FOOD-VALUE-CHAIN PERFORMANCE: AN INTEGRATED FRAMEWORK CONDITIONED BY GOVERNMENT INCENTIVES

Sushmita Annamalai
Faculty of Industrial Management, Universiti Malaysia Pahang Al-Sultan Abdullah, 26300, Pahang, Malaysia
Graduate Engineering and Technological Business School (GET-BS), Universiti Malaysia Pahang Al-Sultan Abdullah, 26300, Pahang, Malaysia

Yudi Fernando[1]
Faculty of Industrial Management, Universiti Malaysia Pahang Al-Sultan Abdullah, 26300, Pahang, Malaysia
Graduate Engineering and Technological Business School (GET-BS), Universiti Malaysia Pahang Al-Sultan Abdullah, 26300, Pahang, Malaysia
Department of Digital Business, Faculty of Social, Economics, and Humanities, Universitas Fort de Kock Bukittinggi, Indonesia
Department of Software Engineering, Daffodil International University, Dhaka, Bangladesh

ABSTRACT

Affordable food availability requires a well-functioning value chain system, yet the food sector faces mounting challenges to sustainable performance amid concerns about food security, environmental degradation, and economic viability. This study develops an integrated framework to examine the determinants of Food Value Chain Performance (FVCP) and the moderating role of government incentives in strengthening these relationships. Using a quantitative cross-sectional survey of key decision-makers across Malaysia's food value chain, the data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to test direct and moderating relationships, and Necessary Condition Analysis (NCA) to assess necessary conditions. Findings show that community support is the strongest predictor of FVCP, followed by environmental collaboration, while technological factors exhibit complex effects. Government incentives significantly moderate the relationship between community support and FVCP, highlighting the role of policy intervention in improving value chain outcomes. The study contributes a unified theoretical framework and offers practical insights for policymakers and practitioners seeking to optimise resource allocation for sustainable food value chain management.
Keywords: Food Value Chain; Government Incentives; Technological; Community Support; Organisational; Technology-Organisation-Environment Theory; Natural Resource-Based View.

Submission: 1st January 2026
Accepted: 10th July 2026
https://doi.org/10.33736/ijbs.14467.2026

---

[1] ♣ Corresponding author: Graduate Engineering and Technological Business School (GET-BS), Faculty of Industrial Management, Universiti Malaysia Pahang Al-Sultan Abdullah, 26300 Kuantan, Malaysia. Tel: +6094315314; Email addresses: yudi@umpsa.edu.my; yudifernando.td@gmail.com

1. INTRODUCTION

Well-managed food systems can end hunger only if all stakeholders, including government agencies, private corporations, and small-scale farmers, collaborate to achieve strong Food Value Chain Performance (FVCP). Meeting food-security, sustainability, and development challenges hinges on strategic levers such as Government Incentives (GI). The Food Supply Chain (FSC) is a complex, multi-tiered system that spans the “farm-to-fork” stages of production, processing, distribution, and disposal. Attributes such as perishability, short life cycles, seasonal production, and fluctuating quality make this system inherently harder to manage than other industrial enterprises (Corallo et al., 2024).

These gaps in food management research lead to significant food loss, directly reducing food availability for vulnerable populations. According to Bhattacharya and Fayezi (2021), one-third of the world's food production is wasted, a major factor in climate change, as food waste is among the top three contributors to carbon dioxide emissions worldwide. While developed nations lose substantial quantities of food during the marketing and consumption phases, developing economies experience a severe crisis earlier in their food supply chain due to factors such as primitive infrastructure, poor handling practices, inadequate storage, and excessive numbers of intermediaries (Bhattacharya & Fayezi, 2021). Consequently, food waste creates a staggering economic burden, costing the global economy hundreds of billions of dollars annually (Yontar, 2023), resulting in lost profit margins for businesses and higher prices for consumers.

Beyond preventing short-term financial loss, societal sustainability and economic imperatives are the primary drivers of FVCP's importance. Enhanced FVCP is associated with higher agricultural value-added per worker, a significant advantage for countries in the Global South (Montalbano & Nenci, 2022). Structural weaknesses, particularly low integration and collaboration, continue to hamper performance. This is largely because high investment costs, deficient digital infrastructure, and skills gaps hinder the adoption of key enablers, including traceability technologies and advanced environmental practices (Anastasiadis et al., 2022; Kumar et al., 2022).

The literature reveals a paradox in addressing these barriers. Studies commonly deploy two technology-focused frameworks: the Technology-Organization-Environment (TOE) framework (Chittipaka et al., 2023; Dora et al., 2021) and the Natural Resource-Based View (NRBV), which connects green practices to competitive advantage (Barbosa et al., 2022). However, both frameworks assume firms possess a baseline of internal resources and financial strength. This assumption rarely holds in developing economies, where internal technological and environmental initiatives can disrupt operations rather than enhance performance (Bhattacharya & Fayezi, 2021).

Existing models therefore fail to capture how firms lacking internal capacity can optimise FVCP. This study addresses that gap by extending and integrating the TOE and NRBV frameworks to explicitly incorporate external societal and policy lifelines. We hypothesise that while community support is vital, firm-level factors alone are structurally insufficient; instead, Government Incentives (GI) serve as a necessary moderating condition. It shifts the theoretical focus from the isolated firm toward systemic, multi-stakeholder integration.

To achieve these purposes, the study addresses two research questions:

- RQ1: What is the relationship between FVCP and its various economic, social, and environmental determinants?
- RQ2: What are the moderating impacts of GI and community support on the relationships between these variables and FVCP?

For policymakers, this study offers research-based guidance for prioritising FVCP-development measures, such as tax exemptions, low-interest loans, and simplified regulations, across both production and consumption phases. For practitioners and managers, it provides a framework for identifying success factors for innovation and collaboration. Overall, the study fills literature gaps by empirically validating technology barriers, integrating CE and triple-bottom-line perspectives, and analysing external moderators such as government support.

The remainder of this paper is structured as follows: Section 2 examines the literature and develops the hypothesis. Section 3 describes the research methodology, including the quantitative approach and data collection. Section 4 presents the empirical findings and hypothesis tests. Finally, Section 5 discusses the findings relative to existing theory, details practical implications, and outlines key contributions, limitations, and directions for future research.

2. LITERATURE REVIEW

This literature review provides the theoretical background, the main performance variables, and the influence of regulation within an integrated FVCP framework.

2.1. Underpinning Theory

2.1.1. Technology-Organisation-Environment (TOE)

The Technology-Organisation-Environment (TOE) framework is an established framework for understanding firms' decision-making on technological innovation. It posits that three contexts, technological, organisational, and environmental, jointly affect technology adoption (Chittipaka et al., 2023). The technological context covers available technologies and their attributes, the organisational context covers internal resources such as size, structure, and financial support; and the environmental context covers external factors such as competition, industry traits, and regulatory support (Chittipaka et al., 2023).

This framework is particularly useful for analysing the adoption of disruptive technologies, such as blockchain in supply chain management. Chittipaka et al. (2023), find that trust, firm size, and regulatory support significantly influence adoption decisions, while Kumar et al. (2022) apply the framework to reveal sector-specific barriers in freight logistics. More recent work integrates Behavioural Reasoning Theory (BRT) to explain managers' blockchain adoption decisions (Oguntegbe et al., 2022) and extends TOE with human factors to identify success factors for AI adoption in the FSC (Dora et al., 2021).

2.1.2. Natural Resources Based View (NRBV)

The Natural Resource-Based View (NRBV) extends the Resource-Based View (RBV) by integrating environmental constraints into firms' strategic decision-making (Barbosa et al., 2022; Owusu Kwateng et al., 2022). Firms create distinctive competitive advantage through active environmental stewardship; specifically, competitive advantage is secured when firms manage natural resources effectively and develop capabilities to respond to environmental change (Barbosa et al., 2022).

NRBV further holds that environmentally friendly cooperation between supply chain partners enhances sustainable performance (Barbosa et al., 2022), positioning stakeholder collaboration as a core criterion of proactive environmental management. Because such collaborative resources are difficult for competitors to replicate, adopting environmental strategies also builds the capacity needed to sustain competitive advantage (Owusu Kwateng et al., 2022).

2.2. Food Value Chain Performance (FVCP)

FVCP is the holistic evaluation of a system that moves food products through a farm-to-fork network encompassing farming, processing, warehousing, transportation, distribution, and marketing. Common performance dimensions include efficiency, flexibility, responsiveness, food and process quality (Zhao et al., 2021).

Continuous evaluation through improvement plans, sustainability reporting, and benchmarking keeps the FSC resilient, agile, and responsive to changing customer needs (Corallo et al., 2024), with operational excellence translating directly into higher revenues and profits. When triple-bottom-line sustainability is incorporated into FVCP measurement, economic aspects typically receive the greatest weight, followed by environmental, circular, and social elements (Kumar et al., 2022).

2.3. Technological Factor and FVCP

While the benefits of new technologies are widely discussed, their risks and failure rates receive far less systematic attention. A theoretical paradox therefore persists: the assumption that technology inherently guarantees superior performance. In practice, considerable resistance stems from disrupted workflows, high capital costs, poor digital infrastructure, and a lack of specialised digital skills, particularly among smallholder farmers (Anastasiadis et al., 2022; Kumar et al., 2022). A substantial adoption gap also persists between small and medium-sized enterprises (SMEs) and large enterprises, as resource-poor rural farmers and SMEs often lack the means to leverage tools such as blockchain profitably. Chittipaka et al. (2023), applying the TOE framework, found that structural factors such as firm size and institutional trust strongly shape adoption success. Technology is therefore not a universal solution; its effectiveness depends on organisational capacity and external support.

When successfully implemented, technology reduces food waste and improves food safety across food supply chains (FSCs). Adopting artificial intelligence (AI) and blockchain enhances visibility and traceability, improving overall performance (Dora et al., 2021), and can boost profitability through better information-sharing for well-resourced firms (Stranieri et al., 2021). However, research on the critical success factors for adopting these technologies remains limited (Dora et al., 2021; Mishra et al., 2022), and their benefits depend on systemic transparency and appropriate government regulation (Sharma et al., 2023).

2.4. Organisational and FVCP

Organisational factors, comprising in-house resources, capabilities, and flexibility, jointly shape firms' adoption and use of innovations. Organisational flexibility is managers' ability to reconfigure internal supply chains quickly in response to changing market and demand conditions (Ramos et al., 2023), enabling firms to operate under uncertainty and create competitive advantages by adjusting processes and products.

Coordination among FSC actors also drives the adoption of product, process, and technological innovations that improve economic, environmental, and social performance (Krishnan et al., 2021). According to Ramos et al. (2023), greater organisational flexibility positively affects supply chain agility (SCA). Collaborative structures such as Farmer Producer Organisations (FPOs) in India illustrate this, generating economic, environmental, and social returns for members and stakeholders alike (Krishnan et al., 2021). However, such collaboration is often costly and time-consuming.

2.5. Environmental and FVCP

Environmental factors include external pressures such as regulatory requirements, competitive pressures, and institutional trust. The food sector contributes substantially to greenhouse gas (GHG) emissions, water footprint, and food loss and waste (FLW) (Barbosa & Cansino, 2024). Environmental cooperation among supply chain partners is essential for reducing these impacts (Barbosa & Cansino, 2024). Adherence to environmental regulations and active environmental stewardship can create inimitable competitive advantages (Shah & Soomro, 2021), while coordinated action helps reduce FLW by standardising quality control and minimising specification misunderstandings. Barbosa and Cansino (2024) find that environmental collaboration positively affects all five dimensions of environmental performance, including GHG emissions, energy, and food waste management, with regulatory pressure mediating this relationship.

2.6. Community Support (CS) and FVCP

The main elements of CS include the participation of external stakeholders, such as NGOs, governments, academia, and research institutions, in value chain activities, directly supporting socially oriented goals, including reduced food waste, improved access to nutritious food, and job creation in rural and underdeveloped areas (Bhattacharya & Fayezi, 2021; Marusak et al., 2021). Involving academia further helps generate knowledge directed at real-world problems (Bhattacharya & Fayezi, 2021). Bhattacharya and Fayezi (2021) argued that such cooperation yields win-win outcomes that advance social sustainability; for example, NGO partnerships with government, communities, and farmers' markets have reduced FLW through food-donation initiatives, positioning community-based organisations as key actors in sustaining community health and well-being.

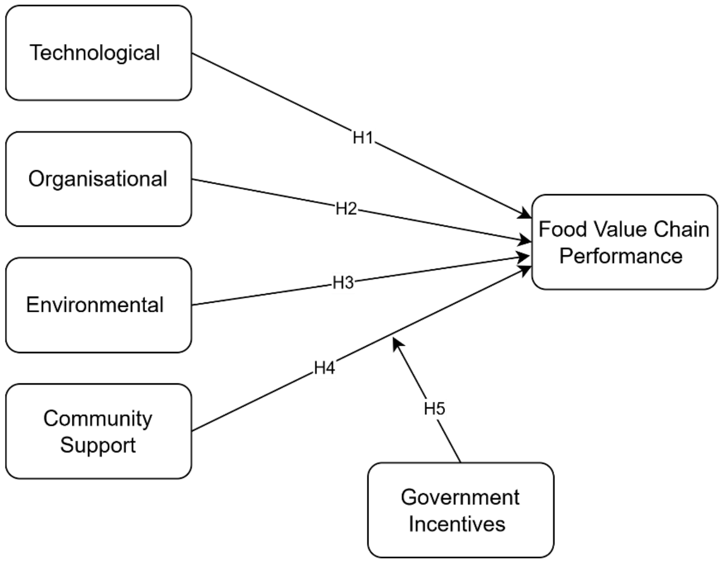
2.7. Government Incentives (GI) as Moderator

GI and support include regulators' efforts to influence outcomes through policies, legislation, funding, tax concessions, and technological support, with governments and NGOs increasingly relying on evidence-based research and advocacy to tackle FLW (Bhattacharya & Fayezi, 2021). Government policy benefits the FVC by coordinating actions towards sustainable resource use and greater agricultural profitability, while incentives can build trust and commitment among supply chain actors (Bhattacharya & Fayezi, 2021). Policymakers also drive reforms that support developing-country participation and modernisation in global value chains (Montalbano & Nenci, 2022), and government policy is a recognised success factor for circular-economy adoption in the food industry. Government incentives such as tax credits or grants can align stakeholder orientations towards reducing FLW (Bhattacharya & Fayezi, 2021), whereas weak regulation and low regulatory trust hinder technology adoption, including blockchain. Regulators can also pressure firms to adopt new supply-chain technologies, and global evidence links greater value-chain participation with higher food value-added per worker (Montalbano & Nenci, 2022).

2.8. Hypotheses Development

Grounded in the NRBV and complemented by the TOE framework, Figure 1 illustrates how firms develop sustainable competitive advantage through strategic environmental capabilities. While NRBV explains how effectively deploying environmental and organisational resources leads to superior performance, the TOE framework provides a structured lens to categorise the key antecedents influencing firms' adoption and implementation of such capabilities. Specifically, technological factors and organisational capabilities represent the "technology" and "organisation" contexts, respectively, whereas environmental factors, community support, and government incentives reflect the broader "environment" context. Together, these frameworks justify the selection of the proposed predictors and explain how internal capabilities and external conditions jointly influence FVCP. Finally, GI further moderates the relationship between community support and FVCP by shaping the extent to which external support translates into performance outcomes.

Figure 1: Conceptual Framework



Although technology adoption is generally understood to benefit FVCP, assuming a simple, linear relationship is misleading. Advanced technologies such as AI and blockchain carry high implementation costs, capability constraints, and operational challenges initially (Khan et al., 2023; Kumar et al., 2022), which can depress performance in the short term as employees adapt (Mishra et al., 2022). Once these capability gaps are bridged, however, the TOE framework suggests that reduced food waste, greater visibility, and improved traceability outweigh the initial burden (Dora et al., 2021), and technological capability helps minimise uncertainty and meet customer demand, supporting supply chain integration (Chatterjee & Chaudhuri, 2022).

H1: There is a significant and positive relationship between technological factors and FVCP.

Organisational capabilities are necessary for firms to survive and remain resilient amid uncertainty. Organisational flexibility, in particular, positively affects supply chain agility (SCA) (Ramos et al., 2023), and together, integration enhances operational performance. Higher internal integration, especially relevant in typically less formal agri-food organisations, improves resource use, internal governance, conflict resolution, and responsiveness to customer needs (Ramos et al., 2023). SCA is thus a requisite dynamic capability that enables supply chains to react swiftly and sustain performance, ultimately underpinning competitive advantage.

H2: There is a significant and positive relationship between organisational factors and FVCP.

Environmental factors, particularly the integration of environmental considerations, can meaningfully improve FVCP as part of broader sustainable performance. Environmental collaboration involves joint activities among supply chain partners to set environmental objectives, share planning, and reduce pollution and other impacts (Barbosa et al., 2022; Barbosa & Cansino, 2024).

This partnership is crucial, as firms cannot achieve sustainable performance goals alone (Barbosa et al., 2022), though cross-organisational environmental practices involve substantial coordination costs. The relationship between environmental factors and FVCP may therefore be non-linear, becoming a strong performance enabler only once a threshold of systemic integration is reached. This study nonetheless hypothesises an overall positive relationship, improving metrics such as greenhouse gas emissions and food waste management.

H3: There is a significant and positive relationship between environmental factors and FVCP.

Community support is positively correlated with FVCP, particularly social performance. Regional food supply chains, embedded in the communities they serve, play an inherent role in sustaining community health and well-being (Marusak et al., 2021). Socially oriented FVCP metrics capture contributions such as rural employment and retained local economic value (Marusak et al., 2021). Collaborative models that directly engage communities and customers, such as consumer purchases of "imperfect" produce, allow farmers and communities to benefit from food that would otherwise be wasted while reducing environmental harm (Bhattacharya & Fayezi, 2021). Social performance is further reflected in farmer empowerment, labour standards, and local job creation.

H4: There is a significant and positive relationship between community support and FVCP.

Government intervention and incentives significantly enhance factors that support social and sustainable performance in the food value chain (Mehmood et al., 2021; Yang et al., 2023). Governments can strengthen the agricultural sector through microcredit or low-interest loans that support technology adoption, while policymakers play an essential role in fostering social projects and creating the regulations and incentives supply-chain operators need (Barbosa & Cansino, 2024). Although existing studies have not extensively examined the direct effect of GI on the CS-FVCP link, government regulation positively moderates the relationship between supply chain strategy and supply chain trust. This suggests that government influence strengthens firms' sustainability-oriented approaches. Consequently, these approaches extend to community activities as well. Conversely, weak government policy and incentive schemes are cited as a major obstacle to sustainability practices, including CE adoption, in the FSC (Kumar et al., 2023).

H5: Government Incentives moderate a significant and positive relationship between community support and FVCP.

3. METHODOLOGY

3.1. Research Design

This study uses a quantitative research approach, in which scholars generate knowledge through observation or experimentation. This method is particularly well suited to test complex relationships and hypotheses (Sells et al., 1995). The study adopts a cross-sectional survey design, in the theoretical model at a single point in time.

This method is well suited to detecting and assessing the effects of factors on performance and to confirming theoretical propositions derived through other means. To mitigate potential data collection issues, this study examines common method bias (CMB), a frequent concern in self-administered cross-sectional surveys. This approach, commonly used for complex models of supply chain performance, typically employs Partial Least Squares Structural Equation Modelling (PLS-SEM).

3.2. Population and Sampling

3.2.1. Target Population

The target population comprises individuals involved in implementing strategic decisions and operational policies within the food sector or manufacturing organisations. Managers, directors, owners and senior managers of food manufacturing enterprises serve as the units of analysis.

3.2.2. Sampling Frame and Technique

The sampling frame drew on lists from industry bodies and databases, including the Federation of Malaysian Manufacturers (FMM), the Malaysian Food and Beverage Executives Association, the Malaysian Trade Development Corporation (MATRADE), the Farmers Organisation Authority (FOA), the Malaysian Franchise Association (food and beverage industries) and industry-specific boards within the Ministry of Agriculture and Food Industries (MAFI).

The study employed purposive stratified sampling, a non-probability method widely used in research to identify respondents with the knowledge needed to address the research questions. This ensured the inclusion of top managers, owners, or senior operations staff with more than two years of relevant experience, capturing decision-makers with first-hand knowledge of supply chain practices, innovation adoption, and organisational capabilities.

The stratification factor involved classification by business size (small, medium, large), position in the value chain (upstream, midstream, downstream), and geographical distribution across Malaysian states, ensuring adequate representation across categories. Where a stratum's population was small, a census approach captured all available members to maximise data points and representativeness.

3.2.3. Sample Size Determination

Sample size determination is crucial for multivariate methods such as PLS-SEM, which performs well even with moderate sample sizes. Using G*Power with a statistical power of 0.85 and a significance level of 0.05, and assuming a medium effect size ($f^2 = 0.15$) and five predictors in the most complex model, the minimum required sample was 92 respondents. Our final sample of N = 171 exceeds this minimum and is adequate for the structural paths in the PLS-SEM analyses. However, the added complexity of moderation, non-linear, and necessity analyses may warrant more conservative inference.

3.3. Data Collection Procedure

3.3.1. Survey Instrument Development

To increase validity and reliability, the survey instrument included multi-item construct measures adapted from established scales in the existing literature (Azman Ong et al., 2023) with indicators measured on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree).

3.3.2. Pilot Study

A pilot study with 20 respondents, involving academic and industry professionals, refined the instrument's clarity, completeness, readability, and suitability. Ambiguous items were modified and, where necessary, pruned based on expert feedback.

3.3.3. Main Survey Procedures

The survey was administered online via Google Forms and distributed by email over four weeks in December 2025. Respondents were predominantly senior managers familiar with organisational policy and strategy. To mitigate non-response bias, follow-up emails were sent, and a cover letter clearly stated the study's purpose, benefits, and confidentiality guarantee.

3.4. Data Analysis Techniques

Data analysis followed a two-step approach. SPSS version 27.0 was used for descriptive statistics and demographic profiling, including frequency distributions, measures of central tendency, and cross-tabulations. PLS-SEM, implemented in SmartPLS 4.1.0.9, was the primary technique for hypothesis testing. This variance-based method is robust to non-normal data, performs well with smaller samples, and is well suited to assessing predictive relationships among latent constructs (Hair et al., 2011).

PLS-SEM evaluates both the measurement model (reliability and validity) and the structural model (hypothesised relationships) simultaneously, and performs well with complex models involving multiple mediating and moderating effects central to FVC activities. Its predictive orientation aligns with the study's goal of identifying factors that shape organisational performance and innovation adoption.

4. RESULTS AND DISCUSSION

4.1. Demographic Profile

Table 1 details the demographic characteristics of the 171 respondents. The sample is well balanced across organisational and geographical dimensions. Medium-sized organisations (51-250 employees) account for the largest share (42.7%), followed by large firms (38.0%) and small enterprises (19.3%). Value chain positions are similarly well distributed: midstream (38.6%), upstream (36.3%), and downstream (25.1%), covering the full farm-to-fork continuum. Geographically, the sample spans the Central/Western (33.9%), Southern (24.0%), Northern (22.2%), and Eastern (19.9%) regions.

Respondent profiles reflect high-level expertise: 43.9% are managing directors or owners, 32.7% are operations managers, 15.2% are sustainability coordinators, and 8.2% are supply chain managers. Most practitioners have 6-10 years of experience (57.3%), 24.0% have 11-15 years, 10.5% have more than 15 years, and only 8.2% have 2-5 years. Represented sectors include fresh produce and vegetables (28.1%), processed foods and beverages (24.6%), dairy and meat products (18.1%), grain and cereal products (15.8%), and speciality foods (13.5%).

Table 1: Demographic Profile of Respondents

Characteristic	Category	Frequency	Percentage (%)
Firm's Size	Small (< 50 employees)	33	19.3
	Medium (51-250 employees)	73	42.7
	Large (>251 employees)	65	38.0
Value Chain Position	Upstream (Production/Farming)	62	36.3
	Midstream (Processing/Manufacturing)	66	38.6
	Downstream (Distribution/Retail)	43	25.1
Geographical Location	Northern Region	38	22.2
	Southern Region	41	24.0
	Central/Western Region	58	33.9
	Eastern Region	34	19.9
Position/Role	Managing Director/Owner	75	43.9
	Operations Manager	56	32.7
	Supply Chain Manager	26	15.2
	Sustainability Coordinator	14	8.2
Work Experience	2-5 years	14	8.2
	6-10 years	98	57.3
	11-15 years	41	24.0
	More than 15 years	18	10.5
Industry Sector	Fresh Produce & Vegetables	48	28.1
	Processed Foods & Beverages	42	24.6
	Dairy & Meat Products	31	18.1
	Grain & Cereal Products	27	15.8
	Speciality Food Products	23	13.5

4.2. Common Method Bias

Procedural remedies were used during data collection to minimise the effects of social desirability bias and CMB. Particularly, respondents received a cover letter assuring complete anonymity and confidentiality to reduce evaluation apprehension (Kock et al., 2021). CMB was assessed statistically using Harman's single-factor test (Bora Semiz & Paylan, 2023) and a complete collinearity analysis (Kock, 2017). Table 2 shows that all constructs have VIF values between 1.315 and 2.477. All VIFs are below the conservative threshold of 3.3, indicating no severe multicollinearity in the model and that multicollinearity is not a major issue (Guevara-Otero et al., 2026). These post-hoc tests do not prove that there is no CMB, but they do indicate that the path coefficient estimates are sufficiently reliable for analysis.

Table 2: Full Collinearity

Item	CS	Env	FVCP	GI	Org	Tech
VIF	2.477	2.042	1.315	2.192	2.139	2.310

4.3. *Measurement Model Assessment*

To test for convergent validity, the measurement model was evaluated by examining the standardised factor loadings, composite reliability (CR), and average variance extracted (AVE) (Cheung et al., 2024). Table 3 shows that all constructs have good convergent validity. The empirical results demonstrate outer loadings ranging from 0.713 to 0.914. Several indicators (CS 4 at 0.713 and Env 1 at 0.715) are near the lower bound of the preferred range (0.70), but they were retained despite not meeting the construct-reliability criteria. Thus, the CR values (0.851–0.894) and AVE values (0.589–0.679) are all well above the recommended values of 0.7 and 0.5, respectively. As the lower-loading indicators are sufficiently reliable and valid, their deletion is not statistically required (Hair et al., 2011).

Table 3: Convergent Validity

Variable	Item	Outer Loading	CR	AVE
Community Support	CS 1	0.730	0.851	0.589
	CS 2	0.860		
	CS 3	0.759		
	CS 4	0.713		
Environmental	Env 1	0.715	0.863	0.614
	Env 2	0.754		
	Env 3	0.832		
	Env 4	0.826		
Food Value Chain Performance	FVCP 1	0.776	0.873	0.633
	FVCP 2	0.791		
	FVCP 3	0.786		
	FVCP 4	0.828		
Government Incentives	GI 1	0.914	0.891	0.672
	GI 2	0.814		
	GI 3	0.726		
	GI 4	0.816		
	Org 1	0.724	0.865	0.616
Organisational	Org 2	0.795		
	Org 3	0.817		
	Org 4	0.800		
Technological	Tech 1	0.847	0.894	0.679
	Tech 2	0.901		

	Tech 3	0.733
	Tech 4	0.806

4.4. *Discriminant Validity*

Discriminant validity assesses how well a construct can be distinguished from unrelated measures (Roemer et al., 2021). This evaluation utilised the HTMT ratio, where values below 0.85 indicate good discriminant validity, although values up to 0.90 may be accepted for conceptually similar constructs (Bora Semiz & Paylan, 2023; Henseler et al., 2015). The analysis revealed that most HTMT ratios are significantly under 0.85, while some relationships, specifically between CS and GI (0.796) and CS and Env (0.827), approach this threshold, indicating some conceptual overlap. To bolster the validity claims, bootstrapped HTMT confidence intervals were assessed and confirmed that none contained 1.0, which provides robust support for discriminant validity (Henseler et al., 2015). Additionally, the interaction term (GI x CS) showed HTMT ratios well beneath critical limits, endorsing the independence of the moderator. Overall, the findings affirm that the measurement model maintains good discriminant validity.

Table 4: HTMT

Item	CS	Env	FVCP	GI	Org	Tech	GI x CS
CS							
Env	0.827						
FVCP	0.555	0.488					
GI	0.796	0.784	0.507				
Org	0.694	0.473	0.342	0.524			
Tech	0.684	0.507	0.259	0.625	0.829		
GI x CS	0.783	0.703	0.226	0.590	0.419	0.395	

4.5. *The Endogeneity Test using Gaussian Copula*

Endogeneity is a persistent concern in supply chain sustainability research, often arising from unobserved management attitudes or reverse causality, whereby higher-performing firms invest more in environmental cooperation. This was examined using the Gaussian copula approach, which estimates regression models without instrumental variables by exploiting the correlation of the potentially endogenous regressor's error term (Becker et al., 2022); a copula-term p-value below 0.05 indicates significant endogeneity.

Table 5 shows that only the ENV-FVCP relationship, exhibits significant non-linearity ($\beta = 0.470$, $p = 0.016$; 95% CI [0.186, 0.904]), suggesting environmental factors may influence FVCP through complex, non-linear pathways. Since Gaussian copula estimation ideally requires samples above 200 (Becker et al., 2022), we interpret this finding conservatively as exploratory and warrant validation in future large-scale studies. We found no significant endogeneity for the technological, organisational, or CS dimensions ($p > 0.05$).

Table 5: Gaussian Copula

Path	STD Beta	STD DEV	T Value	P values	LCL 5%	UCL 95%
GC (Tech -> FVCP) -> FVCP	0.106	0.160	0.661	0.254	-0.126	0.398
GC (Org -> FVCP) -> FVCP	0.149	0.198	0.752	0.226	-0.153	0.498
GC (Env -> FVCP) -> FVCP	0.470	0.220	2.137	0.016	0.186	0.904
GC (CS -> FVCP) -> FVCP	0.032	0.149	0.216	0.414	-0.200	0.290

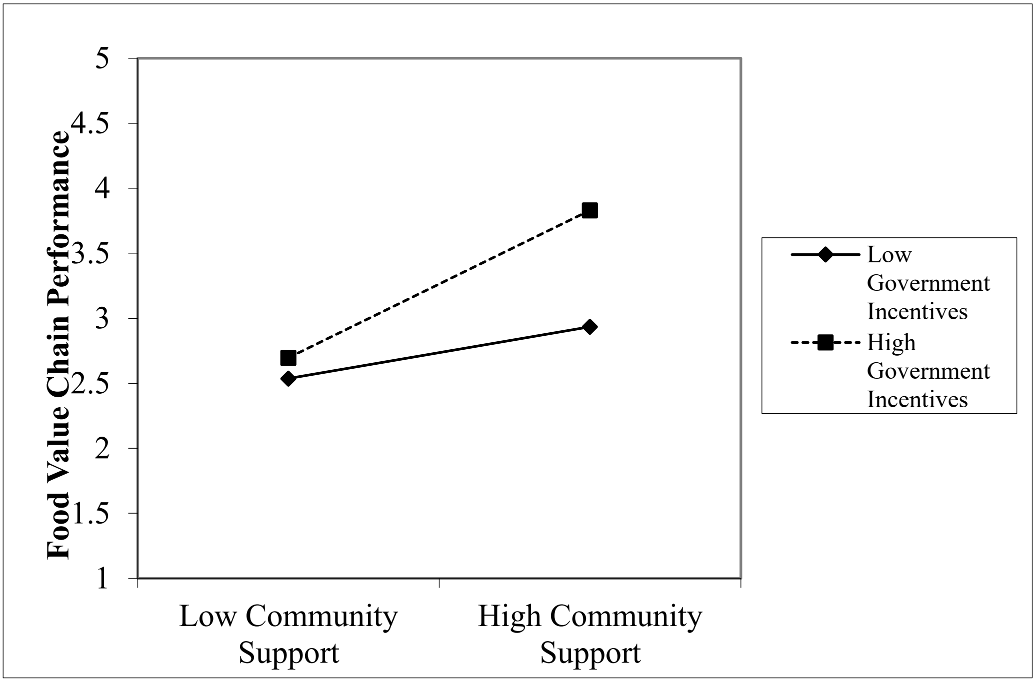
4.6. Hypotheses Testing

The results of the direct effect (Table 6) indicate that all four predictors significantly predict FVCP. Technological factors significantly and positively affect FVCP ($\beta = 0.197$, $p = 0.012$), although the effect size is small (f2 = 0.026), suggesting limited practical impact. Organisational factors also positively influence FVCP ($\beta = 0.145$, $p = 0.047$); however, with a very small effect size ($f^2 = 0.014$), their impact is statistically significant but not practically substantial. Environmental factors also have a positive and significant effect on FVCP ($\beta = 0.205$, $p = 0.044$) with a small effect size (f2 = 0.032), contributing moderately to the model. Notably, the direct impact of CS factors on FVCP ($\beta = 0.383$, $p = 0.004$) and the corresponding effect size ($f^2 = 0.078$) are the largest among the predictors, indicating that these factors have a greater impact on FVCP than the others. Figure 2 illustrates the moderation effect of GI on the relationship between CS and FVCP. The interaction plot shows that the positive relationship between CS and FVCP is strengthened at higher levels of GI. Thus, when GI is high, CS's impact on FVCP becomes more pronounced. This empirical evidence supports the significant moderation effect reported in Table 6 ($\beta = 0.184$, $p = 0.016$), although the effect size remains small ($f^2 = 0.034$).

Table 6: Direct and Moderation Effect

Direct Effect								
Hypo	**Path**	**STD Beta**	**STD DEV**	**T Value**	**P values**	**LCL 5%**	**UCL 95%**	**f^2**
H1	Tech -> FVCP	0.197	0.087	2.252	0.012	0.355	0.072	0.026
H2	Org -> FVCP	0.145	0.087	1.670	0.047	0.006	0.287	0.014
H3	Env -> FVCP	0.205	0.121	1.701	0.044	0.018	0.408	0.032
H4	CS -> FVCP	0.383	0.143	2.674	0.004	0.175	0.651	0.078
Moderation Effect								
Hypo	**Path**	**STD Beta**	**STD DEV**	**T Value**	**P values**	**LCL 5%**	**UCL 95%**	**v^2**
H5	GI x CS -> FVCP	0.184	0.086	2.150	0.016	0.063	0.350	0.034

Figure 2: Moderation Effect



4.7. PLS-Predict

PLS-Predict evaluates the out-of-sample predictive power of a PLS-SEM model, using predictive relevance (Q^2) obtained through blindfolding. This sample-reuse procedure excludes and re-predicts data points (Hair et al., 2011). According to Table 7, all FVCP items report positive Q^2predict values (0.046-0.179), confirming meaningful out-of-sample predictive relevance. Comparing PLS-SEM RMSE values with linear-model and naive-benchmark RMSE shows PLS-SEM performing marginally better across all items, indicating reasonable overall predictive power.

Table 7: PLS- Predict

Item	Q²predict	PLS-SEM_RMSE	LM_RMSE	IA_RMSE	PLS-LM	PLS-IA
FVCP 1	0.046	0.613	0.661	0.628	-0.048	-0.015
FVCP 2	0.103	0.549	0.583	0.580	-0.034	-0.031
FVCP 3	0.123	0.597	0.662	0.637	-0.065	-0.040
FVCP 4	0.179	0.557	0.567	0.615	-0.010	-0.058

4.8. Necessary Condition Analysis

Necessary Condition Analysis (NCA) identifies prerequisite factors for a desired outcome using necessity logic. This approach differs from the sufficiency logic underlying PLS-SEM, which merely shows that performance improves on average as predictors increase. Instead, NCA identifies critical bottlenecks whose presence is required, though not sufficient, for a given performance level (Hauff et al., 2024).

NCA effect size (d) is assessed using ceiling-line methods applied to the scatter plot's ceiling zone, with significance assessed via an approximate permutation test (Hauff et al., 2024). A necessary condition is supported by a medium effect size ($d \geq 0.1$) and p-value < 0.05 (Dul, 2024); the accompanying bottleneck table (Table 8) identifies the conditions critical to achieving specific outcome levels.

CE-FDH results show statistically significant necessity effects for CS ($d = 0.139$, $p = 0.001$), Env ($d = 0.103$, $p = 0.033$), GI ($d = 0.115$, $p = 0.015$), and Tech ($d = 0.092$, $p = 0.050$). At the same time, organisational factors did not meet the necessity threshold ($d = 0.013$, $p = 0.473$). Table 9 and Figure 3 show that no predictors are required at low FVCP levels (0-30%). However, requirements for GI, CS, environmental, and technological factors remain and increase substantially as FVCP rises above 40% toward 100%. Organisational factors are not necessary across the full range. Overall, CS, environmental factors, GI, and technological factors represent conditions that must be met to achieve high FVCP.

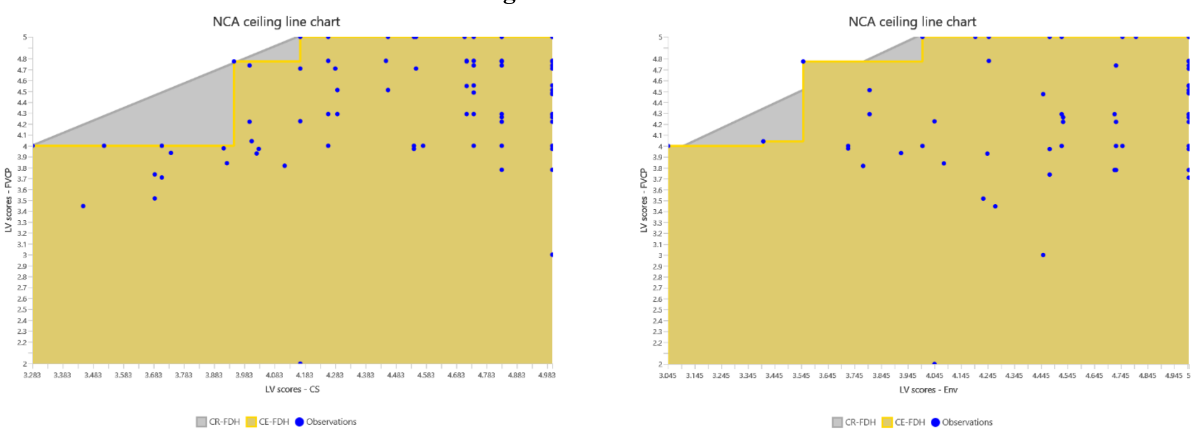
Table 8: NCA

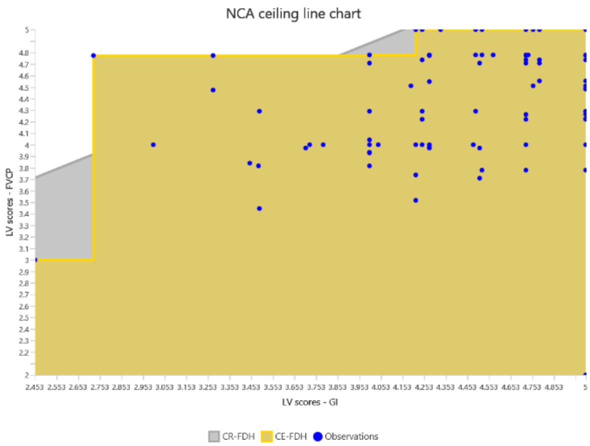
Items	CE-FDH	Permutation p-value
CS	0.139	0.001
Env	0.103	0.033
GI	0.115	0.015
Org	0.013	0.473
Tech	0.092	0.050

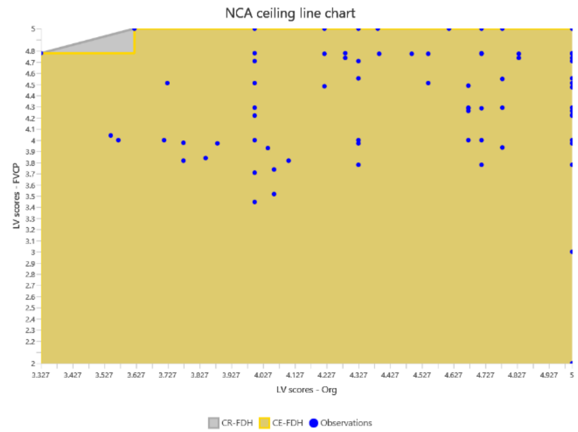
Table 9: Bottleneck Analysis

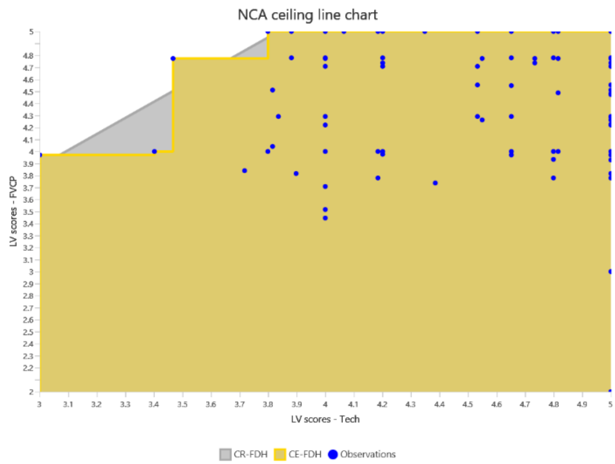
Percentage (%)	FVCP	CS	Env	GI	Org	Tech
0.00	2.000	0.000	0.000	0.000	0.000	0.000
10.00	2.300	0.000	0.000	0.000	0.000	0.000
20.00	2.600	0.000	0.000	0.000	0.000	0.000
30.00	2.900	0.000	0.000	0.000	0.000	0.000
40.00	3.200	0.000	0.000	0.585	0.000	0.000
50.00	3.500	0.000	0.000	0.585	0.000	0.000
60.00	3.800	0.000	0.000	0.585	0.000	0.000
70.00	4.100	5.848	1.170	0.585	0.000	1.754
80.00	4.400	5.848	1.170	0.585	0.000	1.754
90.00	4.700	5.848	1.170	0.585	0.000	1.754
100.00	5.000	11.111	6.433	12.865	2.339	2.924

Figure 3: NCA Charts









5. CONCLUSION

5.1. Discussion

This study addresses key gaps in FVCP knowledge by building an integrated theory that captures the complex interplay of technological, organisational, environmental, and community factors, together with the moderating role of GI. Motivated by the finding that one-third of the world's food production is wasted, and by the urgency of achieving SDG 2 (Zero hunger) and SDG 12 (Responsible Consumption and Production), this study identifies the variables that make sustainable FVCP achievable in developing economies such as Malaysia.

The results directly answer the research questions. For RQ1, all four variables significantly affect FVCP, with community support the strongest predictor, followed by environmental collaboration, underscoring the centrality of multi-stakeholder engagement in managing food loss and waste. For

H1, technological factors have a significant but practically modest effect on FVCP. Advanced technologies such as blockchain, IoT, and AI demand investment, workflow adjustment, and specialised skills that many Malaysian food enterprises struggle to afford, and inadequate digital infrastructure and literacy can turn technology from an enabler into an operational challenge.

For H2, organisational factors are statistically significant but practically negligible (f^2 = 0.014), indicating that internal flexibility and coordination alone are weak levers for improving performance in resource-poor food systems unless integrated with external community networks. For H3, environmental factors show a small but significant positive effect, possibly reflecting limited environmental awareness and data-sharing tools at this early stage of the industry's green transition. Exploratory Gaussian copula results also point to a tentative non-linear threshold effect, worth validating in future large-scale research.

For H4, community support is the strongest predictor of FVCP, reflecting the roles of NGOs, civil society, and research institutions in knowledge transfer, capacity building, and trust-building. NCA results reinforce this: community support has a medium necessity effect (d = 0.139) and functions as a necessary condition (Hauff et al., 2024), meaning a minimum level of social integration is required for high FVCP even though it does not guarantee it. This separation of necessity from sufficiency is a theoretical contribution that extends the TOE and NRBV frameworks.

For H5, GI significantly strengthens the effect of community support on FVCP. However, the moderation effect size is small (f^2 = 0.034), suggesting an implementation gap or funding shortfall that limits the practical influence of current incentives. GI should therefore complement, not substitute for, community-led efforts.

Overall, these findings address the study's central research problem. Most notably, our study focuses on the gap between the well-established importance of FVCP for global sustainability and the persistent failure to achieve it in practice. By showing that community support and environmental collaboration, reinforced by GI, can drive FVCP even in resource-constrained contexts, this study offers a roadmap for moving from linear supply chains to coordinated, value-retaining networks, aligned with SDG targets.

5.2. Implications

5.2.1. Theoretical Implications

This study extends understanding of the NRBV and TOE frameworks in supply chain management, particularly in developing economies such as Malaysia. Sustainable competitive advantage in food systems arises from a strategic combination of internal resources, inter-organisational relations, and environmental stewardship rather than any single factor, highlighting the role of GI in helping organisations manage environmental resources effectively. The study extends TOE by positioning CS as a crucial element shaping organisational capability and value chain performance, with empirical evidence that community engagement is the strongest predictor of firm performance, underscoring the value of collaborative networks with NGOs for resource-constrained firms.

GI strengthens the link between community engagement and FVCP by providing financial backing and legitimacy to sustainability initiatives, lowering collaboration costs, and encouraging broader stakeholder participation. Subsidies and grants build organisations' and small-holders' capacity and infrastructure, while governmental frameworks align actors towards shared goals and build the trust needed for multi-stakeholder collaboration.

The study challenges the assumption that technology adoption is always beneficial, showing instead that its value depends on implementation context and organisational capability. Technology adoption is a complex process involving disruption and resource reallocation; in resource-limited settings, its costs can be high, and success depends on supportive infrastructure, a skilled workforce, and organisational readiness. Environmental technologies, in particular, require complementary organisational capabilities and institutional backing to yield competitive benefits.

5.2.2. Practical Implications

The results offer practical, contextual, effect-size-prioritised recommendations for the Malaysian food sector. The foremost priority is grassroots community integration: policymakers should favour targeted initiatives that empower existing NGOs and Farmer-Producer Organisations (FPOs) over sweeping national programmes. The second priority is targeted micro-incentives, such as accessible microgrants and tax relief for small-holders, rather than broad microloan schemes. The third priority is phased, pragmatic technology adoption, using low-cost capacity-building programmes and local demonstration farms rather than high-technology mandates, introducing technology gradually without imposing an undue financial burden on resource-constrained enterprises.

The Malaysian food industry should encourage all practitioners, from small-holder farmers to large distributors, to form or join FPOs and cooperatives that enable resource sharing and collective bargaining. Collaboration with academic institutions can build technical skills, sustainability certification can help firms attract premium buyers, and regional supply chain groups and shared processing infrastructure can reduce costs and improve environmental performance. Technology adoption should scale with firm size, from basic tools for small enterprises to inventory systems for medium firms and advanced technologies such as blockchain for large firms, supported by government risk-mitigation programmes and networks such as MATRADE and SME Corp Malaysia.

Malaysian NGOs can also serve as intermediaries, linking GI to local sustainability efforts and offering accessible programmes for small-holders and technical guidance for larger enterprises. Learning networks that incorporate indigenous knowledge and document successful innovations in food waste reduction and organic farming can support broader implementation. At the same time, collaboration with research institutions strengthens evidence-based policy advocacy.

5.3. Limitation and recommendation

Several methodological limitations are acknowledged. First, the purposive stratified sampling approach, while necessary to reach knowledgeable decision-makers, is a non-probability method that limits generalisability to the wider Malaysian food sector. Second, reliance on self-reported, single-respondent, cross-sectional data raises the risk of common method bias and social desirability bias; although mitigated through confidentiality assurances and post-hoc Harman's and VIF tests, future research should adopt stronger remedies, such as marker variables, multi-respondent data, or temporal separation.

The sample of 171 is adequate for standard PLS-SEM. Still, it is somewhat small for more advanced techniques such as the Gaussian copula and NCA, which ideally require a sample above 200 to capture non-linearity and endogeneity reliably. The cross-sectional design also precludes causal inference and the observation of temporal or lagged effects, particularly relevant to technology adoption.

Beyond methodological constraints, the study did not account for contextual factors such as market conditions, value chain positioning, and infrastructure quality, and it operationalised social and environmental indicators in a limited way that does not fully capture the mechanisms driving the observed relationships. Practical evaluation of implementation costs and trade-offs, along with contemporary dynamics such as climate resilience and post-pandemic structural shifts, were similarly beyond its scope. These gaps point to valuable directions for future, contextualised research on FVCP.

5.4. *Conclusion*

This study develops a comprehensive model of FVCP, showing that optimal outcomes arise from the interplay of community support, environmental collaboration, organisational capabilities, and supportive government incentives. CS is the most critical determinant, showcasing the pivotal role of NGOs, academic institutions, and local communities in enhancing social capital and knowledge transfer. This core finding directly advances SDG 17 (Partnerships for the Goals): multi-stakeholder partnerships are structurally essential for food value chain optimisation. This integrated framework supports SDG 2 (Zero hunger), specifically Target 2.1 (year-round food access) and Target 2.3 (doubling productivity and incomes of small-scale food producers), by securing food availability, resilience, and economic viability in developing economies. The study reinforces SDG 12 (Responsible Consumption and Production), particularly Target 12.3 (halving food waste and loss along production and supply chains). The significant effects of environmental collaboration and community support show that reducing food loss is a collective responsibility rather than an isolated, firm-level concern. Technological and organisational capabilities, though statistically significant, have small effect sizes, highlighting that firm-level adjustments have limited impact unless embedded in robust community networks and targeted policy interventions. GI act as a vital catalyst that strengthens, rather than replaces, community-driven sustainability initiatives. This study provides an empirical roadmap for policy interventions and practitioner action, showing that aligning multi-stakeholder collaboration with the SDGs can transition linear, wasteful supply chains into sustainable, resilient, value-retaining food networks.

ACKNOWLEDGEMENT

This study is funded by an FRGS grant from the Malaysian Ministry of Higher Education (MOHE), with project IDs FRGS/1/2025/SS01/UMPSA/01/2 and RDU250114. The authors express gratitude to the Division of Research and Innovation at Universiti Malaysia Pahang Al Sultan Abdullah (UMPSA) for supporting this study.

REFERENCES

Anastasiadis, F., Manikas, I., Apostolidou, I., & Wahbeh, S. (2022). The role of traceability in end-to-end circular agri-food supply chains. *Industrial Marketing Management*, *104*, 196–211. https://doi.org/10.1016/j.indmarman.2022.04.021

Azman Ong, M. H., Yusri, M. Y., & Ibrahim, N. S. (2023). Use and behavioural intention using digital payment systems among rural residents: Extending the UTAUT-2 model. *Technology in Society*, *74*. https://doi.org/10.1016/j.techsoc.2023.102305

Barbosa, M. W., & Cansino, J. M. (2024). The impacts of environmental collaboration on the environmental performance of agri-food supply chains: a mediation-moderation analysis of external pressures. *International Journal of Logistics Research and Applications*, *27*(12), 2712–2736. https://doi.org/10.1080/13675567.2024.2310024

Barbosa, M. W., Ladeira, M. B., de Oliveira, M. P. V., de Oliveira, V. M., & de Sousa, P. R. (2022). The effects of internationalisation orientation in the sustainable performance of the agri-food industry through environmental collaboration: An emerging economy perspective. *Sustainable Production and Consumption*, *31*, 407–418. https://doi.org/10.1016/j.spc.2022.03.013

Becker, J. M., Proksch, D., & Ringle, C. M. (2022). Revisiting Gaussian copulas to handle endogenous regressors. *Journal of the Academy of Marketing Science*, *50*(1), 46–66. https://doi.org/10.1007/s11747-021-00805-y

Bhattacharya, A., & Fayezi, S. (2021). Ameliorating food loss and waste in the supply chain through multi-stakeholder collaboration. *Industrial Marketing Management*, *93*, 328–343. https://doi.org/10.1016/j.indmarman.2021.01.009

Bora Semiz, B., & Paylan, M. ali. (2023). A study on the mediating effect of brand trust between perceived legitimacy of influencers and attitude toward brand: evidence from Turkey. *Asia Pacific Journal of Marketing and Logistics*, *35*(9), 2181–2197. https://doi.org/10.1108/APJML-08-2022-0702

Chatterjee, S., & Chaudhuri, R. (2022). Supply chain sustainability during turbulent environment: Examining the role of firm capabilities and government regulation. *Operations Management Research*, *15*(3–4), 1081–1095. https://doi.org/10.1007/s12063-021-00203-1

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, *41*(2), 745–783. https://doi.org/10.1007/s10490-023-09871-y

Chittipaka, V., Kumar, S., Sivarajah, U., Bowden, J. L. H., & Baral, M. M. (2023). Blockchain Technology for Supply Chains operating in emerging markets: an empirical examination of technology-organisation-environment (TOE) framework. *Annals of Operations Research*, *327*(1), 465–492. https://doi.org/10.1007/s10479-022-04801-5

Corallo, A., De Giovanni, M., Latino, M. E., & Menegoli, M. (2024). Leveraging on technology and sustainability to innovate the supply chain: a proposal of agri-food value chain model. *Supply Chain Management*, *29*(3), 661–683. https://doi.org/10.1108/SCM-12-2022-0484

Dora, M., Kumar, A., Kamal, M. M., Mangla, S. K., & Pant, A. (2021). *Critical Success Factors Influencing Artificial Intelligence Adoption in the Food Supply Chains*. https://doi.org/doi.org/10.1080/00207543.2021.1959665

Dul, J. (2024). A different causal perspective with Necessary Condition Analysis. *Journal of Business Research*, *177*. https://doi.org/10.1016/j.jbusres.2024.114618

Guevara-Otero, N., Vargas-Perez, A. M., Rodríguez-Rudi, G., & Sablón-Cossio, N. (2026). Driving intentions to adopt circular business models in SMEs: the impact of entrepreneurial orientation and the mediating role of corporate social responsibility. *Journal of Technology Transfer*. https://doi.org/10.1007/s10961-025-10312-9

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hauff, S., Richter, N. F., Sarstedt, M., & Ringle, C. M. (2024). Importance and performance in PLS-SEM and NCA: Introducing the combined importance-performance map analysis (cIPMA). *Journal of Retailing and Consumer Services*, *78*. https://doi.org/10.1016/j.jretconser.2024.103723

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Khan, S., Kaushik, M. K., Kumar, R., & Khan, W. (2023). Investigating the barriers of blockchain technology integrated food supply chain: a BWM approach. *Benchmarking*, *30*(3), 713–735. https://doi.org/10.1108/BIJ-08-2021-0489

Kock, F., Berbekova, A., & Assaf, A. G. (2021). Understanding and managing the threat of common method bias: Detection, prevention and control. *Tourism Management*, *86*. https://doi.org/10.1016/j.tourman.2021.104330

Kock, N. (2017). Common method bias: A full collinearity assessmentmethod for PLS-SEM. In *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications* (pp. 245–257). Springer International Publishing. https://doi.org/10.1007/978-3-319-64069-3_11

Krishnan, R., Yen, P., Agarwal, R., Arshinder, K., & Bajada, C. (2021). Collaborative innovation and sustainability in the food supply chain- evidence from farmer-producer organisations. *Resources, Conservation and Recycling*, 168, 105253. https://doi.org/10.1016/j.resconrec.2020.105253

Kumar, M., Raut, R. D., Jagtap, S., & Choubey, V. K. (2023). Circular economy adoption challenges in the food supply chain for sustainable development. *Business Strategy and the Environment*, *32*(4), 1334–1356. https://doi.org/10.1002/bse.3191

Kumar, M., Sharma, M., Raut, R. D., Mangla, S. K., & Choubey, V. K. (2022). Performance assessment of circular driven sustainable agri-food supply chain towards achieving sustainable consumption and production. *Journal of Cleaner Production*, *372*. https://doi.org/10.1016/j.jclepro.2022.133698

Kumar, S., Raut, R. D., Agrawal, N., Cheikhrouhou, N., Sharma, M., & Daim, T. (2022). Integrated blockchain and internet of things in the food supply chain: Adoption barriers. *Technovation*, *118*. https://doi.org/10.1016/j.technovation.2022.102589

Marusak, A., Sadeghiamirshahidi, N., Krejci, C. C., Mittal, A., Beckwith, S., Cantu, J., Morris, M., & Grimm, J. (2021). Resilient regional food supply chains and rethinking the way forward: Key takeaways from the COVID-19 pandemic. *Agricultural Systems*, *190*. https://doi.org/10.1016/j.agsy.2021.103101

Mehmood, A., Ahmed, S., Viza, E., Bogush, A., & Ayyub, R. M. (2021). Drivers and barriers towards circular economy in agri-food supply chain: A review. *Business Strategy and Development*, *4*(4), 465–481. https://doi.org/10.1002/bsd2.171

Mishra, R., Singh, R. K., & Subramanian, N. (2022). Impact of disruptions in agri-food supply chain due to COVID-19 pandemic: contextualised resilience framework to achieve operational excellence. *International Journal of Logistics Management*, *33*(3), 926–954. https://doi.org/10.1108/IJLM-01-2021-0043

Montalbano, P., & Nenci, S. (2022). Does global value chain participation and positioning in the agriculture and food sectors affect economic performance? A global assessment. *Food Policy*, *108*. https://doi.org/10.1016/j.foodpol.2022.102235

Oguntegbe, K. F., Di Paola, N., & Vona, R. (2022). Behavioural antecedents to blockchain implementation in agrifood supply chain management: A thematic analysis. *Technology in Society*, *68*. https://doi.org/10.1016/j.techsoc.2022.101927

Owusu Kwateng, K., Tetteh, F. K., Atchulo, H. Ben, & Opoku-Mensah, S. (2022). Effect of corporate environmental strategies on firms' competitiveness, the mediating role of supply chain collaboration. *Journal of Global Responsibility*, *13*(3), 299–316. https://doi.org/10.1108/JGR-02-2021-0026

Ramos, E., Patrucco, A. S., & Chavez, M. (2023). Dynamic capabilities in the "new normal": a study of organisational flexibility, integration and agility in the Peruvian coffee supply chain. *Supply Chain Management*, *28*(1), 55–73. https://doi.org/10.1108/SCM-12-2020-0620

Roemer, E., Schuberth, F., & Henseler, J. (2021). HTMT2–an improved criterion for assessing discriminant validity in structural equation modeling. *Industrial Management and Data Systems*, *121*(12), 2637–2650. https://doi.org/10.1108/IMDS-02-2021-0082

Sells, S. P., Edward Smith, T., & Sprenkle, D. H. (1995). Integrating Qualitative and Quantitative Research Methods: A Research Model. In *Fam Proc* (Vol. 34). Steinglass.

Shah, N., & Soomro, B. A. (2021). Internal green integration and environmental performance: The predictive power of proactive environmental strategy, greening the supplier, and environmental collaboration with the supplier. *Business Strategy and the Environment*, *30*(2), 1333–1344. https://doi.org/10.1002/bse.2687

Sharma, A., Sharma, A., Singh, R. K., & Bhatia, T. (2023). Blockchain adoption in agri-food supply chain management: an empirical study of the main drivers using extended UTAUT. *Business Process Management Journal*, *29*(3), 737–756. https://doi.org/10.1108/BPMJ-10-2022-0543

Stranieri, S., Riccardi, F., Meuwissen, M. P. M., & Soregaroli, C. (2021). Exploring the impact of blockchain on the performance of agri-food supply chains. *Food Control*, *119*. https://doi.org/10.1016/j.foodcont.2020.107495

Yang, Y., Kobbacy, Y., Onofrei, G., & Nguyen, H. (2023). Entrepreneurial strategies for coping with supply chain disruptions in the grocery-retail sector. *Journal of Small Business and Enterprise Development*, *30*(2), 213–233. https://doi.org/10.1108/JSBED-04-2022-0201

Yontar, E. (2023). Critical success factor analysis of blockchain technology in agri-food supply chain management: A circular economy perspective. *Journal of Environmental Management*, *330*. https://doi.org/10.1016/j.jenvman.2022.117173

Zhao, G., Hormazabal, J. H., Elgueta, S., Manzur, J. P., Liu, S., Chen, H., Lopez, C., Kasturiratne, D., & Chen, X. (2021). The impact of knowledge governance mechanisms on supply chain performance: empirical evidence from the agri-food industry. *Production Planning and Control*, *32*(15), 1313–1336. https://doi.org/10.1080/09537287.2020.1809023