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An integrated CRITIC–TOPSIS framework for evaluating IoT-based water quality management strategies in freshwater Prawn farming

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A B S T R A C T

Water quality instability is a major constraint in giant freshwater prawn farming, particularly in land-based systems where fluctuations in environmental conditions can reduce survival and productivity. This study applied an integrated CRITIC–TOPSIS framework to evaluate alternative water quality management strategies for giant freshwater prawn farming under multiple operational and production criteria. Four alternatives, representing different levels of management sophistication from conventional monitoring to a full IoT-based real-time monitoring system, were assessed using five criteria: Cost, Labor, Energy, Survival, and Yield. The CRITIC method was used to determine objective criterion weights, while TOPSIS was employed to rank the alternatives according to their relative closeness to the ideal solution. The CRITIC results indicated that Cost (0.2523) and Energy (0.2506) were the most influential criteria, followed by Labor (0.1681), whereas Survival and Yield each received a weight of 0.1645. The TOPSIS results showed that Alternative 4 was the most suitable option, with the highest closeness coefficient (0.5534), followed by Alternative 3 (0.5084), Alternative 2 (0.4583), and Alternative 1 (0.4466). Alternative 4 also achieved the best production performance, with 93% survival, 4.65 kg yield, and the lowest labor requirement (17 h), although it required the highest cost (13,746 Baht) and energy consumption (35 kWh). Compared with the conventional strategy, Alternative 4 improved survival by 11 percentage points, increased yield by 0.55 kg, and reduced labor by 18 h. The findings demonstrate that the integrated CRITIC–TOPSIS framework can serve as an effective decision-support tool for selecting water quality management strategies in freshwater prawn farming by balancing resource requirements and production outcomes. Under the present evaluation framework, the IoT-based real-time monitoring strategy was identified as the most suitable alternative for land-based giant freshwater prawn farming.

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1. Introduction

Aquaculture has become an increasingly important sector for food security, rural livelihoods, and sustainable economic development. Among freshwater aquaculture species, the giant freshwater prawn (*Macrobrachium rosenbergii*) is widely recognized for its high market value, strong consumer demand, and promising production potential in tropical and subtropical regions. In Thailand, freshwater prawn farming remains an important component of local aquaculture systems, where production efficiency depends strongly on environmental management, particularly water quality control (New, 2002; New et al., 2009; Tidwell et al., 2004; D'Abramo et al., 2006). Water quality is one of the most critical determinants of prawn health, growth, survival, and harvestable yield. Key physicochemical parameters, including temperature, pH, dissolved oxygen, and turbidity, directly influence metabolism, molting, feeding behavior, physiological stress, and overall production performance (Hargreaves, 2013; Yusoff et al., 2024). In land-based culture systems, these parameters can fluctuate rapidly

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due to weather variation, feed input, waste accumulation, water exchange, and biological activity within the culture unit. As a result, unstable water conditions may reduce productivity, increase mortality risk, and undermine the economic sustainability of farming operations. Conventional monitoring in aquaculture is still commonly based on visual inspection, manual sampling, and periodic measurement using portable devices. Although such approaches are simple and practical, they are constrained by low monitoring frequency, delayed response, labor dependence, and limited ability to detect sudden environmental changes. These limitations are particularly critical in giant freshwater prawn farming, where timely intervention is essential to maintain suitable culture conditions and reduce production losses. In this context, recent advances in the Internet of Things (IoT) have created significant opportunities for improving aquaculture monitoring through real-time sensing, wireless communication, cloud-based storage, and remote visualization (Atzori et al., 2010; Gubbi et al., 2013; Zanella et al., 2014; Al-Fuqaha et al., 2015; Ray, 2018). IoT-enabled aquaculture systems can continuously collect and transmit water quality data to centralized platforms for storage, analysis, and decision support, thereby improving monitoring continuity, reducing human error, and enabling more responsive farm management (Ahmed et al., 2024; Flores-Iwasaki et al., 2025; Ubina et al., 2023).

Beyond sensing and communication, cloud-enabled aquaculture platforms increasingly support integrated data management, predictive analysis, anomaly detection, and remote supervision. These developments indicate that smart aquaculture is progressing from isolated monitoring devices toward more comprehensive digital management systems capable of supporting operational decision-making in real farming environments (Orozco-Lugo et al., 2022; Shete et al., 2025; Soon et al., 2025). However, despite this technological progress, much of the existing literature has focused primarily on system architecture, sensor deployment, monitoring performance, or predictive modeling. Comparatively less attention has been paid to the managerial question of how to select the most appropriate water quality management strategy when technical, operational, and production-related criteria must be considered simultaneously.

This unresolved decision problem is highly relevant in practical freshwater prawn farming. In actual farm conditions, alternative management strategies differ not only in monitoring capability, but also in investment cost, labor requirement, energy consumption, survival performance, and production output. A lower-cost alternative may reduce implementation burden but provide weaker environmental control, whereas a more advanced digital system may improve production outcomes while demanding greater technological and operational commitment. Consequently, evaluating alternative strategies using only a single criterion, such as survival, cost, or yield, is insufficient for practical farm-level decision-making. A structured multi-criteria decision-making (MCDM) framework is therefore required to support transparent and balanced evaluation of competing strategies under real operational constraints.

Among MCDM methods, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is one of the most widely used ranking approaches because it identifies the alternative closest to the positive ideal solution and farthest from the negative ideal solution (Hwang and Yoon, 1981). TOPSIS has been successfully applied in supplier selection, environmental management, agriculture, healthcare, transportation, and infrastructure evaluation (Bid and Siddique, 2019; Sriburum et al., 2023; Moreno Rocha & Arenas Buelvas, 2024). Nevertheless, the effectiveness of TOPSIS depends substantially on the criterion weights used in the analysis. To reduce subjectivity in weight determination, the CRITIC method derives objective weights by simultaneously considering the variation of each criterion and its conflict with other criteria (Diakoulaki et al., 1995). For this reason, CRITIC has been increasingly employed in engineering, environmental, and sustainability-related evaluation problems (Wei et al., 2020; Nasawat et al., 2021; Zhang & Wei, 2023).

Recent studies further confirm the applicability of TOPSIS- and CRITIC-based frameworks to water-related and environmental assessment problems. Li et al. (2018) proposed a TOPSIS-based informative weighting and ranking approach for water quality evaluation. Lv et al. (2023) applied an improved TOPSIS model to assess water resource carrying capacity in eastern China, while Du et al. (2024) used an improved TOPSIS-based framework to evaluate water resource carrying potential and associated barrier factors in Gansu Province. These studies demonstrate the flexibility of MCDM methods in complex water-related decision contexts. However, they do not directly address the practical selection of farm-level water quality management strategies in giant freshwater prawn culture, nor do they explicitly integrate field-based aquaculture alternatives with an objective CRITIC–TOPSIS framework.

Accordingly, the main research gap of the present study lies at the intersection of smart aquaculture implementation and multi-criteria decision support. While IoT-based monitoring technologies have been increasingly introduced into aquaculture, limited research has translated these technological options into explicitly defined management alternatives and evaluated them through an objective ranking framework under real farming constraints. This gap is particularly important in land-based giant freshwater prawn farming, where farmers must balance economic feasibility, labor burden, energy use, and biological performance rather than maximize any single outcome in isolation. Therefore, a more rigorous and application-oriented evaluation framework is needed to identify the most suitable management strategy for practical deployment.

To address this gap, the present study applies an integrated CRITIC–TOPSIS framework to evaluate four water quality management alternatives for giant freshwater prawn farming in land-based systems, ranging from conventional monitoring to a full IoT-based real-time monitoring system with dashboard and alert functions. The alternatives are evaluated using five criteria, namely Cost, Labor, Energy, Survival, and Yield, so that both implementation burden and production performance

are considered simultaneously. In this way, the study moves beyond a purely technical description of an IoT monitoring system and develops a structured decision-support model for selecting the most appropriate water quality management strategy in freshwater prawn farming.

The novelty and contribution of this study can be summarized in three aspects. First, it translates a field-based IoT monitoring system into a comparative decision framework by defining four practically meaningful management alternatives with different levels of technological sophistication. Second, it integrates the CRITIC method and TOPSIS in a single objective evaluation framework to simultaneously consider resource-related and production-related criteria in freshwater prawn farming. Third, it provides an application-oriented decision-support approach for land-based aquaculture management by identifying not only the best-performing advanced alternative, but also an intermediate strategy that may be more feasible under constrained operational conditions.

For clarity, the main contributions of this study are as follows: (1) to develop a practical alternative-based evaluation structure for water quality management in giant freshwater prawn farming; (2) to determine objective criterion weights using CRITIC and rank alternatives using TOPSIS under mixed cost and benefit criteria; (3) to evaluate the managerial suitability of an IoT-based real-time monitoring strategy relative to conventional, improved manual, and semi-automatic strategies; and (4) to provide a decision-support framework that can assist smart aquaculture adoption in land-based freshwater prawn farming.

The remainder of this paper is organized as follows. Section 2 presents the research methodology, including the decision matrix, the CRITIC weighting procedure, and the TOPSIS ranking process. Section 3 reports the results of the weighting and ranking analysis. Section 4 discusses the implications of the findings for freshwater prawn farming management. Finally, Section 5 concludes the study and suggests directions for future research.

2. Materials and methods

2.1 Study framework

This study employed a multi-criteria decision-making (MCDM) framework to evaluate four alternative water quality management strategies for giant freshwater prawn farming in land-based systems. The methodological framework consisted of four main stages: (1) defining the four management alternatives, (2) selecting the evaluation criteria, (3) determining objective criterion weights using the CRITIC method, and (4) ranking the alternatives using the TOPSIS method. The overall framework was designed to support decision-making under multiple technical, operational, and production-related considerations.

The four alternatives were formulated to represent different levels of management sophistication, ranging from conventional monitoring practices to a full IoT-based real-time monitoring system with dashboard visualization and alert support. The evaluation criteria were selected to capture both implementation burden and farming performance. In this study, Cost, Labor, and Energy were treated as cost criteria, whereas Survival and Yield were treated as benefit criteria. This framework enabled a balanced assessment of the four alternatives by simultaneously considering resource requirements and production outcomes.

2.2 Study area and practical context

The practical context of this study was giant freshwater prawn farming in land-based tanks located in Saeng Badan Subdistrict, Somdet District, Kalasin Province, Thailand. The study was motivated by the problem of water quality instability under local farming conditions, where temperature, pH, dissolved oxygen, and turbidity are key environmental variables affecting prawn health, growth, and survival. To improve water quality management under these conditions, a real-time monitoring platform was developed by integrating water quality sensors, an ESP32 microcontroller, cloud-based data transmission, database connectivity, and a web-based dashboard for real-time visualization and alert generation.

A comparative field experiment was conducted using four culture ponds, with each pond representing one water quality management alternative. Each pond was stocked with 100 giant freshwater prawns (*Macrobrachium rosenbergii*) and maintained over a 90-day culture period. The four ponds were assigned to Alternative 1, Alternative 2, Alternative 3, and Alternative 4, respectively, so that the performance values of Cost, Labor, Energy, Survival, and Yield could be obtained directly from field implementation under comparable farming conditions.

All culture units were designed as narrow land-based ponds measuring 1 m × 18 m with a maintained water depth of 0.50 m. This configuration was selected to reflect a practical farming model for areas with limited land and restricted water resources. Compared with conventional earthen-pond systems, the proposed design requires less space and water, making it suitable for small-scale farmers and communities facing resource constraints. The relatively shallow water depth also facilitates easier observation, routine management, and timely intervention when abnormal water quality conditions occur.

To ensure comparability among alternatives, all ponds were maintained under the same general husbandry conditions, including pond dimensions, water depth, stocking density, feeding regime, aeration, water exchange, and routine culture

management. The principal difference among the ponds was the monitoring and management configuration assigned to each alternative. Thus, the decision matrix used in this study was constructed from the observed performance data of four field-based alternatives implemented under comparable conditions.

It should be noted that the four ponds were replicate-independent culture units, with each management alternative represented by a single pond. Therefore, the experimental design should be interpreted as a four-treatment field setup without replication. Accordingly, the present study is better regarded as a field-based decision-support case study rather than a fully replicated statistical experiment.

2.3 Definition of alternatives

To evaluate different levels of water quality management in giant freshwater prawn farming, four field-based alternatives were defined, with each alternative implemented in a separate culture pond. These alternatives were designed to represent progressively increasing levels of technological and operational sophistication, ranging from conventional manual monitoring to a fully integrated Internet of Things (IoT)-based real-time monitoring strategy. This alternative structure enabled the study to compare practical management options under comparable field conditions and to construct the decision matrix used in the CRITIC–TOPSIS analysis.

Alternative 1 (Conventional monitoring) represented the baseline management strategy. Under this alternative, water quality was monitored primarily through visual observation and occasional manual measurement using portable instruments. Farm management decisions were based mainly on farmer experience and routine inspection, without continuous sensing, automated recording, or real-time alert support. This alternative reflects common traditional practice in small-scale freshwater prawn farming.

Alternative 2 (Improved manual monitoring) represented a more structured manual management strategy. In this alternative, water quality measurements were conducted more regularly than in the conventional approach, and farm records were maintained more systematically. However, monitoring and corrective actions still depended entirely on manual observation and farmer intervention. This alternative therefore represents an improvement in management discipline without introducing automated sensing or digital connectivity.

Alternative 3 (Semi-automatic monitoring) represented an intermediate strategy between manual monitoring and a fully digital system. Under this alternative, selected measuring devices were used to support routine water quality assessment, thereby improving monitoring consistency and reducing reliance on purely visual inspection. Nevertheless, the main monitoring, interpretation, and decision-making functions remained dependent on the farmer. This alternative was included to represent a practical transitional option for farms seeking technological improvement with a lower implementation burden than a full IoT-based system.

Alternative 4 (Proposed IoT-based real-time monitoring system) represented the most advanced management strategy evaluated in this study. This alternative corresponded to the proposed system developed and implemented in the field experiment. It integrated multi-parameter water quality sensing, edge-level data acquisition and preprocessing through an ESP32 microcontroller, wireless data transmission, cloud-based storage, real-time dashboard visualization, and automated alert support. Unlike the other alternatives, this strategy enabled continuous and near real-time monitoring of water quality conditions, thereby supporting timely intervention and more responsive farm management.

Taken together, the four alternatives were defined to capture the trade-off between implementation burden and production performance under practical land-based farming conditions. As the level of technological support increased from Alternative 1 to Alternative 4, the alternatives reflected a transition from traditional monitoring practices to more advanced and data-driven management. This structure provided the basis for the subsequent multi-criteria evaluation of Cost, Labor, Energy, Survival, and Yield.

Fig. 1 illustrates the overall architecture and operational workflow of the proposed real-time water quality monitoring system for giant freshwater prawn farming. Developed under the Internet of Things (IoT) paradigm, the system integrates in situ sensing, edge-level preprocessing, wireless communication, backend validation and storage, real-time visualization, and automated alert support. The platform is designed for continuous and autonomous operation, enabling systematic monitoring, early anomaly detection, and timely response to changes in water quality. As shown, the system consists of two main phases: Phase 1: Cloud API and Application Server and Phase 2: Backend Validation and Database Layer, which together form a complete cycle of data acquisition, processing, storage, visualization, and response.

The process begins with the multi-parameter sensing module, where sensors installed in the prawn culture tank measure temperature, pH, dissolved oxygen, and turbidity. These parameters were selected because they directly affect prawn metabolism, respiration, feeding behavior, growth, and survival. The sensor signals are then transmitted to the edge data acquisition and preprocessing module, where an ESP32 microcontroller performs initial acquisition, filtering, plausibility checking, and data formatting. This step improves data consistency and reduces noise before transmission.

The processed data are then transmitted to the cloud server over Wi-Fi, utilizing HTTP POST requests in a structured format such as JSON. This enables automated and near real-time transfer of monitoring data from the culture tank to the remote server. Once received, the data enter the backend validation and database layer, where they are checked for completeness, consistency, timestamp validity, and acceptable value ranges. Validated records are stored in PostgreSQL, enabling efficient storage, queries, analysis, and integration with visualization and alerts.

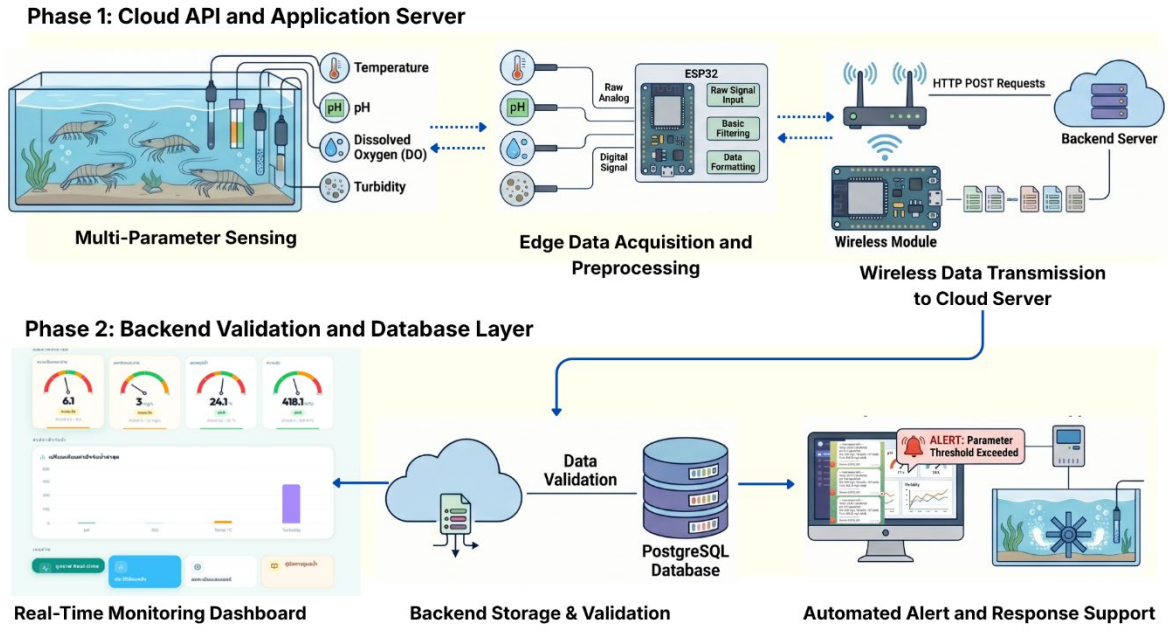

Fig. 1. Alternative 4, the overall architecture and operational workflow of the proposed Internet of Things (IoT)-based water quality monitoring system for smart prawn farming.

2.4 Selection of evaluation criteria

To compare the four alternatives in a consistent and decision-oriented manner, five evaluation criteria were selected to represent both implementation burden and farming performance. The criteria were chosen based on their practical relevance to water quality management in land-based giant freshwater prawn farming and their ability to reflect the trade-off between resource use and production outcomes. In line with the alternative structure defined in Section 2.3, the selected criteria were intended to capture not only the technical sophistication of each management strategy, but also its operational feasibility and biological effectiveness.

The first criterion was Cost (Baht), which represents the total cost associated with implementing and operating each alternative. This criterion includes the financial burden required to support monitoring activities and related management functions. Because lower expenditure is preferable from the farmer's perspective, Cost was treated as a cost criterion.
The second criterion was Labor (hours), defined as the amount of labor time required for monitoring, inspection, and corrective management during the culture period. Labor is particularly important in practical aquaculture because more advanced monitoring systems are often expected to reduce routine workload and dependence on manual observation. Since a lower labor requirement is more desirable, this criterion was also classified as a cost criterion.
The third criterion was Energy (kWh), which represents the energy consumption associated with the monitoring system and related equipment under each alternative. This criterion was included because technologically advanced systems may improve monitoring capability while simultaneously increasing energy demand. From an operational and sustainability perspective, lower energy consumption is preferable; therefore, Energy was treated as a cost criterion.

The fourth criterion was Survival (%), defined as the survival rate of giant freshwater prawns achieved under each management alternative. Survival is one of the most important biological indicators in aquaculture because it directly reflects the effectiveness of environmental management and culture conditions. A higher survival rate indicates better overall farming performance; thus, Survival was treated as a benefit criterion.

The fifth criterion was Yield (kg), which represents the harvestable production obtained under each alternative at the end of the culture period. Yield reflects the productive outcome of the farming system and is closely related to both biological performance and management effectiveness. Since higher production is more desirable, Yield was also classified as a benefit criterion.

Accordingly, the five criteria were grouped into two categories: Cost, Labor, and Energy as cost criteria, and Survival and Yield as benefit criteria. This classification provided the basis for the subsequent CRITIC weighting and TOPSIS ranking procedures. By combining resource-related and production-related measures within the same evaluation framework, the study was able to assess the four alternatives in a balanced and practically meaningful manner.

2.5 Construction of the decision matrix

The decision matrix was constructed to represent the performance of the four water quality management alternatives under the five selected evaluation criteria. In multi-criteria decision-making analysis, the decision matrix serves as the fundamental input for both the CRITIC weighting procedure and the subsequent TOPSIS ranking process. Let the initial decision matrix be defined as

$$X = [x_{ij}]_{m \times n} \tag{1}$$

where x_{ij} denotes the performance value of alternative i under criterion j, m is the number of alternatives, and n is the number of criteria. In this study, $m = 4$ and $n = 5$, corresponding to four water quality management alternatives and five evaluation criteria, respectively.

The alternatives considered in the matrix were Alternative 1 (Conventional monitoring), Alternative 2 (Improved manual monitoring), Alternative 3 (Semi-automatic monitoring), and Alternative 4 (Proposed IoT-based real-time monitoring system). The criteria included Cost, Labor, Energy, Survival, and Yield. Accordingly, each row of the decision matrix represents one management alternative, while each column represents one evaluation criterion.

The values included in the decision matrix were obtained from the field-based implementation of the four alternatives under comparable farming conditions. These values reflect the observed or derived performance of each alternative in terms of implementation burden and production outcome. Specifically, Cost was measured in Baht, Labor in hours, Energy in kilowatt-hours (kWh), Survival in percent, and Yield in kilograms.

The resulting decision matrix provides a structured representation of the trade-offs among the alternatives. Because the criteria are expressed in different units and reflect both cost-type and benefit-type characteristics, the matrix cannot be used directly for ranking purposes. It must first be transformed through normalization and weighting procedures, as described in the following sections. Nevertheless, this matrix constitutes the essential starting point for the CRITIC–TOPSIS analysis carried out in this study.

2.6 Determination of criterion weights using the CRITIC method

The CRITIC method was used to determine objective criterion weights from the data. This method considers both the contrast intensity of each criterion and the conflict among criteria. The original CRITIC framework was proposed by Diakoulaki et al. (1995).

After constructing the decision matrix, the next step was to determine the relative importance of the evaluation criteria using the CRITIC method. In this study, the CRITIC procedure was implemented using max–min normalization, which is suitable for data containing both cost-type and benefit-type criteria. This transformation converts all criteria to a common scale between 0 and 1 while preserving their preference direction. Accordingly, the normalized values were defined so that a larger normalized value always indicates better performance, regardless of whether the original criterion was of cost or benefit type.

For **benefit criteria**, the normalized value was calculated as

$$r_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{2}$$

For **cost criteria**, the normalized value was calculated as

$$r_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{3}$$

where x_{ij} denotes the original performance value of alternative i under criterion j, and r_{ij} denotes the corresponding normalized value. Under this transformation, the best observed value for a criterion receives a normalized score of 1, whereas

the worst observed value receives a normalized score of 0. Accordingly, for cost criteria such as Cost, Labor, and Energy, lower original values are converted into higher normalized scores.

Using Eqs. (2) and (3), the normalized decision matrix was obtained and is presented in Table 2. As shown in the table, Alternative 1 received the highest normalized scores for Cost and Energy because it had the lowest original values for those cost criteria. By contrast, Alternative 4 achieved the highest normalized scores for Survival and Yield because it performed best on the benefit criteria. This confirms that the normalization procedure was applied consistently with the intended preference direction of each criterion.

The second step was to calculate the standard deviation of each normalized criterion. In the CRITIC method, the standard deviation represents the contrast intensity of criterion j, indicating how strongly that criterion differentiates among the alternatives. A larger standard deviation implies that the criterion provides more discriminating information in the evaluation process.

Next, the correlation coefficient between criteria $j$and k, denoted by r_{jk}, was computed in order to assess the degree of conflict or redundancy among criteria. The information content of criterion $j$was then calculated as

$$C_j = \sigma_j \sum_{k=1}^{n} (1 - r_{jk}) \tag{4}$$

where $\sigma_j$is the standard deviation of criterion j, $r_{jk}$is the correlation coefficient between criteria $j$and k, and $C_j$is the resulting information content of criterion j. According to this formulation, a criterion receives a larger information content when it exhibits both high variation across alternatives and low redundancy with the remaining criteria.

The final objective weight of criterion $j$was then obtained by normalizing its information content as follows:

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{5}$$

subject to

$$\sum_{j=1}^{n} w_j = 1 \tag{6}$$

where $w_j$denotes the CRITIC weight of criterion j. These normalized weights reflect the relative importance of the criteria based entirely on the observed data structure, and they were subsequently used in the TOPSIS ranking procedure.

In summary, the CRITIC method provided an objective basis for determining criterion importance by combining dispersion and inter-criterion conflict. This was particularly appropriate for the present study because the evaluation problem involved multiple criteria measured in different units and reflecting different preference directions. The resulting weights therefore provided a transparent and data-driven input for the subsequent ranking of water quality management alternatives.

2.7 Ranking of alternatives using the TOPSIS method

After obtaining the objective criterion weights from the CRITIC method, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was applied to rank the four water quality management alternatives. TOPSIS was originally proposed by Hwang and Yoon (1981) and is based on the principle that the most desirable alternative should be the one closest to the positive ideal solution and farthest from the negative ideal solution.

Let the original decision matrix be denoted by $X = [x_{ij}]$, where x_{ij} represents the performance value of alternative $i$under criterion j, with $i = 1,2, \dots, m$ and $j = 1,2, \dots, n$. Because the criteria in this study were measured in different units, the first step in the TOPSIS procedure was to normalize the original decision matrix using vector normalization. The normalized value of alternative $i$under criterion $j$was calculated as

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{7}$$

where r_{ij} denotes the normalized performance value. This transformation converts the original values into dimensionless form while preserving their relative proportional relationships across alternatives.

Next, the weighted normalized decision matrix was constructed by multiplying each normalized value by its corresponding CRITIC weight. The weighted normalized value was computed as

$$v_{ij} = w_j r_{ij} \tag{8}$$

where w_j is the CRITIC weight of criterion j, and v_{ij} is the weighted normalized performance value of alternative i under criterion j.

Based on the weighted normalized matrix, the positive ideal solution and the negative ideal solution were then determined. The positive ideal solution represents the most desirable combination of criterion values, while the negative ideal solution represents the least desirable combination. These two reference points were defined as

$$A^+ = \{v_1^+, v_2^+, \dots, v_n^+\} \text{ and } A^- = \{v_1^-, v_2^-, \dots, v_n^-\} \tag{9}$$

where, for benefit criteria,

$$v_j^+ = \max_i v_{ij}, v_j^- = \min_i v_{ij}$$

and for cost criteria,

$$v_j^+ = \min_i v_{ij}, v_j^- = \max_i v_{ij}.$$

Accordingly, the positive ideal solution in this study corresponds to the lowest values of Cost, Labor, and Energy together with the highest values of Survival and Yield, whereas the negative ideal solution corresponds to the opposite combination.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \tag{10}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{11}$$

where S_i^+ and S_i^- denote the separation distances of alternative i from the positive and negative ideal solutions, respectively. An alternative is considered more desirable when it has a smaller distance from the positive ideal solution and a larger distance from the negative ideal solution. Finally, the relative closeness coefficient of each alternative was determined as

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{12}$$

where $0 \leq CC_i \leq 1$. A larger CC_i indicates that the alternative is closer to the ideal solution and therefore has a better overall ranking.

In the present study, the TOPSIS procedure was applied after classifying the criteria into cost and benefit types, with Cost, Labor, and Energy treated as cost criteria, and Survival and Yield treated as benefit criteria. The ranking results were then obtained by ordering the alternatives according to their closeness coefficients from the largest to the smallest value. Through this procedure, the study was able to identify the most suitable water quality management strategy by simultaneously considering implementation burden and production performance under a unified decision-making framework.

2.8 Classification of cost and benefit criteria

To ensure consistency in the CRITIC–TOPSIS evaluation procedure, the five criteria were classified according to their preference direction as either cost criteria or benefit criteria. This classification is essential because the decision problem involves criteria for which lower values are desirable as well as criteria for which higher values are preferable.

In this study, Cost, Labor, and Energy were classified as cost criteria, since smaller values indicate lower implementation burden and more efficient resource use. Specifically, lower cost reduces the financial requirement for adopting a given management strategy, lower labor reflects reduced dependence on manual monitoring and intervention, and lower energy consumption indicates better operational efficiency.

By contrast, Survival and Yield were classified as benefit criteria, because larger values represent better farming performance. A higher survival rate indicates more favorable water quality management and improved culture conditions, while a higher yield reflects stronger production output at harvest.

Accordingly, the criteria were classified as follows:

- **Cost criteria:** Cost, Labor, Energy
- **Benefit criteria:** Survival, Yield

This classification was applied consistently in both the normalization and ranking stages of the analysis. In the CRITIC procedure, it ensured that the preference direction of each criterion was preserved during max–min normalization. In the TOPSIS procedure, it provided the basis for defining the positive ideal solution and the negative ideal solution for each criterion. Therefore, the cost–benefit classification served as an important step in establishing a valid and interpretable evaluation framework for the four water quality management alternatives.

2.9 Computational procedure

The complete computational procedure of this study was carried out in a sequential manner to ensure a consistent and transparent evaluation of the four water quality management alternatives. The procedure integrates the CRITIC method for objective weight determination and the TOPSIS method for alternative ranking under mixed cost and benefit criteria.

First, the four management alternatives and the five evaluation criteria were defined based on the practical context of giant freshwater prawn farming in land-based systems. The corresponding decision matrix was then constructed using the observed and derived performance values of each alternative under the selected criteria.

Second, the CRITIC method was applied to determine the objective importance of the criteria. At this stage, the original decision matrix was normalized using max–min normalization in accordance with the cost–benefit classification of the criteria. The standard deviation of each normalized criterion was then calculated to represent its contrast intensity, followed by the computation of inter-criterion correlations to assess the degree of conflict or redundancy among criteria. These quantities were subsequently combined to obtain the information content of each criterion, from which the final normalized CRITIC weights were derived.

Third, the TOPSIS method was employed to rank the alternatives using the CRITIC-based weights. The original decision matrix was first transformed into a dimensionless form through vector normalization. The normalized values were then multiplied by the CRITIC weights to obtain the weighted normalized matrix. Based on this matrix and the classification of criteria into cost and benefit types, the positive ideal solution and the negative ideal solution were identified. The Euclidean distances of each alternative from these two reference points were then calculated, and the relative closeness coefficient of each alternative was determined.

Finally, the alternatives were ranked according to their closeness coefficients, where a larger coefficient indicates that the alternative is closer to the positive ideal solution and farther from the negative ideal solution. Through this procedure, the study was able to identify the most suitable water quality management strategy by simultaneously considering implementation burden and production performance.

For clarity, the main computational steps can be summarized as follows:

1. Define the four alternatives and the five evaluation criteria.
2. Construct the decision matrix from the observed and derived data.
3. Classify the criteria into cost and benefit types.
4. Apply max–min normalization for the CRITIC procedure.
5. Compute the standard deviation and correlation structure of the criteria.
6. Derive the CRITIC information content and normalized criterion weights.
7. Apply vector normalization for the TOPSIS procedure.

8. Construct the weighted normalized matrix.
9. Determine the positive ideal and negative ideal solutions.
10. Compute the Euclidean separation distances of each alternative.
11. Calculate the closeness coefficient of each alternative.
12. Rank the alternatives according to their closeness coefficients.

This computational sequence provided a systematic and objective basis for evaluating the four water quality management strategies considered in this study.

3. Results and discussion

3.1 Decision matrix of water quality management alternatives

The first stage of the CRITIC–TOPSIS analysis was to construct the decision matrix of the water quality management alternatives. This matrix provides the basic input for both the objective weighting process and the subsequent ranking analysis. In this study, four alternatives were evaluated to represent different levels of water quality management for giant freshwater prawn farming in land-based systems, ranging from conventional monitoring to a full IoT-based real-time monitoring system. Five evaluation criteria were used: Cost, Labor, Energy, Survival, and Yield. Among them, Cost, Labor, and Energy were treated as cost criteria, because lower values are preferred, whereas Survival and Yield were treated as benefit criteria, because higher values indicate better production performance. This set of criteria was selected to reflect both implementation burden and farming outcomes. The decision matrix is presented in Table 1.

Table 1
Decision matrix of the alternatives

Alternative	Cost (Baht)	Labor (h)	Energy (kWh)	Survival (%)	Yield (kg)
Alternative 1	12,020	35	25	82	4.10
Alternative 2	12,440	30	28	86	4.30
Alternative 3	12,680	26	30	88	4.40
Alternative 4	13,746	17	35	93	4.65

As shown in Table 1, the alternatives reflect a clear trade-off between resource consumption and production performance. Alternative 1 had the lowest cost and energy requirement, but also the lowest survival and yield. In contrast, Alternative 4 required the highest cost and energy, but achieved the highest survival and yield together with the lowest labor requirement. Alternatives 2 and 3 occupied intermediate positions, showing gradual improvements in production performance with moderate increases in resource use. Overall, the decision matrix shows that no single alternative is superior under all criteria. Therefore, a multi-criteria decision-making framework is necessary to evaluate the alternatives simultaneously and identify the most suitable water quality management strategy for giant freshwater prawn farming.

3.2 Objective weighting results obtained from the CRITIC method

After constructing the revised decision matrix, the next step was to determine the relative importance of the five evaluation criteria by using the CRITIC method. In accordance with the procedure presented in Section 2, the CRITIC analysis consisted of four stages: (1) max–min normalization of the original matrix, (2) calculation of the standard deviation of each criterion, (3) assessment of inter-criterion conflict through the correlation matrix, and (4) derivation of the final normalized criterion weights.

The purpose of this stage was to derive objective weights directly from the data rather than assigning them subjectively. This is appropriate because the evaluation problem involves criteria with different units and preference directions. In the present study, Cost, Labor, and Energy were treated as cost criteria, whereas Survival and Yield were treated as benefit criteria.

Step 1: Max–min normalization of the decision matrix

The first step was to normalize the decision matrix using max–min normalization. For benefit criteria, Eq. (2) was applied, whereas for cost criteria, Eq. (3) was used. This transformation rescales all values into the interval $[0, 1]$while preserving the proper preference direction, so that a larger normalized value always indicates better performance. Based on the data in Table 1, the resulting normalized matrix is presented in Table 2.

Table 2
Max–min normalized decision matrix

Alternative	Cost (Baht)	Labor (h)	Energy (kWh)	Survival (%)	Yield (kg)
Alternative 1	1.0000	0.0000	1.0000	0.0000	0.0000
Alternative 2	0.7567	0.2778	0.7000	0.3636	0.3636
Alternative 3	0.6176	0.5000	0.5000	0.5455	0.5455
Alternative 4	0.0000	1.0000	0.0000	1.0000	1.0000

Table 2 shows that Alternative 1 achieved the most favorable normalized values for Cost and Energy, because it had the lowest original values for those cost criteria. By contrast, Alternative 4 obtained the highest normalized values for Survival and Yield, indicating the strongest production performance. Alternatives 2 and 3 occupied intermediate positions, reflecting a gradual transition from lower-cost management to more advanced but more resource-demanding systems. It should be noted that, for the CRITIC stage, cost criteria were normalized using the reverse max–min form so that lower original values correspond to higher normalized scores. Therefore, for Cost, Labor, and Energy, a value closer to 1 indicates better performance after normalization.

Step 2: Standard deviation of each criterion

The second step was to calculate the standard deviation σ_j of each normalized criterion. In the CRITIC method, the standard deviation represents the contrast intensity of a criterion. A larger standard deviation indicates that the criterion differentiates more strongly among alternatives and therefore contributes more information to the evaluation problem.

Step 3: Examine inter-criterion conflict through correlation analysis

The third step was to assess the degree of conflict among criteria through the correlation matrix. According to Eq. (4), the information content C_j of criterion j is determined by combining its standard deviation with the term $\sum(1 - r_{jk})$, where r_{jk} denotes the correlation coefficient between criteria j and k. Thus, a criterion receives a larger information content when it shows both strong variation and low redundancy with the other criteria. The results are summarized in Table 3.

Table 3
Standard deviation, inter-criterion conflict, and information content

Criterion	Standard deviation (σ_j)	$\sum(1-r_{jk})$	information content (C_j)
Cost (C1)	0.3690	5.9613	2.1998
Labor (C2)	0.3664	4.0006	1.4659
Energy (C3)	0.3640	6.0025	2.1849
Survival (C4)	0.3601	3.9823	1.4339
Yield (C5)	0.3601	3.9823	1.4339

Table 3 indicates that Cost produced the highest information content $\left(C_j = 2.1998\right)$, followed very closely by Energy $\left(C_j = 2.1849\right)$. This means that these two criteria contributed the strongest combined effect of contrast intensity and non-redundancy in distinguishing among the alternatives. Labor ranked next, while Survival and Yield had slightly lower information content values.

A notable observation is that Survival and Yield again produced identical information content values. This occurred because the Yield values followed essentially the same increasing pattern as the Survival values across the four alternatives, causing the two criteria to carry nearly identical information in the CRITIC framework.

Step 4: Final CRITIC weights

The final step of the CRITIC method was to normalize the information content values according to Eq. (5), subject to the summation condition in Eq. (6). The resulting objective weights are presented in Table 4.

Table 4
CRITIC weights of the evaluation criteria

Criterion	Type	Weight
Cost (C1)	Cost	0.2523
Labor (C2)	Cost	0.1681
Energy (C3)	Cost	0.2506
Survival (C4)	Benefit	0.1645
Yield (C5)	Benefit	0.1645

The weighting results show that Cost received the highest weight (0.2523), followed closely by Energy (0.2506). Labor received a moderate weight (0.1681), while Survival and Yield each received 0.1645. These results suggest that the present dataset is influenced most strongly by resource-related criteria, especially economic cost and energy burden.

From a managerial viewpoint, this means that although biological performance remains important, the most informative distinctions among the alternatives arise from their implementation burden. The CRITIC results therefore provide an objective and transparent basis for the subsequent TOPSIS ranking stage.

3.3 TOPSIS-based ranking results

After obtaining the CRITIC weights, the four alternatives were ranked using the TOPSIS method. Following Eqs. (7)–(12), the TOPSIS procedure consisted of: (1) vector normalization of the original decision matrix, (2) construction of the weighted

normalized matrix, (3) identification of the positive and negative ideal solutions, (4) computation of separation distances, and (5) calculation of the relative closeness coefficient for each alternative.

The objective of this stage was to identify the alternative that is closest to the positive ideal solution and farthest from the negative ideal solution, considering all five criteria simultaneously.

Step 1: Vector normalization of the decision matrix

According to Eq. (7), the original decision matrix was first normalized using vector normalization. This step transforms the raw data into dimensionless values while preserving their relative proportional structure. The normalized matrix is presented in Table 5.

Table 5
TOPSIS normalized decision matrix

Alternative	Cost (Baht)	Labor (h)	Energy (kWh)	Survival (%)	Yield (kg)
Alternative 1	0.4718	0.6296	0.4205	0.4694	0.4694
Alternative 2	0.4883	0.5397	0.4710	0.4923	0.4923
Alternative 3	0.4977	0.4677	0.5046	0.5038	0.5038
Alternative 4	0.5396	0.3058	0.5888	0.5324	0.5324

Table 5 shows that Alternative 4 has the highest normalized values for the benefit criteria, but it also has the highest normalized Cost and Energy values. In contrast, Alternative 1 has the most favorable Cost and Energy profile, but the weakest production performance.

Step 2: Construct the weighted normalized matrix

The normalized values in Table 5 were then multiplied by the CRITIC weights in Table 4 according to Eq. (8), producing the weighted normalized matrix shown in Table 6.

Table 6
Weighted normalized matrix

Alternative	Cost (Baht)	Labor (h)	Energy (kWh)	Survival (%)	Yield (kg)
Alternative 1	0.1191	0.1059	0.1054	0.0772	0.0772
Alternative 2	0.1232	0.0907	0.1180	0.0810	0.0810
Alternative 3	0.1256	0.0786	0.1265	0.0829	0.0829
Alternative 4	0.1361	0.0514	0.1475	0.0876	0.0876

Because **Cost** and **Energy** received the highest CRITIC weights, alternatives with lower values for these two criteria gained a notable advantage in the ranking stage.

Step 3: Determine the positive and negative ideal solutions

Following Eq. (9), the next step was to determine the positive ideal solution $(A^+)$and the negative ideal solution (A^-). For cost criteria, the positive ideal value is the minimum weighted normalized value, whereas for benefit criteria, the positive ideal value is the maximum weighted normalized value. The opposite rule applies to the negative ideal solution. The resulting ideal solutions are shown in Table 7.

Table 7
Positive and negative ideal solutions

Criterion	Positive ideal (A^+)	Negative ideal (A^-)
Cost (C1)	0.1191	0.1361
Labor (C2)	0.0514	0.1059
Energy (C3)	0.1054	0.1475
Survival (C4)	0.0876	0.0772
Yield (C5)	0.0876	0.0772

The positive ideal solution therefore represents the most desirable theoretical combination: the lowest Cost, Labor, and Energy together with the highest Survival and Yield.

Step 4: Compute the separation distances

Using Eqs. (10) and (11), the Euclidean distance of each alternative from the positive ideal solution $(S_i^+)$and from the negative ideal solution $(S_i^-)$was calculated. These distances indicate how close each alternative is to the best case and how far it is from the worst case.

Step 5: Calculate closeness coefficients and rank the alternatives

Finally, the relative closeness coefficient CC_i was computed using Eq. (12). A larger CC_i indicates a more preferable alternative. The results are shown in Table 8.

Table 8
Separation distances, closeness coefficients, and final ranking

Alternative	S^+	S^-	CC_i	Rank
Alternative 1	0.0564	0.0455	0.4466	4
Alternative 2	0.0425	0.0360	0.4583	3
Alternative 3	0.0357	0.0369	0.5084	2
Alternative 4	0.0455	0.0564	0.5534	1

As seen in Table 8, the TOPSIS results indicate that Alternative 4 (Proposed alternative) is the most suitable water quality management strategy under the revised decision matrix. Although this alternative has the highest Cost and Energy burden, it also achieves the highest Survival and Yield and the lowest Labor requirement. Under the current weighting structure, these advantages are sufficient to compensate for its higher resource demands, resulting in the highest closeness coefficient. In addition to the ranking results, the proposed alternative also showed favorable culture outputs after 90 days of rearing. As illustrated in Fig. 2, the harvested freshwater prawn from the proposed pond reached an individual weight of approximately 53 g, indicating acceptable growth and marketable harvest quality. This practical output is consistent with the high survival and yield values obtained for Alternative 4, and further supports its suitability as the most favorable water quality management strategy under the present evaluation framework.

Fig. 2. Representative giant freshwater prawn harvested from **Alternative 4** after 90 days of culture, showing a marketable body size with an individual weight of approximately 53 g.

Fig. 3 illustrates the physical configuration of the experimental pond used for giant freshwater prawn culture under the proposed system. The pond was designed as a land-based culture unit with a rectangular structure that allowed convenient installation of monitoring equipment and routine farm management. The culture area was covered to reduce the direct effects of sunlight and environmental fluctuations, thereby helping maintain more stable rearing conditions. This pond configuration was suitable for integrating the proposed water quality management system, including real-time sensing, data transmission,

and practical observation during the culture period. Therefore, the experimental pond provided an appropriate setting for evaluating the performance of the proposed strategy under actual farming conditions.

Fig. 3. Experimental pond used for giant freshwater prawn culture in the proposed study.

Alternative 3 ranked second. This result suggests that a semi-automatic or intermediate monitoring strategy may provide a strong compromise between implementation burden and production benefit. Compared with Alternative 2, it offers improved Survival and Yield while still remaining less demanding than Alternative 4.

Alternative 2 ranked third. Although it improves both Survival and Yield relative to Alternative 1, the gains are still moderate compared with Alternatives 3 and 4. **Alternative 1** ranked last because its favorable Cost and Energy profile was not sufficient to offset its weak biological performance.

The integrated CRITIC–TOPSIS results indicate that the most suitable alternative is not determined by a single criterion, but by the trade-off among all five criteria. Under the present dataset, Alternative 4 provides the best balance between operational burden and production performance, while Alternative 3 also appears to be a competitive option when a more moderate implementation level is preferred.

3.4 Discussion of the integrated CRITIC–TOPSIS results

The integrated CRITIC–TOPSIS analysis provides a clearer understanding of how the four water quality management alternatives differ when both resource-related constraints and production-related benefits are evaluated simultaneously. While the CRITIC method objectively determined the relative importance of the criteria from the observed data structure, the TOPSIS method translated those weights into a final ranking of the alternatives according to their closeness to the ideal solution. Taken together, these two methods offer a more comprehensive basis for decision-making than a direct comparison of raw values alone.

A key finding of the CRITIC analysis was that Cost and Energy received the largest weights, whereas Survival and Yield received slightly lower but still meaningful weights. This result suggests that, under the present dataset, the alternatives are distinguished most strongly by their implementation burden rather than by production outcomes alone. In other words, although higher survival and yield are important in freshwater prawn farming, the major source of variation among the alternatives lies in how much cost and energy are required to achieve those outcomes. This is an important result from a management perspective because it indicates that the decision problem is not dominated purely by biological performance, but by the balance between performance and operational feasibility.

The TOPSIS ranking results further reinforce this interpretation. Alternative 4 was identified as the best option because it achieved the highest closeness coefficient among the four alternatives. This means that, when all criteria were considered together, Alternative 4 showed the best overall balance relative to the positive ideal solution. Although this alternative had the highest values for Cost and Energy, it also achieved the highest Survival and Yield and the lowest Labor requirement. Therefore, the additional resource burden associated with the full IoT-based system was compensated by its superior production performance and reduced operational workload.

This result is particularly meaningful in the context of smart aquaculture. The underlying field-based system in this study was developed to provide real-time monitoring, dashboard-based visualization, and alert-supported management for giant freshwater prawn farming in land-based tanks. The earlier system-oriented results in the manuscript showed that real-time monitoring contributed to more stable water-quality conditions and improved survival in the experimental pond relative to the conventionally managed pond. The present CRITIC–TOPSIS results extend that practical finding by showing that, even when economic and operational burdens are explicitly incorporated into the evaluation framework, the advanced monitoring alternative can still emerge as the most suitable overall strategy. In this sense, the integrated MCDM analysis strengthens the managerial interpretation of the field results.

At the same time, the ranking pattern also shows that Alternative 3 remained highly competitive and was ranked second. This is an important point because it suggests that a fully advanced system is not the only viable option for practical freshwater prawn farming. Alternative 3 offers a relatively strong compromise between technological improvement and implementation burden. Compared with Alternatives 1 and 2, it provides better survival and yield. Compared with Alternative 4, it requires less cost and energy. Therefore, for farmers or small-scale operators who may face budget or infrastructure limitations, Alternative 3 could represent a realistic transitional strategy toward smart aquaculture adoption.

The positions of Alternative 2 and Alternative 1 provide additional insight into the structure of the decision problem. Alternative 2 improved upon Alternative 1 in both survival and yield while maintaining only a moderate increase in operational burden. However, its overall ranking remained below that of Alternatives 3 and 4 because the improvement in production performance was not strong enough to outweigh the advantages of the more advanced systems. Alternative 1, despite being the least demanding in terms of cost and energy, was ranked lowest because its weak survival and yield performance significantly reduced its overall desirability. This confirms that minimizing resource use alone is not sufficient to identify the best management strategy in freshwater prawn farming. Instead, acceptable biological and production outcomes must also be maintained.

Another important interpretation concerns the relationship between Survival and Yield. In the present dataset, these two criteria followed almost identical trends across the four alternatives, which led them to receive similar CRITIC weights. This reflects the practical reality that higher survival in freshwater prawn farming generally contributes directly to higher harvestable output. However, from a methodological perspective, the strong association between these two criteria also means that they provide overlapping information. This explains why their CRITIC weights were not dominant despite their practical importance. Thus, the weighting results should not be interpreted as implying that survival and yield are less important in aquaculture practice. Rather, they indicate that within this specific decision matrix, the two variables moved together and therefore carried partially redundant information.

The integrated results also highlight the value of combining objective weighting and distance-based ranking in one analytical framework. If the alternatives had been judged only by raw survival rate, Alternative 4 would still have appeared superior, but the analysis would not have shown whether the gain in production performance was justified relative to the additional cost, labor reduction, and energy use. Similarly, if the decision had been based only on cost minimization, Alternative 1 would have appeared attractive despite its weaker biological outcomes. The CRITIC–TOPSIS framework avoids both extremes by incorporating all criteria simultaneously and objectively. This is one of the key methodological contributions of the study, because it transforms the evaluation from a simple comparison of monitoring systems into a structured decision-support model for freshwater prawn farm management.

From a practical standpoint, the findings suggest that the suitability of a water quality management strategy depends on the farmer's decision context. If the objective is to maximize production performance and reduce routine labor burden, then Alternative 4 is clearly the most desirable option. If the decision-maker seeks a balance between improved productivity and more moderate implementation demands, Alternative 3 may be an attractive choice. In contrast, reliance on conventional or minimally improved monitoring strategies may be less desirable when long-term production efficiency and stability are considered. Therefore, the present results support the broader transition from traditional monitoring toward more intelligent and data-driven aquaculture management.

These findings are also consistent with the broader literature cited in the manuscript. Previous studies have shown that IoT-based systems improve monitoring continuity, environmental visibility, and management responsiveness in aquaculture. However, many of those studies focus primarily on the development and technical performance of monitoring systems. The current study contributes beyond that level by introducing a formal MCDM layer, allowing management alternatives to be

evaluated under multiple criteria. This aligns the work not only with the smart aquaculture literature, but also with recent applications of CRITIC–TOPSIS in water-related and aquaculture decision problems discussed in the introduction.

Despite these strengths, the present analysis should still be interpreted within the scope of the available data. The number of alternatives was limited to four, and the decision matrix reflected a structured comparison of representative management configurations rather than a large-scale survey of farms. In addition, Yield was highly aligned with Survival, which reduced the independence of the production-related criteria in the CRITIC stage. Future studies may therefore strengthen the framework by including additional criteria, such as maintenance complexity, system reliability, return on investment, or response time to abnormal water-quality events. It would also be valuable to compare the current ranking results with those obtained from other MCDM approaches, such as Entropy–TOPSIS, AHP–TOPSIS, or VIKOR, in order to assess the robustness of the conclusions. A promising extension is the use of DEA-based cross-efficiency as a complementary ranking approach. Unlike conventional efficiency scoring, cross-efficiency improves discrimination among alternatives by incorporating peer evaluation in the post-analysis stage, making it suitable for multi-criteria assessment problems (Thongmual et al., 2024; Wichapa et al., 2025). Therefore, future studies may compare the present CRITIC–TOPSIS results with those obtained from DEA cross-efficiency to examine ranking robustness and provide a more comprehensive basis for evaluating water quality management strategies in freshwater prawn farming. Another limitation is that each management alternative was represented by a single pond, resulting in a four-treatment design without replication. Although the four ponds were replicate-independent and maintained under comparable physical and operational conditions, the absence of replicated treatment units limits the extent to which formal statistical inference can be made regarding treatment effects. Therefore, the present findings should be interpreted primarily as evidence from a field-based case study designed to support comparative decision-making under practical farming conditions.

The integrated CRITIC–TOPSIS results confirm that the selection of a water quality management strategy in giant freshwater prawn farming should be based on a balanced consideration of both resource consumption and production performance. Under the current evaluation framework, Alternative 4 provides the most favorable compromise and is therefore identified as the most suitable strategy. At the same time, Alternative 3 also emerges as a practically relevant option for situations in which a more moderate level of investment is preferred. These findings demonstrate that the proposed MCDM framework can serve as a useful decision-support tool for advancing smart and sustainable aquaculture management.

4. Conclusions

This study applied an integrated CRITIC–TOPSIS framework to evaluate four alternative water quality management strategies for giant freshwater prawn farming in land-based systems. The evaluation considered five criteria, namely Cost, Labor, Energy, Survival, and Yield, in order to identify the most suitable strategy under both operational and production-related considerations. The analytical framework followed the objective weighting procedure of CRITIC and the ranking procedure of TOPSIS as presented in the current manuscript structure.

The CRITIC results showed that the most influential criteria in the decision problem were Cost and Energy, with weights of 0.2523 and 0.2506, respectively. These were followed by Labor with a weight of 0.1681, while Survival and Yield each received a weight of 0.1645. These results indicate that the alternatives were distinguished most strongly by their implementation burden, especially economic cost and energy requirement, although production-related criteria also contributed meaningfully to the evaluation.

Based on the TOPSIS results, Alternative 4 was identified as the most suitable water quality management strategy, with the highest closeness coefficient of 0.5534. This alternative also showed the best production performance, achieving 93% survival and 4.65 kg yield, while requiring 17 h labor, although it had the highest cost (13,746 Baht) and energy consumption (35 kWh). Alternative 3 ranked second with a closeness coefficient of 0.5084, followed by Alternative 2 with 0.4583, and Alternative 1 with 0.4466. These findings show that the best alternative was not the one with the lowest resource use alone, but the one that provided the most favorable overall trade-off between operational burden and production performance.

The comparison among alternatives further confirmed the practical value of the framework. Relative to the conventional strategy (Alternative 1), the highest-ranked option (Alternative 4) improved survival from 82% to 93%, increased yield from 4.10 kg to 4.65 kg, and reduced labor from 35 h to 17 h, although this improvement required higher cost and energy input. Meanwhile, Alternative 3 emerged as a competitive option because it provided 88% survival and 4.40 kg yield with a lower implementation burden than Alternative 4, suggesting that it may serve as a realistic intermediate strategy for farmers who cannot immediately adopt a full IoT-based system.

Overall, the study demonstrates that the integration of CRITIC and TOPSIS provides both an objective weighting mechanism and a practical ranking framework for selecting water quality management strategies in freshwater prawn farming. Under the present evaluation framework, the full IoT-based real-time monitoring strategy was found to be the most suitable option, while the semi-automatic alternative also showed strong practical potential. These findings support the use of multi-criteria decision-making as a valuable decision-support tool for smart aquaculture management.

Future research should expand the framework by incorporating additional quantitative criteria such as maintenance cost, system reliability, return on investment, and response time to abnormal water-quality events. It would also be beneficial to compare the current ranking results with those obtained from other MCDM techniques, such as Entropy–TOPSIS, AHP–TOPSIS, or VIKOR, and to validate the framework using larger-scale field data across multiple farms and production cycles.

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