Research Article

Factors Influencing the Adoption of Smart Farming among Vegetable Farmers in Malaysia

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Abstract | To increase agricultural production, sustainability and food security, smart farming technologies have emerged as viable tools. However, there is a significant disparity between technological progress and its practical application, as seen by the low adoption rate among smallholder vegetable producers in Malaysia. The purpose of this research is to identify the factors that encourage or discourage smallholder farmers in Peninsular Malaysia from using smart farming technology. Five main constructs were examined in the 387 replies using Partial Least Squares Structural Equation Modelling (PLS-SEM), namely Adoption, Performance Expectancy, Effort Expectancy, Facilitating Conditions and Social Influence. Using convergent validity, composite reliability and internal consistency tests, it was demonstrated that the measurement model was valid and reliable. Findings revealed that factors, including perceived usefulness, ease of use, social impact and availability of resources, have significant influences on adoption decisions. Policymakers and agricultural stakeholders can gain valuable insights from the findings by tackling the hurdles to adoption. Proposed policies include initiatives to teach farmers according to their socioeconomic status, improve digital infrastructure and provide targeted financial aid. To create a fairer, more resilient and environmentally friendly agricultural sector in Malaysia, closing the adoption gap is vital, enabling the widespread use of smart farming technologies.

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Introduction

According to the Department of Agriculture (DOA, 2022), the vegetable industry in Malaysia is still an essential part of the country's agricultural landscape as it aids food security, rural development and economic sustainability. The diversified agro-ecological zones and pleasant tropical climate of Malaysia allow for year-round vegetable growing, which helps meet national consumption demands and supports rural livelihoods (Ahmad *et al*., 2019). The demand for fresh produce has been further boosted by the growing public consciousness about the need for a healthy diet and shifting dietary habits (Roslan *et al*., 2020). As a result, the government of Malaysia has instituted several programmes to bolster the industry, including funding for infrastructure, sustainable farming techniques, as well as research and development (FAO, 2017).

Nevertheless, smallholder farmers have mounting hurdles as they strive to enhance productivity while grappling with climatic unpredictability, further rising production costs and ongoing manpower shortages (Bach and Mauser, 2018). The advent of smart agricultural technologies, including automation, digital sensors, Internet of Things (IoT) solutions and data-driven platforms, presents significant opportunities for raising efficiency, minimising input consumption and bolstering resilience (Supreetha *et al*., 2018; López-García *et al*., 2020). Notwithstanding these benefits, the uptake of such technologies by smallholder vegetable growers in Peninsular Malaysia is minimal (Omar *et al*., 2024). The restricted adoption is especially alarming, considering the pivotal role smallholders have in maintaining the national vegetable supply and promoting Malaysia's food self-sufficiency goals.

Many types of behavioural and structural impediments have contributed to this adoption gap, many of which are specific to the local Malaysian setting. A considerable number of smallholders, particularly older persons or those with less formal education, have inadequate digital literacy, which restricts their interaction with contemporary farming technology (Michels *et al*., 2020). Moreover, inadequate internet connectivity in rural regions limits access to cloud-based apps, advisory platforms and real-time data (Wee and Lim, 2022). Other than that, financial constraints constitute a significant barrier, since the initial expenditures for smart farming technologies sometimes exceed the capabilities of small-scale farmers. The restricted availability of training programmes and inadequate exposure to digital technologies jointly impede the digital transformation of Malaysia's smallholder agricultural industry (Ravindran *et al*., 2024).

Literature review and theoretical framework

This study utilises the Unified Theory of Acceptance and Use of Technology (UTAUT), formulated by Venkatesh *et al*. (2003), to investigate the behavioural determinants influencing the adoption of smart farming. UTAUT synthesises components from many prior models to elucidate humans' desire to embrace new technology. It delineates four principal factors of behavioural intention: performance expectancy, effort expectancy, social influence and enabling circumstances.

Performance expectation is the degree to which farmers anticipate that the utilisation of smart farming technology will result in enhanced results, including heightened productivity, efficiency, or profitability. In agricultural contexts, the anticipated advantages, including enhanced crop yields and more accurate resource management, can profoundly affect adoption behaviour. Previous studies indicated that farmers are more inclined to utilise digital technologies when they foresee operational enhancements or cost reductions. For instance, Bonke *et al*. (2018) discovered that perceived performance enhancements elevated the probability of adopting crop protection systems.

Effort expectation, conversely, reflects farmers' perceptions of the ease of utilising this technology. In populations with limited digital literacy, technology adoption is more probable when the technologies are user-friendly, intuitive and require minimal technical training. Rose *et al*. (2016) noted that farmers have a greater propensity to embrace mobile agriculture applications that provide intuitive interfaces and contextually pertinent information. This viewpoint aligns with the Technology Acceptance Model (Davis, 1989), which emphasises perceived ease of use as a crucial determinant of technology acceptance.

Social influence denotes the effect of peers, community leaders, or agricultural consultants on a farmer's decision to embrace technology. In Malaysian agricultural communities characterised by robust social norms and networks, this effect is important. Research conducted by Ambrosius *et al*. (2015), as well as Schaak and Musshoff (2018), demonstrated that farmers frequently emulate the behaviours of their peers, particularly when those peers have attained favourable outcomes from technological adoption. Additionally, Venkatesh and Davis (2000) similarly mentioned that social affirmation may augment perceived value and promote adoption.

Meanwhile, facilitating conditions pertain to the accessibility of essential infrastructure and resources necessary for the successful use of technology, which include access to mobile internet, digital tools, localised technical assistance and apps developed in the native tongue. In Malaysia, inadequate rural broadband infrastructure and insufficient institutional support continue to hinder technology adoption. Michels *et al.* (2020) emphasised that insufficient infrastructure and poorly integrated extension services might substantially hinder the adoption of smart agricultural technologies in rural areas.

Despite the extensive use of UTAUT across many industries, its implementation within the Malaysian agricultural setting, particularly among smallholder vegetable producers, is notably restricted. Prior research, like that of Wee and Lim (2022) and Ravindran *et al.* (2024), has predominantly concentrated on extensive commercial agriculture or broader rural demographics, frequently neglecting the unique difficulties encountered by smallholder farmers. These issues, including budgetary constraints, deficiencies in digital skills and insufficient localised assistance, necessitate further examination.

This study utilises the UTAUT framework to investigate the behavioural and environmental factors affecting the adoption of smart farming technology among smallholder vegetable producers in Peninsular Malaysia. It seeks to uncover the main drivers of adoption intention to guide the formulation of inclusive agriculture policies, encompassing investments in rural connectivity, accessible digital training and financial incentives for smallholders. A comprehensive comprehension of these processes is crucial for facilitating the digital revolution in agriculture and ensuring long-term food sustainability.

Drawing upon the UTAUT framework and the particular context of smallholder vegetable producers in Peninsular Malaysia (Figure 1), the subsequent hypotheses are posited:

- H_1: Performance expectancy is positively correlated with the intention to embrace smart agricultural technology.
- H_2: Effort Expectancy is positively correlated with the ambition to embrace smart agricultural technology.
- H_3: Social influence is positively correlated with the inclination to use smart agricultural technology.
- H_4: Facilitating conditions are positively correlated with the inclination to embrace smart agricultural technology.

Materials and Methods

Sampling strategy and data collection

This study utilised a quantitative research design with structured questionnaires to examine the factors affecting the adoption of smart farming technology among smallholder vegetable farmers in Peninsular Malaysia. A cluster sampling approach was implemented owing to the extensive geographical dispersion of farmers and the absence of a comprehensive sampling frame. According to Taniguchi and Thompson (2014), this strategy is suitable when population lists are deficient and when logistical efficiency and cost control are paramount.

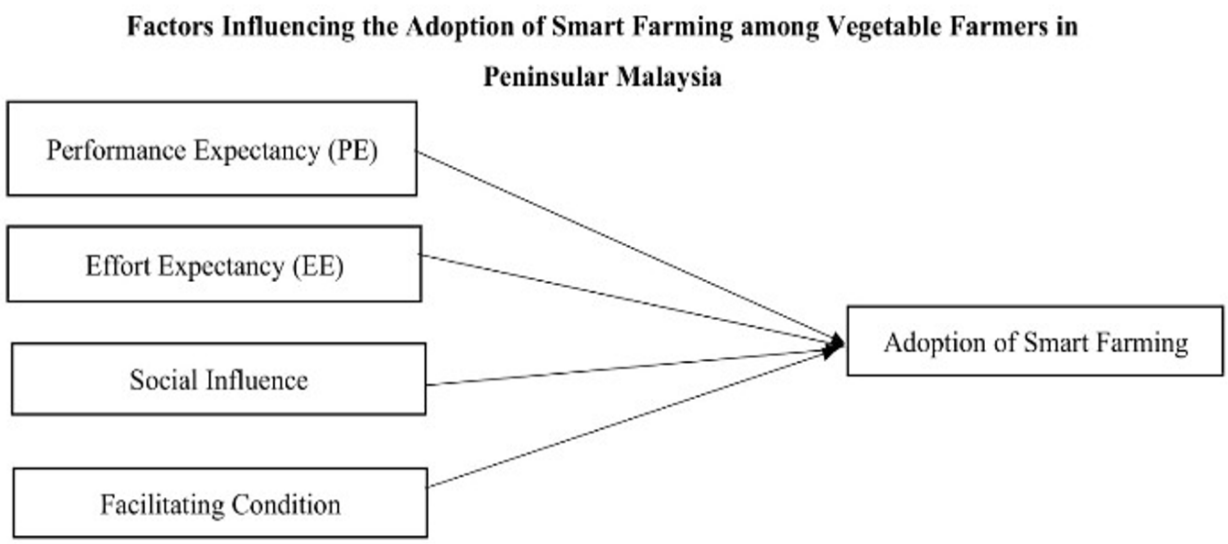

Figure 1: *The research framework*

Each of the 11 states in Peninsular Malaysia, namely Johor, Kedah, Kelantan, Melaka, Negeri Sembilan, Pahang, Penang, Perak, Perlis, Selangor and Terengganu, was regarded as a separate cluster (Table 1). A two-stage cluster sampling method was utilised: initially, all states were incorporated to guarantee extensive geographical representation, followed by the random selection of a certain number of respondents within each cluster. A total of 35 farmers were questioned from each state, with the exception of Selangor, which contained 37 respondents owing to enhanced accessibility and a larger density of smart farming initiatives. This culminated in a total sample size of 387 respondents.

The data collection was executed in partnership with the Department of Agriculture and the Rubber Industry Smallholders Development Authority (RISDA), whose support enabled access to the intended respondents. The data were examined using Structural Equation Modelling (SEM) with SmartPLS 4 software to assess the links between theoretical structures and the desire to use smart agricultural technology. The sampling strategy and sample size conformed to Babbie's (2020) guidelines, guaranteeing that the study's results are rigorous and representative of smallholder vegetable growers in Peninsular Malaysia.

Data analysis method

Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 4 software was employed in this study to examine the structural links among latent constructs. PLS-SEM is a powerful statistical method frequently used in social sciences, management and behavioural research owing to its efficacy in managing intricate models, especially when the main aim is prediction rather than model fit (Hair *et al*., 2017). In contrast to Covariance-Based SEM (CB-SEM), which focuses on replicating the observed covariance matrix, PLS-SEM emphasises the maximisation of explained variance in dependent variables, rendering it more suitable for exploratory and theory-development research (Hair *et al*., 2021).

The application of PLS-SEM in this research is warranted on many methodological bases. For instance, the sample size of 387 respondents satisfies the minimal criteria for PLS analysis, especially when evaluating models with several components and indicators. Secondly, initial diagnostics indicated that the data failed to satisfy the requirements of multivariate normality, hence reinforcing the appropriateness of PLS-SEM, which exhibits reduced sensitivity to non-normal data distributions (Chin *et al*., 2003). This research aims to anticipate

Table 1: *Production of vegetable in malaysia (2020 – 2022*).*

Country	2020		2021		2022*	
	Planted area (ha)	Production (mt)	Planted area (ha)	Production (mt)	Planted area (ha)	Production (mt)
Johor	14,844	208,260	17,187	242,214	17,579	260,708
Kedah	1,555	12,791	1,318	12,910	1,348	13,895
Kelantan	4,512	128,327	4,641	132,053	4,747	142,136
Melaka	941	13,222	769	10,940	787	11,776
Negeri Sembilan	1,757	23,393	1,720	21,367	1,759	22,999
Pahang	15,967	361,971	18,159	381,530	18,574	410,662
Perak	7,192	120,424	7,190	125,308	7,354	134,877
Perlis	266	2,023	404	1,839	413	1,980
Pulau Pinang	813	10,324	997	12,154	1,019	13,083
Selangor	2,338	31,660	2,521	34,051	2,578	36,651
Terengganu	981	11,874	1,185	15,112	1,212	16,266
Peninsular malaysia	51,165	924,270	56,090	989,480	57,370	1,065,033
Sabah	4,364	43,272	4,161	41,449	4,256	44,614
Sarawak	6,058	62,163	5,595	56,648	5,723	60,973
Wilayah persekutuan labuan	27	359	65	462	67	498
Malaysia	61,614	1,030,064	65,911	1,088,039	67,416	1,171,118

Source: Department of agriculture (2023) smallholder farmers' intention to embrace smart agricultural technology, besides investigating the variables influencing that intention, in accordance with PLS-SEM's focus on predictive modelling.

Furthermore, PLS-SEM supports the evaluation of reflective and formative constructs, along with the examination of intricate interactions, including mediating and moderating effects. The method employs an iterative estimating approach to reduce the divergence between observed and anticipated values, thereby enhancing model accuracy and dependability. PLS-SEM is effective in scenarios characterised by significant multicollinearity, a prevalent concern in behavioural research (Gefen *et al*., 2011).

This study's measuring model included five principal latent constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Smart Farming Adoption (SFA). The constructs were operationalised using many indicators, all modified from recognised and previously proven tools in the field of technology adoption research (such as Venkatesh *et al*., 2003; Ravindran *et al*., 2024). An example of Performance Expectancy (PE) is: *"Adopting smart farming in the farm enables farmers to manage farms easily and efficiently"* (PE1), demonstrating the perceived value of the technology in improving agricultural production. The item *"I found it easy to manage the smart farming system after joining courses by local agriculture agencies"* (EE1) reflects the perceived ease of use subsequent to technical help or training in the context of Effort Expectancy (EE). Social Influence (SI) was evaluated using statements such as *"There is someone I know who has successfully adopted smart farming"* (SI1), highlighting the impact of peer adoption and social norms on technology adoption. An illustration of an item pertaining to Smart Farming Adoption (SFA) is *"I need to adopt smart farming to increase knowledge and information about areas of growth"* (SFA1), signifying the knowledge-driven impetus for adoption. A comprehensive enumeration of all measurement items, including those for Facilitating Conditions (FC), is provided in Appendix A.

This study applied PLS-SEM to provide a statistically robust analysis of the adoption behaviour of smallholder vegetable growers in Peninsular Malaysia. It confirms the measurement model and examines the hypothesised structural linkages within the theoretical framework, consequently enhancing academic comprehension and practical policymaking in the agriculture sector.

Results and Discussion

Description of socio-demographic

To place the findings of the agricultural innovation adoption survey into context, it is crucial to understand the demographics of the respondents. This present study measured the adoption of smart farming by surveying 387 participants. It was found that out of the total number of respondents, 282 (72.9%) identified as male and 105 (27.1%) as female. This distribution clearly reveals a gender disparity in the sample, since there are more male respondents than female respondents. It is not surprising that men make up a bigger percentage of the agricultural workforce, given that this study confirms previous data. This phenomenon has been covered extensively in the literature on agricultural studies. Many factors contribute to the gender imbalance in farming, including unequal participation in family decision-making, unequal access to education and resources, as well as societal norms (Doss, 2001; Kabeer, 2005).

Table 2 shows the age distribution of the respondents who grow vegetables in Peninsular Malaysia. In the order in which most responses fell, individuals between the ages of 30 and 39 (35%), 40 and 49 (31%), as well as 50 and 59 (20%) were the successive age categories. A mere 5% of those who took the survey were 60 and above, with an even smaller fraction (only 10%) being in the 20-29 age bracket. The data indicated that more than half of the respondents were over 40 and identified as part of the elderly population. The availability of labour, patterns of generational succession and accumulated agricultural experience are three potential causes of the boom in the number of middle-aged persons employed in agriculture (Kramer *et al*., 2020). Malays make up nearly 90.2% of the population, with 349 respondents, indicating domination in the survey regarding age distribution. This information is crucial for developing targeted outreach and intervention strategies in smart farming. For the remaining 7.2% and 2.6%, or 38 people, respectively, the respondents were of Chinese and Indian descent. There are not many compelling explanations for the racial imbalance in the sample pool. Populations were grouped according to location instead of race in the survey. While surveys are often done at random within a given area, it is quite uncommon for members of the same racial group to congregate in proximity to one another, even though their local distributions may differ considerably (Alam *et al*., 2010).

Table 2: *Descriptive analysis of smallholders demographic*

Variable	Categories	Number of respondents	Percentage 10
Gender	Male	282	72.9
	Female	105	27.1
Age	20-29	38	10
	30-39	134	35
	40-49	120	31
	50-59	76	20
	More than 60	19	5
Race	Malay	349	90.2
	Chinese	28	7.2
	Indian	10	2.6
Educational level	Primary school	48	12.4
	Secondary school	209	54
	Certificate	20	5.2
	Diploma	67	17.3
	Degree	42	10.9
	Others	1	0.3
Marital status	Single	69	17.8
	Married	318	82.2
Household	1	5	1.3
	2	13	3.4
	3	69	17.8
	4	113	29.2
	5	100	25.8
	6	49	12.7
	7	23	5.9
	8	14	3.6
	9	1	0.3
Planting mode	Full time	286	73.9
	Part time	101	26.1
Experience	0 - 9	241	62
	10-19	89	23
	20 - 29	50	13
	More than 30	7	2
Ownership	Family Farm	218	56.3
	Self-owned	143	37
	Renting	26	6.7
Crop	Chili	150	38.8
	Green Vegetables	174	45
	Others	63	16.3
Incomes	0 - 1999	200	51.7
	2000 - 3999	139	36
	4000 - 5999	21	5.4
	6000 - 7999	11	3
	more than 8000	16	4.1
Land size	0 - 2.0	172	44.4
	2.1 - 4.0	172	44.4
	4.1 - 6.0	15	3.9
	6.1 - 8.0	16	4.1
	more than 8.1	12	3.1

Field survey (2023)

Those who grow vegetables in Peninsular Malaysia have varying degrees of education, as seen in Table 2. The majority of respondents had completed secondary school (54.0%), with a diploma level of education coming in at 17.3%. While a smaller percentage obtained a certificate (5.2%) or a degree (10.9%), a considerable portion (12.4%) had finished elementary school. Furthermore, just a tiny fraction of the population reported having any prior educational background. There is an extensive range of educational attainment in the agricultural community, as seen by the educational profile of the respondents. This discrepancy may reflect different levels of formal education and potential disparities in the capacity to use current agricultural equipment, according to Padhy and Jena (2015). Higher levels of education may indicate better access to information and analytical ability, but those with less formal education may still have valuable experiential knowledge about agricultural practices (Bryan *et al*., 2010).

Of the people who filled out the survey, 82.2% were married, while 17.8% were reported as single. The distribution reveals that married persons constitute the bulk of the agricultural community, similar to that mentioned by Bebbington (1999). It appears that the region's agriculture is heavily reliant on family-based agricultural practices. Agricultural decisions made by married farmers in families are often influenced by shared responsibilities and family dynamics (Agarwal, 1997). The greater collaboration and assistance among married farmers in the household may facilitate the adoption and implementation of new agricultural practices (Kumar and Quisumbing, 2015). One benefit of marriage is the increased social support it provides, which can lead to the exchange of ideas on innovative agricultural practices (Dercon *et al*., 2009).

The results showed that the sample included households of different sizes. Most households had 4 (29.2%) or 5 (25.8%) members. The next most common sizes were 3 (17.8%) and 6 (12.7%) persons. A smaller number of respondents said their households had 2 (3.4%), 7 (5.9%), 8 (3.6%), or 1 (1.3%) people. Only one person disclosed that their home had 9 (0.3%) members.
Ellis (2000) asserted that family-oriented farming practices often constitute the core of livelihood strategies among rural families in Peninsular Malaysia, a phenomenon seen in the distribution of household sizes. Economies of scale in agricultural production may benefit bigger families by facilitating diversification of production activities and optimising labour allocation (Binswanger-Mkhize *et al*., 2018). Conversely, smaller households may encounter more challenges in securing labour and resources, thus hindering their ability to adopt and implement contemporary agricultural practices (Marenya *et al*., 2011). Most of the people who answered (73.9%) said they were full-time planters, while 26.1% mentioned that they were part-time planters. The decision on how to plant can have a significant influence on how smart farming technologies are used and embraced. Full-time farmers may be more motivated to invest in and experiment with innovative agricultural practices from their greater allocation of time and energy to farming operations (Hossain *et al*., 2017). Conversely, part-time farmers may have challenges in acquiring resources and allocating time and energy to adopt new technologies, as they may have alternate income sources or employment (Kumar *et al*., 2020).

The bulk of responses came from those with 0 to 9 years of experience, representing 62% of the sample. Also, 23% of the people who answered indicated they had 11 to 19 years of experience, while 13% declared they had 20 to 29 years of experience. Fewer than 2% of those who answered indicated they have been cultivating vegetables for more than 30 years. The varying levels of experience among survey respondents reveal the diverse range of skills and knowledge within the agriculture business. Van den Putte *et al*. (2014) asserted that less experienced farmers may exhibit a greater willingness to adopt new technologies and methods, as their established routines and habits are not as deeply entrenched. Conversely, experienced farmers may rely more on traditional methods and require greater motivation and incentives to adopt smart farming practices (Bielza *et al*., 2015).

Meanwhile, 56.3% of the respondents claimed that they owned their farms as part of a family business. Also, 37.0% of those who answered said they owned their farms on their own, whereas 6.7% stated they rented their farmed property. An individual-owned farm signifies a higher level of autonomy and authority over the resources and decisions pertaining to agricultural production. Hossain *et al*. (2017) contended that self-owned farms may enhance the adoption of new agricultural technology through their increased responsiveness to the choices and objectives of individual farmers.

The findings indicated that most respondents grow green vegetables, comprising 45% of the sample. The cultivation of chilli peppers is also widespread, with 38.8% of respondents choosing this crop. A lesser percentage of responders (16.3%) indicated the cultivation of unspecified vegetable varieties. The diversity of vegetable cultivation techniques in Peninsular Malaysia is emphasised by the spread of crop choices. Gautam *et al*. (2019) asserted that green vegetables, encompassing cruciferous and leafy varieties, are commonly grown for their nutritional value and culinary versatility. In contrast, chilli peppers are fundamental to Malaysian cuisine and hold significant economic and cultural value for several local farmers (Chin *et al*., 2014).

More than half (51.7%) of the respondents in this study indicated wages ranging from RM 0 to RM 1999. Additionally, 36% of participants indicated their salaries ranged from RM 2000 to RM 3999, while a lesser proportion reported earnings in higher brackets: 5.4% earned between RM 4000 and RM 5999, 3% earned between RM 6000 and RM 7999, and 4.1% disclosed incomes exceeding RM 8000. The income levels of farmers in Peninsular Malaysia underscore their varied economic backgrounds.

There is some evidence showing that larger farms are more likely to adopt agricultural technology (Giller *et al*., 2009). In comparison to small farmers, larger farmers have the financial means to dedicate a specific area of their property to the adoption of new technology, making them more inclined to do so

(Hu *et al*., 2022). While 44.4% of respondents were in the 0-2.0 acre group and 2.1-4.0 acre group, the vast majority of landowners and managers were in the 0 to 4.0 acre range. In addition, fewer people (3.9% for the 4.1-6.0-acre group and 4.1% for the 6.1-8.0-acre category) reported land sizes ranging from 4.1 to 8.0 acres. The percentage of respondents whose land sizes were more than 8.1 acres was a meagre 3.1%. It is clear from the distribution of land sizes that smallholder agricultural techniques are prevalent in Peninsular Malaysia. Smallholder farmers face challenges such as limited resources, lack of technology and economies of scale, as stated by Jayne *et al*. (2010). They often operate on smaller pieces of land. According to Hazell *et al*. (2010), smallholder agriculture plays a crucial role in rural livelihoods and food security, particularly in emerging nations.

Partial least squares structural equation modelling (PLS-SEM)

Analysis of partial least squares structural equation modelling (PLS-SEM)

Effort Expectancy (X1), Facilitating Condition (X2), Performance Expectancy (X3), Social Influence (X4), and Adoption of Smart Farming (Y1) are the four characteristics that comprise the study model. Examining the reflecting measurement model's internal consistency, discriminant validity and convergent validity for each concept is a crucial step.

Reliability and internal consistency

Policymakers and stakeholders aiming to promote sustainable agriculture practices and boost productivity in the digital era should benefit significantly from these results, which add to a detailed knowledge of the variables driving smart farming adoption. The internal consistency of critical dimensions connected to smart farming adoption was checked in this study using Cronbach's alpha analysis. With Cronbach's alpha values higher than the suggested 0.7, these findings demonstrated high levels of internal consistency throughout all constructs. The Adoption construct displayed the best degree of internal consistency (α = 0.919), with Social Influence, Performance Expectancy, Effort Expectancy and Facilitating Conditions following closely behind. The present research instrument is strengthened by these findings, which indicate that the items that make up each construct accurately assess the underlying ideas.

Using an evaluation of construct internal consistency, the Composite Reliability analysis determines how reliable the measurement model is. In accordance with the recommendations stated by Gefen *et al*. (2000), composite reliability was evaluated to ascertain internal consistency. The targeted composite dependability value of the threshold should be more than 0.6 but lower than 0.95, according to Vaske *et al*. (2017). Results illustrated that composite dependability was high across all constructs, with values higher than the suggested cutoff of 0.7. Composite reliability was best for the Adoption construct (0.92), then for Social Influence (0.919), Performance Expectancy (0.906), Effort Expectancy (0.89) and Facilitating Conditions (0.888). This research's instrument is strengthened by these results, which indicate that the elements making up each construct accurately assessed the underlying concepts they represent.

Convergent validity

The degree to which one item positively correlates with other items sharing similar characteristics is known as convergent validity. To determine convergent validity, the Average Variance Extracted (AVE) approach is employed. For a study to be considered genuine, researchers must follow the guidelines laid out by Hair *et al*. (2017) and make sure the outer loading value is higher than the 0.708 threshold. A value of 0.5 represents the AVE, which is the same as 0.708 squared. This study employed the AVE analysis, which measures the construct's share of variance extracted relative to the measurement error, to check if the proposed measurement model was convergently valid. All components except Facilitating Conditions had AVE values more than 0.5, indicating favourable results. Effort Expectancy (AVE=0.820), Performance Expectancy (AVE=0.722), Social Influence (AVE=0.739) and Adoption (AVE=0.756) were the top four constructs in terms of AVE. This study instrument's convergent validity is supported by these results, highlighting that the constructs appropriately represent the variation in the examined items.

Discriminant validity

The built model was put through its paces using a two-stage process recommended by Gerbing (1988). According to Hair and Alamer (2022) and Ramayah *et al*. (2018), the instruments' validity and reliability were verified by examining the measurement model. The theory was subsequently evaluated using the structural model. The measurement model was examined through an evaluation of the loadings, AVE and CR coefficients, which should all be at least 0.5, 0.7 and 0.5, respectively. All of the AVEs and CRs were more than 0.5 and 0.7, respectively, as shown in Table 3. The bulk of the loadings met the permissible criterion of 0.708, according to Hair and Alamer (2022). With the goal of offering empirical insights into the smart farming setting, this study built upon previous research that laid the theoretical groundwork for technology adoption, such as that of Davis (1989), Venkatesh *et al*. (2003) and Rogers (2003).

Table 3: *Cronbach's alpha, composite reliability and Average Variance Extracted*

Variable	Cronbach's alpha (>0.5)	Composite reliability	Average variance extracted
Adoption of smart farming	0.919	0.939	0.756
Effort expectancy	0.89	0.932	0.82
Facilitating condition	0.889	0.918	0.692
Performance expectancy	0.903	0.928	0.722
Social influence	0.91	0.934	0.739

Table 4: *Cross loading of variables*

Construct	Item	Loading (>0.7)
Adoption smart farming	AD1	0.86
	AD2	0.902
	AD3	0.877
	AD4	0.864
	AD5	0.843
Effort expectancy	EE1	0.886
	EE2	0.919
	EE3	0.912
Facilitating condition	FC1	0.852
	FC2	0.835
	FC3	0.82
	FC4	0.835
	FC5	0.818
Performance expectancy	PE1	0.863
	PE2	0.846
	PE3	0.895
	PE4	0.873
	PE5	0.767
Social influence	S15	0.897
	SI1	0.766
	SI2	0.911
	SI3	0.896
	SI4	0.817

The significance of each construct in the adoption process was highlighted in this study, which revealed significant loading factors in Table 4. There was a high correlation between the perceived advantages and the likelihood of adoption, as seen by the robust loadings across all items of the Adoption construct (AD1-AD5), which exceeded the customary criterion of 0.7. Stakeholders perceive smart farming as straightforward and easily adaptable to existing practices, as indicated by Effort Expectancy, which also exhibited strong loadings for its items (EE1-EE3). Moreover, significant loadings were seen in the Facilitating Conditions (FC1–FC5), emphasising the importance of resources and support systems in encouraging adoption. Perceptions of smart farming's advantages varied across performance expectation, with social influence being a key component, highlighting the impact of peer networks and social norms.

In the second part of the investigation, this study employed the suggestions made by Franke and Sarstedt (2019) to evaluate the discriminant validity using the HTMT criteria. The stricter standard stipulated that HTMT levels are required to be less than 0.85, whereas the lenient standard permitted readings up to 0.90. The results, shown in Table 5, showed that the four constructs were clearly differentiated in the participants' understanding, since all HTMT values were below the lenient criterion. These evaluations provide credence to the measuring tool's validity and reliability.

SEM model evaluation

Correlation coefficient evaluation: Partial least squares (PLS) modelling with Smart PLS 4 was used to assess the study's variance inflator factor analysis, measurement and structural model. Since it does not assume data normality, a prerequisite that is sometimes absent from survey datasets, this software is particularly well-suited to evaluating survey data (Chin *et al*., 2003).

Following the recommendations of Kock and Lynn (2012) and Kock (2015), a comprehensive collinearity review was conducted to address the issue of Common Method Bias, given that all of the data originated from a single source. The collinearity analysis findings are displayed in Table 6, along with the corresponding VIF values. A VIF criterion of less than 3.3 was advocated by Diamantopoulus and Sigouw (2006);

Table 5: *Results of heterotrait-monotrait ratio (HTMT) matrix*

	Adoption smart farming	Effort expectancy	Facilitating condition	Performance expectancy
Adoption smart farming				
Effort expectancy	0.743			
Facilitating condition	0.617	0.859		
Performance expectancy	0.808	0.795	0.77	
Social influence	0.633	0.911	0.905	0.67

```
Sample size:  387
Number of variables:  5

Univariate skewness and kurtosis
                         Skewness SE_skew  Z_skew Kurtosis SE_kurt Z_kurt
ADOPTION._SMART.FARMING   -2.142   0.124 -17.273    4.518   0.247 18.257
EFFORT_EXPECTANCY         -1.836   0.124 -14.800    4.389   0.247 17.735
FACILITATING._CONDITION   -1.660   0.124 -13.383    3.999   0.247 16.163
PERFORMANCE._EXPECTANCY   -1.878   0.124 -15.138    5.176   0.247 20.919
SOCIAL._INFLUENCE         -1.745   0.124 -14.065    3.046   0.247 12.310

Mardia's multivariate skewness and kurtosis
                 b          z p-value
Skewness  30.10402 1941.70953       0
Kurtosis 104.45175   81.65065       0
```

Figure 2: *Output of skewness and kurtosis calculation*

however, a requirement of 5 for VIF values was put out by Hair *et al*. (2019). Values below 5 imply moderate correlation, whereas values over 5 indicate strong correlation, according to Kyriazos and Poga (2023), when evaluating the VIF result.

Table 6: *Full collinearity testing*

Variable	VIF
Adoption of smart farming	2.418
Effort expectancy	3.982
Facilitating condition	3.580
Performance expectancy	2.304
Social influence	4.081

Testing hypotheses for direct effects

This study aimed to determine if there is a significant relationship between the desire of smallholder vegetable farmers to use smart farming technology and factors of Effort Expectancy (EE), Performance Expectancy (PE), Social Influence (SI) and Facilitating Conditions (FC). Path coefficients (β) and p-values were employed in this study to ascertain the importance of these direct linkages.

Signs of a non-normal data distribution, such as skewness (β = 30.10, $p < 0.01$) and kurtosis (β = 104.45, $p < 0.01$), were detected in the initial tests for multivariate normality, which showed significant violations (Figure 2). The results were obtained using PLS-SEM, which is appropriate for prediction-oriented models and resilient to non-normal data, as suggested by Hair and Alamer (2022) and Cain *et al*. (2017).

Table 7 indicates that EE and PE significantly increased the intention to use smart farming, lending credence to the idea that people are more inclined to embrace innovations if they think they will be helpful and easy to use. Confirming the importance of performance and usability in shaping adoption behaviour, these results are in line with those of Venkatesh *et al*. (2003) and Teo (2012).

On the other hand, it was shown that SI and FC had no significant impacts. Problems with dependable internet access, insufficient extension services and a lack of a robust digital infrastructure may all contribute to FC's lack of relevance in rural Malaysia (Awa *et al*., 2015). The existing systems of assistance may be too complex or out of reach for many elderly farmers (Ena and Siewa, 2022).

Similarly, SI may not have much of an impact since smallholder farmers in Malaysia tend to operate alone, making decisions without consulting others or succumbing to peer pressure. This goes against what has been seen in more networked agricultural contexts (Schepers and Wetzels, 2007), which implies that SI's function can vary depending on the circumstances.

Table 7: *Path coefficient*

Hypothesis	Construct	Beta	T statistics	P values <0.05	Decision
H1	Effort expectancy -> Adoption Smart farming	0.273	3.526	0.001	Accept
H2	Facilitating condition -> adoption smart farming	-0.141	1.703	0.089	Reject
H3	Performance expectancy -> adoption smart farming	0.563	7.303	0.001	Accept
H4	Social influence -> Adoption smart farming	0.129	1.688	0.091	Reject

In terms of policy, these results stress the need to develop technologies that are functional and easy to use, as well as providing specialised assistance to farmers who are older or less tech-savvy. Possible initiatives to increase adoption include digital literacy programmes, simpler smart tools and subsidies depending on needs (Ravindran *et al*., 2024). Prioritising the usability and accessibility of support systems for end users should take precedence over concentrating just on infrastructure.

Ultimately, the findings highlight the significance of customising smart farming approaches to suit the specific circumstances, such as the demographics and infrastructure of smallholders. This would promote inclusive agricultural innovation and help Malaysia achieve its larger objectives of food security.

Coefficient of determination (R^2)

In this study, the R^2 analysis sheds light on how well the latent constructs explain the dependent variable's variation through prediction. An R^2 value of 0.596 (Table 8) was observed by the Adoption of Smart Farming, which means that the independent variables in the model explained around 59.6% of the variation in smart farming adoption behaviour. The identified constructs are crucial for understanding and forecasting adoption behaviour in the agriculture industry as they indicate a high level of predictive potential.

Table 8: *R Square (R^2)*

Variable	R^2
Adoption of Smart Farming	0.596

Effect size (f^2)

The f^2 analysis assesses the contribution of each independent variable by quantifying the additional variation in the dependent variable explained beyond that attributed to other predictors in the model (Cohen, 1988). Among the assessed constructs, Performance Expectancy (PE) had the most significant impact, with an f^2 value of 0.340, categorising it into the moderate effect size category (Table 9). This study underscores the essential influence of farmers' perceptions of the utility and performance advantages of smart agricultural technology on their adoption choices.

In contrast, Effort Expectancy (EE) had a minimal impact size (f^2 = 0.046). Despite being statistically significant, its effect was very moderate, indicating that perceived ease of use aids in adoption but is less influential than anticipated performance results. Facilitating Conditions (FC) and Social Influence (SI) had minimal effects, with f^2 values of 0.0014 and 0.01, respectively, signifying restricted explanatory capacity in this context.

Table 9: *The effects of size (f2)*

Factor (exogenous)	Endogenous	f^2	Effect Size
Effort expectancy	Adoption of smart farming	0.046	Small effect
Facilitating condition	Adoption of smart farming	0.014	Small effect
Performance expectancy	Adoption of smart farming	0.340	Moderate effect
Social influence	Adoption of smart farming	0.01	Small effect

According to Cohen's (1988) criteria, where $f^2 \geq 0.35$ indicates a strong effect, $0.15 \leq f^2 < 0.35$ signifies a moderate effect, and $0.02 \leq f^2 < 0.15$ denotes a little effect, the results affirmed that PE was the most significant construct, whereas EE served a supporting yet modest function, while FC and SI have limited influence on the adoption of smart farming. These findings are essential for selecting policy and intervention initiatives. Moreover, in accordance with the guidance of Sullivan and Feinn (2012), presenting effect sizes and statistical significance offers a more comprehensive insight into the practical implications of the findings. The size effect of variables was calculated using the formula:

$$f^2 = \frac{(R^2 included - R^2\ excluded)}{(1 - R^2\ included)}$$

Predictive relevance (Q^2)

The structural model assessment concludes with the computation of the predictive relevance (Q^2) value (Stone, 1974; Geisser, 1975). Prediction relevance testing is necessary to demonstrate that the assessed model produces reliable predictions. The method for evaluating Q^2 is the blindfolding process (Chin, 1998). The validity of the model's predictions is shown by a Q^2 value larger than zero (Fornell and Cha, 1994). Table 10 shows that a Q^2 value of 0.442 met the criterion of being larger than zero ($Q^2 > 0$). This result confirmed the predictive significance of the built model. Moreover, Figure 3 visually depicts the structural model meant to enhance the adoption of smart farming.

Table 10: *Predictive relevance, Q2*

Variable	Q2
Adoption of smart farming	0.442

The figure shows how smallholders' adoption of smart agricultural technology is favourably impacted by each element individually. The adoption of smart farming was strongly correlated with performance expectation (r = 0.563), and there was a very significant association between performance expectation and

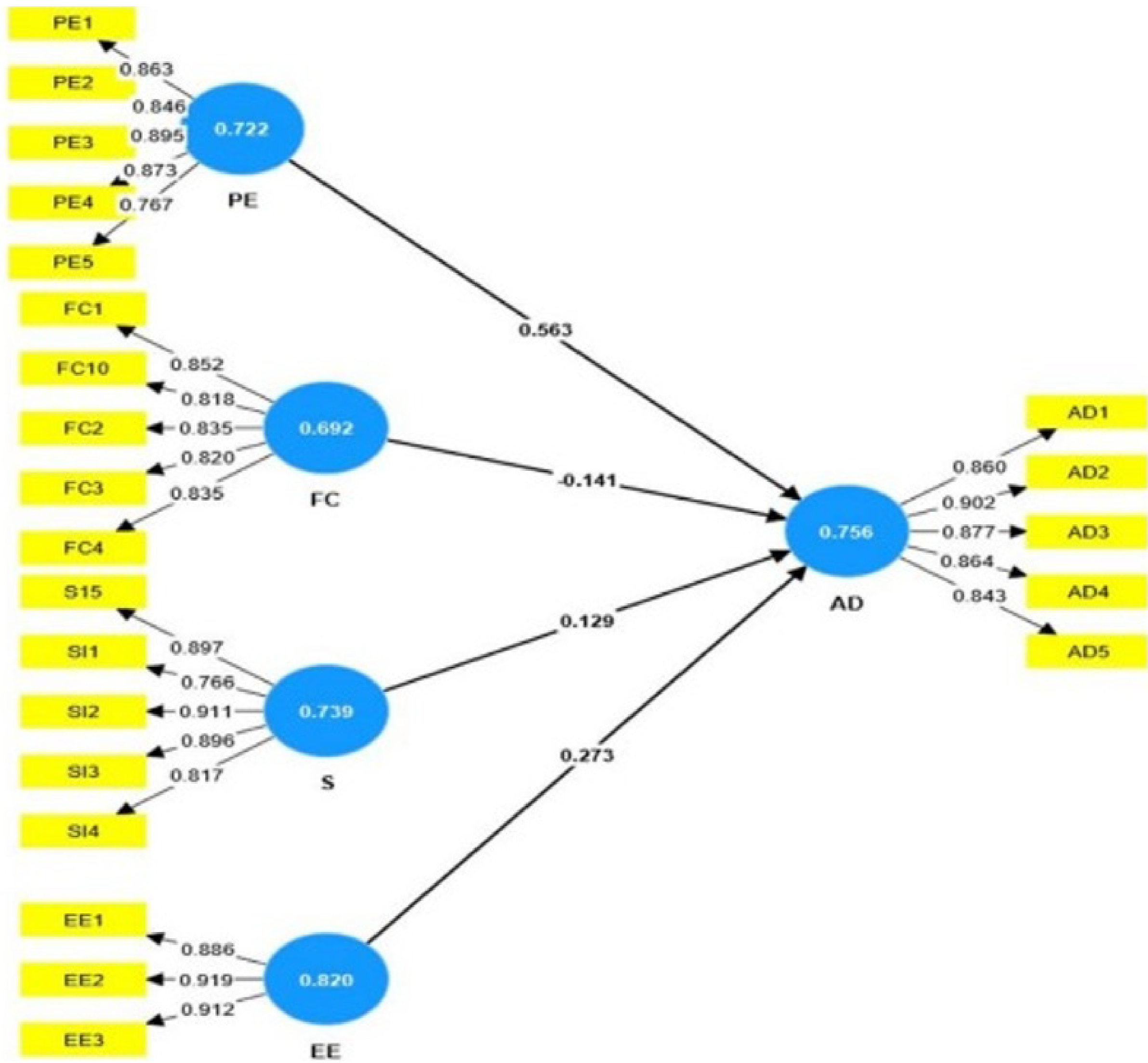

Figure 3: *Conceptual model of factor influencing the adoption of smart framing*

effort expectation (r = 0.273). These results indicate that farmers' expectations of performance and the impact of effort expectancies on adoption decisions are impacted by their perceptions of the availability of resources and supporting conditions for applying smart farming technology (Venkatesh *et al*., 2003). All things considered, these findings highlight how crucial it is to create favourable conditions to encourage the use of smart agricultural technology, as these factors greatly impact social effects and also affect performance expectations. This information may be used by stakeholders and policymakers to create focused interventions that improve enabling conditions, leading to more general acceptance and development in agricultural techniques.

The interrelated nature of the factors impacting the adoption of smart agricultural technologies is made apparent by this outcome overall. Adoption decisions are influenced by performance expectations and effort expectancies, according to Rahim *et al*. (2020). By highlighting the significance of perceived advantages and social dynamics in determining adoption rates, these insights may be considered by stakeholders and policymakers as they formulate policies to encourage the use of smart agricultural technology.

Correlation coefficient

Table 11 shows the coefficients of correlation that indicate how strongly and in what direction various concepts are related to one another. Venkatesh *et al*. (2003) discovered a somewhat favourable connection (r = 0.743) between effort expectation and adoption. According to Ravindran *et al*. (2024), stakeholders are more inclined to implement smart agricultural technologies if they see them as user-friendly. There was a slight positive association between Adoption and Facilitating Conditions (r = 0.614), indicating that the relationship between resource availability, favourable circumstances and adoption may be less pronounced than with other variables. Meanwhile, Adoption and Performance Expectancy were highly correlated (r = 0.809). In general, people are more likely to use smart agricultural technology if they believe it will lead to better performance (Michels *et al*., 2020). There was also a moderate positive association between Adoption and Social Influence (r = 0.63). According to Marra *et al*. (2010), there are additional factors that have a larger impact on adoption decisions than peer pressure and societal standards.

Table 11: *CFA Covariance-based structural equation modeling (CB-SEM) correlation*

	Adoption smart farming	**Effort expectancy**	**Facilitating condition**	**Performance expectancy**
Effort expectancy	0.743			
Facilitating condition	0.614	0.862		
Performance expectancy	0.809	0.793	0.76	
Social influence	0.63	0.911	0.914	0.666

Facilitating condition, performance expectation and social influence all exhibited high positive correlations with effort expectation (r = 0.862, r = 0.793 and r = 0.911, respectively). According to Pingattini *et al*. (2015), stakeholders are more inclined to embrace smart farming technologies if they are perceived as user-friendly, accompanied by strong societal pressure, high performance expectations and sufficient support. The results showcased clear trends that point to a strong relationship between perceived ease of use and several factors impacting adoption, including social norms, performance expectations and the availability of resources. Insights like this can help stakeholders and policymakers craft more precise plans to increase the use of smart farming techniques, further boosting agricultural sustainability and innovation.

Conclusions and Recommendations

The purpose of this quantitative study was to use Partial Least Squares Structural Equation Modelling (PLS-SEM) to identify the factors that influence smallholder vegetable farmers in Peninsular Malaysia to implement smart farming technologies. Two important factors that were shown to be significant predictors of adoption intention were performance expectation and effort expectation. According to these findings, farmers are more likely to use smart agricultural technologies if they see a direct correlation between the technology and increased productivity, along with intuitive and easy-to-use tools.

Statistically, however, neither Facilitating Conditions nor Social Influence had any discernible impacts. In rural locations with poor internet access, little technical help, or elderly farmers who may have trouble with digital literacy, this result could be a reflection of the inadequacy of the existing infrastructure or support systems. The lack of strong peer networks and the autonomous character of smallholder farming may likely contribute to the low impact of social influence.

In order to encourage smallholder vegetable farmers in Peninsular Malaysia to use smart farming technology, this study's findings provide several important policy suggestions. Prioritising practical and demonstrative methods, such as model farms, hands-on field training, and peer-led demonstrations, should be a priority for agricultural extension programmes when it comes to Performance Expectancy (PE). This will help to clearly showcase the tangible productivity and efficiency benefits of adopting smart farming tools. To help farmers better understand the significance of these technologies, experiential learning methods would be the best option.

Additionally, it would be beneficial to create specific programmes to help elderly farmers and those without much digital knowledge increase their Effort Expectancy (EE). These programmes need to be designed to foster digital literacy, self-assurance and usability while also being culturally aware and offered in local languages. To make smart agricultural instruments seem approachable and simple to use, interactive and practical courses are crucial.

Third, encouraging learning from one another and increasing participation in one's community are two ways to boost social influence (SI). Early adopters' successes can be magnified by programmes that encourage farmers to share information through farmer field schools, cooperative networks, or internet platforms. These success stories have the power to normalise the use of technology in social and farming circles, which in turn can increase adoption by fostering trust.

Fourth, investments in rural infrastructure, especially dependable internet connectivity and the availability of digital devices appropriate for agricultural settings, are necessary to improve Facilitating Conditions (FC). For offering useful technical advice, extension services should likewise be provided with training and enough funding. On the other hand, smallholder farmers face unique financial challenges that require solutions, including low-interest loan schemes, targeted subsidies and grants.

It is worth mentioning that having access to technology is not enough. The socioeconomic realities of smallholders, such as their age, education level, income and infrastructure restrictions, must be considered by policymakers as they develop integrated support systems centred on farmers. Smart farming efforts may face difficulties in gaining significant acceptance unless these contextual constraints are addressed.

Also, it should be noted that the results of this study may not be generalisable to East Malaysia, as it focuses on smallholder vegetable producers in Peninsular Malaysia; factors like infrastructure and socioeconomic status may influence adoption behaviour differently. For a more in-depth knowledge of structural and behavioural obstacles, future studies should consider using mixed-methods approaches and expanding the geographical reach.

Ultimately, it takes more than just deploying technology to speed up the adoption of smart farming. For Malaysia's agricultural transformation to be inclusive and sustainable, a comprehensive plan is pertinent. This approach should incorporate usability, perceived advantages, social encouragement and supporting infrastructure.

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Novelty Statement

This study delivers a comprehensive quantitative assessment of smart farming adoption among Malaysian vegetable producers, a context with little empirical research. Unlike conceptual or qualitative investigations, this research provides statistical evidence on crucial adoption characteristics, improving the model's explanatory and predictive power in a non-urban agricultural context. The analysis also provides context-specific, data-driven recommendations for targeted policy actions and smart farming technology distribution, particularly in the context of developing and smallholder farming systems.

Author's Contribution

Zubaidah Omar: Literature review, methodology, results and discussion, references, and conclusion
Abdul Rahman bin Saili: Conceptualization and review
Ahmad Shahir Abd Aziz: Literature review
Fay Rola-rubzen: Methodology
Ahmad Safuan bin Bujang: Results and discussion
Zubaidah Yusop: Literature review
Fazleen Abdul Fatah: Methodology, results and discussion

Generative AI and AI-assisted technology statement
The authors declare that no generative AI and AI assisted technology was used in the creation of this manuscript.

Conflict of interest
The authors have declared no conflict of interest.

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