

HIERARCHICAL CAUSAL MAPPING AND PRIORITISATION OF POST-HARVEST FISH LOSSES RISK IN AQUACULTURE SUPPLY CHAIN USING AN INTEGRATED FDM-FDEMATEL

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ARTICLE INFO	ABSTRACT
<i>Article history:</i> Received: October 2025 Received in the revised form: March 2026 Accepted: April 2026 <i>Keywords:</i> Post-Harvest Fish Losses, Aquaculture Supply Chain, Hierarchical Causal Analysis, Risk Factors Prioritization	Post-Harvest Fish Losses (PHFL) remain a significant constraint in the aquaculture supply chain, where rapid quality deterioration can reduce the value and availability of food, especially in tropical contexts such as Indonesia. Prior PHFL research is dominated by capture-fisheries studies and primarily descriptive evidence, leaving aquaculture-specific, multi-echelon causal mechanisms, particularly those related to processing capabilities and supporting infrastructure, that are not sufficiently prioritized. This study develops a causal mapping and prioritization framework for PHFL risk factors for a sustainable aquaculture supply chain using an integrated Fuzzy Delphi Method (FDM) and Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL) approach. Judgments from 23 experts representing four echelons (farmers, intermediaries, processors, retailers/consumers) were elicited to screen and structure risks under uncertainty. FDM retained 17 key risk factors from 30 candidates. FDEMATEL then produced a prioritized causal structure, in which inadequate harvesting techniques and equipment (RF17), limited cold-chain availability (RF21), and inadequate handling techniques and equipment (RF18) emerge as the strongest causal drivers, shaping downstream outcomes related to safety, storage, and market performance. Theoretically, the study contributes a two-level (hierarchical) causal architecture (aspect and risk-factor levels) that moves beyond determinant lists to explain propagation pathways. Managerially, this provides evidence-based priorities for interventions in initial handling capabilities, cold chain continuity, and IT coordination/integration to guide investment and policy decisions for reducing PHFL in the aquaculture supply chain in Indonesia.

Introduction

Post-Harvest Fish Losses (PHFL) continue to undermine food security and value creation in fisheries and aquaculture value chains, where quality can deteriorate rapidly without adequate time-temperature control (Tefay et al., 2017; Maulu et al., 2020; Bedane et al., 2022). A recent global assessment estimates that in 2021, approximately 23.8 million tonnes of edible aquatic foods, about 14.8% of global production, were lost or wasted (Giron et al., 2024). These losses occur across harvesting, handling, processing, storage, and distribution, translating into reduced profitability for producers and higher prices for consumers (Kaminski et al., 2020; Solo et al., 2023). In tropical developing countries, high ambient temperatures, combined with weak cold-chain continuity and limited logistics capacity, amplify spoilage risks (Malik et al., 2021; Acharjee et al., 2023).

Indonesia is among the world's leading aquaculture producers. It is also an archipelagic market, where products often travel long distances from farms to consumers. This creates multiple exposure points to spoilage. Despite significant growth in per capita fish consumption (Ministry of Marine Affairs and Fisheries, 2024), studies estimate that PHFL of roughly 20–30% can occur due to inefficiencies across the supply chain (Poernomo et al., 2020; Irianto et al., 2021). Rather than being confined to a single stage, losses are frequently related to nodes where the maintenance of cold-chain continuity, transport reliability, and hygienic handling is hardest. This applies particularly during distribution and marketing (Malik et al., 2021; Bedane et al., 2022; Mramba et al., 2022). Moreover, processing and packaging constraints can accelerate biochemical and microbial spoilage, reducing market quality and safety (Acharjee et al., 2021; Bedane et al., 2022; García et al., 2022).

While numerous studies have examined PHFL within capture fisheries, evidence for aquaculture supply chains remains comparatively limited and often fragmented across single actors or stages (Acharjee et al., 2021; Mavuru et al., 2022; Abelti et al., 2024). Prior work frequently emphasizes upstream practices (e.g., harvesting and handling) and reports associations between training, hygiene, or market conditions and spoilage outcomes. However, it rarely explains how downstream processing capability and physical/logistics infrastructure interact with economic and social conditions to propagate losses across the chain (Kaminski et al., 2020; Maulu et al., 2020). For example, improved handling and training can reduce deterioration, but their effectiveness is contingent on complementary investments in cold-chain and transport infrastructure (Odoli et al., 2019; Singh et al., 2023), while limited market access and purchasing power can trigger early rejection or distress selling that increases waste (Viana et al., 2022; Acharjee et al., 2023). Overall, the literature points to multidimensional drivers but lacks an integrated, causal mapping and prioritisation framework, especially in sustainable aquaculture contexts.

From a sustainability perspective, PHFL determinants are commonly grouped into economic, social, environmental, technical, and organizational dimensions. Economically, purchasing power and financial access shape the feasibility of refrigeration and preservation investments (Setiawan et al., 2021; Bennett et al., 2024), while social collaboration and information flows affect coordination and demand–supply matching (Aura et al., 2019; Pascoe et al., 2019). Environmental factors (e.g., temperature extremes and flood events) are frequently cited as exacerbating risks, but their relative salience can be context-dependent and mediated by controllable cold-chain and handling practices (Davis et al., 2021; Malik et

al., 2021). Technically and organizationally, harvesting/handling capability, processing equipment, storage, and logistics/IT infrastructure determine whether quality can be maintained across echelons (Kaminski et al., 2020; García et al., 2022; Syanya et al., 2024; Utama et al., 2025). However, it remains unclear how these dimensions interact causally and which leverage points should be prioritized to reduce PHFL in sustainable aquaculture supply chains.

Previous research has (i) identified PHFL determinants and (ii) proposed stage-specific strategies but has not (iii) quantified the causal interdependencies and prioritised influence among risk factors in aquaculture supply chains. Existing analyses are primarily descriptive or based on isolated surveys, providing limited insight into the relative influence and prioritisation of risk factors (Odoli et al., 2019; Maulu et al., 2020). In particular, processing capability (techniques/equipment), cold-chain continuity, and physical/logistics infrastructure are repeatedly cited but rarely prioritized empirically as system-level drivers in aquaculture contexts (Maulu et al., 2020; Prodhon et al., 2022). Thus, it remains unclear which factors exert the most significant causal influence on PHFL and how effects propagate across the supply chain.

To address these gaps, this study integrates the Fuzzy Delphi Method (FDM) and the Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL) to identify, validate, map cause-and-effect relationships, and prioritize PHFL risk factors in sustainable aquaculture supply chains. FDM screens and consolidates expert judgments under uncertainty, while FDEMATEL models interdependencies and separates cause-group drivers from effect-group outcomes. This hybrid approach enables a nuanced understanding of how technical and infrastructural deficiencies interact with economic and social conditions. Rather than presuming a single dominant driver, the study examines whether constraints in harvesting/handling capability, cold-chain and logistics infrastructure, and processing equipment act as upstream causes shaping downstream safety, storage, and market access outcomes. By establishing a two-level causal analysis (aspects and risk factors), this research strengthens the theoretical account of PHFL dynamics. Here, ‘hierarchical’ denotes the two-level structure (aspect and risk-factor levels) and the prioritised upstream–downstream cause–effect ordering from FDEMATEL. It provides an evidence base for prioritizing policy and managerial interventions in Indonesia’s aquaculture supply chain.

This study contributes (i) methodologically by integrating FDM–FDEMATEL to derive a causal mapping and prioritisation model of PHFL risks under uncertainty, (ii) theoretically by explaining how sustainability dimensions interact through an explicit causal architecture, and (iii) managerially by prioritising intervention leverage points for Indonesia’s aquaculture supply chain.

Literature Review

PHFL persists across fishery and aquaculture value chains because fish quality can deteriorate rapidly when time–temperature control, hygienic handling, and logistics coordination are inadequate. PHFL may appear as physical losses (spoilage, discard) and quality/value losses (downgrading and price penalties), both of which reduce profitability and undermine food security (Tesfay et al., 2017; Maulu et al., 2020; Bedane et al., 2022). Prior research has identified recurring determinants and proposed stage-specific remedies; however, evidence

remains limited on which determinants act as upstream causes and how their effects propagate across supply-chain stages and echelons. Accordingly, this section synthesizes key themes from prior studies and identifies the gaps motivating the present study.

Post-Harvest Fish Losses

The PHFL literature consistently shows that deterioration risks accumulate across harvesting, handling, processing, storage, and distribution. At harvesting and landing, exposure to high ambient temperatures, delays, and physical damage are repeatedly linked to rapid quality decline (Tesfay et al., 2017; Mramba et al., 2022). During post-harvest handling, poor hygiene and inadequate packaging increase contamination risks and accelerate spoilage (Bedane et al., 2022). During storage and distribution, cold-chain discontinuities and insufficient temperature control are widely cited as major contributors to losses, especially in tropical contexts (Kaminski et al., 2020; Mramba et al., 2022).

A second theme is that many PHFL interventions depend on enabling conditions that are not always present. While improved handling skills and preservation technologies (icing, refrigeration, freezing) are commonly recommended, their adoption is frequently constrained by financing barriers and weak infrastructure (Odoli et al., 2019; Kaminski et al., 2020). Studies further suggest that processing capability and supporting facilities condition the effectiveness of best practices: where processing equipment, packaging solutions, and basic services are inadequate, shelf life and safety are compromised even when upstream handling improves (Maulu et al., 2020; Bedane et al., 2022; García et al., 2022; Syanya et al., 2024). These findings imply that PHFL is shaped not only by “on-the-ground” practices but also by structural constraints that determine whether interventions can be implemented consistently.

Despite broad agreement on key determinants, many studies remain focused on isolated stages or single actors, limiting system-level understanding of how losses propagate downstream. Several syntheses argue that interdependencies – such as the combined effect of inadequate refrigeration and weak handling practices during distribution – are under-examined, constraining comprehensive risk mitigation strategies (Teklu, 2015; Minten et al., 2021; Mavuru et al., 2022). Taken together, the literature highlights multifactor drivers but provides limited guidance on prioritising risk factors and on the mechanisms by which upstream constraints cascade into downstream losses.

PHFL in Sustainable Supply Chains

A sustainability perspective frames PHFL as an outcome shaped by the interactions among economic, social, environmental, technical, and organizational conditions. Economically, purchasing power and financial access influence incentives and the feasibility of investments in cold-chain and processing technologies (Setiawan et al., 2021; Bennett et al., 2024). Socially, collaboration and information flows affect coordination quality and demand–supply matching, while safety practices and hygiene training reduce contamination risks (Aura et al., 2019; Pascoe et al., 2019; Bedane et al., 2022). Environment-related stressors (e.g., high temperatures and extreme events) can intensify deterioration and disrupt flows, but their impacts are often mediated by controllable practices such as cold storage, disciplined handling, and robust logistics (Davis et al., 2021; Malik et al., 2021). Technically, harvesting/handling capability, processing equipment, packaging, and storage determine shelf life

and market quality (Tesfay et al., 2017; García et al., 2022; Syanya et al., 2024). Organizationally, inventory discipline, IT integration, and physical/logistics infrastructure shape responsiveness and cold-chain continuity across echelons (Kaminski et al., 2020; Utama et al., 2025).

Across these dimensions, a recurring insight is that PHFL is often driven by cross-dimensional interactions (e.g., financing enabling cold-chain investment; infrastructure enabling hygienic processing; coordination improving distribution timing). However, prior work seldom translates this multidimensional view into an explicit causal structure that distinguishes upstream drivers (causes) from downstream manifestations (effects). This motivates the need for approaches that can integrate multidimensional risks and prioritize leverage points based on causal influence rather than descriptive frequency alone.

Research Gaps and Study Positioning

Despite a growing body of research documenting PHFL determinants, the evidence base remains fragmented across isolated stages and actors, limiting system-level understanding of how losses propagate along aquaculture supply chains (Mavuru et al., 2022; Abelti et al., 2024). Many studies identify recurring drivers—such as temperature exposure, hygiene practices, market conditions, and infrastructure constraints—yet these factors are typically examined independently or through descriptive approaches, providing limited insight into interdependencies and causal propagation mechanisms (Teklu, 2015; Minten et al., 2021). As a result, it remains unclear which upstream constraints act as dominant “cause” drivers, and which downstream outcomes are primarily “effect” manifestations of underlying structural weaknesses.

In particular, processing capability, cold-chain continuity, and physical/logistics infrastructure are frequently cited as constraints but are rarely empirically validated and prioritized as system-level drivers in aquaculture contexts (Kaminski et al., 2020; Maulu et al., 2020). Furthermore, while sustainability framing encourages integration across economic, social, environmental, technical, and organizational dimensions, prior work seldom translates this multidimensional view into a causal mapping and prioritisation structure that can guide intervention sequencing under uncertainty (Setiawan et al., 2021; Bennett et al., 2024). Accordingly, this study positions itself to address these gaps by deriving an integrated, sustainability-oriented causal structure of PHFL risk factors in aquaculture supply chains, enabling better prioritization of leverage points for subsequent managerial and policy action.

Materials and Methods

Effective identification and prioritisation of PHFL risk factors requires a structured analytical design that integrates qualitative expertise with quantitative reasoning. Given the multidimensional nature of PHFL, which encompasses technical, economic, social, environmental, and organisational factors, this study adopts a hybrid fuzzy decision-support framework. Specifically, we integrate the FDM and FDEMATEL to (i) consolidate and screen candidate risk factors under expert uncertainty and (ii) model interdependencies to derive a cause-and-effect mapping and prioritisation among the retained factors. The integration of the FDM and FDEMATEL enables the validation of expert opinions under uncertainty and the exploration

of causal interrelationships among risk factors (Murray et al., 1985; Govindan et al., 2014; Anand et al., 2022). This combined framework is adapted from previous applications in sustainability and supply-chain risk analysis (Gardas et al., 2018; Ho et al., 2018; Kurrahman et al., 2025). For transparency and reproducibility, the following subsection describes the process of expert opinion collection, the procedures used to reduce bias, the linguistic/Triangular Fuzzy Number (TFN) scale, and the defuzzification steps and procedures for each method.

Study Context and Data Collection

This study was conducted within Indonesia's aquaculture supply chain and considers four primary echelons – pond farmers, intermediaries, fish processors, and retailers/consumers – to reflect the end-to-end flow from production to final markets. In this study, pond farmers make key harvest and first-handling decisions; intermediaries purchase and aggregate fish and manage first-mile transport; processors oversee processing, hygiene, and cold storage; and retailers/consumers (traditional/modern sellers and frequent buyers) represent downstream actors who handle and assess quality at the point of sale/consumption. Extending prior PHFL studies that often focus on one or two echelons (Teklu, 2015; Maulu et al., 2020; Acharjee et al., 2021), this research adopts a four-echelon scope to support system-level assessment of PHFL risk factors and their interactions.

An expert panel of 23 participants was recruited using purposive, criterion-based sampling to ensure (i) coverage across all echelons and (ii) sufficient domain expertise (average experience ≈ 16 years) for structured judgment elicitation. Eligibility criteria for inclusion were: (i) currently active in the respective echelon within the study context, (ii) direct involvement and decision authority in at least one post-harvest activity (e.g., harvesting, handling, storage, transport, processing, or retail display), (iii) a minimum of five years of sustained professional experience in the relevant role (for consumers: regular purchasing and consumption of aquaculture fish for at least one year), and (iv) willingness and ability to participate in repeated evaluations using the provided linguistic scales. Expert qualification additionally required practical exposure to PHFL outcomes (spoilage and/or quality downgrading/rejection). The panel comprised three pond farmers, three intermediaries, four processing business owners, three traditional retailers, four modern retail managers, three resellers, and three consumers. Rather than targeting statistical representativeness, the panel size was chosen to balance diversity of perspectives with the feasibility of repeated expert evaluations required by FDM and FDEMATEL, consistent with expert-based decision-modelling practice (Bouzon et al., 2016; Tabatabaee et al., 2021).

Data collection followed a three-step sequence: (1) an evidence-based compilation of 30 candidate PHFL risk factors from prior studies; (2) expert consultation to contextualize factors, clarify definitions, and remove overlaps among factors; and (3) structured questionnaires to elicit expert judgments for the FDM screening and FDEMATEL pairwise influence assessments. To reduce potential dominance and groupthink effects, expert ratings were collected individually using the exact instructions and linguistic scales, and responses were aggregated at the panel level for analysis. The respondent profiles are summarised in Appendix 1, and the preliminary risk-factor list is provided in Table 3.

Fuzzy Delphi Method (FDM)

FDM was used to screen and validate the initially identified PHFL risk factors by consolidating expert judgments under uncertainty (Murray et al., 1985; Bouzon et al., 2016; Ho et al., 2018). The output of this stage is a reduced set of retained risk factors for subsequent causal analysis in FDEMATEL. Experts provided importance ratings using five linguistic terms, which were mapped to a TFN to capture the vagueness inherent in subjective assessments (Ma et al., 2011; Ali et al., 2014; Mahdiyar et al., 2020). This five-level scale is widely used in FDM applications because it balances respondent cognitive load with adequate discrimination among importance levels. The linguistic terms and TFN mappings used in this study are presented in Table 1. All notation used in this section is defined in Appendix 2.

Table 1.

Triangular Fuzzy Number Linguistic Scale (Delphi) (Mahdiyar et al., 2020; Tabatabaee et al., 2021)

Linguistic Variables	Triangular Fuzzy Number
No Importance (N)	(1, 1, 3/2)
Low Importance (L)	(3/2, 2, 5/2)
Moderate Importance (M)	(5/2, 3, 7/2)
High Importance (H)	(7/2, 4, 9/2)
Very High Importance (VH)	(9/2, 5, 5)

Expert judgments were aggregated across panel members to obtain a single TFN per candidate risk factor. Specifically, the lower bound was set to the minimum of the experts' lower values, the modal value to the geometric mean of the experts' modal values, and the upper bound to the maximum of the experts' upper values, consistent with prior FDM application. The aggregation procedure was performed using Equations (1) and (2); notation is provided in Appendix 2.

$$E_e(a) = (l_e, m_e, u_e), e = 1, 2, \dots, n \quad (1)$$

$$A(a) = (l_A, m_A, u_A) = (\min l_e, GM m_e, \max u_e), e = 1, 2, \dots, n \quad (2)$$

The aggregated TFN for each factor was then defuzzified to obtain a crisp importance score representing panel consensus using the centroid-based defuzzification in Equation (3). To screen for factors, a threshold value was computed as the average crisp score across all candidate risk factors using Equation (4) (Bouzon et al., 2016). Factors with $C_{A(a)} \geq T$ were retained for the next stage, whereas factors with $C_{A(a)} < T$ were excluded. This step reduces the factor set before pairwise influence assessment in FDEMATEL.

$$C_{A(a)} = \frac{(l_A + 4 \times m_A + u_A)}{6} \quad (3)$$

$$T = \frac{\sum_{a=1}^s C_{A(a)}}{s} \quad (4)$$

This screening process is consistent with prior FDM applications in sustainability and supply-chain risk contexts (Kurrahman et al., 2025). Importantly, FDM was used here for

consensus-based screening rather than causal inference. The retained risk factors were subsequently analysed using FDEMATEL to model interdependencies and to derive a cause-and-effect structure and risk factor prioritization.

Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL)

FDEMATEL was employed to model interdependencies and to derive a cause-and-effect analysis of the PHFL risk factors retained from the FDM stage. FDEMATEL is widely used to analyse complex systems by quantifying direct and indirect influences among factors, thereby enabling structured prioritisation (Govindan et al., 2014; Dehdasht et al., 2017; Anand et al., 2022). By incorporating fuzzy logic, the method accommodates linguistic ambiguity in expert evaluations, which is particularly relevant in sustainability-oriented decision contexts (Gardas et al., 2018; Santoso et al., 2024; Kurrahman et al., 2025). All notation used in this section is defined in Appendix 2.

Table 2.

Triangular Fuzzy Number Linguistic Scale (DEMATEL) (Govindan et al., 2014; Anand et al., 2022)

Linguistic Variables	Triangular Fuzzy Number
Not Influential (N)	(0, 0, 0.25)
Very Low Influence (VL)	(0, 0.25, 0.50)
Low Influence (L)	(0.25, 0.50, 0.75)
High Influence (H)	(0.50, 0.75, 1)
Very High Influence (VH)	(0.75, 1, 1)

Experts assessed the degree of influence that one factor exerts on another using a five-point fuzzy linguistic scale shown in Table 2. The linguistic responses were first transformed into TFN values and then defuzzied using the Converting Fuzzy Data into Crisp Scores (CFCS) method, as described in Equations (5)-(10). This conversion process enabled the construction of the initial direct-relation matrix (T), which represents the direct influence of each pair of factors.

Normalization

$$w = \max r_{ij}^n - \min l_{ij}^n \quad (5)$$

$$xr_{ij}^n = \frac{(r_{ij}^n - \min l_{ij}^n)}{w}; xp_{ij}^n = \frac{(m_{ij}^n - \min l_{ij}^n)}{w}; xl_{ij}^n = \frac{(\min l_{ij}^n)}{w} \quad (6)$$

Determine the left normalization value (ls) and the right normalization value (rs) for $j = 1, \dots, J$

$$xls_{ij}^n = \frac{xp_{ij}^n}{(1 + xp_{ij}^n - xl_{ij}^n)}; xrs_{ij}^n = \frac{xr_{ij}^n}{(1 + xr_{ij}^n - xp_{ij}^n)} \quad (7)$$

Determine the normalized total crisp value for $j = 1, \dots, J$

$$x_{ij}^n = \frac{[xls_{ij}^n(1 - xls_{ij}^n) + xrs_{ij}^n xrs_{ij}^n]}{[1 - xls_{ij}^n + xrs_{ij}^n]} \quad (8)$$

Calculate the crisp value for $j = 1, \dots, J$

$$Z_{ij}^n = \min l_{ij}^n + x_{ij}^n \times w \quad (9)$$

Integrating all crisp values

$$Z_{ij} = \frac{1}{h} \times (Z_{ij}^1 + Z_{ij}^2 + \dots + Z_{ij}^h) \quad (10)$$

The normalised direct-relation matrix (G) was derived using Equations (11) and (12), ensuring that all influence values fell within the range of 0 to 1. Subsequently, the total-relation matrix (M) was calculated using Equation (13), incorporating both direct and indirect relationships among factors. The row sums (Rs) and column sums (Cs) of matrix M were obtained using Equation (14), where (Rs + Cs) represents the total degree of influence and (Rs - Cs) distinguishes cause and effect groups.

$$W = \frac{1}{\max_{1 \leq i \leq n} \sum_{j=1}^n a_{ij}} \sum_{j=1}^n a_{ij} \quad (11)$$

$$X = W \times E \quad (12)$$

$$M = X(I - X)^{-1} \quad (13)$$

$$Rs = [\sum_{j=1}^n m_{ij}] n \times 1; Cs = [\sum_{j=1}^n m_{ij}] 1 \times n \quad (14)$$

The cause-and-effect diagram of PHFL risk factors was constructed using the horizontal axis ($Rs + Cs$) and the vertical axis ($Rs - Cs$). The horizontal axis shows the importance of factors, while the vertical axis shows their influence. If ($Rs - Cs$) is positive, then the factor is in the cause group. Conversely, if the ($Rs - Cs$) is negative, then the factor is in the effect group. Cause-and-effect diagrams can transform complex factor relationships into easy-to-understand structural models, providing insight for problem solving (Seker et al., 2017). The level of influence among the factors studied is determined based on Equation (15), where M is $[m_{ij}]_{n \times n}$, $i, j = 1, 2, \dots, n$.

$$\beta = \frac{\sum_{i=1}^n m_{ij}}{M^2} \quad (15)$$

β is the threshold for filtering the influence between two factors. If $m_{ij} > \beta$, then there is an interaction between two factors, and the degree of influence corresponds to m_{ij} . This results in an interaction matrix $V = [v_{ij}]_{n \times n}$. The categorization of influence levels was then obtained using Equation (16), where $\beta_1 = \frac{\sum v_{ij}}{\text{count}(v_{ij} > \beta)}$, and $\beta_2 = \max(v_{ij})$.

$$\text{Influence Level} = \begin{cases} v_{ij} < \beta_1 : \text{weak} \\ \beta_1 < v_{ij} < \frac{\beta_1 + \beta_2}{2} : \text{medium} \\ v_{ij} > \beta_2 : \text{strong} \end{cases} \quad (16)$$

The final step in the FDEMATEL method is to calculate the importance level of the risk factors. The importance weight of the factors is obtained by normalizing the absolute influence score with Equation (17). Here, W_i represents the final importance weight of each factor analyzed.

$$W_i = \frac{|Rs-Cs|}{\sum_j |Rs-Cs|} \quad (17)$$

The methodological rigor of this stage aligns with prior applications of fuzzy-based causal analysis for risk and sustainability assessment (Baykasoğlu et al., 2013; Hasheminezhad et al., 2021; Khalilzadeh et al., 2021). This procedure ensures that the final causal structure reflects the interdependencies across technical, economic, and organisational dimensions.

Results

This section presents the key empirical findings from the integrated FDM–FDEMATEL analysis to (i) validate PHFL risk factors and (ii) map the cause–and–effect structure at both aspect and risk-factor levels and (iii) prioritize risk factors. Methodological procedures and equations are detailed in Section 3. Accordingly, this section focuses on the substantive outputs (Tables 3–7; Figures 1–2), while the discussion and implications are reserved for Section 5.

FDM Results: Validation of PHFL Risk Factors

Of the 30 candidate PHFL risk factors, the FDM screening retained 17 key factors that exceeded the consensus threshold, while 13 were excluded (Table 3). The retained set spans economic, social, technical, and organizational dimensions, indicating that PHFL in the analyzed aquaculture chain is shaped by multidimensional constraints rather than a single dominant determinant. Notably, the retained factors are concentrated around (i) information/co-ordination and safety practices, (ii) handling–processing capability, (iii) storage and cold-chain continuity, and (iv) enabling IT and logistics infrastructure (Table 3).

FDM results indicate that consensus is strongest on technical and organizational constraints. Economically, only RF1 (low consumer purchasing power) was retained (Table 3). Socially, the retained set comprises RF6, RF8, RF9, RF10, and RF11, with the highest social scores observed for RF8 (3.036) and RF10 (2.982). Technically, RF17–RF21 were retained, and the highest technical scores were RF20 (3.046), RF18 (2.898), and RF19 (2.860) (Table 3). Organizationally, RF24–RF27 and RF29–RF30 were retained, led by RF25 (2.991) and RF26 (2.975). Notably, environment-related candidates (RF12–RF16) were not retained, suggesting that – within the expert panel’s context – PHFL is perceived to be more immediately driven by controllable operational and infrastructure constraints than by environmental hazards (Table 3).

Table 3.
FDM Analysis Results

Sustainability Dimension	Aspects		PHFL Risk Factors		FDM (C ₄)	Decision
Economy	AS1	Purchasing Power and Market	RF1	Low Consumer Purchasing Power.	2.825	Accepted
			RF2	Inability of producers to compete in a highly competitive market.	2.578	Rejected
			RF3	Delivering fish to market at the wrong time.	2.580	Rejected
	AS2	Financial Access	RF4	Financial inability to adopt cooling technology.	2.568	Rejected
Social	AS3	Collaboration and Information	RF5	Lack of connection between institutions (research centers), industry, and government.	2.492	Rejected
			RF6	Low Market Information Dissemination Ability.	2.875	Accepted
			RF7	Inadequate communication system.	2.618	Rejected
			RF8	Lack of Knowledge About Supply and Demand.	3.036	Accepted
			RF9	Lack of Knowledge About Distribution Channels.	2.819	Accepted
	AS4	Safety and Welfare	RF10	Low Safety Levels Along the Supply Chain.	2.982	Accepted
			RF11	Unhygienic Handling Practices.	2.921	Accepted
	Environment	AS5	Climate and Weather	RF12	Climate and weather conditions.	2.543
RF13				Related disasters such as floods, droughts, and erosion.	2.502	Rejected
AS6		Environmental Management	RF14	Inadequate pond waste management.	2.705	Rejected
			RF15	Inability to prevent predator disturbance.	2.605	Rejected
			RF16	Excessive air pollution.	2.293	Rejected
Technical	AS7	Processing Techniques and Equipment	RF17	Inadequate Harvesting Techniques and Equipment.	2.779	Accepted
			RF18	Inadequate Handling Techniques and Equipment.	2.898	Accepted
			RF19	Inadequate processing techniques and equipment.	2.860	Accepted
	AS8	Storage Facilities	RF20	Insufficient Storage Facilities.	3.046	Accepted
			RF21	Limited availability of cold chain facility.	2.763	Accepted
			RF22	Lack of knowledge about ice cooling techniques.	2.678	Rejected
			RF23	Lack of appropriate packaging.	2.678	Rejected
Organizational	AS9	Technology and Inventory Management	RF24	Lack of Strict Inventory Policies.	2.861	Accepted
			RF25	Lack of integrated IT systems among supply chain members.	2.991	Accepted
	AS10	Physical and Logistics Infrastructure	RF26	Inadequate Logistics Infrastructure.	2.975	Accepted
			RF27	Inadequate market infrastructure.	2.888	Accepted
			RF28	Inadequate electricity infrastructure.	2.487	Rejected
RF29			Inadequate public transportation infrastructure.	2.878	Accepted	
RF30			Distance from the main market.	2.940	Accepted	
Threshold					2.755	

FDEMATEL Results: Causal Relationships and Prioritisation

FDEMATEL was applied to the retained (screened) factors to derive the cause-and-effect structure at the aspect and risk-factor levels (Tables 4–7). At the aspect level, Tables 4–5 and Figure 1 show that AS7 (Processing Techniques and Equipment) and AS10 (Physical and Logistics Infrastructure) form the cause group (positive R_s-C_s), indicating net-driving roles within the system (AS7: $R_s-C_s = 1.233$; AS10: $R_s-C_s = 0.285$). These two upstream aspects influence downstream (effect-group) aspects, including AS1 (Purchasing Power and Market), AS3 (Collaboration and Information), AS8 (Storage Facilities), and AS9 (Technology and Inventory Management) (Table 5).

Table 4.

Total Relationship Matrix between Aspects

	AS1	AS3	AS4	AS7	AS8	AS9	AS10	R_s
AS1	3.942	3.692	3.765	3.598	3.737	3.698	3.564	25.996
AS3	3.715	3.522	3.555	3.406	3.518	3.502	3.366	24.584
AS4	3.772	3.534	3.639	3.449	3.579	3.541	3.428	24.942
AS7	3.849	3.609	3.678	3.561	3.659	3.615	3.493	25.464
AS8	3.786	3.548	3.638	3.481	3.636	3.573	3.444	25.108
AS9	3.682	3.465	3.520	3.377	3.496	3.504	3.339	24.384
AS10	3.661	3.439	3.517	3.359	3.496	3.447	3.376	24.295
C_s	26.408	24.809	25.312	24.231	25.123	24.881	24.010	3.567

Table 5.

Coordinate Cause and Effect Diagram for Aspects

Factor	R_s	C_s	R_s+C_s	R_s-C_s	Type
AS1	25.996	26.408	52.404	-0.412	Effect
AS3	24.584	24.809	49.393	-0.225	Effect
AS4	24.942	25.312	50.253	-0.370	Effect
AS7	25.464	24.231	49.695	1.233	Cause
AS8	25.108	25.123	50.231	-0.015	Effect
AS9	24.384	24.881	49.265	-0.497	Effect
AS10	24.295	24.010	48.305	0.285	Cause

Figure 1 highlights the propagation pathway among aspects: AS7 and AS10 operate as upstream drivers that shape downstream outcomes, with a notable channel running through AS1 (Purchasing Power and Market). Although AS1 exhibits the highest prominence ($R_s+C_s = 52.404$), it remains an effect group aspect ($R_s-C_s = -0.412$), indicating that its strong connectivity is primarily driven by upstream technical and infrastructure constraints rather than acting as a root cause. This pattern supports a cascading effect in which improvements in processing capability and enabling logistics infrastructure are expected to yield downstream benefits in coordination (AS3), safety and welfare (AS4), storage (AS8), and technology/inventory management (AS9) (Table 5; Figure 1).

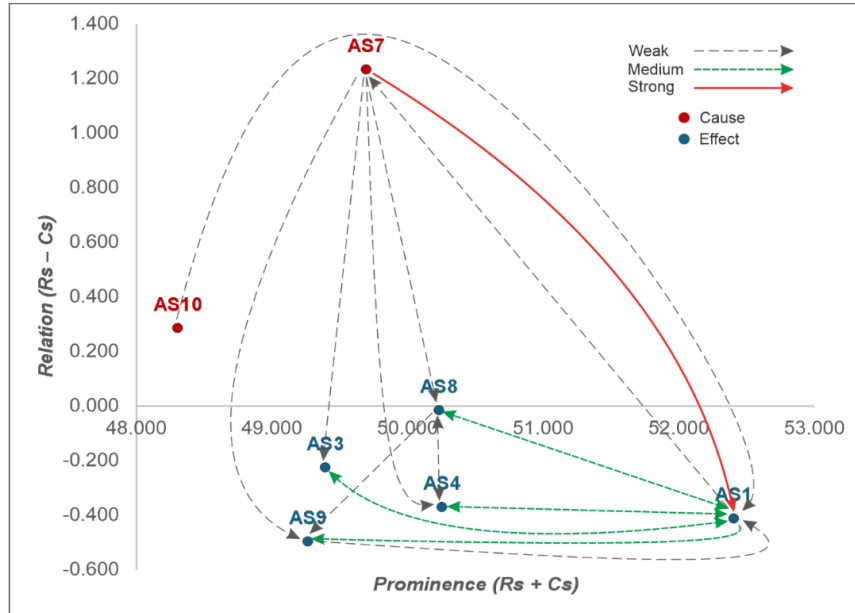


Figure 1. Diagram of Cause-and-Effect Relationships between Aspects

Table 6.

Coordinate Cause Effect Diagram & Weight Result for Risk Factors

Factor	R_s	C_s	$R_s + C_s$	$R_s - C_s$	Type
RF1	13.973	14.231	28.204	-0.257	Effect
RF6	13.063	12.987	26.050	0.076	Cause
RF8	13.272	13.497	26.770	-0.225	Effect
RF9	13.532	13.391	26.924	0.141	Cause
RF10	13.166	12.967	26.133	0.199	Cause
RF11	13.188	13.066	26.254	0.122	Cause
RF17	13.068	12.630	25.698	0.438	Cause
RF18	13.131	12.886	26.017	0.245	Cause
RF19	12.982	13.000	25.981	-0.018	Effect
RF20	12.879	13.217	26.095	-0.338	Effect
RF21	13.107	12.836	25.943	0.271	Cause
RF24	12.425	12.518	24.942	-0.093	Effect
RF25	12.877	12.717	25.594	0.160	Cause
RF26	12.774	12.660	25.434	0.115	Cause
RF27	12.507	12.407	24.914	0.101	Cause
RF29	12.269	12.256	24.525	0.014	Cause
RF30	11.695	12.645	24.339	-0.950	Effect

At the risk-factor level, Table 6 and Figure 2 separate upstream drivers from downstream manifestations. The cause group comprises RF6, RF9–RF11, RF17–RF18, RF21, RF25–

RF27, and RF29, indicating that information/market dissemination, safety–hygiene, front-end handling capability, cold-chain availability, and enabling IT/logistics infrastructure act as primary drivers of PHFL propagation. In contrast, the effect group includes RF1, RF8, RF19–RF20, RF24, and RF30, suggesting that market outcomes, storage adequacy, inventory discipline, and distance to market are predominantly downstream consequences of upstream operational and infrastructure constraints in the studied chain (Table 6; Figure 2).

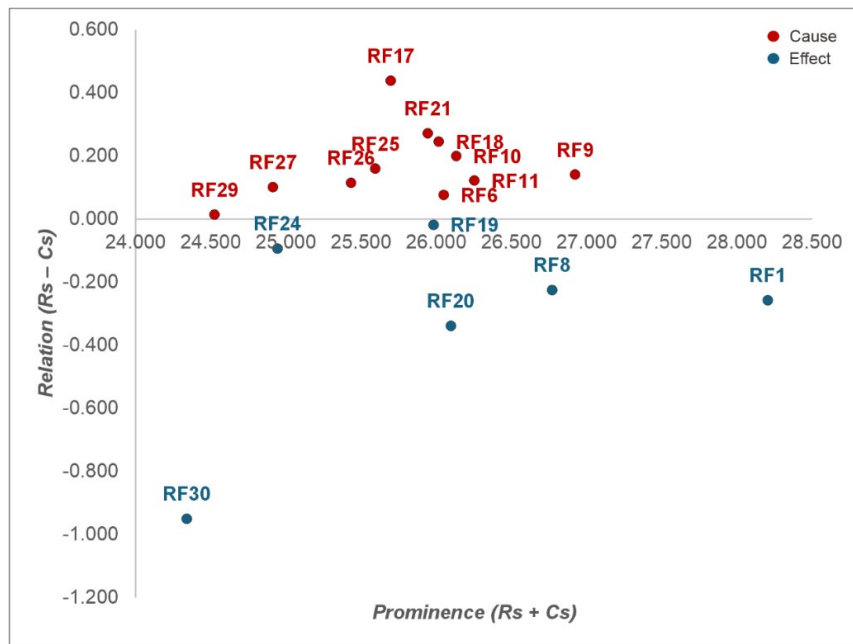


Figure 2. Diagram of Cause-and-Effect Relationships between Risk Factor

The importance-weight results (Table 7) reinforce the causal prioritisation by identifying the most influential upstream leverage points. The top three drivers are RF17 (23.31%), RF21 (14.42%), and RF18 (13.02%), followed by RF10, RF25, RF9, and RF11. Collectively, these rankings indicate that PHFL reduction in the studied aquaculture chain is most sensitive to front-end harvesting/handling capability and cold-chain continuity, supported by safety–hygiene enforcement and digital/logistics enablers (Table 7).

Table 7.
Importance Weight Results of PHFL Risk Factors

<i>Factor</i>	<i>Rs-Cs</i>	<i>Type</i>	<i>W</i>	<i>Rank</i>
RF6	0.076	Cause	4.04%	10
RF9	0.141	Cause	7.48%	6
RF10	0.199	Cause	10.59%	4
RF11	0.122	Cause	6.48%	7
RF17	0.438	Cause	23.31%	1
RF18	0.245	Cause	13.02%	3
RF21	0.271	Cause	14.42%	2
RF25	0.160	Cause	8.48%	5
RF26	0.115	Cause	6.09%	8
RF27	0.101	Cause	5.35%	9
RF29	0.014	Cause	0.73%	11

Discussion and Implications

The integrated FDM–FDEMATEL results indicate a propagation pattern in which front-end technical capability and enabling infrastructure act as upstream constraints that shape downstream PHFL outcomes. At the aspect level, processing techniques/equipment (AS7) and physical/logistics infrastructure (AS10) emerge as the primary cause-group drivers, while market-facing and coordination outcomes predominantly manifest as effect-group outcomes. This pattern is theoretically significant because it shifts PHFL framing from “multiple independent determinants” to a structured mechanism: constraints in handling/processing and logistics capacity create time–temperature exposure and hygiene failures that then translate into safety and market penalties. These findings align with prior evidence that emphasises time–temperature control, hygiene, and cold-chain continuity as central loss pathways in tropical settings (Tesfay et al., 2017; Maulu et al., 2020; Malik et al., 2021; Bedane et al., 2022). For example, when fish are harvested without immediate icing and experience delays at aggregation and non-refrigerated transport, cumulative time–temperature abuse increases spoilage, leading to processor downgrades/rejections and higher retail waste; immediate icing, insulated containers, and faster dispatch can reduce rejection rates and extend retail shelf life—creating cascading benefits across echelons.

A key nuance from the two-level model is that processing capability functions as a system-level driver (AS7) even when certain processing-related risk factors can appear as effect factors at the risk-factor level (e.g., RF19). This is not a contradiction: it indicates that the effectiveness of processing depends on upstream constraints – particularly harvesting/handling discipline (RF17–RF18) and cold-chain continuity (RF21) – which determine the quality entering processing and the time–temperature exposure before/after processing. Theoretical novelty lies in this interaction pattern, which clarifies why investments in “better processing” may underperform if cold-chain breaks and handling practices remain binding constraints. Thus, processing upgrades yield limited gains if fish arrives warm due to weak harvest/handling and cold-chain breaks; stabilising intake quality enables processing hygiene and chilling/freezing investments to deliver their full effect.

This study contributes theoretically by specifying a two-level causal architecture (aspect-level and risk-factor-level) that links sustainability dimensions to a prioritised cause-and-effect structure for PHFL risk management. Relative to prior PHFL research that often remains descriptive or single-stage, the causal map clarifies which constraints are upstream causes (e.g., harvesting/handling capability, cold-chain availability, and enabling infrastructure/IT) and which are downstream effects (e.g., market outcomes and storage sufficiency). This distinction matters for theory because it frames PHFL as a propagation problem under capacity constraints, where interventions should be sequenced to relax binding constraints before addressing secondary outcomes.

Methodologically, the integrated FDM–FDEMATEL workflow provides a transparent approach to (i) screen risk factors under uncertainty and (ii) quantify interdependencies to derive a prioritised causal structure when measured loss data are limited. The added value is not merely “using fuzzy methods,” but producing a defensible prioritisation of upstream leverage points that managers and policymakers can act on. This addresses a gap repeatedly noted in sustainability and risk modelling literature, moving from determinant lists to prioritised causal structures that support decision-making (Baykasoğlu et al., 2013; Anand et al., 2022).

While the proposed framework is adaptable to other perishable supply chains, the resulting prioritization of causal influence should be treated as context sensitive. In environments with stronger logistics infrastructure, different factors (e.g., market governance or environmental shocks) may become dominant. In contrast, in infrastructure-constrained settings, the prioritized causal drivers are likely to remain anchored in cold-chain continuity and handling capability. This boundary-condition framing strengthens theoretical interpretation by positioning prioritization as a contingent mechanism rather than a universal ranking.

The causal ranking indicates that PHFL reduction is most sensitive to RF17 (harvesting techniques/equipment), RF21 (cold-chain availability), and RF18 (handling techniques/equipment), supported by safety–hygiene enforcement (RF10–RF11) and coordination, information, and IT integration (RF6, RF9, RF25). For Indonesia’s aquaculture supply chain – often characterized by multiple transfer points and uneven cold-chain coverage across regions – an evidence-based sequencing is: (i) standardize and enforce handling and hygiene SOPs at harvest and first-mile transfer points (e.g., immediate icing, clean covered crates/containers, and time targets for transfer), (ii) expand cold-chain access where temperature excursions are most likely (e.g., ice/cold-storage hubs at aggregation points, insulated boxes, and refrigerated transport for longer routes), and (iii) strengthen coordination through integrated IT/information dissemination to reduce delays and mismatches that prolong exposure time (e.g., shared scheduling/dispatch groups and recording of harvest times/temperatures). These priorities translate the model’s causal prioritization into implementable levers—targeting binding constraints first rather than dispersing resources across downstream issues. These actions align with prior empirical evidence on infrastructure and enabling constraints in fish value chains (Kaminski et al., 2020; Maulu et al., 2020; Acharjee et al., 2021; Prodhan et al., 2022) and with findings that digital coordination can strengthen traceability and decision quality in multi-actor supply chains (Santoso et al., 2024). Actor involvement is aligned with the four echelons: farmers implement harvest/first-handling SOPs; intermediaries/resellers manage aggregation conditions, icing/packaging, and first-mile transport; processors set receiving standards and invest in hygienic processing and cold storage; retailers maintain

cold display/storage and inventory rotation; and policymakers/industry bodies support training, standards enforcement, and investment in shared cold-chain infrastructure at strategic nodes.

Conclusions

This study applied an integrated fuzzy-based framework combining the FDM and FDEMATEL to identify, validate, and analyze the cause-and-effect mapping and prioritization of risk factors influencing PHFL in Indonesia's sustainable aquaculture supply chain. FDM screening retained 17 key risk factors, concentrated in economic, social, technical, and organizational dimensions, with technical capability and enabling infrastructure emerging as dominant leverage points. At the risk-factor level, FDEMATEL identifies a clear prioritization of causal influence: upstream constraints in harvesting techniques and equipment (RF17), handling techniques and equipment (RF18), and cold-chain availability (RF21) act as the strongest causal drivers shaping downstream outcomes related to safety and quality loss and, ultimately, market performance.

The integrated FDM–FDEMATEL approach maps how upstream technical deficiencies and infrastructure constraints propagate across echelons, providing a decision-support basis for sequencing interventions rather than implementing isolated fixes. From a managerial and policy perspective, the results indicate three priorities: (1) upgrading harvesting and handling equipment and standard operating procedures (RF17–RF18), (2) improving cold-chain continuity at critical transfer points (RF21 and infrastructure-related factors), and (3) strengthening coordination and visibility through integrated information systems and dissemination (e.g., RF25 and information-related factors). In Indonesia's context, these priorities imply investing in cold storage and ice supply and in reliable transport along distribution nodes, while coupling infrastructure upgrades with training and compliance mechanisms to reduce safety and hygiene risks.

The study contributes theoretically by specifying a two-level causal architecture (aspect level and risk-factor level) that links sustainability dimensions to a prioritized cause-and-effect structure for PHFL risk management. Methodologically, it demonstrates how integrated fuzzy screening (FDM) and causal mapping (FDEMATEL) can yield a defensible prioritization of causal influence when measured loss data are limited and expert judgments are uncertain. Limitations include reliance on expert elicitation, a cross-sectional design, and context specificity to the sampled Indonesian aquaculture supply chain, which may affect generalizability. Future research should therefore test the stability of causal prioritization across regions and commodities, combine expert-based models with measured loss and temperature-excursion data, and evaluate the effectiveness of targeted interventions (e.g., cold-chain upgrades or handling SOPs).

Author Contributions: Conceptualization, M.F.I. and I.S.; methodology, M.F.I.; software, M.F.I.; resources, M.F.I., I.S., S.A.M. and R.A.; data curation, M.F.I.; writing—original draft preparation, M.F.I. and I.S.; writing—review and editing, M.F.I.; visualization, M.F.I.; supervision, I.S., S.A.M. and R.A.; project administration, M.F.I. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Funding: This research was funded by INDONESIAN EDUCATION SCHOLARSHIP, CENTER FOR HIGHER EDUCATION FUNDING AND ASSESSMENT, AND INDONESIAN ENDOWMENT FUND FOR EDUCATION, Grant number 00559/BPPT/BPI.06/01/2025.

References

- Abelti, A. L., & Teka, T. A. (2024). Intervening fish post-harvest losses to narrow the gap between demand and supply: A review on magnitude of fish post-harvest losses in some Sub-Saharan African countries. *Aquaculture, Fish and Fisheries*, 4(2), e168. doi:<https://doi.org/10.1002/aff2.168>
- Acharjee, D. C., Alam, G. M. M., Gosh, K., Haque, A. B. M. M., & Hossain, M. I. (2023). Fish value chain and the determinants of value addition decision: Empirical evidence from Bangladesh. *Journal of the World Aquaculture Society*, 54(4), 931-944. doi:<https://doi.org/10.1111/jwas.12941>
- Acharjee, D. C., Hossain, M. I., & Alam, G. M. M. (2021). Post-harvest fish loss in the fish value chain and the determinants: empirical evidence from Bangladesh. *Aquaculture International*, 29(4), 1711-1720. doi:<https://doi.org/10.1007/s10499-021-00711-8>
- Ali, J. S., & Maryam, M. (2014). Environmental Risk Assessment of Dams by Using Multi-Criteria Decision-Making Methods: A Case Study of the Polrood Dam, Guilan Province, Iran. *Human and Ecological Risk Assessment: An International Journal*, 20(1), 69-85. doi:<https://doi.org/10.1080/10807039.2012.725159>
- Anand, S., & Barua, M. K. (2022). Modeling the key factors leading to post-harvest loss and waste of fruits and vegetables in the agri-fresh produce supply chain. *Computers and Electronics in Agriculture*, 198, 106936. doi:<https://doi.org/10.1016/j.compag.2022.106936>
- Aura, C. M., Nyamweya, C. S., Njiru, J. M., Odoli, C., Musa, S., Ogari, Z., . . . Oketch, R. (2019). Using fish landing sites and markets information towards quantification of the blue economy to enhance fisheries management. *Fisheries Management and Ecology*, 26(2), 141-152. doi:<https://doi.org/10.1111/fme.12334>
- Baykasoğlu, A., Kaplanoğlu, V., Durmuşoğlu, Z. D. U., & Şahin, C. (2013). Integrating fuzzy DEMATEL and fuzzy hierarchical TOPSIS methods for truck selection. *Expert Systems with Applications*, 40(3), 899-907. doi:<https://doi.org/10.1016/j.eswa.2012.05.046>
- Bedane, T. D., Agga, G. E., & Gutema, F. D. (2022). Hygienic assessment of fish handling practices along production and supply chain and its public health implications in Central Oromia, Ethiopia. *Scientific Reports*, 12(1), 13910. doi:<https://doi.org/10.1038/s41598-022-17671-5>
- Bennett, M., March, A., & Failler, P. (2024). Blue Economy Financing Solutions for the Fisheries and Aquaculture Sectors of Caribbean Island States. *Fishes*, 9(8). doi:<https://doi.org/10.3390/fishes9080305>
- Bouzon, M., Govindan, K., Rodriguez, C. M. T., & Campos, L. M. S. (2016). Identification and analysis of reverse logistics barriers using fuzzy Delphi method and AHP. *Resources, Conservation and Recycling*, 108, 182-197. doi:<https://doi.org/10.1016/j.resconrec.2015.05.021>
- Davis, K. F., Downs, S., & Gephart, J. A. (2021). Towards food supply chain resilience to environmental shocks. *Nature Food*, 2(1), 54-65. doi:<https://doi.org/10.1038/s43016-020-00196-3>
- Dehdasht, G., Mohamad Zin, R., Ferwati, M. S., Mohammed Abdullahi, M. a., Keyvanfar, A., & McCaffer, R. (2017). DEMATEL-ANP Risk Assessment in Oil and Gas Construction Projects. *Sustainability*, 9(8). doi:<https://doi.org/10.3390/su9081420>
- García, M. R., Ferez-Rubio, J. A., & Vilas, C. (2022). Assessment and Prediction of Fish Freshness Using Mathematical Modelling: A Review. *Foods*, 11(15). doi:<https://doi.org/10.3390/foods11152312>

- Gardas, B. B., Raut, R. D., & Narkhede, B. (2018). Evaluating critical causal factors for post-harvest losses (PHL) in the fruit and vegetables supply chain in India using the DEMATEL approach. *Journal of Cleaner Production*, 199, 47-61. doi:<https://doi.org/10.1016/j.jclepro.2018.07.153>
- Giron, A., & Pickerel, T. (2024). Investigating Global Aquatic Food Loss and Waste. In: World Economic Forum.
- Govindan, K., Kannan, D., & Shankar, K. M. (2014). Evaluating the drivers of corporate social responsibility in the mining industry with multi-criteria approach: A multi-stakeholder perspective. *Journal of Cleaner Production*, 84, 214-232. doi:<https://doi.org/10.1016/j.jclepro.2013.12.065>
- Hasheminezhad, A., Hadadi, F., & Shirmohammadi, H. (2021). Investigation and prioritization of risk factors in the collision of two passenger trains based on fuzzy COPRAS and fuzzy DEMATEL methods. *Soft Computing*, 25(6), 4677-4697. doi:<https://doi.org/10.1007/s00500-020-05478-3>
- Ho, C.-C., Huang, C., & Ou, C.-Y. (2018). Analysis of the Factors influencing Sustainable Development in the Insurance Industry. *Corporate Social Responsibility and Environmental Management*, 25(4), 391-410. doi:<https://doi.org/10.1002/csr.1467>
- Irianto, H. E., & Giyatmi. (2021). Susut dan Limbah Pangan (Food Loss and Waste) Hasil Perikanan. In M. Mahendradatta, W. P. Rahayu, U. Santoro, Giyatmi, Ardiansyah, D. L. N. Fibri, F. Kusnandar, & Y. Witono (Eds.), *Inovasi Teknologi Pangan Menuju Indonesia Emas - Kumpulan Pemikiran Anggota PATPI*. Bogor: IPB Press.
- Kaminski, A. M., Cole, S. M., Al Haddad, R. E., Kefi, A. S., Chilala, A. D., Chisule, G., Ward, A. R. (2020). Fish Losses for Whom? A Gendered Assessment of Post-Harvest Losses in the Barotse Floodplain Fishery, Zambia. *Sustainability*, 12(23), 10091. doi:<https://doi.org/10.3390/sul22310091>
- Khalilzadeh, M., Shakeri, H., & Zohrehvandi, S. (2021). Risk identification and assessment with the fuzzy DEMATEL-ANP method in oil and gas projects under uncertainty. *Procedia computer science*, 181, 277-284. doi:<https://doi.org/10.1016/j.procs.2021.01.147>
- Kurrahman, T., Tsai, Feng M., Sethanan, K., Chen, C.-C., & Tseng, M.-L. (2025). Assessing a Hierarchical Structure for Circular Supply Chain Management Performance: Improving Firms' Eco-Innovation and Technological Performance. *Business Strategy and the Environment*, 34(2), 2035-2064. doi:<https://doi.org/10.1002/bse.4066>
- Ma, Z., Shao, C., Ma, S., & Ye, Z. (2011). Constructing road safety performance indicators using Fuzzy Delphi Method and Grey Delphi Method. *Expert Systems with Applications*, 38(3), 1509-1514. doi:<https://doi.org/10.1016/j.eswa.2010.07.062>
- Mahdiyar, A., Mohandes, S. R., Durdyev, S., Tabatabaee, S., & Ismail, S. (2020). Barriers to green roof installation: An integrated fuzzy-based MCDM approach. *Journal of Cleaner Production*, 269, 122365. doi:<https://doi.org/10.1016/j.jclepro.2020.122365>
- Malik, I. A., Elgasim, E. A., Adiamo, O. Q., Ali, A. A., & Mohamed Ahmed, I. A. (2021). Effect of frozen storage on the biochemical composition of five commercial freshwater fish species from River Nile, Sudan. *Food Science & Nutrition*, 9(7), 3758-3767. doi:<https://doi.org/10.1002/fsn3.2340>
- Maulu, S., Hasimuna, O. J., Monde, C., & Mweemba, M. (2020). An assessment of post-harvest fish losses and preservation practices in Siavonga district, Southern Zambia. *Fisheries and Aquatic Sciences*, 23(1), 25. doi:<https://doi.org/10.1186/s41240-020-00170-x>
- Mavuru, A., Mhlanga, L., & Nhwatiwa, T. (2022). An assessment of Post-Harvest Fish Losses (PHFLs) in the artisanal fishery of Lake Kariba, Zimbabwe. *Scientific African*, 16, e01124. doi:<https://doi.org/10.1016/j.sciaf.2022.e01124>
- Minten, B., Tamru, S., & Reardon, T. (2021). Post-harvest losses in rural-urban value chains: Evidence from Ethiopia. *Food Policy*, 98, 101860. doi:<https://doi.org/10.1016/j.foodpol.2020.101860>
- Mramba, R. P., & Mkude, K. E. (2022). Determinants of fish catch and post-harvest fish spoilage in small-scale marine fisheries in the Bagamoyo district, Tanzania. *Heliyon*, 8(6), e09574. doi:<https://doi.org/10.1016/j.heliyon.2022.e09574>

- Murray, T. J., Pipino, L. L., & van Gigch, J. P. (1985). A pilot study of fuzzy set modification of Delphi. *Human Systems Management*, 5(1), 76-80. doi:<https://doi.org/10.3233/HSM-1985-5111>
- Odoli, C. O., Owiti, H., Kobingi, N., Obiero, M., Ogari, Z., Mugo, J., Aura, C. M. (2019). Post-harvest interventions in small-scale fisheries: a boon or bane to food and nutritional security in Kenya? *Food Security*, 11(4), 855-868. doi:<https://doi.org/10.1007/s12571-019-00950-x>
- Pascoe, S., Cannard, T., Dowling, N. A., Dichmont, C. M., Breen, S., Roberts, T., Leigh, G. M. (2019). Developing Harvest Strategies to Achieve Ecological, Economic and Social Sustainability in Multi-Sector Fisheries. *Sustainability*, 11(3). doi:<https://doi.org/10.3390/su11030644>
- Ministry of Marine Affairs and Fisheries. (2024). *Data Angka Konsumsi Ikan (AKI)*. Retrieved from: <https://statistik.kkp.go.id/home.php?m=aki&i=209#panel-footer>
- Poernomo, A., & HP, S. a. (2020). Susut Pasca-panen Pangan dan Gizi Bidang Perikanan. *Kertas Kerja Seri 2 Jejaring Pasca-Panen untuk Gizi Indonesia*.
- Prodhan, M. M. H., Khan, M. A., Palash, M. S., & Rahman, M. T. (2022). Nature, extent, and causes of post-harvest losses at fisher and farmer level: An in-depth study. *Aquaculture*, 550, 737856. doi:<https://doi.org/10.1016/j.aquaculture.2021.737856>
- Santoso, I., Wafi'uddin, I., Lu'ayya, N. M., Choirun, A. u., Purnomo, M., & Sulianto, A. A. (2024). An integrated performance assessment method for SMEs fruit processing sustainability in Indonesia. *Cogent Engineering*, 11(1), 2374941. doi:<https://doi.org/10.1080/23311916.2024.2374941>
- Seker, S., & Zavadskas, E. K. (2017). Application of Fuzzy DEMATEL Method for Analyzing Occupational Risks on Construction Sites. *Sustainability*, 9(11). doi:<https://doi.org/10.3390/su9112083>
- Setiawan, E. A., Thalib, H., & Maarif, S. (2021). Techno-Economic Analysis of Solar Photovoltaic System for Fishery Cold Storage Based on Ownership Models and Regulatory Boundaries in Indonesia. *Processes*, 9(11). doi:<https://doi.org/10.3390/pr9111973>
- Singh, G., Daultani, Y., Rajesh, R., & Sahu, R. (2023). Modeling the growth barriers of fresh produce supply chain in the Indian context. *Benchmarking: An International Journal*, 30(2), 653-677. doi:<https://doi.org/10.1108/BIJ-09-2021-0517>
- Solo, M. K., Lako, J., Mani, F., & Brodie, G. (2023). Assessment of Post-harvest Practices of Tuna Sold at the Honiara Fish Market in the Solomon Islands. *International Journal of Food Science*, 2023(1), 6594017. doi:<https://doi.org/10.1155/2023/6594017>
- Syanya, F. J., Harikrishnan, M., Simiyu, N. N., Khanna, A. R. N., Litabas, J. A., & Mathia, W. M. (2024). Aquaculture: A hidden goldmine for the rural poor—A cost–benefit analysis of fish farming for sustainable development and food security in Vihiga County, Kenya. *Business Strategy & Development*, 7(2), e348. doi:<https://doi.org/10.1002/bsd2.348>
- Tabatabaee, S., Mahdiyar, A., & Ismail, S. (2021). Towards the success of Building Information Modelling implementation: A fuzzy-based MCDM risk assessment tool. *Journal of Building Engineering*, 43, 103117. doi:<https://doi.org/10.1016/j.jobbe.2021.103117>
- Teklu, D. (2015). Determinant factors for wasted fish during harvesting at Amerti and Fichawa Reservoirs Oromia/Ethiopia. *Journal of Fisheries Sciences and Aquaculture*, 3(1), 12
- Tesfay, S., & Teferi, M. (2017). Assessment of fish post-harvest losses in Tekeze dam and Lake Hashenge fishery associations: northern Ethiopia. *Agriculture & Food Security*, 6(1), 4. doi:<https://doi.org/10.1186/s40066-016-0081-5>
- Utama, D. M., Santoso, I., Hendrawan, Y., & Dania, W. A. P. (2025). A sustainable production-inventory model with CO2 emission, electricity and fuel consumption under quality degradation and stochastic demand: a case study in the agri-food industry. *Environment, Development and Sustainability*, 27(4), 9569-9608. doi:<https://doi.org/10.1007/s10668-023-04271-0>
- Viana, F. M., Monteiro, M. L. G., Ferrari, R. G., Mutz, Y. S., Martins, I. B. A., Salim, A. P. A. A., Conte-Junior, C. A. (2022). Multivariate Nature of Fish Freshness Evaluation by Consumers. *Foods*, 11(14). doi:<https://doi.org/10.3390/foods11142144>

HIERARCHICZNE MAPOWANIE PRZYCZYNOWE I PRIORYTETYZACJA RYZYKA STRAT RYB PO ZBIORACH W ŁAŃCUCHU DOSTAW AKWAKULTURY Z WYKORZYSTANIEM ZINTEGROWANEGO PODEJŚCIA FDM–FDEMATEL

Streszczenie. W łańcuchu dostaw akwakultury, gdzie szybkie pogarszanie jakości może obniżyć wartość i dostępność żywności (szczególnie w warunkach tropikalnych, takich jak Indonezja), straty ryb po zbiorach (Post-Harvest Fish Losses, PHFL) pozostają istotnym ograniczeniem. Dotychczasowe badania nad PHFL zdominowały analizy dotyczące rybołówstwa morskiego. Dostarczają one głównie dowodów o charakterze opisowym, pozostawiając niedostatecznie zbadane i usystematyzowane specyficzne dla akwakultury, wielopoziomowe mechanizmy przyczynowe, zwłaszcza te związane ze zdolnościami przetwórczymi oraz infrastrukturą wspierającą. W niniejszym badaniu autorzy opracowali ramy mapowania przyczynowego i priorytetyzacji czynników ryzyka PHFL w zrównoważonym łańcuchu dostaw akwakultury. Wykorzystali w tym celu zintegrowane podejście metody rozmytego Delphi (Fuzzy Delphi Method, FDM) oraz rozmytej metody DEMATEL (Fuzzy Decision-Making Trial and Evaluation Laboratory, FDEMATEL). Opinie 23 ekspertów reprezentujących cztery poziomy łańcucha (producenci, pośrednicy, przetwórcy, detaliści/konsumenci) autorzy pozyskali, aby wyselekcjonować i ustrukturyzować ryzyko w warunkach niepewności. Metoda FDM wyłoniła 17 kluczowych czynników ryzyka spośród 30 kandydatów. Następnie metoda FDEMATEL umożliwiła opracowanie uporządkowanej struktury przyczynowej, w której niewystarczające techniki i wyposażenie zbioru (RF17), ograniczona dostępność łańcucha chłodniczego (RF21) oraz niewystarczające techniki i wyposażenie manipulacyjne (RF18) stanowią najsilniejsze czynniki przyczynowe. Wpływają one na dalsze rezultaty związane z bezpieczeństwem, przechowywaniem i funkcjonowaniem rynku. Z perspektywy teoretycznej badanie wnosi dwupoziomą (hierarchiczną) architekturę przyczynową (aspektów i czynników ryzyka), wykraczającą poza listy determinant poprzez wyjaśnienie ścieżek propagacji. Z punktu widzenia zarządzania dostarcza ono oparte na dowodach priorytetów dla interwencji w zakresie początkowych zdolności obsługi, ciągłości łańcucha chłodniczego oraz koordynacji i integracji IT, co może wspierać decyzje inwestycyjne i polityczne ukierunkowane na redukcję PHFL w łańcuchu dostaw akwakultury w Indonezji.

Słowa kluczowe: straty ryb po zbiorach, łańcuch dostaw akwakultury, hierarchiczna analiza przyczynowa, priorytetyzacja czynników ryzyka

Appendices

Appendix 1.

Respondents profile information

Respondent ID	Actor Categories in the Supply Chain	Role	Experience (years)
R1	Fish Farmers	Business Owner	22
R2	Fish Farmers	Business Owner	23
R3	Fish Farmers	Business Owner	49
R4	Middleman	Business Owner	15
R5	Middleman	Business Owner	16
R6	Middleman	Business Owner	23
R7	Fish Product Processor	Business Owner	23
R8	Fish Product Processor	Business Owner	13
R9	Fish Product Processor	Business Owner	13
R10	Fish Product Processor	Business Owner	7
R11	Modern Retail	Fresh Food Manager	3
R12	Modern Retail	Fresh Food Manager	3
R13	Modern Retail	Fresh Food Manager	2
R14	Modern Retail	Fresh Food Manager	2
R15	Traditional Retail	Business Owner	5
R16	Traditional Retail	Business Owner	13
R17	Traditional Retail	Business Owner	22
R18	Re-seller	Business Owner	39
R19	Re-seller	Business Owner	16
R20	Re-seller	Business Owner	7
R21	Consumers	Consumers	26
R22	Consumers	Consumers	15
R23	Consumers	Consumers	14

Appendix 2:

Notations

Fuzzy Delphi Method (FDM)

e	Expert indeks in FDM
a	Candidate risk factor index in FDM
s	Number of candidate strategies in FDM
$E_e(a)$	TFN evaluation by expert e for risk factor/mitigation strategy a
$A(a)$	Aggregated TFN for risk factor/mitigation strategy a
l_A, m_A, u_A	Components of aggregated TFN $A(a)$
GM	Geometric mean operator
$C_{A(a)}$	Defuzzified (crisp) aggregated score for risk factor/mitigation strategy a
T	Threshold value in FDM

Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL)

i, j	Risk factor index (row/column) in FDEMATEL
n	Number of risk factors analyzed in FDEMATEL
h	Number of experts (or number of individual crisp matrices) aggregated
w	Normalization range in CFCS
$l_{ij}^n, m_{ij}^n, r_{ij}^n$	Lower, modal, and upper TFN components used in CFCS normalization
$xr_{ij}^n, xp_{ij}^n, xl_{ij}^n$	Normalized TFN components
xls_{ij}^n, xrs_{ij}^n	Left and right normalized values
x_{ij}^n	Normalized total crisp value
Z_{ij}^n	Crisp value
Z_{ij}	Integrated crisp value over experts
T	Fuzzy direct relation matrix
E	Initial direct relation matrix (crisp)
G	Normalized direct relation matrix (entries scaled to $[0, 1]$)
W	DEMATEL normalization coefficient
X	Normalized direct relation matrix
I	Identity matrix
M	Total-relation matrix
Rs	Row-sum vector of M
Cs	Column-sum vector of M
$Rs + Cs$	Prominence (overall importance)
$Rs - Cs$	Relation (cause/effect indicator; positive = cause, negative = effect)
β	Threshold value for filtering influences
V	Interaction matrix after thresholding
W_i	Final importance weight of factor i