurity	3.0643	3.2201	3.3393	3.1532	2.9038
Technology Acceptance Model (TAM)					
Perceived Usefulness	4.219	4.0532	3.9008	3.8602	3.5962
Perceived Ease of Use	3.7238	3.6409	3.5345	3.586	3.3077
Entrepreneurial Ambidexterity (EA)					
Exploration Propensity	3.9714	3.8734	3.603	3.7871	3.4692
Exploitation Propensity	3.9257	3.7269	3.7227	3.5355	3.3269
Intention to Adopt IoT	4.1571	4.0793	3.8479	3.8548	3.6058

CONCLUSIONS

Research findings demonstrate that technology readiness motivators enhance technology acceptance, while perceived usefulness strongly predicts IoT adoption intention. Moreover, entrepreneurial ambidexterity serves as an important mediator, helping farmers bridge challenges when technology appears difficult to use through both exploratory and exploitative behaviors. These outcomes suggest the creation of more targeted policy and intervention strategies that support farmers in adopting IoT through tailored training, awareness-building, and infrastructure development. Although full adoption faces institutional, structural, and environmental challenges, consistent collaborative efforts such as capacity building, financial assistance, and improved connectivity could accelerate the transition toward modernized farming practices. Ultimately, IoT adoption holds promise for enhancing productivity, improving farmers' livelihoods, and increasing resilience in Sabah's agriculture, provided interventions are designed with long-term sustainability in mind.

LIMITATION & FURTHER RESEARCH

The study acknowledges several limitations, including challenges in data collection due to linguistic barriers and the simplification of technical terms beyond the required level; the risk of sampling bias stemming from imbalanced representation across districts; and the restricted inclusion of urban or non-affiliated farmers. These constraints call for more inclusive sampling and refined methodological designs. Future research could extend TAM (Davis, 1989) by considering demographic differences and the evolving dynamics of perceived ease of use, and by addressing sociocultural and behavioral dimensions such as trust and community influences. Methodologically, workshop-based exposure to IoT technologies and complementary qualitative approaches could yield richer insights, and practical work could examine financing, training, and sustainability monitoring for IoT implementations. Further exploration of entrepreneurial ambidexterity would also clarify how innovation and optimization interact to shape adoption and productivity. Collectively, these directions could strengthen both theoretical and practical views on IoT technology adoption intention.

REFERENCES

Abu Dardak, R., Tahir, M. A. M., Shafie, K. A., & Muhamad, R. M. (2022). Transfer of smart agriculture technology from MARDI to young agropreneurs in Malaysia: The case of high-value vegetable production by AgroCube. *FFTC Journal of Agricultural Policy, 3*, 14–26. https://doi.org/10.56669/pwbk6929

Adnan, N., Nordin, S. M., & Rasli, A. M. (2019). A possible resolution of Malaysian sunset industry by green fertilizer technology: Factors affecting the adoption among paddy farmers. *Environmental Science and Pollution Research, 26*, 27198–27224. https://doi.org/10.1007/s11356-019-05650-9

Ahmad, D. S. N. A., Fatah, F. A., Saili, A. R., Saili, J., Hamzah, N. M., Nor, R. C. M., & Omar, Z. (2025). Exploration of the challenges in adopting smart farming among smallholder farmers: A qualitative study. *Journal of Advanced Research in Applied Sciences and Engineering Technology, 45*(1), 17–27. https://doi.org/10.37934/araset.45.1.1727

Ahmad Tarmizi, H., Kamarulzaman, N. H., Abd Rahman, A., & Atan, R. (2020). Adoption of internet of things among Malaysian halal agro-food SMEs and its challenges. *Food Research, 4*(1), 256–265. https://doi.org/10.26656/fr.2017.4(s1).s26

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin, 103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Aris, N. F. M., Fatah, F. A., & Zailani, S. H. M. (2021). The pull and push factors towards the adoption of Agricultural Revolution 4.0 (AR 4.0) for agro-food supply chain (AFSC) in SMIs agro-based in Malaysia. In *Proceedings of the Second Asia Pacific International Conference on Industrial Engineering and Operations Management*.

Arman, M., & Lamiyar, U. R. (2023). Exploring the implication of ChatGPT AI for business: Efficiency and challenges. *Applied Quantitative Analysis, 3*(2), 38–57. https://doi.org/10.31098/quant.1385

Asif, M., & de Vries, H. J. (2015). Creating ambidexterity through quality management. *Total Quality Management & Business Excellence, 26*(11–12), 1226–1241.

https://doi.org/10.1080/14783363.2014.926609
Bahari, M., Arpaci, I., Der, O., Akkoyun, F., & Ercetin, A. (2024). Driving agricultural transformation: Unraveling key factors shaping IoT adoption in smart farming with empirical insights. *Sustainability, 16*(5), Article 2129. https://doi.org/10.3390/su16052129
Becker, J. M., Ringle, C. M., Sarstedt, M., & Völckner, F. (2015). How collinearity affects mixture regression results. *Marketing Letters, 26*(4), 643–659. https://doi.org/10.1007/s11002-014-9299-9
Benner, M. J., & Tushman, M. L. (2003). Exploitation, exploration, and process management: The productivity dilemma revisited. *Academy of Management Review, 28*(2), 238–256. https://doi.org/10.2307/30040711
Blut, M., & Wang, C. (2020). Technology readiness: A meta-analysis of conceptualizations of the construct and its impact on technology usage. *Journal of the Academy of Marketing Science, 48*, 649–669. https://doi.org/10.1007/s11747-019-00680-8
Bujang, A. S., & Bakar, B. H. A. (2019). Agriculture 4.0: Data-driven approach to galvanize Malaysia's agro-food sector development. *Developing Innovation Strategies in the Era of Data-Driven Agriculture*. FFTC Agricultural Policy Platform. https://doi.org/10.56669/qwpy5362
Buyle, R., Van Compernolle, M., Vlassenroot, E., Vanlishout, Z., Mechant, P., & Mannens, E. (2018). Technology readiness and acceptance model as a predictor for the use intention of data standards in smart cities. *Media and Communication, 6*(4), 127–139. https://doi.org/10.17645/mac.v6i4.1679
Castiblanco Jimenez, I. A., Cepeda García, L. C., Marcolin, F., Violante, M. G., & Vezzetti, E. (2021). Validation of a TAM extension in agriculture: Exploring the determinants of acceptance of an e-learning platform. *Applied Sciences, 11*(10), Article 4672. https://doi.org/10.3390/app11104672
Cegarra-Sánchez, J., Cegarra-Navarro, J. G., Chinnaswamy, A. K., & Wensley, A. (2020). Exploitation and exploration of knowledge: An ambidextrous context for the successful adoption of telemedicine technologies. *Technological Forecasting and Social Change, 157*, Article 120089. https://doi.org/10.1016/j.techfore.2020.120089
Chen, S., & Yu, D. (2022). The impacts of ambidextrous innovation on organizational obsolescence in turbulent environments. *Kybernetes, 51*(3), 1009–1037. https://doi.org/10.1108/K-08-2020-0514
Chiu, W., & Cho, H. (2021). The role of technology readiness in individuals' intention to use health and fitness applications: A comparison between users and non-users. *Asia Pacific Journal of Marketing and Logistics, 33*(3), 807–825. https://doi.org/10.1108/APJML-09-2019-0534
Cochran, W. G. (1977). *Sampling techniques* (3rd ed.). John Wiley & Sons.
Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Sage.
DAFF. (2026, May 20). *Sustainable Agriculture Facilitators (SAF).* Department of Agriculture, Fisheries and Forestry, Australian Government. https://www.agriculture.gov.au/agriculture-land/farm-food-drought/natural-resources/landcare/climate-smart/sustainable-agriculture-facilitators
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008
Dillon, A., & Morris, M. G. (1996). User acceptance of information technology: Theories and models. *Annual Review of Information Science and Technology, 31*, 3–32.
Department of Agriculture Malaysia. (2022). *Booklet statistik tanaman (Sub-sektor tanaman makanan) 2022.*
Department of Statistics Malaysia. (2023). *Gross domestic product (GDP) by state, 2022.*

Drucker, P. F. (1985). *Innovation and entrepreneurship: Practice and principles.* Harper & Row.

Duncan, R. B. (1976). The ambidextrous organization: Designing dual structures for innovation. In *The management of organization* (Vol. 1, pp. 167–188).

Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: A comparison of four procedures. *Internet Research, 29*(3), 430–447. https://doi.org/10.1108/INTR-12-2017-0515

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90. https://doi.org/10.2307/30036519

Gibson, C. B., & Birkinshaw, J. (2004). The antecedents, consequences, and mediating role of organizational ambidexterity. *Academy of Management Journal, 47*(2), 209–226.

Glasgow, G. (2005). Stratified sampling types. In K. Kempf-Leonard (Ed.), *Encyclopedia of social measurement* (pp. 683–688). Elsevier. https://doi.org/10.1016/B0-12-369398-5/00066-9

Godoe, P., & Johansen, T. S. (2012). Understanding adoption of new technologies: Technology readiness and technology acceptance as an integrated concept. *Journal of European Psychology Students, 3*(1), 38–52.

Good, D., & Michel, E. J. (2013). Individual ambidexterity: Exploring and exploiting in dynamic contexts. *The Journal of Psychology, 147*(5), 435–453. https://doi.org/10.1080/00223980.2012.710663

Guenther, P., Guenther, M., Ringle, C. M., Zaefarian, G., & Cartwright, S. (2023). Improving PLS-SEM use for business marketing research. *Industrial Marketing Management, 111*, 127–142. https://doi.org/10.1016/j.indmarman.2023.03.010

Gupta, A. K., Smith, K. G., & Shalley, C. E. (2006). The interplay between exploration and exploitation. *Academy of Management Journal, 49*(4), 693–706. https://doi.org/10.5465/AMJ.2006.22083026

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2018). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM).* Sage.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

Harun, R., Suhaimee, S., Mohd Amin, M. Z., & Sulaiman, N. H. (2015). Benchmarking and prospecting of technological practices in rice production. *Economic and Technology Management Review, 10B*, 77–88.

Hashem, G., Aboelmaged, M., & Ahmad, I. (2024). Proactiveness, knowledge management capability and innovation ambidexterity: An empirical examination of digital supply chain adoption. *Management Decision, 62*(1), 129–162. https://doi.org/10.1108/MD-02-2023-0237

Hashim, M. I. (2022, January 30). *Leading Sabah's digital transformation*. Daily Express. https://www.dailyexpress.com.my/read/4661/leading-sabah-s-digital-transformation/

He, Z.-L., & Wong, P.-K. (2004). Exploration vs. exploitation: An empirical test of the ambidexterity hypothesis. *Organization Science, 15*(4), 481–494. https://doi.org/10.1287/orsc.1040.0078

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*, 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hindrawati, G., Inayah, I., Hermawan, I., & Suharmanto, S. (2025). Human capital profiling in education: Teachers' competence in integrating AR technology for character education development. *Applied Quantitative Analysis, 5*(2), 40–58. https://doi.org/10.31098/quant.3936

IBM Corp. (2022). *IBM SPSS Statistics for Windows* (Version 29.0) [Computer software]. IBM Corp.

Jabatan Pertanian Sabah. (2022). *Ringkasan imbangan dagangan bagi seksyen makanan, 2021 dan 2022*.https://tani.sabah.gov.my/wpcontent/uploads/2022/maklumat_pertanian/sumbangan_sektor/imbangan_dagangan/2021-2022.pdf

Jansen, J. J. P., Van den Bosch, F. A. J., & Volberda, H. W. (2006). Exploratory innovation, exploitative innovation, and performance: Effects of organizational antecedents and environmental moderators. *Management Science, 52*(11), 1661–1674. https://doi.org/10.1287/mnsc.1060.0576

Jin, C. H. (2019). Predicting the use of brand application based on a TRAM. *International Journal of Human–Computer Interaction, 36*(2), 156–171. https://doi.org/10.1080/10447318.2019.1609227

Kauppila, O. P., & Tempelaar, M. P. (2016). The social-cognitive underpinnings of employees' ambidextrous behaviour and the supportive role of group managers' leadership. *Journal of Management Studies, 53*(6), 1019–1044. https://doi.org/10.1111/joms.12192

Keung, E. Z., McElroy, L. M., Ladner, D. P., & Grubbs, E. G. (2020). Defining the study cohort: Inclusion and exclusion criteria. In T. M. Pawlik & J. A. Sosa (Eds.), *Clinical trials* (pp. 39–49). Springer. https://doi.org/10.1007/978-3-030-35488-6_5

Khalil, C. A., Conforti, P., Ergin, I., & Gennari, P. (2017). *Defining small-scale food producers to monitor Target 2.3 of the 2030 Agenda for Sustainable Development*. Food and Agriculture Organization of the United Nations. https://www.fao.org/3/i6858e/i6858e.pdf

Kim, T., & Chiu, W. (2019). Consumer acceptance of sports wearable technology: The role of technology readiness. *International Journal of Sports Marketing and Sponsorship, 20*(1), 109–126. https://doi.org/10.1108/IJSMS-06-2017-0050

Kim, Y., Park, Y., & Choi, J. (2017). A study on the adoption of IoT smart home service using a value-based adoption model. *Total Quality Management & Business Excellence, 28*(9–10), 1149–1165. https://doi.org/10.1080/14783363.2017.1310708

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

Kock, N. (2017). Common method bias: A full collinearity assessment method for PLS-SEM. In H. Latan & R. Noonan (Eds.), *Partial least squares path modeling: Basic concepts, methodological issues and applications* (pp. 245–257). Springer. https://doi.org/10.1007/978-3-319-64069-3_11

Khazanah Research Institute. (2024). *Understanding the landscape of agrifood smallholders in Malaysia: Climate risks, sustainable standards, and gender gap*. https://www.krinstitute.org/Publications-@-Understanding_the_Landscape_of_Agrifood_Smallholders_in_Malaysia-;_Climate_Risks,_Sustainable_Standards,_and_Gender_Gap.aspx

Kuo, K.-M., Liu, C.-F., & Ma, C.-C. (2013). An investigation of the effect of nurses' technology readiness on the acceptance of mobile electronic medical record systems. *BMC Medical Informatics and Decision Making, 13*(1), Article 88. https://doi.org/10.1186/1472-6947-13-88

Lee, G.-S., & Park, K.-S. (2015). A stratified multi-proportions randomised response model. *Korean Journal of Applied Statistics, 28*(6), 1113–1120. https://doi.org/10.5351/KJAS.2015.28.6.1113

Lestari, N. S., Rosman, D., Faridi, A., Sukma, B. E., Rokhmah, S., & Gunawan, A. (2023). The effect of technology readiness and customers' acceptance on online hotel booking intention. In *Proceedings of the 8th International Conference on Business and Industrial Research (ICBIR 2023)* (pp. 759–764). IEEE. https://doi.org/10.1109/ICBIR57571.2023.10147648

Li, W., Clark, B., Taylor, J. A., Kendall, H., Jones, G., Li, Z., & Frewer, L. J. (2020). A hybrid modelling approach to understanding adoption of precision agriculture technologies in Chinese cropping systems. *Computers and Electronics in Agriculture, 172*, Article 105305. https://doi.org/10.1016/j.compag.2020.105305

Lidow, D. B. (2022). The prehistoric entrepreneur: Rethinking the definition. *Journal of Management History, 28*(4), 458–475. https://doi.org/10.1108/JMH-11-2021-0058

Lin, C.-H., Shih, H.-Y., & Sher, P. J. (2007). Integrating technology readiness into technology acceptance: The TRAM model. *Psychology & Marketing, 24*(7), 641–657. https://doi.org/10.1002/mar.20177

Liu, G., Wang, W., Duan, Y., Chin, T., & Mirone, F. (2025). How entrepreneurial orientation influences innovation performance? The effect of knowledge coupling. *Journal of Knowledge Management, 29*(1), 247–258. https://doi.org/10.1108/JKM-04-2024-0506

Ministry of Agriculture and Food Industry. (2021). *Dasar Agromakanan Negara 2.0 2021–2030*. https://www.fama.gov.my/dasar-agromakanan-negara-2.0-dan2.0-

Ministry of Agriculture and Food Security. (2023). *Program dan inisiatif kementerian*. https://www.kpkm.gov.my/agropreneur-muda

Malay Mail. (2022, December 10). *Sabah TYT: Malaysia's strength assessment based on food production ability*. https://www.malaymail.com/news/malaysia/2022/12/10/sabah-tyt-malaysias-strength-assessment-based-on-food-production-ability/44579

MAMPU. (2016). *Keluasan tanaman pertanian mengikut daerah di negeri Sabah (2016).* https://archive.data.gov.my/data/ms_MY/dataset/keluasan-tanaman-pertanian-mengikut-daerah-di-negeri-sabah

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science, 2*(1), 71–87. https://doi.org/10.1287/orsc.2.1.71

Mat Lazim, R., Mat Nawi, N., Masroon, M. H., Abdullah, N., & Che Mohammad Iskandar, M. (2020). Adoption of IR4.0 into agricultural sector in Malaysia: Potential and challenges. *Advances in Agricultural and Food Research Journal, 1*(2). https://doi.org/10.36877/aafrj.a0000140

Michels, M., von Hobe, C. F., von Ahlefeld, P. J. W., & Musshoff, O. (2021). The adoption of drones in German agriculture: A structural equation model. *Precision Agriculture, 22*, 1728–1748.

Ministry of Digital. (2025, February 16). *Sabah ranks second highest in Malaysia for Digital AGTECH System usage.* https://www.digital.gov.my/en-GB/siaran/Sabah-Negeri-Kedua-Tertinggi-Di-Malaysia-Dalam-Penggunaan-Sistem-Digital-AGTECH

Mishra, N., Bhandari, N., Maraseni, T., Devkota, N., Khanal, G., Bhusal, B., Basyal, D. K., Paudel, U. R., & Danuwar, R. K. (2024). Technology in farming: Unleashing farmers' behavioral intention for the adoption of Agriculture 5.0. *PLOS ONE, 19*(8), e0308883. https://doi.org/10.1371/journal.pone.0308883

Mohd Yaakub, N. A., Sumin, V., & Ung, L. L. (2024). Exploring technology readiness and acceptance of small-scale farmers in Sabah towards the adoption of Internet of Things technology. *International Student Conference on Business, Education, Economics, Accounting, and Management (ISC-BEAM), 1*(1), 688–705. https://doi.org/10.21009/isc-beam.011.49

Mohr, S., & Kühl, R. (2021). Acceptance of artificial intelligence in German agriculture: An application of the technology acceptance model and the theory of planned behavior. *Precision Agriculture, 22*(6), 1816–1844. https://doi.org/10.1007/s11119-021-09814-x

Mom, T. J. M., Van Den Bosch, F. A. J., & Volberda, H. W. (2007). Investigating managers' exploration and exploitation activities: The influence of top-down, bottom-up, and horizontal knowledge inflows. *Journal of Management Studies, 44*(6), 910–931. https://doi.org/10.1111/j.1467-6486.2007.00697.x

Mom, T. J. M., Van Den Bosch, F. A. J., & Volberda, H. W. (2009). Understanding variation in managers' ambidexterity: Investigating direct and interaction effects of formal structural and personal coordination mechanisms. *Organization Science, 20*(4), 812–828. https://doi.org/10.1287/orsc.1090.0427

Montes de Oca Munguia, O., Pannell, D. J., & Llewellyn, R. (2021). Understanding the adoption of innovations in agriculture: A review of selected conceptual models. *Agronomy, 11*(1), Article 139. https://doi.org/10.3390/agronomy11010139

Muk, A., & Chung, C. (2015). Applying the technology acceptance model in a two-country study of SMS advertising. *Journal of Business Research, 68*(1), 1–6. https://doi.org/10.1016/j.jbusres.2014.06.001

Negm, E. (2023a). Intention to use Internet of Things (IoT) in higher education online learning—The effect of technology readiness. *Higher Education, Skills and Work-Based Learning, 13*(1), 53–65. https://doi.org/10.1108/HESWBL-05-2022-0121

Negm, E. (2023b). Internet of Things (IoT) acceptance model—Assessing consumers' behavior toward the adoption intention of IoT. *Arab Gulf Journal of Scientific Research, 41*(4), 539–556. https://doi.org/10.1108/AGJSR-09-2022-0183

Pallant, J. (2020). *SPSS survival manual: A step by step guide to data analysis using IBM SPSS* (7th ed.). Routledge.

Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2*(4), 307–320. https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined Technology Readiness Index: TRI 2.0. *Journal of Service Research, 18*(1), 59–74. https://doi.org/10.1177/1094670514539730

Park, Y. S., Konge, L., & Artino, A. R., Jr. (2020). The positivism paradigm of research. *Academic Medicine, 95*(5), 690–694. https://doi.org/10.1097/ACM.0000000000003093

Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers, 36*(4), 717–731. https://doi.org/10.3758/BF03206553

Raisch, S., & Birkinshaw, J. (2008). Organizational ambidexterity: Antecedents, outcomes, and moderators. *Journal of Management, 34*(3), 375–409. https://doi.org/10.1177/0149206308316058

Raisch, S., Birkinshaw, J., Probst, G., & Tushman, M. L. (2009). Organizational ambidexterity: Balancing exploitation and exploration for sustained performance. *Organization Science, 20*(4), 685–695. https://doi.org/10.1287/orsc.1090.0428

Ramayah, T., Cheah, J., Chuah, F., Ting, H., & Memon, M. A. (2018). *Partial least squares structural equation modeling (PLS-SEM) using SmartPLS 3.0: An updated guide and practical guide to statistical analysis* (2nd ed.). Pearson Malaysia.

Ray, J. (2020). Cross-sectional research designs in criminology and criminal justice. *Oxford Bibliographies*. https://doi.org/10.1093/OBO/9780195396607-0281

Ringle, C. M., Wende, S., & Becker, J. M. (2024). *SmartPLS 4*. SmartPLS. https://www.smartpls.com

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Ryan, G. (2018). Introduction to positivism, interpretivism and critical theory. *Nurse Researcher, 25*(4), 14–20. https://doi.org/10.7748/nr.2018.e1466

Sabah State Government. (2021). *Sabah Maju Jaya 1.0 roadmap*. Department of Public Services of Sabah State Government.

Saidu, M., Shagari, S. L., Kabir, M. A., & Abubakar, A. (2023). Improving university students' data analysis outputs through effective data collection, cleaning, screening and normalisation. *Applied Quantitative Analysis, 3*(2), 28–37. https://doi.org/10.31098/quant.1951

Sarstedt, M., Ringle, C. M., Cheah, J. H., Ting, H., Moisescu, O. I., & Radomir, L. (2022). Structural model robustness checks in PLS-SEM. *Tourism Economics, 28*(5), 1274–1294. https://doi.org/10.1177/1354816618823921

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*. Harvard University Press.

Setia, M. S. (2016). Methodology series module 3: Cross-sectional studies. *Indian Journal of Dermatology, 61*(3), 261–264. https://doi.org/10.4103/0019-5154.182410

Shariff, S., Katan, M., Ahmad, N. Z. A., Hussin, H., & Ismail, N. A. (2022). Towards achieving long-term agriculture sustainability: A systematic review of Asian farmers' modern technology farming behavioural intention and adoption key indicators. *International Journal of Professional Business Review, 7*(6), e01130. https://doi.org/10.26668/businessreview/2022.v7i6.1130

Sinha, B. B., & Dhanalakshmi, R. (2022). Recent advancements and challenges of Internet of Things in smart agriculture: A survey. *Future Generation Computer Systems, 126*, 169–184. https://doi.org/10.1016/j.future.2021.08.006

SmartAgriHubs. (2023). *SmartAgriHubs*. https://www.smartagrihubs.eu/

Snehvrat, S., Chaudhary, S., & Majhi, S. G. (2022). Ambidexterity and absorptive capacity in boundary-spanning managers: Role of paradox mindset and learning goal orientation. *Management Decision, 60*(12), 3209–3231. https://doi.org/10.1108/MD-03-2021-0328

Sorce, J., & Issa, R. R. A. (2021). Extended technology acceptance model (TAM) for adoption of information and communications technology (ICT) in the US construction industry. *Journal of Information Technology in Construction, 26*, 227–248. https://doi.org/10.36680/j.itcon.2021.013

Stephan, F. F. (1941). Stratification in representative sampling. *Journal of Marketing, 6*(1), 38–46. https://doi.org/10.1177/002224294100600107

Suffian, F., & Suffian, F. (2022). Food insecurity in rich resource state: The case of Sabah. In *Proceedings of the International Conference on Food and Industrial Crops 2022* (pp. 22–25). Faculty of Agricultural and Forestry Sciences, Institute of Ecosystem Science Borneo, Universiti Putra Malaysia Bintulu Sarawak Campus.

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Pearson.

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing, 22*, 960–967. https://doi.org/10.1016/j.promfg.2018.03.137

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Tushman, M. L., & O'Reilly, C. A. (1996). Ambidextrous organizations: Managing evolutionary and revolutionary change. *California Management Review, 38*(4), 8–29. https://doi.org/10.2307/41165852

Venkatesh, V. (1999). Creation of favorable user perceptions: Exploring the role of intrinsic motivation. *MIS Quarterly, 23*(2), 239–260. https://doi.org/10.2307/249753

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research, 11*(4), 342–365. https://doi.org/10.1287/isre.11.4.342.11872

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Vroom, V. H. (1964). *Work and motivation*. Wiley.

Walczuch, R., Lemmink, J., & Streukens, S. (2007). The effect of service employees' technology readiness on technology acceptance. *Information & Management, 44*(2), 206–215. https://doi.org/10.1016/j.im.2006.12.005

Wang, X., & Cheng, Z. (2020). Cross-sectional studies: Strengths, weaknesses, and recommendations. *Chest, 158*(1S), S65–S71. https://doi.org/10.1016/j.chest.2020.03.012

Yapp, W., Rahman, A. W., Shim, Y. L., & Yeo, B. K. (1999). *An overview of the food industry in Sabah: The way ahead*. Institute for Development Studies (Sabah).

Yusof, N. A. B., & Annuar, S. N. S. (2023). Market strategy and its influence on Sabah small farmers' economic, social, and environmental sustainability performance. In *Proceedings of the International Conference on Communication, Language, Education and Social Sciences (CLESS 2022)* (pp. 117–131). Atlantis Press. https://doi.org/10.2991/978-2-494069-61-9_13

Zaman, N. B. K., Raof, W. N. A. A., Saili, A. R., Aziz, N. N., Fatah, F. A., & Vaiappuri, S. K. (2023). Adoption of smart farming technology among rice farmers. *Journal of Advanced Research in Applied Sciences and Engineering Technology, 29*(2), 268–275. https://doi.org/10.37934/araset.29.2.268275