Assessing the Efficiency of Post-Harvest Fish Losses Risk Mitigation Strategies in Aquaculture Supply Chain Using Fuzzy-Based Data Envelopment Analysis

Muhammad Faisal Ibrahim 1,2,a), Imam Santoso1,b), Siti Asmaul Mustaniroh1,c), Retno Astuti1,d)

1 Agroindustrial Technology Department, Universitas Brawijaya, Malang, Indonesia

2 Logistics Engineering Department, Universitas Internasional Semen Indonesia, Gresik, Indonesia

a) Corresponding author: faisalibrahim.ie@gmail.com

b) imamsantoso@ub.ac.id

c) asmaul\_m@ub.ac.id

d) retno\_astuti@ub.ac.id

**Abstract.**  The fisheries industry, particularly aquaculture, plays a crucial role in global food security. Despite its significant contributions, this sector faces major challenges, including high Post-Harvest Fish Losses (PHFL), especially in Indonesia, which can reach 20–30% of total production. This study aims to evaluate the efficiency of PHFL risk mitigation strategies in the aquaculture supply chain in Indonesia using a fuzzy-based Data Envelopment Analysis (DEA) approach. The methodology involves determining input variables (investment costs, human resources, physical resources, and implementation complexity) and output variables (reduction in PHFL rates). The analysis results indicate that 40% of the evaluated strategies achieve full efficiency, demonstrating optimal resource utilization in reducing PHFL. Conversely, 60% of the strategies showed inefficiency, primarily due to high investment costs and reliance on skilled human resources. Further discussion revealed significant challenges in terms of physical infrastructure and implementation complexity that must be addressed to improve efficiency. These findings emphasize the importance of targeted investments in cooling technology, workforce capacity development, and infrastructure improvement as key factors in reducing PHFL and enhancing the resilience of Indonesia's aquaculture supply chain.

**Keywords:** Post-Harvest Fish Losses; Aquaculture Supply Chain; Risk Mitigation Strategies; Data Envelopment Analysis; Efficiency Evaluation.

# INTRODUCTION

The fisheries industry plays an increasingly critical role in global food security as production expands to meet growing demand. Recent data show that global fisheries production has reached record highs, underscoring its vital role in providing food and nutrition for the future [1]. In addition to its contribution to food availability, increased fisheries production positively impacts employment, supporting the livelihoods of millions, particularly in developing countries [2, 3]. Asia remains the leading region for aquaculture, contributing 91.6% of total global aquaculture production [1]. According to IBRD [4], Indonesia ranks second after China with an aquaculture production contribution of 14,633,869 tons out of a total global aquaculture production of 126,935,293 tons. Fish consumption is also rising significantly, driven by the relatively lower price of fish compared to other animal protein sources, making it an accessible option for many populations [5-7]. However, fish is among the most perishable commodities and is highly susceptible to quality degradation and spoilage, particularly in tropical regions such as Indonesia [7-9]. Post-harvest fish losses (PHFL) remain a significant challenge, as the volume of fish that successfully enters the downstream supply chain is often disproportionate to the quantities harvested, resulting in substantial losses along the supply chain [10].

PHFL can occur across all stages of the aquaculture product supply chain, from harvest at the upstream level to final consumption at the downstream end [11-13]. Although official data on PHFL values in Indonesia, particularly for aquaculture production, remain unavailable, previous studies have estimated PHFL in Indonesia to range between 20% and 30% of total aquaculture production [13, 14]. These high losses are primarily attributed to inefficiencies across the supply chain, resulting in reduced product quality and significant economic losses [7, 15, 16]. In Southeast Asia, including Indonesia, the distribution stage contributes the largest proportion of PHFL, accounting for approximately 15% of total fisheries production, followed by processing and packaging (9%), harvesting (8.2%), and post-harvest handling and storage (6%) [11]. Losses at the consumption stage, while present, constitute a relatively smaller percentage, estimated at around 2% [11, 13].

Over the past decade, research on PHFL has primarily focused on three key outcomes: the evaluation of PHFL values, the identification of risk factors, and the formulation of mitigation strategies. However, among the existing studies, only two studies conducted by Teklu [17] and Acharjee, Hossain [18] specifically examined PHFL within the aquaculture sector. These studies, while valuable, have limitations as they only assessed PHFL values within the aquaculture sectors of Ethiopia and Bangladesh, respectively, regions with significantly smaller aquaculture production compared to Indonesia [4]. In the Indonesian context, an assessment of PHFL values in aquaculture was previously conducted by Wibowo, Utomo [19], yet comprehensive studies on associated risk factors and structured mitigation strategies remain limited. Although Teklu [17] and Acharjee, Hossain [18] provided recommendations related to risk factors and mitigation strategies, these were not derived using systematic methods, limiting their applicability. Furthermore, previous studies generally involved a narrow focus on one to three actors within the supply chain, namely farmers, collectors, and retailers, reflecting the relatively simple supply chain structures in Ethiopia and Bangladesh, which account for only 0.007% and 18.6% of Indonesia’s aquaculture production respectively. In contrast, Indonesia’s substantial aquaculture production is characterized by more complex and extensive supply chain networks involving a greater number of actors. Studies by Azizah, Ishihara [20], Jakaria and Rini [21], and Manzilati, Kornitasari [22] have shown that, within Indonesia, there are at least three intermediaries between pond farmers and end consumers, including collectors, retailers, processors, and resellers. Additionally, these supply chain practices can vary significantly across regions due to differences in local resources, regulatory environments, and cultural practices.

Risk management processes need to be implemented continuously through effective and efficient mitigation strategies to reduce the impacts of risks within supply chains [23]. Therefore, mitigation strategies should not only focus on addressing the root causes of risks but also utilize resources efficiently to ensure their practicality and sustainability [24]. However, previous studies on risk mitigation strategies have largely overlooked the assessment of efficiency, particularly in terms of comprehensively evaluating the required inputs (such as costs and resources) and the outputs produced by these strategies. The Data Envelopment Analysis (DEA) model has been identified as a suitable tool for analyzing the efficiency of risk mitigation strategies [25]. Unlike methods that aim to identify a single best alternative, DEA is designed to identify a set of efficient alternatives within a decision-making environment [26]. Through DEA, efficiency measurements can incorporate all inputs (such as funding and other required resources) and the outputs of mitigation strategies, providing managers with comprehensive insights to guide the selection of appropriate strategies [25]. Despite its potential, the practical application of DEA in evaluating mitigation strategies faces challenges, particularly due to the reliance on subjective assessments in the collection of necessary data, which may affect the robustness of the analysis.

In this study, a set of PHFL risk mitigation strategies identified through a comprehensive literature review will be evaluated in terms of their efficiency. To conduct this analysis, four input variables and one output variable were determined based on expert observations and interviews. The input variables include investment costs, human resources required, physical resources required, and implementation complexity, while the output variable is the reduction in the post-harvest fish losses rate. To address the limitations of previous studies that did not consider the efficiency of mitigation strategies comprehensively, this study will employ a Fuzzy DEA VRS Output-Oriented model. This approach will enable the identification of the most efficient PHFL risk mitigation strategies within the analyzed set of alternatives, providing a structured and practical decision-support tool for managers in selecting effective and resource-efficient mitigation strategies.

# METHODS

Data Envelopment Analysis (DEA) is a non-parametric linear programming technique that enables the assessment and comparison of efficiency among different Decision Making Units (DMUs) based on various inputs (resources) and outputs (results) [27, 28]. The definition of a DMU is general and flexible, referring to any entity whose efficiency is to be measured and compared with other entities that share homogeneous characteristics in terms of input and output types [27]. DEA was originally developed to evaluate how efficiently organizations convert inputs into outputs [29, 30]. The efficiency measured using DEA is relative, depending on the set of DMUs included in the analysis, and therefore reflects performance within the context of the comparison group [28]. A DMU is considered fully efficient (scoring 1) if there is no evidence, based on the available data, that some of its inputs can be reduced or outputs increased without adversely affecting other inputs or outputs [27]. This type of efficiency is commonly referred to as "technical efficiency" within the field of economics. DEA assigns an efficiency score of less than 1 to inefficient DMUs while efficient DMUs receive a score of exactly 1, resulting in all efficient DMUs having the same efficiency score within the analysis [31].

In DEA, two primary orientations can be applied: input-oriented and output-oriented models [32]. In the output-oriented approach, a DMU is considered inefficient if its outputs can still be increased without requiring additional inputs or reducing other outputs, thereby focusing on maximizing outputs while maintaining the same level of inputs. Conversely, in the input-oriented approach, a DMU is deemed inefficient if it is possible to reduce its inputs without increasing other inputs or decreasing any outputs, emphasizing the minimization of inputs while preserving the current level of outputs. Apart from orientation, DEA also includes two fundamental models: the Charnes-Cooper-Rhodes (CCR) model, also known as the Constant Returns to Scale (CRS) model, and the Banker-Charnes-Cooper (BCC) model, also referred to as the Variable Returns to Scale (VRS) model. Both models provide a structured framework for evaluating the transformation of inputs into outputs, with their primary distinction lying in their assumptions regarding returns to scale in measuring efficiency.

The CCR or CRS model, developed by Charnes, Cooper [29], serves as the foundational DEA model widely applied for measuring efficiency across various sectors [33]. The CRS model operates under the assumption that outputs change proportionally with inputs, implying that a doubling of inputs will result in a doubling of outputs, thus reflecting a consistent efficiency environment irrespective of the scale of operations. In contrast, the VRS, incorporated in the BCC model developed by Banker, Charnes [34], allows efficiency to vary with the scale of operations. This model recognizes that the efficiency of a firm may differ depending on its operational scale, which is particularly relevant in sectors where the benefits or costs associated with scaling up operations are not uniform. The BCC model acknowledges that increases in input do not always lead to proportional increases in output, capturing the realities of increasing, constant, or decreasing returns to scale across different operational contexts.



**FIGURE 1**. Research Method

Figure 1 illustrates the methodology employed in this study. In this research, a Decision Making Unit (DMU) is defined as a set of alternative PHFL risk mitigation strategies. The first step involved identifying PHFL risk mitigation strategies through a comprehensive literature review, as detailed in Table 1. Subsequently, the input and output variables for the analysis were determined and collected through field observations and expert interviews. The input variables include investment costs (input 1), human resources required (input 2), physical resources required (input 3), and implementation complexity (input 4), while the output variable is the reduction in the post-harvest fish loss rate. A structured questionnaire was then developed based on these input and output variables and distributed to experts across the relevant supply chain networks under study. The profile of respondents used in this study is presented in Table 2. The questionnaire was designed using linguistic variables. Details of the linguistic variables and scales using triangular fuzzy numbers can be seen in Table 3.

Subsequently, the questionnaire assessment results were fuzzyfied and aggregated using Equations (1) and (2). Where , represents the TFN responses from experts for variable , is the aggregation of all expert responses for variable . On the other hand, it is the minimum lower limit value given by the experts, the geometric mean of the most likely values given by the experts, and the maximum upper limit value given by the experts. Then, the aggregation of these responses is defuzzified to obtain crisp values representing the consensus among the expert panel using Equation (3) [35]. Where is the aggregation of responses that have been defuzzified for variable .

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**TABLE 1.** Alternative PHFL Risk Mitigation Strategies Obtained from Literature Review.

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| --- | --- | --- |
| Code | Mitigation Strategy | References |
| DMU 1 | Improving the capacity of actors in the aquaculture supply chain. | [17]; [19]; [36]; [5]; [2]; [18]; [7]; [37] |
| DMU 2 | Implementing best practices and technological investments in the handling of aquaculture products. | [38]; [12] |
| DMU 3 | Improving knowledge of ice cooling techniques during the distribution of aquaculture products. | [17]; [39]; [36]; [3]; [37] |
| DMU 4 | Improving hygiene practices throughout the aquaculture supply chain. | [38]; [2]; [40] |
| DMU 5 | Standardizing aquaculture products harvesting tools. | [17]; [41] |
| DMU 6 | Standardizing packaging materials for aquaculture products. | [42] |
| DMU 7 | Standardizing the conditions of aquaculture product storage facilities. | [43] |
| DMU 8 | Deploying solar power in areas with poor electrical infrastructure. | [17] |
| DMU 9 | Implementing cold chain facilities in the primary preservation area. | [44]; [2]; [5]; [16] |
| DMU 10 | Government support for marketing and processing of aquaculture products. | [45] |
| DMU 11 | Provision of adequate infrastructure facilities for the aquaculture sector by the government. | [15]; [45]; [18]; [9]; [7] |
| DMU 12 | Improving facilities at the fish market. | [37] |
| DMU 13 | Promotion of aquaculture by the government as a form of political commitment. | [46] |
| DMU 14 | Development of an information system that provides accurate and timely information on market conditions. | [18] |
| DMU 15 | Implementation of demand forecasting techniques. | [47] |

**TABLE 2.** Respondents Profile.

|  |  |  |  |
| --- | --- | --- | --- |
| Respondents | Actor Categories in the Aquaculture Supply Chain | Role | Experience (years) |
| R1 | Fish Farmers | Head of the Fish Farmers Group | 49 |
| R2 | Fish Farmers | Fishpond Owner | 23 |
| R3 | Processed Food Producers | Business Owner | 7 |
| R4 | Processed Food Producers | Business Owner | 13 |
| R5 | Exporter | Business Owner | 37 |
| R6 | Modern Retail | Fresh Product Supervisor | 2 |
| R7 | Traditional Retail | Business Owner | 22 |
| R8 | Department of Fisheries | Head of Aquaculture Division | 28 |
| R9 | Department of Fisheries | Head of Fisheries Resource Management and Supervision |  |
| R10 | Department of Fisheries | Head of Fisheries Product Processing and Marketing Division | 7 |
| R11 | Academic / Researcher | Lecturer & Researcher in Agroindustrial Risk Management | 30 |
| R12 | Academic / Researcher | Lecturer & Researcher in Agroindustrial Risk Management | 10 |

**TABLE 3.** Linguistic Variables and Triangular Fuzzy Number

|  |  |  |
| --- | --- | --- |
| **Linguistic Variables** | **Crisp Scale** | **Triangular Fuzzy Number** |
| Very Low | 1 | (1, 1, 3/2) |
| Low | 2 | (3/2, 2, 5/2) |
| Moderate | 3 | (5/2, 3, 7/2) |
| High | 4 | (7/2, 4, 9/2) |
| Very High | 5 | (9/2, 5 ,5) |

In assessing the efficiency of each risk mitigation strategy, changes in output are not necessarily directly proportional to changes in input. In addition, the orientation used is output orientation, as it focuses on increasing output while maintaining the same level of input. Thus, the technical efficiency of output produced from several inputs can be obtained using equation (4). The standard output-oriented VRS DEA problem model according to Ray [48] is shown in equations (5) to (9).

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Where is the expansion coefficient, is the weight of DMU j, is the output of DMU j, and is the input of DMU j. The output-oriented VRS DEA problem can also be solved using various computer programs such as DEAP (Data Envelopment Analysis (Computer) Program) Version 2.1 [49].

# RESULTS AND DISCUSSION

The aquaculture supply chain in Indonesia involves various key actors, ranging from fish farmers as the main producers, collectors, processed product manufacturers, traders (both traditional and modern retailers), to end consumers. The product flow begins at the ponds and moves to collection points, where it is processed or distributed to markets. Additionally, there are information flows regarding market prices and demand, as well as financial flows that drive each stage of the supply chain. PHFL risks can occur at various points in the supply chain, so this study considers all actors in the aquaculture supply chain to formulate PHFL risk mitigation strategies. Table 3 shows the crisp values of each input and output variable aggregated from all respondents. These crisp values were obtained by processing the questionnaire summary data using equations (1), (2), and (3).

**TABLE 3.** Aggregated Response Results

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **DMU** | **Input Variable** | | | | **Output Variable** |
| **Input 1** | **Input 2** | **Input 3** | **Input 4** | **Output 1** |
| DMU 1 | 3.003 | 3.589 | 3.287 | 3.233 | 3.840 |
| DMU 2 | 3.952 | 3.532 | 3.573 | 3.840 | 4.236 |
| DMU 3 | 3.209 | 3.603 | 3.180 | 3.319 | 3.648 |
| DMU 4 | 3.528 | 3.718 | 3.589 | 3.778 | 4.133 |
| DMU 5 | 3.938 | 3.528 | 3.718 | 3.952 | 3.952 |
| DMU 6 | 3.573 | 3.211 | 3.233 | 3.126 | 3.166 |
| DMU 7 | 3.952 | 3.233 | 3.342 | 3.840 | 3.682 |
| DMU 8 | 3.682 | 2.671 | 2.776 | 3.178 | 3.003 |
| DMU 9 | 4.092 | 3.826 | 3.826 | 3.840 | 4.161 |
| DMU 10 | 3.189 | 3.457 | 3.230 | 3.470 | 3.314 |
| DMU 11 | 3.634 | 3.251 | 3.457 | 3.647 | 3.094 |
| DMU 12 | 4.184 | 3.470 | 3.589 | 3.476 | 3.457 |
| DMU 13 | 3.457 | 3.336 | 3.158 | 3.024 | 2.732 |
| DMU 14 | 3.718 | 3.648 | 3.233 | 3.648 | 3.211 |
| DMU 15 | 3.180 | 3.840 | 3.401 | 3.648 | 3.211 |

This study uses the Data Envelopment Analysis (DEA) model with the assumption of Variable Returns to Scale (VRS) to evaluate the technical efficiency of 15 Decision Making Units (DMUs) representing various PHFL risk mitigation strategies. Table 4 shows the results obtained using the Data Envelopment Analysis (Computer) Program (DEAP) Version 2.1 and equations (4) to (9). The analysis results indicate that 6 DMUs (40%) achieved full efficiency with a score of 1.000, reflecting optimal resource utilization in maximizing PHFL reduction. Meanwhile, 9 DMUs (60%) showed inefficiency with efficiency scores ranging from 0.815 to 0.995. Efficient DMUs, such as DMU 1, DMU 2, DMU 4, DMU 6, DMU 8, and DMU 13, serve as benchmarks that can be applied to other strategies. On the other hand, inefficient DMUs indicate room for improvement, as reflected in the input slack values, which indicate excess resource use or insufficient output. Table 4 also presents the slack values for each input, indicating the input values that can be further reduced without decreasing outputs to achieve a fully efficient PHFL risk mitigation strategy.

To gain a deeper understanding of the inefficiencies in some strategies, this study conducted a further analysis that identified high investment costs as the main obstacle to the implementation of mitigation strategies. This is indicated by the slack investment costs (Input 1). Some strategies that require large investment costs include improving knowledge of ice cooling techniques (DMU 3), standardizing storage facilities (DMU 7), implementing cold chain facilities (DMU 9), government support for marketing and processing products (DMU 10), improving fish market facilities (DMU 12), and developing market information systems (DMU 14). This aligns with the findings of Maulu, Hasimuna [5], who stated that inadequate cooling infrastructure plays a significant role in PHFL, requiring substantial investment in cooling technology. Additionally, Assefa, Abunna [36] emphasized the importance of targeted investment in equipment and training to reduce product damage. High environmental temperatures in tropical regions further exacerbate this issue, making investments in temperature control increasingly urgent [7]. Based on these findings, it can be concluded that although they require substantial investments, these strategies are crucial steps toward enhancing the resilience and efficiency of the aquaculture supply chain.

**TABLE 4.** Efficiency Analysis Results using VRS Model

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **DMU** | **Technical Efficiency** | **Condition** | **Slacks** | | | | **DMU Peers (Weight of Peers)** |
| **Input 1** | **Input 2** | **Input 3** | **Input 4** |
| DMU 1 | 1 | Efficient | 0 | 0 | 0 | 0 | DMU 1 (1.000) |
| DMU 2 | 1 | Efficient | 0 | 0 | 0 | 0 | DMU 2 (1.000) |
| DMU 3 | 0.995 | Inefficient | 0.064 | 0.206 | 0 | 0.098 | DMU 8 (0.209); DMU 1 (0.791) |
| DMU 4 | 1 | Efficient | 0 | 0 | 0 | 0 | DMU 4 (1.000) |
| DMU 5 | 0.936 | Inefficient | 0 | 0 | 0.153 | 0.124 | DMU 2 (0.981); DMU 8 (0.006); DMU 1 (0.013) |
| DMU 6 | 1 | Efficient | 0 | 0 | 0 | 0 | DMU 6 (1.000) |
| DMU 7 | 0.967 | Inefficient | 0.094 | 0 | 0.046 | 0.230 | DMU 2 (0.653); DMU 8 (0.347) |
| DMU 8 | 1 | Efficient | 0 | 0 | 0 | 0 | DMU 8 (1.000) |
| DMU 9 | 0.982 | Inefficient | 0.140 | 0.294 | 0.253 | 0 | DMU 2 (1.000) |
| DMU 10 | 0.885 | Inefficient | 0.041 | 0 | 0 | 0.213 | DMU 2 (0.052); DMU 1 (0.808); DMU 8 (0.141) |
| DMU 11 | 0.832 | Inefficient | 0 | 0 | 0.225 | 0.178 | DMU 2 (0.420); DMU 8 (0.342); DMU 1 (0.238) |
| DMU 12 | 0.883 | Inefficient | 0.721 | 0 | 0.238 | 0 | DMU 1 (0.486); DMU 2 (0.410); DMU 8 (0.104) |
| DMU 13 | 1 | Efficient | 0 | 0 | 0 | 0 | DMU 13 (1.000) |
| DMU 14 | 0.856 | Inefficient | 0.643 | 0.156 | 0 | 0.421 | DMU 8 (0.106); DMU 1 (0.894) |
| DMU 15 | 0.815 | Inefficient | 0 | 0.208 | 0.012 | 0.231 | DMU 4 (0.337); DMU 1 (0.663) |

In addition to investment costs, DEA analysis also shows that the success of several mitigation strategies is highly dependent on the availability of skilled human resources. This leads to inefficiencies in the PHFL risk mitigation strategy. This is indicated by the slack human resources (Input 2). Strategies such as improving knowledge of ice cooling techniques (DMU 3), implementing cold chain facilities (DMU 9), developing market information systems (DMU 14), and implementing demand forecasting (DMU 15) are highly dependent on the technical skills of workers. Without trained workers, the implementation of hygiene protocols and temperature control can be disrupted, which in turn increases the risk of microbial contamination and product damage. As highlighted by Assefa, Abunna [36], adequate training in post-harvest handling is key to reducing spoilage. Therefore, workforce capacity development and skill enhancement in the areas of cooling technology and data-driven logistics management are essential for the successful implementation of PHFL mitigation strategies.

Furthermore, the DEA results also reveal that some PHFL mitigation strategies require significant physical resources to be successfully implemented. This leads to inefficiencies in the PHFL risk mitigation strategy. This is indicated by the slack physical resources (Input 3). Strategies such as standardization of harvesting tools (DMU 5), standardizing storage facilities (DMU 7), implementing cold chain facilities (DMU 9), government-provided infrastructure (DMU 11), and improving fish market facilities (DMU 12) require investment in adequate infrastructure. Maulu, Hasimuna [5] and Assefa, Abunna [36] identified that a lack of appropriate harvesting tools and storage facilities can cause product damage and a decline in fish quality, leading to PHFL. High temperatures commonly experienced in tropical regions exacerbate this issue, making effective cooling systems and proper storage facilities crucial for maintaining product quality during distribution [7]. Kaminski, Cole [41] added that access to modern equipment, particularly for women in the fisheries sector, remains limited, making inclusive and equitable infrastructure essential to reduce disparities in this sector.

The analysis results also indicate that seven PHFL mitigation strategies face complex implementation challenges, which limit their operational efficiency. This is indicated by the slack implementation complexity (Input 4). Strategies such as improving knowledge of ice cooling techniques (DMU 3) and standardization of harvesting tools (DMU 5) require the integration of advanced infrastructure and complex logistical coordination to ensure effective and efficient distribution. Solo, Lako [37] and Bedane, Agga [40] emphasize that without proper cooling, product quality will decline significantly. Similar issues arise with strategies involving storage standards and demand forecasting, which require technical training and coordination among various stakeholders [5, 41]. Therefore, while these mitigation strategies are highly promising, the complex implementation challenges they face must be addressed through a coordinated and collaborative approach involving public and private sectors, as well as other stakeholders.

The findings from this study emphasize that while several strategies for mitigating PHFL in Indonesia's aquaculture supply chain show promising potential, they also face significant challenges. High investment costs, dependency on skilled human resources, the need for substantial physical infrastructure, and implementation complexity are the key factors contributing to inefficiencies in some strategies. Despite these challenges, the study highlights the critical importance of targeted investments in cooling technology, workforce development, and infrastructure improvements. Addressing these obstacles will not only enhance the resilience and efficiency of the aquaculture supply chain but also ensure a more sustainable and effective mitigation of PHFL. To achieve these goals, a coordinated effort involving both public and private sectors, along with all relevant stakeholders, is essential.

# CONCLUSIONS

This study evaluates the efficiency of various post-harvest fish loss (PHFL) risk mitigation strategies within Indonesia’s aquaculture supply chain using the Data Envelopment Analysis (DEA) method. The findings reveal that 40% of the strategies analyzed achieved full efficiency, indicating optimal resource use in reducing PHFL, while the remaining strategies showed inefficiencies, particularly due to high investment costs, the need for skilled human resources, and significant physical infrastructure requirements. Notably, strategies such as improving knowledge of ice cooling techniques, implementing cold chain facilities, and standardizing storage conditions were identified as requiring substantial financial and human resources for successful implementation.

The results emphasize the critical importance of targeted investments in both technology and workforce development to address inefficiencies in PHFL mitigation. While these strategies show promise in enhancing the aquaculture supply chain’s resilience, challenges such as high implementation complexity and the need for substantial physical infrastructure remain. These findings contribute to the existing body of knowledge by applying the DEA model to a complex, multi-actor supply chain and offering a systematic assessment of PHFL risk mitigation strategies in Indonesia’s aquaculture sector.

In addition, future studies can integrate the efficiency values obtained with DEA with various decision-making methods. This will enable the best risk mitigation strategies to be obtained while considering efficiency to further optimize risk management in aquaculture supply chains.

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