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Empowering Vegetable Farmers through Skill Development to Tackle Post-COVID-19 Challenges: Insights from Partial Least Squares Modelling

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Abstract
The post-COVID-19 era has posed significant challenges to farmers, particularly in ensuring food security and maintaining agricultural productivity. Farmers' readiness to navigate these challenges relies heavily on their skillsets. During the pandemic lockdowns, restricted movement led to financial losses and wastage of agricultural produce, including fruits and vegetables. This study explores the impact of key skills—technology, implementation, leadership, and decision-making skill—on the readiness of vegetable farmers in Peninsular Malaysia. Using structural equation modeling via the Partial Least Squares (PLS) technique, the research examines the relationship between these skills and farmers' readiness. Data were collected through a structured questionnaire distributed to a randomly selected sample of vegetable farmers. The findings revealed that leadership and decision-making skills significantly influence readiness, with p-values of 0.032 and 0.000, respectively. These results underscore the importance of integrating leadership and decision-making skill development into extension programs. This study contributes to the design of targeted training and capacity-building initiatives to empower farmers in overcoming post-COVID-19 challenges and achieving sustainable agricultural progress.
Keywords: COVID-19 Challenges, Farmers' Empowerment, Farmers Readiness, Partial Least Squares (Pls), Capacity Building

Introduction
The COVID-19 pandemic exposed critical vulnerabilities in global food security and agricultural systems, underscoring the need to enhance resilience in food value chains. Legislative measures such as lockdowns and movement restrictions, though essential for controlling the virus, triggered a severe global recession and widespread food supply chain disruptions. These

disruptions disproportionately affected the world's poor, threatening food and nutrition security and emphasizing the fragility of current systems (Swinnen & McDermott, 2020). The effects varied significantly across product types, supply chain structures, and economic contexts, highlighting the urgent need for adaptive and sustainable solutions in food systems. Local food systems, in particular, revealed substantial differences in socio-economic and environmental impacts based on supply chain types and regional contexts (Enthoven & Broeck, 2021). This growing instability is compounded by economic contractions, with a 2–3% rise in global poverty rates for every percentage point of economic decline, further exacerbating challenges faced by vulnerable populations (Laborde et al., 2020).

In Malaysia, the pandemic's impact on the agricultural sector was unprecedented. The government implemented the Movement Control Order (MCO) in March 2020, effectively curbing virus transmission but causing significant disruptions in agricultural supply chains and rural livelihoods (Prime Minister’s Office, 2020). The MCO hindered food chain operations, limiting the availability of production inputs and creating bottlenecks in the distribution of agricultural produce. Farmers, especially vegetable growers, faced severe losses due to delays and wastage of perishable products, exposing the fragility of fresh food supply chains reliant on efficient logistics (Laborde et al., 2020; Pu & Zhong, 2020). These disruptions amplified socio-economic challenges, including psychological and emotional strain on affected communities (Mahmood & Zahari, 2022).

The pandemic's ripple effects on global food systems extend beyond COVID-19, as previous crises like avian flu and African swine fever demonstrated similar vulnerabilities in agricultural output and food security. COVID-19 further highlighted the interplay between labour shortages, disrupted trade flows, and shifts in food demand, emphasizing the need for proactive strategies to safeguard supply chains during crises (Laborde et al., 2020; Falkendal et al., 2021). In Malaysia’s Cameron Highlands, a critical agricultural hub, logistical disruptions during the MCO resulted in substantial vegetable wastage, emphasizing the urgent need for resilient and adaptable agricultural systems (Ishak, 2021).

Empowering vegetable farmers through skill development is essential to addressing these challenges and building resilience. Farmers’ readiness to adapt to post-pandemic challenges depends on their competencies in leadership, decision-making, technology adoption, and implementation. These skills enable them to navigate disruptions, optimize resources, and sustain productivity under adverse conditions. This study explores the relationship between key farmer skills and their readiness to overcome post-pandemic challenges, employing Partial Least Squares (PLS) modeling to identify critical skill dimensions and their impacts. By focusing on skill enhancement, this research addresses a pressing need for actionable insights that inform targeted training programs and policy interventions, ultimately contributing to more resilient and sustainable agricultural systems.

The COVID-19 pandemic has ignited critical discussions on the vulnerability of global food supply systems and the role of localized versus international supply chains in ensuring food security (Aday & Aday, 2020; Swinnen & McDermott, 2020). This underscores the importance of comprehensive food security planning to build resilient supply chains. The lessons from the pandemic highlight the need for targeted efforts to equip farmers with the skills necessary to adapt to disruptions and maintain agricultural sustainability in the face of future crises.

Farmers rely heavily on government support to address these challenges, with agricultural extension agents playing a pivotal role. Extension agents are responsible for managing farms, training farmers to address emerging issues, implementing sound agricultural practices, and disseminating crucial knowledge and information (Shah et al., 2013). The readiness of farmers to confront agricultural challenges is directly tied to their ability to anticipate, mitigate, and respond to future shocks. Consequently, farmers must possess a high level of knowledge and skills to effectively manage agricultural activities (Demiryurek et al., 2008). Given that agricultural products are often perishable, a pandemic crisis can exert immediate pressure on food supply systems. These supply chains involve a complex network of interactions between farmers, agricultural input suppliers, processing plants, transporters, retailers, and other stakeholders. The result can be an accumulation of unsold fresh produce on farms, contributing to significant food waste (Rashidi et al., 2021).

Although several studies have explored how different countries addressed the impacts of COVID-19, few have specifically examined its effects on agriculture, particularly in Malaysia. This study aims to fill this gap by investigating the readiness and skill levels of farmers in smallholding communities, focusing on the factors that exacerbated the difficulties they faced during the pandemic. Similar to other developing countries, Malaysia expressed concern about how the COVID-19 crisis would affect food security and delay the achievement of the Sustainable Development Goals (SDGs) by 2030, particularly for smallholder farmers and rural communities dependent on agriculture (United Nations [UN], 2015). In addition to supply disruptions, other challenges include shifting consumer preferences for cheaper, less nutritious meals and the volatility of food prices. COVID-19 has had the most immediate and severe impact on food access, exacerbating issues of food insecurity (Laborde et al., 2020). The readiness of farmers is closely linked to their knowledge levels, with more knowledge generally leading to higher levels of preparedness (Fairuz et al., 2018).

The conceptual framework illustrated in Figure 1 highlights the relationships between key components discussed above. This study uses four skill areas—technology, implementation, leadership, and decision-making—to assess how prepared farmers were to handle the post-pandemic challenges arising from the MCO. These skills, identified as independent variables in this study, are essential for farmers to thrive, improve productivity, and further their education in the agricultural sector. This study aims to contribute to sustainable agricultural progress by equipping vegetable farmers with the necessary skills to thrive in the post-pandemic era, ensuring food security and socio-economic stability.

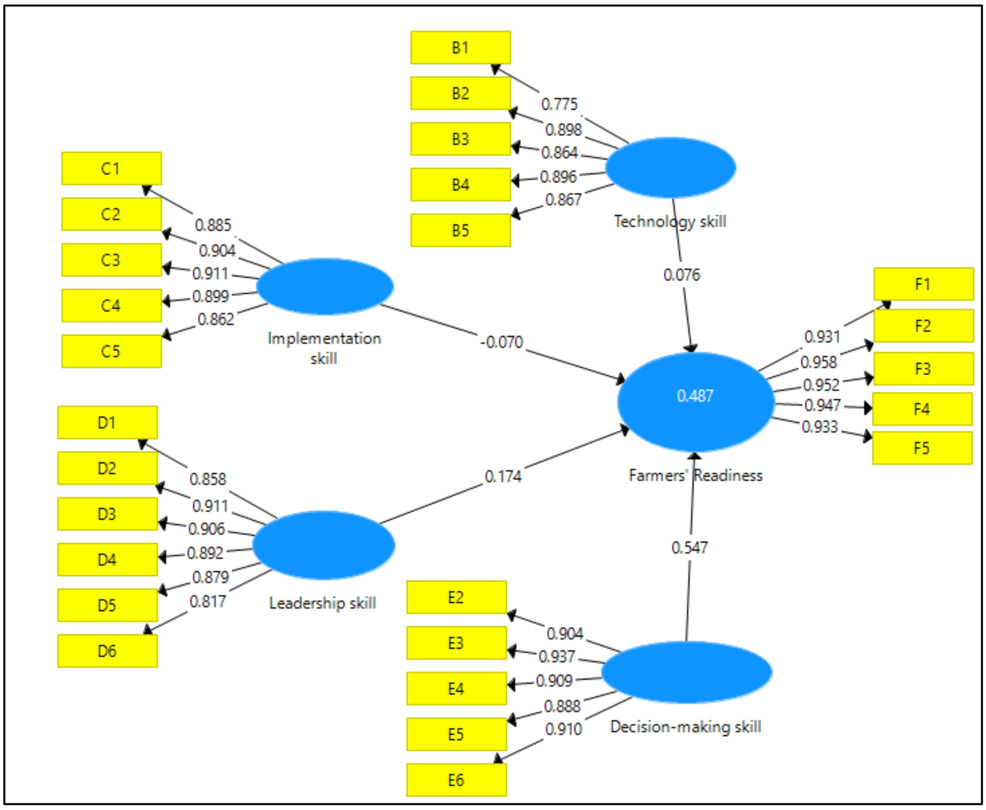

Figure 1. Outer model assessment

Materials and Methods

Online and manual approaches were also used to gather the data for this investigation. The questionnaire for the first technique was created online using Google Forms. With the assistance of the Department of Agriculture extension officers, the researchers sent this online questionnaire to the responders via a link through the WhatsApp app (DOA). Researchers, DOA extension workers, professors, and students distributed the questionnaire to the respondents. The second strategy involved hand distribution of the questionnaires and same-day data collection from responders.

Questionnaire

The aims and research questions of the survey were used to build the questionnaire's construct. The questionnaire's questions were all created in the Malay language as the respondent's preference and conversation languages is in Malay. In addition, there were six sections in the questionnaire. On the designed instrument, the following details were revealed in more details:

1) The first part of the questionnaire collects data on the respondents' personal demographic and farm profiles. Farmers' profile contains six (6) items: location of the project, phone number, age, gender, race, and level of education. While the farm profile contains four (4) items on crop information, they include; type of vegetables, My GAP certificates, year of receiving the certificate, type of guidance, type of incentives, and estimated income loss.
2) The second part of the study measures technical skill, represented by Section B, which contains seven questions. This section includes questions about vegetable production schedules, fertilizer application, disease and weed control, and phone and online marketing knowledge.

3) The third section was implementation skill. This section includes questions about vegetable planting, fertilizer application, plant disease, plant pest management, weed control management, and phone and web marketing skills. Seven questions on implementation skill are included in Section C.
4) The fourth part was leadership skill. There are seven questions in Section D about leadership skill. During the disaster, this section includes questions on planting schedules, fertilizer schedules, disease control, insect control, harvesting schedules, production schedules, and SOP.
5) The fifth part of the study was about decision-making skill. Plant production, plant disease management, weed control management, fertilizer management, and online marketing are all covered in this area. There are seven questions in section E about decision-making skill.
6) The respondents' perceptions of the given statements in the questionnaire were measured using a six-point scale option (1=strongly disagree to 6=strongly agree). The sixth part of the questionnaire was about farmers' readiness. The last part of the questionnaire. With seven questions about project planning, implementation, and evaluation, becoming an independent farmer, online communication in catastrophic occurrences, and internet marketing in a catastrophic circumstance, Section F gauges farmers' readiness for catastrophe issues. uestions were modified from Mazlan's (2021) and Azemi's (2021) earlier study. To better meet the objectives of study, the statements were modified in part. A six-point scale from strongly disagree to strongly agree was used to rate the respondents' perceptions. Following pilot testing, the final version was enhanced with the assistance of experts in developing instruments. Each item is detailed in Table 1.

Table 1
Questionnaire items

Constructs	Labels	Indicator
Technology skill	B1	My knowledge level in preparing vegetable production schedules according to the demand
	B2	My knowledge level of preparing the correct vegetable fertilization schedule
	B3	My knowledge level to determine the correct rate of vegetable fertilizer
	B4	My knowledge level to prepare a proper schedule for vegetable disease control
	B5	My knowledge level in preparing a schedule for weed control
	B6	My knowledge level of using the phone for communication
	B7	My knowledge level of marketing products through online
Implementation skill	C1	My skill level in planting vegetables in the right way
	C2	My skill level in applying vegetable fertilizer correctly
	C3	My skill level in identifying vegetable diseases
	C4	My skill level in identifying vegetable pests
	C5	My skill level in controlling weed
	C6	My skill level in using the phone to communicate
	C7	My skill level in marketing products through online

	D1	My compliance level with following the vegetable crop schedule provided
Leadership skill	D2	My compliance level with following the fertilization schedule
	D3	provided
	D4	My compliance level with controlling vegetable diseases
		My compliance level to control weeds in the vegetable project
	D5	area
		My compliance level with harvesting the products according to
	D6	the specified time
		My compliance level to supply the products according to the
	D7	schedule set by the customer
		My compliance level to follow the SOP provided by the government during MCO
	E1	My confidence level in deciding to choose the right type of fertilizer for vegetables
Decision-making skill	E2	My confidence level in determining the appropriate fertilizer rate for vegetables
	E3	My confidence level in deciding to continue vegetable production during MCO
	E4	My confidence level in deciding to choose the right type of herbicide according to the type of vegetable diseases
		My confidence level in deciding to choose the right type of
	E5	weedicide according to the weeds
	E6	My confidence level in deciding to identify the vegetable diseases
	E7	My confidence level in determining to market the product online
Farmers' Readiness	F1	My readiness level to plan my vegetable project after Covid-19 Pandemic.
	F2	My readiness level to implement the vegetable project by myself after the Covid-19 Pandemic
	F3	My readiness level to monitor vegetable projects personally after the Covid-19 Pandemic
	F4	My readiness level to lead myself after the Covid-19 Pandemic My
	F5	readiness level to be independent after the Covid-19 Pandemic
		My readiness level to communicate online after the Covid-19
	F6	Pandemic
		My readiness level to market the products online after the Covid-
	F7	19 Pandemic

Population and Sample

This study focused on vegetable farmers in Peninsular Malaysia. The target population for this study was defined to include selective vegetable farmers according to the type of vegetables they plant. Mustard, spinach, okra, long beans, and eggplant are the selected agricultural commodities with high value per capita consumption in Malaysia (Department of Statistics Malaysia, 2020).

This research was used a simple random sampling method. Using this method, all farmers in the selected population have the same probability of being selected as the sample units.

According to the Department of Agriculture (DOA)/MAFS statistics, 35,780 farmers in the targeted demographic meet the above requirements. According to Raosoft.com's sample size computation, the sample size required 381 farmers based on the population indicated. Thus, in this study, the online application was used to send the link to questionnaires to all intended respondents**.**

Data Analysis

Partial Least Squares Structural Equation Modeling (PLS-SEM) can be used as a path or regression model to predict one or more dependent variables based on a set of independent variables (Garson, 2016). The following are the stages and objectives involved in processing primary data using Smart-PLS for model estimation and evaluation in structural equation modeling:

a. Construction of the Path Diagram

A path diagram is used to illustrate the relationships between indicators and constructs, as well as the relationships between constructs. In PLS-SEM, this diagram represents the link between latent variables and their respective indicators. The path diagram includes both the outer and inner models, providing a comprehensive view of the model. A detailed path diagram simplifies the visualization of complex relationships for researchers, aiding in the clearer interpretation of data.

b. Outer Model

The outer model specifies the relationship between latent variables and their indicators. Key aspects of the outer model include assessing convergent validity, which involves examining the loading factor values, as well as discriminant validity, which is measured using cross-loading factors and the discriminant value for each construct. Other important metrics in the outer model are composite reliability, average variance extracted (AVE), and Cronbach's alpha, all of which help ensure the reliability and validity of the measurement model.

c. Inner Model (Structural Model)

The inner model represents the structural relationships between latent variables, offering insight into the pathways that connect these variables. The inner model allows for the estimation of parameter coefficients and their significance levels, which are crucial for understanding the predictive power of the model. Key metrics in the inner model include R-squared (R^2) and Q-squared (Q^2), which provide information on the model's predictive accuracy and its ability to explain the variance in the dependent variables. These measures are essential for assessing the overall effectiveness and robustness of the structural model.

Results and Discussion

Assessment of Outer Model

In this study, the relationship between farmers' skills and their readiness to tackle post-pandemic challenges was examined using the Partial Least Squares (PLS) methodology. The measurement model, or outer model, in PLS analysis is essential for evaluating the validity of the constructs outlined in the theoretical framework. This model validates whether the variables measured through the survey questionnaire accurately reflect the constructs of interest—namely, technology, implementation, leadership, and decision-making skills—and their impact on farmers' readiness for dealing with challenges, particularly in the aftermath of the COVID-19 pandemic. The evaluation of the outer model involves assessing key indicators such as factor loadings, composite reliability (CR), and the average variance extracted (AVE) for both independent variables (IVs) and the dependent variable (DV).

Construct Validity

Construct validity determines whether the indicators used to measure a construct accurately reflect the intended concept. It is assessed through factor loadings and cross-loadings, with loadings above 0.50 on the relevant construct and below 0.50 on others considered indicative of strong construct validity (Hair et al., 2011). Table 2 shows that all indicators measuring a given construct exceed the 0.50 threshold on the relevant construct while remaining below this value for others, supporting the construct validity. Additionally, Hair et al. (2011) recommend a stricter factor loading cutoff of 0.60, which was followed in this study. The factor loadings for the 26 observed variables ranged from 0.772 to 0.937, with all values exceeding the threshold and confirming the construct validity of the measurement model.

Table 2
Outer Loadings

	Technology skill	Implementation skill	Leadership skill	Decision-making skill	Farmers' Readiness
B1	0.772	0.619	0.620	0.569	0.472
B2	0.870	0.747	0.680	0.687	0.501
B3	0.843	0.743	0.663	0.686	0.484
B4	0.861	0.768	0.708	0.700	0.487
B5	0.838	0.732	0.667	0.681	0.540
B6	0.577	0.488	0.326	0.361	0.348
B7	0.575	0.467	0.335	0.388	0.429
C1	0.713	0.846	0.702	0.678	0.489
C2	0.754	0.878	0.722	0.704	0.492
C3	0.743	0.889	0.712	0.756	0.561
C4	0.702	0.870	0.694	0.735	0.470
C5	0.682	0.837	0.716	0.737	0.577
C6	0.497	0.520	0.336	0.354	0.399
C7	0.496	0.478	0.318	0.375	0.418
D1	0.686	0.675	0.838	0.659	0.493
D2	0.714	0.719	0.901	0.728	0.539
D3	0.700	0.765	0.892	0.787	0.593
D4	0.701	0.767	0.876	0.759	0.586
D5	0.620	0.675	0.881	0.710	0.528
D6	0.592	0.606	0.819	0.656	0.570

D7	0.418	0.437	0.634	0.529	0.535
E1	0.465	0.475	0.562	0.694	0.588
E2	0.690	0.752	0.750	0.895	0.674
E3	0.664	0.743	0.743	0.915	0.636
E4	0.670	0.739	0.743	0.888	0.650
E5	0.651	0.700	0.723	0.867	0.552
E6	0.696	0.741	0.744	0.883	0.599
E7	0.542	0.503	0.410	0.508	0.490
F1	0.556	0.571	0.605	0.684	0.922
F2	0.552	0.582	0.613	0.692	0.937
F3	0.555	0.591	0.630	0.697	0.929
F4	0.547	0.577	0.631	0.685	0.929
F5	0.523	0.538	0.598	0.658	0.917
F6	0.457	0.487	0.409	0.493	0.663
F7	0.425	0.422	0.357	0.409	0.551

* Loadings that are above the value of 0.70 are in bold.

Convergent Validity

Convergent validity examines whether multiple indicators that measure the same construct are consistent with one another. This can be assessed using factor loadings, composite reliability (CR), and average variance extracted (AVE) (Hair et al., 2011). Initially, several indicators were removed to improve CR and the overall reliability of the measurement model. Specifically, two indicators from the technology skill category (B6 and B7), two from the implementation category (C6 and C7), one from the leadership category (D7), two from the decision-making category (E1 and E7), and two from the readiness category (F6 and F7) were excluded. This removal followed the criteria established by Hair et al. (2011), which suggest removing items with factor loadings between 0.40 and 0.70 to improve scale reliability. After the removal of these items, the remaining factor loadings, CR, and AVE values all surpassed the minimum recommended thresholds, indicating the measurement model's convergent validity.

Table 3 presents the factor loadings and CR values for each latent construct. The composite reliability for all constructs ranged from 0.775 to 0.958, surpassing the recommended cutoff of 0.70 (Hair et al., 2011), signifying that the constructs are reliably measured. Additionally, the AVE, which represents the proportion of variance in the observed variables explained by the latent variables (Ramayah et al., 2013), is above the acceptable threshold of 0.50 for all constructs, ranging from 0.741 to 0.892 (Barclay et al., 1995). These results confirm the convergent validity of the measurement model. Figure 1 illustrates these findings, demonstrating that the five constructs—technology, implementation, leadership, decision-making, and farmers' readiness—are legitimate and statistically significant measures of their respective dimensions ($p < 0.05$).

Table 3
Measurement Model

Construct	Indicators	Outer Loadings	Cronbach > 0.708	Rho-a >0.708	CR[b] >0.708	AVE[a] >0.501
Technology skill	B1	0.775				
	B2	0.898				
	B3	0.864	0.912	0.915	0.935	0.741
	B4	0.896				
	B5	0.867				
Implementation skill	C1	0.885				
	C2	0.904				
	C3	0.911	0.936	0.940	0.951	0.796
	C4	0.899				
	C5	0.862				
Leadership skill	D1	0.858				
	D2	0.911				
	D3	0.906	0.940	0.944	0.953	0.770
	D4	0.892				
	D5	0.879				
	D6	0.817				
Decision-making skill	E2	0.904				
	E3	0.937				
	E4	0.909	0.948	0.951	0.960	0.828
	E5	0.888				
	E6	0.910				
Farmers' Readiness	F1	0.931				
	F2	0.958				
	F3	0.952	0.970	0.970	0.976	0.892
	F4	0.947				
	F5	0.933				

[a] Average variance extracted (AVE) = (summation of the square of the factor loadings)/{(summation of the square of factor loadings) + (summation of the error variances)}.
[b] Composite reliability (CR) = (square of the summation of the factor loadings)/{(square of the summation of the factor loadings) + (square of the summation of the error variances)}.

Discriminant Validity

Discriminant validity evaluates whether constructs are distinct from one another. It is determined by examining whether the square root of the AVE for each construct is greater than the correlation between that construct and the other constructs. As noted by Fornell and Larcker (1981), a construct achieves discriminant validity when the square root of its AVE exceeds the correlation between that construct and others. In Table 4, the square roots of the AVE (highlighted in bold off-diagonal values) for each construct are greater than the correlations between that construct and the others, indicating strong discriminant validity. This confirms that the constructs—technology, implementation, leadership, decision-making, and readiness—are distinct and measure different aspects of farmers' preparedness for challenges, particularly in the post-COVID-19 landscape.

Table 4
Discriminant Validity

	Technology skill	Implementation skill	Leadership skill	Decision-making skill	Farmers' Readiness
Technology skill	0.861				
Implementation skill	0.838	0.892			
Leadership skill	0.780	0.801	0.878		
Decision-making skill	0.771	0.828	0.807	0.910	
Farmers' Readiness	0.575	0.586	0.619	0.689	0.945

Note: The off-diagonals depict the variable correlations; meanwhile, the diagonals represent the square root of the AVE.

Assessment of Inner Model

The next phase of analysis focuses on the structural model, or inner model, which examines the relationships between the constructs associated with farmers' readiness to face challenges. This stage includes evaluating the coefficient of determination (R^2) for the dependent variable, which measures the extent of variation explained by the model. Additionally, effect size (f^2) and predictive relevance (Q^2) are calculated to assess the practical significance of the model and its predictive capabilities. The path coefficients, representing the strength of associations between variables, were evaluated for statistical significance through bootstrapping techniques, producing t-values.

The R^2 value for the endogenous variable, as shown in Table 5, is 0.487, indicating that leadership and decision-making skills explain 48.7% of the variation in farmers' readiness. This suggests that these two factors play a significant role in shaping how prepared farmers are to confront challenges, particularly those related to catastrophes such as the COVID-19 pandemic. The effect size (f^2) analysis for the independent variables—leadership and decision-making skills—was conducted to assess the practical impact each of these constructs has on the dependent variable, farmers' readiness. Cohen (1988) provides guidelines for interpreting effect size: a large effect is indicated by $f^2 \geq 0.35$, a medium effect by $f^2 \geq 0.15$, and a small effect by $f^2 \geq 0.03$. The results revealed that decision-making skills have a moderate effect on farmers' readiness to face catastrophe challenges, with a medium effect size ($f^2 = 0.158$), while leadership skills were found to have a weak relationship with farmers' readiness, yielding a small effect size ($f^2 = 0.045$).

Table 5
Structural Model

Structural Construct	F^2	R^2	Q^2
Decision-making skill	0.147		
Leadership skill	0.016		
Farmers Readiness		0.487	0.431

Predictive relevance, measured by Q^2, assesses how well the model predicts the observed values for the endogenous variables. According to Stone (1974), Q^2 represents the model's ability to recreate the observed data based on its parameter estimates. To evaluate predictive relevance, the blindfolding method was used in conjunction with function fitting and cross-validation (Vinzi, 2010). Structural models with Q^2 values greater than zero are considered to have predictive relevance (Hair et al., 2011). In this study, the predictive relevance for variance, as indicated by a Q^2 value of 0.431, is considered highly relevant, suggesting that the model has strong predictive power in explaining farmers' readiness to face catastrophe challenges.

Hypothesis Testing and Discussion

This study examines the critical relationship between farmers' readiness and four key skills: technology, implementation, leadership, and decision-making. These skills were hypothesized to positively influence farmers' readiness to confront challenges, especially those arising from unpredictable events such as natural catastrophes or climate change-related disturbances. The four hypotheses tested in this research include:

- H1: There is a positive relationship between technology skill and farmers' readiness.
- H2: There is a positive relationship between implementation skill and farmers' readiness.
- H3: There is a positive relationship between leadership skill and farmers' readiness.
- H4: There is a positive relationship between decision-making skill and farmers' readiness.

The results of the study, as presented in Table 6, Table 7 and Figure 2, validate the significant relationships between leadership and decision-making skills and farmers' readiness. Notably, decision-making skills demonstrated the strongest relationship with readiness, accounting for 70% of the variance, whereas leadership skills, though significant, showed a weaker influence, contributing only 33.3%. This finding directly aligns with the central objective of the study: to explore how specific skills contribute to enhancing farmers' preparedness for challenging and unpredictable circumstances, such as those brought on by climate change or other external shocks.

Table 6
Construct hypotheses

Hypothesis	**Std. Deviation**	**T Statistics**	**p-values**	Decision
Technology skill -> Farmers' Readiness	0.068	1.109	0.268	Not supported
Implementation skill -> Farmers' Readiness	0.097	0.721	0.471	Not supported
Leadership skill -> Farmers' Readiness	0.081	2.147	**0.032**	Supported
Decision-making skill -> Farmers' Readiness	0.080	6.816	**0.000**	Supported

Table 7
Strength and decision on hypotheses

Hypothesis	Construct	P<0.050	Relationship	Strength	Decision
There is a positive relationship between decision-making skills on farmers' readiness.	Decision-making skill -> Farmers' Readiness	0.000	70.0%	Strong	Accepted
There is a positive relationship between leadership skills on farmers' readiness	Leadership skill -> Farmers' Readiness	0.032	33.3%	Weak	Accepted

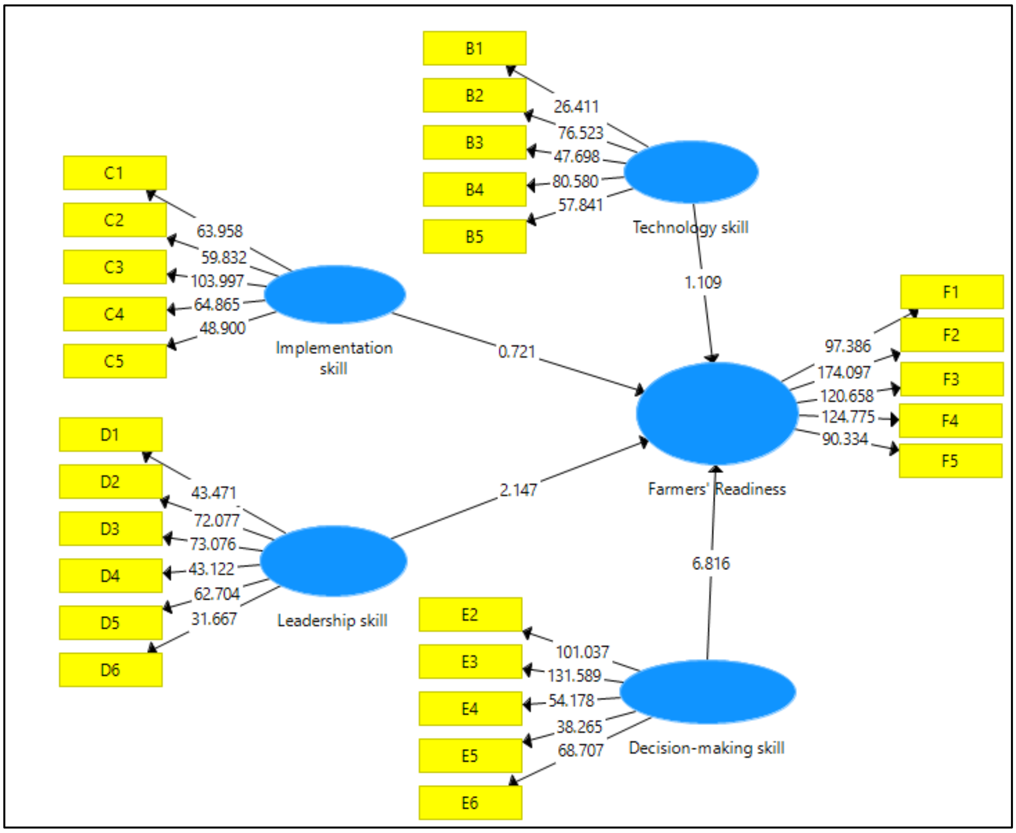

Figure 2. The inner model's graphic representation follows the bootstrapping process.

The findings of this study underscore the critical role of decision-making skills in enhancing farmers' readiness to face both current and future agricultural challenges. Decision-making is particularly significant in the context of the growing uncertainties within the agricultural sector, exacerbated by climate change, global economic fluctuations, and frequent disruptions in food systems. Farmers' ability to assess risks, analyze complex situations, and implement adaptive strategies directly influences their resilience in the face of both environmental and market shocks. The importance of decision-making skills extends beyond immediate crisis response, offering a framework for long-term strategic planning, sustainable farming practices, and proactive risk management. In an era marked by unpredictability, decision-making capacity has emerged as an indispensable skill, enabling farmers to not only survive but thrive in the face of adversity. This study's findings highlight the urgency of integrating decision-making skill development into agricultural training and policy frameworks to enhance the overall resilience of the farming community.

The implications of these findings are far-reaching, particularly for policymakers and agricultural extension agencies. By focusing on decision-making skills, the study provides a significant contribution to agricultural development strategies, offering valuable insights into the competencies that should be prioritized within training programs. While traditional agricultural education has primarily centered on technical skills—such as crop management, pest control, and soil health—this study illustrates the pressing need to expand these curricula to include decision-making and leadership training. Policymakers must recognize that building decision-making capacity among farmers is just as critical as providing technical knowledge, particularly when considering the rapid pace of change in the agricultural sector. The integration of these skills into national agricultural training programs could serve as a powerful tool for fostering a more resilient farming population capable of adapting to the challenges posed by both local and global disruptions.

In addition to decision-making skills, leadership also emerged as a significant factor influencing farmers' preparedness for crises. The study aligns with existing research, such as the work of Ulvenblad (2018), which underscores the importance of leadership development in enhancing farmers' capacity to navigate and manage agricultural challenges. Effective leadership fosters innovation, strengthens social and professional networks, and drives the adoption of new technologies, all of which are crucial for adapting to changing circumstances. However, this study highlights that leadership alone is insufficient in ensuring farmers' readiness for catastrophic events. This finding reveals a critical gap in current agricultural education and training systems, which typically emphasize technical training over leadership development. As such, leadership training should be integrated into comprehensive, multifaceted agricultural development programs that also prioritize decision-making and technical skills. Such programs would better prepare farmers to manage their enterprises effectively, particularly in times of crisis, while also fostering long-term sustainability.

Leadership training programs can significantly enhance farmers' ability to innovate and expand their networks, ultimately strengthening their resilience. As noted by Ishak and Manaf (2020), farmers who rely heavily on intermediaries often lack the intrinsic motivation to develop leadership skills. Training initiatives that promote entrepreneurial leadership can address this gap by encouraging farmers to take ownership of their enterprises and seek out new opportunities for growth and innovation. Structured interventions that focus on cultivating entrepreneurial thinking could empower farmers to leverage industry trends, adopt new technologies, and build networks that enhance their long-term viability. Policymakers should ensure that leadership and entrepreneurial development are incorporated into national agricultural extension services to better equip farmers with the skills necessary to navigate the evolving agricultural landscape.

While technology skills were not the primary focus of this study, the findings suggest that they play a critical role in enhancing farmers' readiness, particularly in the context of the increasing digitalization of agriculture. Precision farming, digital tools, and climate adaptation technologies are increasingly becoming integral components of modern farming practices, offering farmers new avenues for improving productivity and resilience. However, as this study reveals, many farmers, particularly smallholders, face challenges in integrating these technologies into their operations due to a lack of adequate technological skills. The role of technology in building agricultural resilience cannot be overstated, and addressing the digital divide between rural and urban populations is essential for ensuring that all farmers have equal access to the tools necessary for innovation and growth. Policymakers must prioritize policies aimed at enhancing digital literacy, providing greater access to technology, and integrating smart farming solutions into agricultural training programs. Such efforts would enable farmers to harness the full potential of digital tools for decision-making, resource management, and crisis response, ultimately strengthening their ability to adapt to and mitigate the effects of environmental and market disruptions.

The study also found that implementation skills, while important, exhibited a weaker relationship with farmers' readiness during catastrophic events. This suggests that while the ability to execute plans and strategies is critical in stable agricultural conditions, the ability to make effective decisions and provide leadership during crises takes precedence. This finding points to the importance of context-specific training that prioritizes the most relevant skills during periods of uncertainty. In stable conditions, implementation skills may be sufficient for managing daily operations; however, during times of crisis, the need for strategic decision-making, leadership, and technological adaptation becomes more pronounced.

Given these findings, it is clear that a holistic approach to agricultural training is necessary. Such an approach should integrate leadership, decision-making, technology adoption, and implementation skills into comprehensive training programs. Agricultural policies and extension services must evolve to address the increasing complexity of agricultural challenges, which require a multi-dimensional skill set. In addition to training, investments in climate-resilient infrastructure—such as improved water management systems and disaster-resistant farming technologies—are essential to supporting farmers in building their resilience. Policymakers should prioritize infrastructure projects that foster resilience to climate change and other unforeseen crises, ensuring that farmers have the necessary resources to adapt and thrive in a rapidly changing world.

In conclusion, this study highlights the vital role that decision-making, leadership, and technology adoption play in enhancing farmers' readiness to face both immediate and long-term challenges. The findings underscore the need for a paradigm shift in agricultural training, with a greater emphasis on developing these critical skills alongside technical competencies. By fostering a more well-rounded skill set among farmers, agricultural policies and training programs can better equip them to navigate the complexities of a changing agricultural landscape. This, in turn, will contribute to ensuring food security, economic stability, and the long-term sustainability of agricultural systems, benefiting farmers, their communities, and society as a whole.

Conclusions and Recommendations

In conclusion, this study highlights the pivotal role of leadership and decision-making skills in enhancing farmers' readiness to address the increasing challenges posed by climate change and other global disruptions. As agricultural sustainability faces growing uncertainties, it is essential for agricultural education and policy frameworks to evolve in ways that equip farmers not only with technical skills but also with the strategic leadership and decision-making abilities necessary to navigate modern agricultural challenges. This research underscores the importance of integrating these core competencies into educational programs, ensuring that farmers possess the capacity to respond to both immediate crises and long-term sustainability needs.

The findings of this research align with the theoretical framework and empirical studies, confirming the critical relationship between leadership and decision-making skills and farmers' readiness to cope with catastrophic events. These results validate the necessity of cultivating effective leadership at the community level, enabling farmers to manage resources, inspire change, and foster a collaborative environment to overcome challenges. In line with the theories of leadership as described by Bass (1990) and Kouzes (2007), this study emphasizes that leadership is not solely about directing but also about understanding contexts, making informed decisions, and engaging with others to meet common objectives. The ability of leaders to align personnel, set direction, and create a culture of decision-making can significantly impact farmers' preparedness and resilience.

Given the current global challenges, such as climate change, economic disruptions, and unpredictable agricultural risks, there is an urgent need for agricultural education systems to adapt. Policymakers and agricultural extension services must prioritize leadership development, decision-making capacity, and technological literacy in their training programs. These skills are not only essential for immediate crisis management but are also critical in fostering long-term resilience within the agricultural sector. The ability of farmers to make informed decisions, based on both technical knowledge and strategic insights, will enhance their preparedness to cope with unforeseen challenges.

In light of these findings, it is evident that policy interventions must integrate these skill sets into agricultural education. Governments should actively invest in leadership and decision-making training programs aimed at empowering farmers, especially smallholders, with the skills needed to enhance their agricultural practices and adapt to changing conditions. This holistic approach to education will equip farmers with the tools necessary for sustained growth and development. Additionally, current agricultural policies should be revisited to ensure they support the development of these critical skills, especially considering the vulnerabilities exposed by the COVID-19 pandemic. Stronger collaborations between governments, agricultural organizations, and the private sector are essential to ensure the continuity of essential agricultural inputs such as seeds, fertilizers, and labor, particularly in times of crisis.

Finally, the growing emphasis on technological innovation and digital transformation in agriculture necessitates a shift in how agricultural training is delivered. Digital literacy should be embedded within agricultural curricula, ensuring that farmers are not only technically proficient but also capable of leveraging technology to make data-driven decisions that enhance their farm management practices. By doing so, farmers will be better positioned to respond to challenges posed by climate change, market volatility, and other disruptions, ultimately contributing to a more resilient and sustainable agricultural sector.

Novelty Statement
This study creates awareness and educates people, including farmers or agriculture people especially extension agents to understand the factors influencing farmers' readiness to face the challenges of the catastrophe phenomenon. Farmers will practice the skills that are lacking in order to face catastrophe phenomenon challenges. Furthermore, this study also will be beneficial to the agencies such as the Department of Agriculture Malaysia to create a planning program based on the research findings and to create new policies according to "New Norms".

Conflict of Interest
The authors have declared no conflict of interest

References
Aday, S., & Aday, M. (2020). Impacts of COVID-19 on Food Supply Chain. Food Quality and Safety. https://doi.org/10.1093/fqsafe/fyaa024.
Alam, G. M., and Khatun, M. N. (2021). Impact of COVID-19 on vegetable supply chain and food security: Empirical evidence from Bangladesh. *Plos one*, *16*(3), e0248120. https://doi.org/10.1371/journal.pone.0248120
Barclay, D., Higgins, C., and Thompson, R. (1995). The partial least squares (PLS) approach to casual modeling: personal computer adoption and use as an Illustration. *Technology Studies* 2(2): 285–309
Bass, B. M., and Bass, R. (2008). *Handbook of leadership: Theory, research, and application*. Free Press.
Carter, S. (2001). "Multiple Business Ownership in the Farm Sector - Differentiating Monoactive, Diversified and Portfolio Enterprises." *International Journal of Entrepreneurial Behavior & Research* 7 (2): 43–59. https://doi.org/10.1108/13552550110695552
Chin, W. W., Gopal, A., and Salisbury, W. D. (1997). Advancing the theory of adaptive structuration: The development of a scale to measure faithfulness of appropriation. *Information systems research*, *8*(4), 342-367. https://doi.org/10.1287/isre.8.4.342
Christmas, T. H. (2005). *Using partial least squares approach to predict factors that contribute to the impact of e-folios on pre-service teachers' learning*. Louisiana State University and Agricultural & Mechanical College.
Coteur, I., Wustenberghs, H., Debruyne, L., Lauwers, L., & Marchand, F. (2020). How do current sustainability assessment tools support farmers' strategic decision making?. Ecological Indicators, 114, 106298. https://doi.org/10.1016/j.ecolind.2020.106298.
Demiryurek, K., Erdem, H., Ceyhan, V., Atasever, S., and Uysal, O. (2008). Agricultural information systems and communication networks: the case of dairy farmers in Samsun province of Turkey. *Information Research*, 13(2), 13-2.
Department of Statistics Malaysia. (2020). Retrieved from https://www.dosm.gov.my/v1/index.php?r=column/pdfPrev&id=Tm5OaVh6RFpFM2VGOTIrZzltbWg3QT09
Dvir, T., Eden, D., Avolio, B. J., and Shamir, B. (2002). Impact of transformational leadership on follower development and performance: A field experiment. *Academy of management journal*, *45*(4), 735-744. https://doi.org/10.5465/3069307

Enthoven, L., & Broeck, G. (2021). Local food systems: Reviewing two decades of research. Agricultural Systems, 193, 103226. https://doi.org/10.1016/J.AGSY.2021.103226.

Fairuz, K., Idris, A. G., Syahrizan, S., and Hatijah, K. (2018). Assessing farmers' community readiness towards the enhancement of natural enemy population in rice fields in Malacca. In *AIP Conference Proceedings* (Vol. 1940, No. 1, p. 020028). AIP Publishing LLC. https://doi.org/10.1063/1.5027943

Falkendal, T., Otto, C., Schewe, J., Jägermeyr, J., Konar, M., Kummu, M., Watkins, B., & Puma, M. (2021). Grain export restrictions during COVID-19 risk food insecurity in many low- and middle-income countries. Nature Food, 2, 11 - 14. https://doi.org/10.1038/s43016-020-00211-7.

Fornell C. and Larcker D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research* 18(1): 39–50. https://doi.org/10.2307/3151312

Hair J.F., Ringle C.M. and Sarstedt M. (2011). PLS-SEM: Indeed a silver bullet. *The Journal of Marketing Theory and Practice* 19(2): 139–152. https://doi.org/10.2753/mtp1069-6679190202

Ishak, S. M., and Manaf, Z. A. (2020). Influence of Knowledge, Attitude and Skill on Good Agriculture Practices of Seedling Assistance Scheme Participant toward Oil Palm Production in Sabah and Sarawak. *Oil Palm Industry Economic Journal* (Vol. 20, Issue 1).

Ishak. (2021). Ishak A. Cameron Highlands farmers fear "wilting" industry amid COVID-19. 2021. [7 April 2022]. https://www.malaysiakini.com/news/579130

Iza, C., & Dentoni, D. (2020). How entrepreneurial orientation drives farmers' innovation differential in Ugandan coffee multi-stakeholder platforms. Journal of Agribusiness in Developing and Emerging Economies. https://doi.org/10.1108/jadee-01-2020-0007.

Khan, N. (2021). Drastic impacts of COVID-19 on food, agriculture and economy. Pesquisa Agropecuaria Brasileira, 10. https://doi.org/10.19045/bspab.2021.100008.

Kouzes, J. M., and Posner, B. Z. (2006). *The leadership challenge* (Vol. 3). John Wiley & Sons.

Kumar, U., Werners, S., Paparrizos, S., Datta, D., & Ludwig, F. (2021). Co-producing climate information services with smallholder farmers in the Lower Bengal Delta: How forecast visualization and communication support farmers' decision-making. Climate Risk Management. https://doi.org/10.1016/j.crm.2021.100346.

Laborde, D., Martin, W., Swinnen, J., & Vos, R. (2020). COVID-19 risks to global food security. *Science*, *369*(6503), 500-502. https://doi.org/10.1126/science.abc4765

Mahajan, K., & Tomar, S. (2020). COVID-19 and Supply Chain Disruption: Evidence from Food Markets in India†. American Journal of Agricultural Economics, 103, 35 - 52. https://doi.org/10.1111/ajae.12158.

Mahmood, R., & Zahari, A. (2022). Covid19: The Impact of Movement Control Order (MCO) Enforcement on Socio-emotional Well-being among University Students. International Journal of Academic Research in Business and Social Sciences. https://doi.org/10.6007/ijarbss/v12-i3/12318.

Milone, P., & Ventura, F. (2019). New generation farmers: Rediscovering the peasantry. Journal of Rural Studies, 65, 43-52. https://doi.org/10.1016/J.JRURSTUD.2018.12.009.

Organization for Economic Co-Operation and Development. 2020. *COVID-19 and the food and agriculture sector: Issues and policy responses*. OECD Publishing.

Papa, C., Nzokou, P., & Mbow, C. (2020). Farmer Livelihood Strategies and Attitudes in Response to Climate Change in Agroforestry Systems in Kedougou, Senegal.

Environmental Management, 66, 218-231. https://doi.org/10.1007/s00267-020-01302-8.

Pu, M., & Zhong, Y. (2020). Rising concerns over agricultural production as COVID-19 spreads: Lessons from China. Global Food Security, 26, 100409 - 100409. https://doi.org/10.1016/j.gfs.2020.100409.

Ramayah, T., Lee, J. W. C., and In, J. B. C. (2011). Network collaboration and performance in the tourism sector. *Service Business*, *5*(4), 411-428. https://doi.org/10.1007/s11628-011-0120-z

Ramayah, T. Y. J. A., Yeap, J. A., and Ignatius, J. (2013). An empirical inquiry on knowledge sharing among academicians in higher learning institutions. *Minerva*, *51*(2), 131-154. https://doi.org/10.1007/s11024-013-9229-7

Rashidi, M. N., Abdul Fatah, F., and Saili, A. R. (2021). COVID-19 and food security in Malaysia: implications on smallholding agriculture. *Food Research*, 46-55. https://doi.org/10.26656/fr.2017.5(s4).010

Shah, J. A., Asmuni, A., and Ismail, A. (2013). Roles of extension agents towards agricultural practice in Malaysia. *International Journal on Advanced Science, Engineering and Information Technology*, *3*(1), 59-63. https://doi.org/10.18517/ijaseit.3.1.278

Schutter, O. D. (2014). The reform of the Committee on World Food Security: The quest for coherence in global governance. In *Rethinking food systems* (pp. 219-238). Springer, Dordrecht. https://doi.org/10.1007/978-94-007-7778-1_10

Swinnen, J., and McDermott, J. (2020). COVID-19 and global food security. *EuroChoices*, *19*(3), 26-33. https://doi.org/10.2499/p15738coll2.133762

Ulvenblad, P., and Cederholm Björklund, J. (2018). A leadership development programme for agricultural entrepreneurs in Sweden. *The Journal of Agricultural Education and Extension*, *24*(4), 327-343. https://doi.org/10.1080/1389224x.2018.1473260

Ulvenblad, P., Wall, A., Cederholm, J., and Hedin, E. (2012). *Ledarpraktikan: Konsten att leda Mig själv, Mina medarbetare och Min verksamhet*. LRF.

United Nations. (2015). *Global Sustainable Development Report*. New York: United Nations.