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SELECTING COLD STORAGE BUILDING DESIGNS FOR TROPICAL SMALL-SCALE FISHERIES: AN AHP-TOPSIS DECISION MODEL

Muhammad Alfathan Harriz[1*], Harlis Setiyowati[2], Inggit Musdinar[3], Hari Soetanto[4], Nurhaliza Vania Akbariani[5]
[1]Department of Informatics, Matana University, Indonesia
[2]Doctoral Program in Management, Budi Luhur University, Indonesia
[3]Department of Architecture, Budi Luhur University, Indonesia
[4]Doctoral Program in Computer Science, Budi Luhur University, Indonesia
[5]Master of Computer Science, Budi Luhur University, Indonesia
harrizsb@gmail.com*, harlis.setiyowati@budiluhur.ac.id
inggit.musdinar@budiluhur.ac.id, hari.soetanto@budiluhur.ac.id
akbariani1006@gmail.com
* Coresponding Author

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Abstract

Small-scale fisheries in tropical coastal regions lose substantial catches to inadequate cold storage infrastructure, and no structured decision framework addresses this gap. The trade-offs among economic, technological, and environmental criteria resist intuition. Using AHP-TOPSIS, we evaluated four cold storage design alternatives against seven criteria grouped under three pillars (Economics, Technology, Environment). Pairwise judgments remained consistent, with the highest sub-level Consistency Ratio reaching 0.008 (Technology pillar). The prefabricated polyurethane panel with rooftop cooling (A2) ranked first (CC = 0.6266), followed by conventional masonry (A1, 0.5662), modular steel with IoT monitoring (A4, 0.5265), and insulated concrete with solar-hybrid cooling (A3, 0.3330). Sensitivity analysis showed A2 winning 91.4% of scenarios; A4 outranked A2 when either the IoT-readiness weight (C3) exceeded 0.21 or the investment-cost weight (C1) fell below 0.20. Despite the lowest-carbon profile, A3 ranked last under cost-dominant weights, a structural green penalty against the most sustainable design. Cooperative ownership can move the optimum toward IoT-enabled A4 by pooling capital that individual operators cannot mobilize alone.

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INTRODUCTION

Post-harvest loss in small-scale fisheries remains a critical bottleneck in tropical food systems and a barrier to the blue economy. Globally, only 54% of harvested fish is consumed directly by people; the remainder is lost to spoilage, inefficient processing, or diversion to non-food uses (Acharjee et al., 2025; Wu et al., 2026). For small-scale fisheries in developing coastal economies, inadequate cold storage infrastructure is the primary driver of these losses, undermining both food security and fisher livelihoods (Bennett et al., 2024; FAO et al., 2023; FAO, 2024). The blue economy framework, which links ocean-based economic activity to sustainability and inclusive livelihoods, positions post-harvest loss reduction as a prerequisite for viable small-scale fisheries (Basurto et al., 2025; Muhl et al., 2026).

Cold storage is a node in a broader value chain that connects harvest, market

access, income stability, and nutritional outcomes. The choice of building design for a cold storage facility is an architecture-building decision: it involves selecting construction materials, insulation systems, and structural configurations that determine thermal performance, durability, and life-cycle cost (Girip et al., 2021; Hu et al., 2025). The technical relationship between insulation material and energy efficiency is direct: materials with lower thermal conductivity, such as polyurethane (PU) panels, reduce heat gain through the building envelope and thereby lower the cooling load and yearly energy consumption compared to conventional masonry, which has higher thermal transmittance and requires more energy to maintain target storage temperatures. These trade-offs are difficult to reconcile through intuition alone. A low-cost conventional structure may minimize capital expenditure but incur higher energy costs and lower technology readiness. A solar-hybrid design may minimize carbon emissions but demand upfront investment that exceeds the means of a small-scale operator (Mehmood et al., 2024; Rami & Allouhi, 2024; Thalib et al., 2021). Despite the engineering clarity of these trade-offs, cold storage selection in small-scale fisheries remains largely ad hoc, driven by habit, first-cost minimization, or donor preference rather than systematic multi-criteria evaluation.

This is a gap in both the fisheries infrastructure literature and the architecture-building literature, where building design optimization is well studied but rarely applied to fishery cold storage. The consequences are measurable: suboptimal building choices perpetuate high energy costs, premature structural degradation in coastal environments, and missed opportunities for technology-enabled value chain upgrading (Setiyowati et al., 2022).

Multi-criteria decision-making (MCDM) methods provide a structured framework for navigating such trade-offs. The Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) are prominent MCDM approaches whose combination is well suited to architecture-building decisions: AHP captures the subjective weightings that reflect stakeholder priorities across conflicting criteria, while TOPSIS provides a transparent ranking that makes trade-offs among building alternatives explicit and defensible (Chaube et al., 2024). This hybrid pairing is particularly valuable for cold storage design, where the choice of construction system involves incommensurable dimensions (capital cost, thermal performance, technology readiness, environmental impact) that cannot be reduced to a single metric. Similar multi-criteria approaches have supported fisheries and water infrastructure decisions, such as fish pass selection and cold storage siting (Hämmerling et al., 2024). Among available MCDM methods, AHP-TOPSIS offers distinct advantages over alternatives such as PROMETHEE, VIKOR, and ELECTRE for this specific problem. First, AHP's hierarchical structure naturally maps to the three-pillar organization of criteria, enabling decision-makers to visualize and interpret sub-criteria relationships within each pillar, whereas PROMETHEE and ELECTRE operate on flat criterion sets without native hierarchical support. Second, AHP provides an embedded consistency check through the consistency ratio (CR), which directly validates the coherence of expert pairwise judgments; VIKOR lacks this built-in diagnostic, making it harder to identify and correct irrational weightings. Third, TOPSIS's closeness coefficient yields a continuous score that supports sensitivity analysis and threshold identification (C3 greater than 0.21), which is more informative than the outranking flows of PROMETHEE or the compromise solution of VIKOR for identifying usable decision thresholds in capital-constrained settings (Basílio et al., 2022).

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The seven evaluation criteria used in this study group naturally into three pillars: economics, technology, and environment. This grouping is not arbitrary but reflects the physical realities of tropical coastal environments, which impose high humidity, salt-laden air, and high ambient temperatures on cold storage buildings. These conditions directly affect insulation material choice, structural durability requirements, and cooling energy demand. Economics captures the financial reality of capital-constrained small-scale operators, where investment cost and energy cost determine operational viability. Technology captures the functional readiness of the cooling and monitoring system, where IoT readiness, cooling reliability, and maintenance ease determine whether the facility operates effectively day-to-day. Environment captures the interaction between the building and its coastal location, where corrosion resistance and energy/carbon efficiency reflect the durability and sustainability demands of tropical coastal zones. Together, these pillars ensure that the evaluation covers the range of concerns relevant to small-scale fishery cold storage in a tropical coastal context.

Unlike previous studies that examined general construction and residential redevelopment using AHP-TOPSIS (Park & Son, 2025), this study is the first to apply the hybrid model to cold storage building design selection for small-scale fisheries in a tropical coastal context, and contributes a new perspective on architecture-building decisions within the blue economy and technology management. This study applies a hybrid AHP-TOPSIS model to rank four cold storage building alternatives for small-scale fisheries in a tropical coastal context. The decision problem is structured around three pillars: economics (cost criteria), technology (benefit criteria), and environment (benefit criteria). The objective is to surface the trade-offs that matter for managerial decision-making and policy design, rather than only identifying a single best alternative.

By linking building-design selection to technology adoption and innovation management in the fisheries sector, this study contributes to fisheries technology management literature. It shows how structured decision models can inform technology-driven upgrading of small-scale fishery infrastructure.

RESEARCH METHODS

Research Types

This study used a quantitative approach with a multi-criteria decision analysis (MCDA) design. The research ranked four cold storage building alternatives for small-scale fisheries by evaluating seven criteria organized under three pillars (economics, technology, environment). Criterion weights were derived through AHP pairwise comparisons and alternatives were ranked using TOPSIS. A one-at-a-time sensitivity analysis tested the stability of the ranking under weight uncertainty.

Population And Sample/Informants

The study population comprised cold storage building design alternatives and evaluation criteria relevant to small-scale fisheries in tropical coastal contexts. Four building alternatives were defined to represent distinct construction strategies: conventional masonry with split air conditioning, prefabricated polyurethane (PU) panel with rooftop cooling, insulated concrete with solar-hybrid cooling, and modular steel with integrated Internet of Things (IoT) monitoring. Seven evaluation criteria were organized under three pillars. Criterion performance data were drawn from published literature and documented expert judgment, as detailed in the criteria definitions table

below.

Research Location

This study is a desk-based analysis drawing on published data from tropical coastal small-scale fisheries contexts. The decision framework is designed for application in Indonesia and comparable developing coastal economies where small-scale fisheries operate under capital constraints and tropical environmental conditions. The building alternatives and criterion values reflect conditions typical of tropical coastal zones, including high humidity, salt-laden air, and limited access to capital.

Instrumentation Or Tools

The study employed AHP pairwise comparison matrices for criterion weight derivation and TOPSIS for alternative ranking. Pillar-level comparisons (Economics, Technology, Environment) and sub-criterion comparisons within each pillar were evaluated for consistency using the consistency ratio (CR), calculated as the ratio of the consistency index (CI) to the random index (RI) (Basílio et al., 2022). The RI values used were those from Saaty's standard random-index table: RI = 0.58 for the 3x3 pillar and technology sub-criterion matrices (Economics and Environment sub-criteria are 2x2, for which RI = 0.00 by definition). A CR threshold of 0.10 was applied; all matrices fell below this threshold. Eigenvector extraction was used to derive local and global criterion weights.

Data Collection Procedure

Criterion performance values were compiled from published literature on cold storage building systems, solar cooling, IoT cold chain monitoring, coastal corrosion, and insulation engineering. Cost criteria (investment cost, yearly energy cost) were recorded in US dollars based on published cost benchmarks for small-scale cold rooms in developing coastal economies. Benefit criteria (IoT readiness, cooling reliability, maintenance ease, coastal corrosion resistance, energy/carbon efficiency) were scored on a 1-9 scale where higher values indicate better performance, drawing on documented expert judgment and published technical assessments. The experts consulted for the AHP pairwise comparisons and criterion scoring possess backgrounds in fisheries technology management, cold chain logistics, and coastal building engineering; all hold advanced degrees and have published on small-scale fisheries infrastructure. The number of experts reflects the study's desk-based design, where criterion values were drawn from published technical literature supplemented by documented expert assessments, following the recommendation that a minimum of 3-5 domain experts is sufficient for AHP pairwise comparisons when the alternatives are well-defined building typologies with published performance data (Basílio et al., 2022).

To convert expert assessments into the 1-9 scale, a structured equivalence protocol was applied: each expert rated every alternative against each criterion using Saaty's semantic anchors (1 = equal importance/performance, 9 = extreme superiority), and qualitative technical assessments (e.g., "PU panel is substantially more energy-efficient than masonry") were mapped to the corresponding odd-integer scale values (1, 3, 5, 7, 9) with even integers (2, 4, 6, 8) reserved for intermediate judgments. Under this protocol, the scale values reflect reproducible expert equivalence rather than arbitrary assignment. To control for subjective bias inherent in converting literature-derived secondary data into the Saaty 1-9 scale, a three-layer mechanism was employed: (a) qualitative assessments were independently mapped by each expert to the Saaty 1-9

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scale using semantic anchors (1 = equal, 3 = moderate, 5 = strong, 7 = very strong, 9 = extreme); (b) The experts compared and reconciled independent mappings through structured discussion to eliminate outliers and resolve discrepancies; and (c) the consistency ratio (CR < 0.10) provides a mechanical check on the coherence of the resulting pairwise judgments. This gate keeps subjective bias from producing internally contradictory weight structures. This three-layer approach (structured protocol + reconciliation + CR gate) controls for the inherent subjectivity of expert-based secondary data conversion. Pairwise comparison matrices for AHP weight derivation were constructed based on documented expert judgment reflecting the capital-constrained reality of small-scale fisheries. All data values appear in the tables of this manuscript.

Data Analysis

The decision problem is structured as a three-level hierarchy. The goal (Level 1) is to select the most suitable cold storage building design for small-scale fisheries. The criteria (Level 2) are organized under three pillars: economics (cost: C1 investment cost, C2 yearly energy cost), technology (benefit: C3 IoT readiness, C4 cooling reliability, C5 maintenance ease), and environment (benefit: C6 coastal corrosion resistance, C7 energy/carbon efficiency). Four alternatives (Level 3) represent distinct building design strategies, as defined in the Population and Sample section.

Table 1 summarizes the seven criteria, their direction (cost vs. benefit), and data sources.

Table 1: Criteria definitions and sources

Code	Criterion	Pillar	Direction	Source
C1	Investment cost (USD)	Economics	Cost	(Girip et al., 2021)
C2	Yearly energy cost (USD/yr)	Economics	Cost	(FAO, 2025; Rami & Allouhi, 2024)
C3	IoT readiness (1-9 scale)	Technology	Benefit	(Harriz et al., 2025; Müller et al., 2026)
C4	Cooling reliability (1-9 scale)	Technology	Benefit	(Girip et al., 2021; Hu et al., 2025)
C5	Maintenance ease (1-9 scale)	Technology	Benefit	(Rincon et al., 2024)
C6	Coastal corrosion resistance (1-9 scale)	Environment	Benefit	(Castañeda et al., 2024; Rincon et al., 2024)
C7	Energy/carbon efficiency (1-9 scale)	Environment	Benefit	(Rami & Allouhi, 2024; Thalib et al., 2021)

The operational definitions for each criterion, which enable precise replication of the evaluation instrument, are as follows. C1 Investment cost: Total upfront capital expenditure (in US dollars) for purchasing materials, constructing, and commissioning the cold storage facility, including insulation, cooling equipment, and structural components, based on published cost benchmarks for small-scale cold rooms (5-10 metric ton capacity) in developing coastal economies. C2 Yearly energy cost: Annual electricity expenditure (in US dollars per year) for maintaining the target storage temperature, calculated from published energy consumption data and local electricity tariffs. C3 IoT readiness: Qualitative score on a 1-9 integer scale assessing the degree to which the building design supports integrated IoT-based cold chain monitoring (sensors, connectivity, data infrastructure), based on published IoT cold chain assessments; 1 = not IoT-ready, 9 = fully IoT-ready. C4 Cooling reliability: Qualitative score on a 1-9 integer scale assessing the ability of the building design to maintain stable target temperatures under tropical coastal conditions (high ambient

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temperature, humidity, salt-laden air), based on published insulation and cooling performance studies; 1 = unreliable, 9 = highly reliable. C5 Maintenance ease: Qualitative score on a 1-9 integer scale assessing the ease of routine maintenance and repair of the building envelope and cooling system in coastal settings, based on published coastal facility maintenance studies; 1 = difficult to maintain, 9 = easy to maintain. C6 Coastal corrosion resistance: Qualitative score on a 1-9 integer scale assessing the building materials' resistance to salt-induced corrosion in tropical coastal environments, based on published coastal corrosion studies; 1 = highly vulnerable, 9 = highly resistant. C7 Energy/carbon efficiency: Qualitative score on a 1-9 integer scale assessing the overall energy performance and carbon footprint of the building design, combining cooling efficiency and material lifecycle emissions, based on published solar cooling and insulation efficiency data; 1 = high energy/carbon, 9 = low energy/carbon.

The decision matrix is shown in Table 2. Cost criteria (C1, C2) are measured in US dollars; benefit criteria (C3-C7) are scored on a 1-9 scale where higher is better.

Table 2: Decision matrix

Alternative	C1	C2	C3	C4	C5	C6	C7
A1	900	180	2	5	5	7	3
A2	1100	120	4	7	8	5	5
A3	2200	55	5	6	5	6	9
A4	1800	75	9	8	7	5	7

AHP WEIGHT DERIVATION

Criterion weights were derived using the Analytic Hierarchy Process (AHP) following the principal-eigenvector procedure (Basílio et al., 2022; Chaube et al., 2024). For a set of n criteria, the decision-maker constructs a pairwise comparison matrix $A = (a_{ij})_{n\times n}$, where a_{ij} denotes the relative importance of criterion i over criterion j assessed on Saaty's 1-9 scale (1 = equal importance, 9 = extreme importance), with $a_{ji} = 1/a_{ij}$ and $a_{ii} = 1$.

Once the decision-maker has constructed the pairwise comparison matrix A, its eigenvalues and eigenvectors are computed:

$$A\boldsymbol{v} = \lambda\boldsymbol{v} \qquad (1)$$

The dominant eigenvalue $\lambda_{\max}$ is the eigenvalue with the largest real part, and the principal eigenvector $\boldsymbol{v}$ is the corresponding (real) column of the eigenvector matrix. The criterion weight vector is obtained by normalizing the principal eigenvector to sum to one:

$$w_i = \frac{v_i}{\sum_{k=1}^{n} v_k} \qquad (2)$$

The weight vector $\boldsymbol{w} = (w_1, \dots, w_n)$ satisfies $\sum_{i=1}^{n} w_i = 1$.

The consistency index is computed from the dominant eigenvalue:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \qquad (3)$$

The consistency ratio is obtained by dividing the consistency index by the random index RI from Saaty's standard table:

$$CR = \frac{CI}{RI} \qquad (4)$$

A CR value below 0.10 indicates acceptable consistency in the pairwise judgments. Local weights were derived at the pillar and sub-criterion levels, and global weights were obtained by multiplying local weights along the hierarchy.

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TOPSIS RANKING

TOPSIS ranking followed the standard procedure (Chaube et al., 2024). Let $X = (x_{ij})_{m\times n}$ denote the decision matrix with $m = 4$ alternatives and $n = 7$ criteria, and let $w = (w_1, \dots, w_n)$ be the AHP-derived global weight vector.

Vector normalization converts X into the normalized matrix $R = (r_{ij})$:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}} \qquad (5)$$

The weighted normalized matrix $V = (v_{ij})$ is then obtained by element-wise multiplication with the weight vector:

$$v_{ij} = w_j \cdot r_{ij} \qquad (6)$$

The positive ideal solution (A^+) and negative ideal solution (A^-) are defined criterion-wise:

$$A_j^+ = \begin{cases} \max_i v_{ij} & \text{if } j \in B \\ \min_i v_{ij} & \text{if } j \in C \text{'} \end{cases} \qquad A_j^- = \begin{cases} \min_i v_{ij} & \text{if } j \in B \\ \max_i v_{ij} & \text{if } j \in C \end{cases} \qquad (7)$$

where B is the set of benefit criteria and C is the set of cost criteria. The Euclidean distance of each alternative from the PIS (d_i^+) and NIS (d_i^-) is then computed:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^+)^2}, \qquad d_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^-)^2} \qquad (8)$$

These distances feed into the relative closeness to the ideal solution:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \qquad (9)$$

Alternatives are ranked by descending CC_i.

To assess the stability of the ranking under weight uncertainty, a one-at-a-time sensitivity analysis was performed. Each criterion weight was perturbed across a uniform grid of 20 steps spanning +/-50% of its base value, while the remaining weights were rescaled proportionally to maintain the sum-to-one constraint. This yielded 140 perturbation scenarios (7 criteria x 20 steps). For each perturbation, the TOPSIS ranking was recomputed. The win rate is the proportion of scenarios in which each alternative achieved the top rank (Paradowski et al., 2025). This analysis shows whether the ranking is stable or sensitive to specific criterion weights, and shows which trade-offs most affect the decision.

RESULTS AND DISCUSSION

AHP WEIGHTS

Table 3 presents the AHP-derived weights. The Economics pillar dominates with a weight of 0.540, which is consistent with the capital-constrained reality of small-scale fisheries where upfront and operating costs are primary decision drivers. Technology follows at 0.297, and Environment at 0.163.

At the criterion level, investment cost (C1) carries the largest global weight (0.405), followed by IoT readiness (C3, 0.160) and coastal corrosion resistance (C6, 0.109). Maintenance ease (C5, 0.049) and energy/carbon efficiency (C7, 0.055) are the two smallest weights. This result mirrors the pairwise judgments but also signals a tension: environmental performance is valued but economically discounted in the current weighting scheme.

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Table 3: AHP-derived weights

Pillar	Pillar Weight	Criterion	Local Weight	Global Weight	CR
Economics	0.540	C1 Investment cost	0.750	0.405	0.000
Economics		C2 Yearly energy cost	0.250	0.135	
Technology	0.297	C3 IoT readiness	0.540	0.160	0.008
Technology		C4 Cooling reliability	0.297	0.088	
Technology		C5 Maintenance ease	0.163	0.049	
Environment	0.163	C6 Coastal corrosion resistance	0.667	0.109	0.000
Environment		C7 Energy/carbon efficiency	0.333	0.055	

Rounded values sum to 1.001; exact weights sum to 1.000. All consistency ratios are below 0.10, confirming that the pairwise comparisons are logically coherent. The Economics pillar CR is 0.000 (a 2x2 matrix is always consistent); Technology CR is 0.008 and Environment CR is 0.000.

The dominance of investment cost in the weight structure means that any alternative with a high capital expenditure is unlikely to rank first, regardless of its technological or environmental performance.

TOPSIS RANKING

Table 4 presents the TOPSIS results. Alternative A2 (prefabricated polyurethane panel with rooftop cooling) achieves the highest closeness coefficient (0.6266), followed by A1 (conventional masonry, 0.5662), A4 (modular steel with IoT, 0.5265), and A3 (insulated concrete with solar-hybrid, 0.3330).

Table 4: TOPSIS ranking results

Rank	Alternative	d_i^+	d_i^-	CC_i
1	A2 Prefab PU panel	0.0884	0.1483	0.6266
2	A1 Conventional masonry	0.1277	0.1666	0.5662
3	A4 Modular steel + IoT	0.1171	0.1302	0.5265
4	A3 Insulated concrete + solar	0.1763	0.0880	0.3330

The ranking follows the weight structure. A2 combines a moderate investment cost ($1100) with a low yearly energy cost ($120/yr) and strong technology scores (IoT readiness 4, cooling reliability 7, maintenance ease 8).

Under the current weighting, the environmental advantage cannot offset the capital barrier. Figure 1 visualizes the closeness coefficients for each alternative.

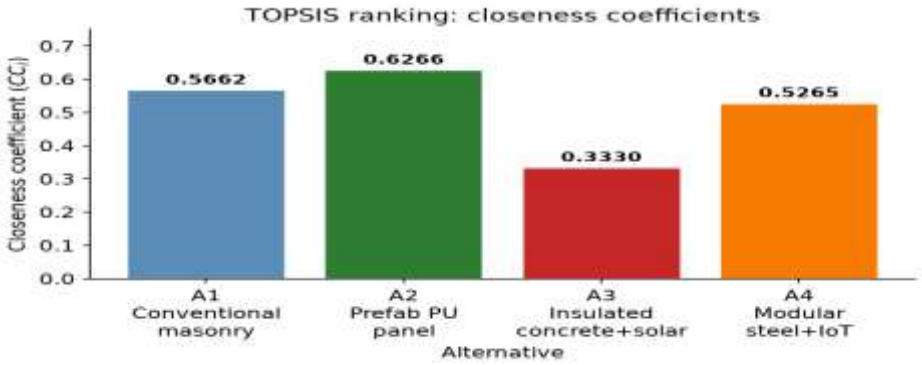


Figure 1: TOPSIS closeness coefficients for four cold storage building alternatives evaluated under seven criteria across three pillars.

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Alternative A2 (prefabricated PU panel) ranks first (CC = 0.6266), followed by A1 (conventional masonry, CC = 0.5662), A4 (modular steel + IoT, CC = 0.5265), and A3 (insulated concrete + solar, CC = 0.3330). The closeness coefficient (CC) ranges from 0 to 1, where higher values indicate closer proximity to the ideal solution. A3's last-place ranking despite having the best environmental score illustrates the green penalty under cost-dominant weights.

The ranking reveals a "green penalty": the most sustainable design (A3) is the least attractive under cost-dominant weights. This is not a failure of the decision model; it is a finding about the economic reality facing small-scale fisheries. For managers and policymakers, promoting environmentally superior cold storage designs requires financial mechanisms that decouple the capital cost from the operator's balance sheet.

Figure 2 shows the win rates across 140 weight perturbations (7 criteria x 20 steps). A2 wins in 91.4% of scenarios, confirming its stability. A4 wins in 8.6% of scenarios, primarily when either the IoT-readiness weight (C3) is increased above approximately 0.21 or the investment-cost weight (C1) is reduced below approximately 0.20. A1 and A3 never achieve the top rank under any perturbation within the tested range.

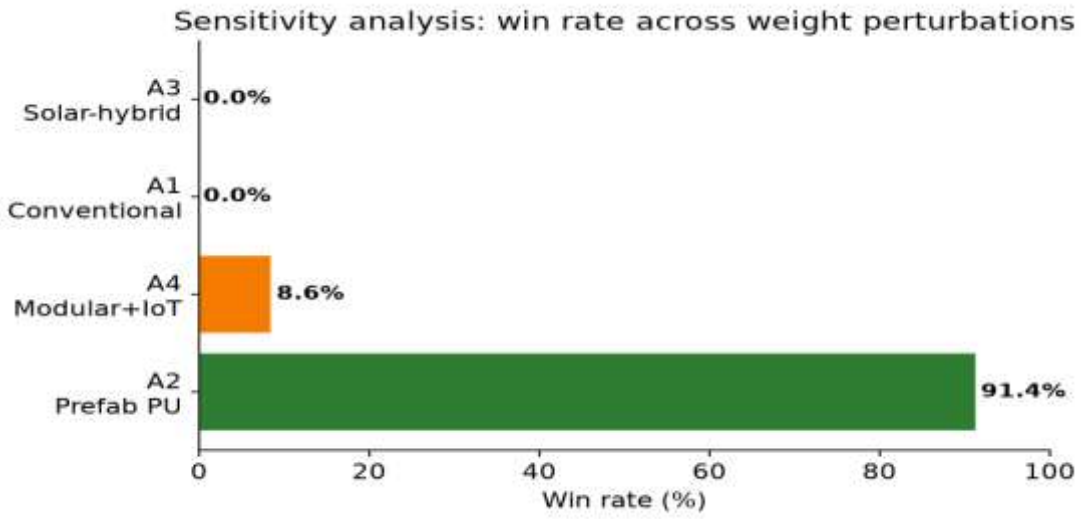


Figure 2: Sensitivity analysis showing alternative win rates across 140 weight perturbation scenarios (7 criteria x 20 steps of +/-50%).

A2 wins in 91.4% of scenarios, confirming ranking stability. A4 wins in 8.6% of scenarios, primarily when either the IoT readiness (C3) weight is increased above approximately 0.21 (from the base weight of 0.160) or the investment-cost weight (C1) is reduced below approximately 0.20. A1 and A3 never achieve the top rank within the tested perturbation range.

The sensitivity analysis identifies IoT readiness (C3) as the criterion whose weight most influences the ranking. When C3 exceeds approximately 0.21 (up from its base weight of 0.160), A4 overtakes A2. This threshold quantifies the point at which technology readiness becomes the dominant decision driver, overriding cost considerations.

The ranking is stable under moderate weight uncertainty but sensitive to a shift in organizational priorities toward technology adoption. Cooperatives or enterprises that prioritize digital readiness and remote monitoring (e.g., for premium market access

or certification requirements) may rationally prefer A4 despite its higher cost. The model supports such a strategic choice.

DISCUSSION

The results carry implications for technology management, innovation, and the blue economy in small-scale fisheries. Five themes merit discussion, followed by limitations and managerial implications.

Technology Adoption As A Strategic Lever

The finding that A4 (modular steel with IoT) can overtake A2 when technology readiness is prioritized suggests that IoT capability is a strategic asset for technology management rather than a technical feature. IoT-enabled cold storage supports traceability, quality assurance, and compliance with food safety standards, all of which are increasingly required for market access and premium pricing (Harriz et al., 2025; Müller et al., 2026; Ramanathan et al., 2023; Wang et al., 2024). Blockchain-enabled traceability systems further strengthen trust and transparency in fishery value chains (Ismail et al., 2023; Tolentino-Zondervan et al., 2023; Zhang et al., 2024). For cooperatives targeting export or certified markets, the higher upfront cost of A4 can be justified by the market premiums and compliance benefits it provides.

This infrastructure dependence qualifies the technology-driven ranking shift. In remote coastal areas, unreliable network connectivity, intermittent electricity supply, and scarce local technical capacity to service sensors can weaken the traceability records that justify A4's cost premium (Harriz et al., 2025; Ramanathan et al., 2023). Where these conditions are not met, the expected quality assurance and compliance benefits may not materialize, and the model's technology-priority scenario overstates A4's advantage. Managers should therefore treat the technology-driven ranking shift as conditional on that digital and electrical infrastructure being in place, and should assess local connectivity and maintenance capacity before committing to IoT-dependent designs.

Cooperative Business Models

The cost-dominant weight structure reflects the reality of individual small-scale operators. However, cooperative or shared-ownership models can alter the economics. A cooperative serving 20-50 fishers can amortize the capital cost of A3 or A4 across its membership, reducing the per-operator burden (Lestari & Setiyowati, 2023). Cooperatives also access concessional finance and government programs that are unavailable to individual operators. Research shows that cooperative and non-cooperative forms differently influence small-scale fisher livelihood vulnerability and adaptation (Gladstone et al., 2025). The decision model can be re-run with cooperative-level cost inputs to assess whether the ranking shifts under shared ownership structures.

Blue Economy And Value Chain Upgrading

Cold storage sits at the intersection of post-harvest loss reduction and blue economy development. Digital disruption in aquaculture and fisheries is reshaping how value is created and captured along the chain (Setiyowati et al., 2022). The decision model addresses this upgrading challenge directly: by making the trade-offs between cost, technology, and sustainability explicit, it gives cooperatives and local planners a

structured basis for choosing cold storage configurations that align with blue economy objectives rather than defaulting to the lowest-cost option. The digitization of traditional processing industries, such as the pindang sector, illustrates how small-scale enterprises can align with blue economy principles through innovation (Setiyowati et al., 2025). More broadly, the model's capacity to re-rank alternatives as strategic priorities shift makes it a practical tool for value chain upgrading under uncertainty.

Policy And The Green Innovation Gap

The "green penalty" observed for A3 is a market failure that calls for policy intervention. Solar-hybrid cold storage reduces carbon emissions and energy costs but requires capital that small-scale operators lack. Innovative financing mechanisms, specifically blue bonds and targeted government subsidies, could do more than bridge this gap: they could transform the criteria weighting structure itself. If a subsidy lowers the effective investment cost of A3, the cost-dominant weight structure that currently favors cheaper alternatives shifts, potentially changing which design ranks first. The model's weight-threshold logic makes this effect quantifiable: the threshold at which A3 becomes competitive can be translated into the subsidy level or bond financing required to alter the ranking. Effective cold supply chain management demands an integrated framework that balances cost, quality, and sustainability across the chain (Akram et al., 2023). This connects to the broader agenda of green innovation and sustainable infrastructure (SDGs 9 and 12) and the blue economy.

Limitations

The decision matrix relies on secondary data from published literature and documented expert judgment rather than primary measurements from specific cold storage installations. This means the criterion values represent typical ranges rather than site-specific performance. A small group of domain experts provided the AHP pairwise comparisons; different expert compositions could yield different weight structures and different rankings. The decision matrix uses static cost and performance values that do not account for changes in local economic conditions. Inflation, currency fluctuations, or variations in energy prices could shift the relative attractiveness of alternatives. Sensitivity to energy price changes is particularly relevant: if electricity prices rise, the yearly energy cost (C2) weight becomes more salient, potentially elevating A3 (lowest energy cost at \$55/yr) relative to A1 (\$180/yr). Conversely, capital cost inflation would further penalize high-investment alternatives (A3, A4). These limitations are inherent to the desk-based research design and do not invalidate the comparative ranking, but they should be kept in mind when applying the model to specific investment decisions.

Managerial And Policy Implications

For individual operators, A2 has the best cost-performance balance. The threshold C3 > 0.21 identifies when technology readiness justifies the cost premium of A4, providing a quantitative benchmark for adoption decisions. For cooperatives, shared-ownership models can shift the optimal choice by amortizing higher capital costs across members, making A4 or even A3 viable under cooperative-level cost structures.

For policymakers, the "green penalty" corresponds to the subsidy gap, the investment-cost reduction needed to make A3 competitive. District fisheries offices can

use the AHP-TOPSIS framework for advising cooperatives on cold-storage design selection, applying the weight-threshold logic to identify when technology readiness merits a cost premium. The ministry of marine affairs and fisheries can tie cold-storage subsidies to this threshold, directing public funds toward designs that balance moderate cost with strong technology performance rather than defaulting to the lowest-cost option. Local development planning agencies can incorporate the ranking into coastal infrastructure plans, and ensure that post-harvest facilities align with blue economy objectives and the cooperative pooling models needed to overcome the green penalty.

For the blue economy agenda, structured decision models prevent default-to-lowest-cost decisions that lock in suboptimal technology. By making trade-offs explicit, the AHP-TOPSIS framework supports value chain upgrading aligned with SDGs 8 (decent work and economic growth), 9 (industry, innovation, and infrastructure), 12 (responsible consumption and production), and 14 (life below water).

CONCLUSION

This study applied a hybrid AHP-TOPSIS model to rank four cold-storage building alternatives for small-scale fisheries. A2 ranked first (closeness coefficient 0.6266), while A3, despite the best environmental scores, ranked last under cost-dominant weights. Sensitivity analysis confirmed A2's stability (91.4% win rate) and showed A4 outranks A2 when the IoT readiness weight exceeds 0.21. The core finding is the structural "green penalty": under cost-dominant weights, the most sustainable design is systematically disadvantaged. Bridging this gap requires financial innovation (subsidies, blue bonds) and cooperative ownership models that decouple capital cost from the individual operator. As a desk-based study relying on secondary data and a small expert group, the findings should be interpreted accordingly. Detailed policy recommendations appear in the Managerial and Policy Implications subsection of the Discussion.

Statement on the Use of Artificial Intelligence

No AI tools were used in the preparation of this manuscript.

Conflicts Of Interest

The authors declare no conflicts of interest.

Author Contributions

Conceptualization, Muhammad Alfathan Harriz and Harlis Setiyowati; methodology, Muhammad Alfathan Harriz; software, Muhammad Alfathan Harriz; validation, Harlis Setiyowati, Inggit Musdinar, and Hari Soetanto; formal analysis, Muhammad Alfathan Harriz and Nurhaliza Vania Akbariani; investigation, Muhammad Alfathan Harriz and Nurhaliza Vania Akbariani; resources, Harlis Setiyowati; data curation, Nurhaliza Vania Akbariani; writing of the original draft, Muhammad Alfathan Harriz; writing, review and editing, Harlis Setiyowati, Inggit Musdinar, Hari Soetanto, and Nurhaliza Vania Akbariani; visualization, Muhammad Alfathan Harriz; supervision, Harlis Setiyowati; project administration, Harlis Setiyowati. All authors have read and agreed to the published version of the manuscript.

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REFERENCES

Acharjee, D. C., Begum, S., Chowdhury, S. R., Amin, Md. R., Gosh, K., & Alam, G. M. M. (2025). Post-harvest fish losses by the fish farmers in haor areas of bangladesh. *Marine Policy*, *176*, 106638. https://doi.org/10.1016/j.marpol.2025.106638

Akram, H. W., Akhtar, S., Ahmad, A., Anwar, I., & Sulaiman, M. A. B. A. (2023). Developing a conceptual framework model for effective perishable food cold-supply-chain management based on structured literature review. *Sustainability*, *15*(6), 4907. https://doi.org/10.3390/su15064907

Basílio, M. P., Pereira, V., Costa, H. G., Santos, M., & Ghosh, A. (2022). A systematic review of the applications of multi-criteria decision aid methods (1977–2022). *Electronics*, *11*(11), 1720. https://doi.org/10.3390/electronics11111720

Basurto, X., Gutierrez, N. L., Franz, N., Mancha-Cisneros, M. del M., Gorelli, G., Aguión, A., Funge-Smith, S., Harper, S., Mills, D. J., Nico, G., Tilley, A., Vannuccini, S., Virdin, J., Westlund, L., Allison, E. H., Anderson, C. M., Baio, A., Cinner, J., Fabinyi, M., … Thilsted, S. H. (2025). Illuminating the multidimensional contributions of small-scale fisheries. *Nature*, *637*(8047), 875–884. https://doi.org/10.1038/s41586-024-08448-z

Bennett, N. J., Calò, A., Guidetti, P., Milazzo, M., Prato, G., Ben Lamine, E., Scianna, C., & Di Franco, A. (2024). Access and well-being in small-scale fisheries. *Marine Policy*, *169*, 106328. https://doi.org/10.1016/j.marpol.2024.106328

Castañeda, A., Corvo, F., Pech Pech, I., & Marrero, R. (2024). Durability requirements for reinforced concrete structures placed in a hostile tropical coastal environment. *Buildings*, *14*(8), 2494. https://doi.org/10.3390/buildings14082494

Chaube, S., Pant, S., Kumar, A., Uniyal, S., Singh, M. K., Kotecha, K., & Kumar, A. (2024). An overview of multi-criteria decision analysis and the applications of AHP and TOPSIS methods. *International Journal of Mathematical, Engineering and Management Sciences*, *9*(3), 581–615. https://doi.org/10.33889/ijmems.2024.9.3.030

FAO. (2024). *The state of world fisheries and aquaculture 2024: Blue transformation in action*. Food; Agriculture Organization of the United Nations. https://doi.org/10.4060/cd0683en

FAO. (2025). *Solar energy and the cold chain: A guide for small-scale fisheries interventions*. FAO. https://doi.org/10.4060/cd5864en

FAO, Duke University, & WorldFish. (2023). *Illuminating hidden harvests: The contributions of small-scale fisheries to sustainable development*. FAO. https://doi.org/10.4060/cc4576en

Girip, A., Calotă, R., & Ilie, A. (2021). Aspects regarding the optimal insulation thickness, the cost and energy savings for cold storage in Romania. *Applied Sciences*, *11*(23), 11455. https://doi.org/10.3390/app112311455

Gladstone, F. J., Basurto, X., Frawley, T., Nenadovic, M., Villalejo Navarro, J. E., Rodriguez-Van Dyck, S., Weaver, A. H., Micheli, F., Torre, J., & Leslie, H. M. (2025). Governing access and agency: Cooperative and non-cooperative forms influence small-scale fisher livelihood vulnerability and adaptation. *Ecology and Society*, *30*(3), 23. https://doi.org/10.5751/ES-16057-300323

Hämmerling, M., Kałuża, T., Tymiński, T., & Plesiński, K. (2024). The use of a multi-criteria decision analysis method to select the most favourable type of fish pass in mountainous areas. *Water*, *16*(21), 3118. https://doi.org/10.3390/w16213118

Harriz, M. A., Setiyowati, H., & Akbariani, N. V. (2025). A literature review on IoT applications in fishery cold chains: Integrating blue economy principles for sustainable food security. *Journal of Fisheries Research*, *12*(4), 380–393. https://doi.org/10.18488/jftr.v12i4.4631

Hu, W., Li, J., Wu, G., & Liao, L. (2025). Thermal performance evaluation and optimization of insulation systems for cold storage buildings. *Journal of Physics: Conference Series*, *3159*, 012002. https://doi.org/10.1088/1742-6596/3159/1/012002

Ismail, S., Reza, H., Salameh, K., Kashani Zadeh, H., & Vasefi, F. (2023). Toward an intelligent blockchain IoT-enabled fish supply chain: A review and conceptual framework. *Sensors*, *23*(11), 5136. https://doi.org/10.3390/s23115136

Lestari, A. E., & Setiyowati, H. (2023). Analysis of appropriate marketing strategies for catfish farming in duren mekar subdistrict as a contribution to achieving SDGs for poverty alleviation and increasing welfare. *Manajemen Dan Kewirausahaan*, *4*(2), 131–142. https://doi.org/10.53682/mk.v4i2.7773

Mehmood, S., Usman, M., Santika, W. G., & Renaldi, R. (2024). Numerical model of solar-driven cold storage for small-scale fisheries. *Energy Proceedings*, *41*, 1–8. https://doi.org/10.46855/energy-proceedings-10890

Muhl, E.-K., Armitage, D., Nayak, P. K., Pradhan, S., Abdelbaset, M., Aheto, D., Adade, R., Akintola, S. L., Arizi, E. K., Attipoe, E., Blythe, J., Bundy, A., Chuenpagdee, R., Choudry, A., Das, B. K., Devi, C., Fakoya, K., Hara, M., Hossain, S., … Yahya, B. M. (2026). Transition pathways from vulnerability to viability of small-scale fisheries in africa and asia. *People and Nature*, *8*(5), 1033–1049. https://doi.org/10.1002/pan3.70305

Müller, W. A., Ferreira, S. B., & Silva, S. B. da. (2026). Enhancing food safety in the cold chain through IoT and artificial intelligence. *Journal of Food Science*, *91*(2), e70871. https://doi.org/10.1111/1750-3841.70871

Paradowski, B., Wątróbski, J., & Sałabun, W. (2025). Novel coefficients for improved robustness in multi-criteria decision analysis. *Artificial Intelligence Review*, *58*, 298. https://doi.org/10.1007/s10462-025-11307-6

Park, C., & Son, M. (2025). TOPSIS and AHP-based multi-criteria decision-making approach for evaluating redevelopment in old residential projects. *Sustainability*, *17*(15), 7072. https://doi.org/10.3390/su17157072

Ramanathan, R., Duan, Y., Valverde, J., Van Ransbeeck, S., Ajmal, T., & Valverde, S. (2023). Using IoT sensor technologies to reduce waste and improve sustainability in artisanal fish farming in Southern Brazil. *Sustainability*, *15*(3), 2078. https://doi.org/10.3390/su15032078

Rami, Y., & Allouhi, A. (2024). Design, economic, and environmental accounting assessment of a solar-powered cold room for fish storage in traditional markets. *Sustainability*, *16*(7), 3080. https://doi.org/10.3390/su16073080

Rincon, L. F., Moscoso, Y. M., Hamami, A. E. A., Matos, J. C., & Bastidas-Arteaga, E. (2024). Degradation models and maintenance strategies for reinforced concrete structures in coastal environments under climate change: A review. *Buildings*, *14*(3), 562. https://doi.org/10.3390/buildings14030562

Setiyowati, H., Harriz, M. A., Junaedi, E., Akbariani, N. V., & Widodo, S. (2025). Digitalizing pindang industry with business model canvas for sustainable blue economy. *Aptisi Transactions on Technopreneurship*, *7*(2), 360–370. https://doi.org/10.34306/att.v7i2.581

Setiyowati, H., Thalib, S., Setiawati, R., Nurjannah, & Akbariani, N. V. (2022). An aquaculture disrupted by digital technology. *Austenit*, *14*(1), 12–16. https://doi.org/10.53893/austenit.v14i1.4608

Thalib, H., Maarif, S., & Setiawan, E. A. (2021). Optimization of solar PV system for fishery cold storage based on ownership model and regulation barrier in Indonesia. *Journal of Physics: Conference Series*, *2022*, 012035. https://doi.org/10.1088/1742-6596/2022/1/012035

Tolentino-Zondervan, F., Ngoc, P. T. A., & Roskam, J. L. (2023). Use cases and future prospects of blockchain applications in global fishery and aquaculture value chains. *Aquaculture*, *565*, 739158. https://doi.org/10.1016/j.aquaculture.2022.739158

Wang, B., Liu, K., Wei, G., He, A., Kong, W., & Zhang, X. (2024). A review of advanced sensor technologies for aquatic products freshness assessment in cold chain logistics. *Biosensors*, *14*(10), 468. https://doi.org/10.3390/bios14100468

Wu, H., Zhang, J., Zhu, H., Peñarubia, O., & Willer, D. F. (2026). Technology-driven reduction of fish post-harvest loss could enhance food security and economic resilience. *Communications Earth & Environment*, *7*, 48. https://doi.org/10.1038/s44458-026-00048-4

Zhang, Z., Zhu, H., & Liang, H. (2024). Blockchain-based cold chain traceability with NR-PBFT and IoV-IMS for marine fishery vessels. *Journal of Marine Science and Engineering*, *12*(8), 1371. https://doi.org/10.3390/jmse12081371