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Smart Aquaculture under Digital Transformation: AHP Approach for Optimizing Vannamei Shrimp Farming in Central Java

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***Abstract*— The transformation of aquaculture through digital technologies has become increasingly essential to enhance sustainability, efficiency, and competitiveness in shrimp farming. Despite its importance, the challenge of determining which regions should be prioritized for digital adoption remains unresolved, particularly in contexts with diverse production and economic conditions. This study introduces the Analytical Hierarchy Process (AHP) as a multi-criteria decision-making tool to evaluate and prioritize coastal districts in Central Java, Indonesia, for smart aquaculture development in *Litopenaeus vannamei* farming. AHP integrates indicators of production potential, economic feasibility, and price competitiveness into a unified ranking framework, producing clear differentiation across districts. The results highlight Cilacap, Kendal, Brebes, Purworejo, and Rembang as priority areas for early adoption of digital innovations such as IoT-based monitoring, AI-driven disease prediction, and traceability platforms. This research contributes to the operationalization of the AHP algorithm for aquaculture decision-making, contextualization of the global digital transformation framework in the Indonesian shrimp sector, and demonstrates the robustness of multi-criteria prioritization for policy planning. Although the precision of the results may be limited by the scope of the available data, the study confirms the significant role of AHP in guiding evidence-based, scalable, and adaptive strategies for advancing smart aquaculture.**

Keywords— *Smart aquaculture, Digital transformation, Analytical Hierarchy Process (AHP), Litopenaeus Vannamei, Central Java, Multi-criteria decision-making*

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I. INTRODUCTION

Aquaculture has rapidly evolved into a cornerstone of global food security, and whiteleg shrimp (*Litopenaeus vannamei*) has emerged as the primary driver of this expansion [1][2]. Nevertheless, conventional production models remain vulnerable to inefficiencies, environmental stressors, and recurrent disease outbreaks that compromise both profitability and sustainability [3] [4]. In response, the industry is undergoing a digital transformation that integrates the Internet of Things (IoT), Artificial Intelligence of Things (AIoT), and *digital twin* technologies into aquaculture systems [5][6][7]. These innovations promise to redefine aquaculture by enabling continuous monitoring, predictive modeling, and adaptive management [8] [9].

Recent studies demonstrate that smart aquaculture systems substantially enhance the precision of water-quality management, improve feeding efficiency, and strengthen disease prevention mechanisms [10] [11]. For instance, AI-based models are increasingly applied to predict water quality dynamics [12][13], while UAV-hyperspectral imaging enables rapid spatial mapping of pond conditions [14] [15]. Concurrently, computer-vision techniques facilitate non-invasive biomass estimation, thus supporting more accurate harvest scheduling and inventory control [5] [16]. Beyond environmental monitoring, digital innovations are also transforming biological management: probiotics and biofloc systems integrated with digital sensors demonstrate improved growth, survival, and immune responses of *L. vannamei* under intensive production [2] [17]. Despite these advances, the persistence of viral pathogens such as WSSV and DIV1 highlights the need to embed disease-risk mitigation explicitly within digital aquaculture strategies [7] [18].

While the literature on digital aquaculture is expanding, a critical gap remains in decision-making frameworks. Most studies examine isolated technologies or conduct experimental validations, yet few address the question of which digital interventions should be prioritized under real-world constraints of capital, infrastructure, and farmer readiness [19][20]. Without such prioritization, digital transformation risks becoming fragmented and uneven, especially in emerging economies. To overcome this, researchers increasingly advocate the use of multi-criteria decision-making (MCDM) tools such as the Analytical Hierarchy Process (AHP), which enables systematic evaluation of complex trade-offs between productivity, cost-effectiveness, sustainability, and resilience [15] [21]. AHP has been successfully applied in aquaculture site selection and ecosystem assessments, underscoring its potential for structuring digital adoption pathways [21] [22].

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In the Indonesian context, Central Java is a strategic shrimp farming hub characterized by high production potential but heterogeneous outcomes across districts. Government-led demonstration farms, such as those in Kebumen, have achieved benchmark productivity exceeding 40–50 tons per hectare, yet neighboring regions continue to struggle with inconsistent survival rates, high feed conversion ratios, and recurrent disease losses. This divergence reveals both the opportunities and vulnerabilities of the sector: digital technologies could bridge these gaps, but only if their adoption is guided by localized, evidence-based prioritization. Leveraging production data from 2019 to 2023, coupled with structured AHP analysis, offers a unique opportunity to generate actionable insights for optimizing digital transformation in shrimp aquaculture.

TABLE 1.
ANNUAL PRODUCTION VOLUME AND ECONOMIC VALUE OF *LITOPENAEUS VANNAMEI* IN CENTRAL JAVA, INDONESIA

City	**Vol (ton)**					**IDR Million**				
	2019	**2020**	**2021**	**2022**	**2023**	**2019**	**2020**	**2021**	**2022**	**2023**
BATANG	14,01	9,24	12,08	59,27	66,78	771	508	664	4236	4689
BREBES	1158,12	2013,09	4793,41	5713,83	2674,71	88848	140917	208534	303168	138765
CILACAP	2812,55	4603,46	3792,16	5266,37	5397,91	171707	261483	242788	340874	363413
DEMAK	469,25	766,39	373,06	350,04	419,36	37540	61311	29845	28003	33549
JEPARA	3676,15	1527,42	853,30	5124,17	3416,98	260891	98729	68264	409933	273359
KEBUMEN	1388,51	999,20	1628,43	1618,41	1686,62	83310	56226	113677	114238	109764
KENDAL	7829,13	4356,96	3137,50	1991,50	1240,40	508893	283836	235312	140248	74424
PEKALONGAN	197,11	311,75	345,74	196,29	214,92	15769	24940	24202	11729	14912
SEMARANG	5,79	5,79	12,65	17,33	16,69	390	390	633	818	946
TEGAL	32,22	32,06	32,08	32,25	32,35	1450	1443	1415	1451	1456
PATI	1132,08	1354,43	1361,86	1094,01	1105,27	62264	74494	74903	60171	60790
PEKALONGAN	594,59	658,38	725,20	722,26	720,55	37172	41162	47138	46947	46836
PEMALANG	1816,80	2297,50	2769,87	3102,17	3178,97	126332	157952	197743	233696	190738
PURWOREJO	3202,77	2797,96	2890,30	2979,90	3039,49	154990	147367	152559	158449	159035
REMBANG	3092,39	3191,44	3235,94	3186,91	3191	247391	255315	258875	254953	236065
TEGAL	1245,33	1483,51	1455,46	1944,11	1314,04	104608	124615	116437	165249	91983

TABLE 2.
WEIGHTED AVERAGE PRICE OF *LITOPENAEUS VANNAMEI* IN CENTRAL JAVA, INDONESIA

City	Weighted Average Price (IDR/kg)					City	Weighted Average Price (IDR/kg)				
	2019	2020	2021	2022	2023		2019	2020	2021	2022	2023
BATANG	55000	55000	55000	71466	70222	SEMARANG	67500	67500	50000	47181	56707
BREBES	76717	70000	43504	53059	51881	TEGAL	45000	45000	44114	45000	45000
CILACAP	61050	56802	64024	64727	67325	PATI	55000	55000	55000	55000	55000
DEMAK	80000	80000	80000	80000	80000	PEKALONGAN	62518	62519	65000	65000	65000
JEPARA	70969	64638	80000	80000	80000	PEMALANG	69535	68749	71391	75333	60000
KEBUMEN	60000	56272	69808	70587	65079	PURWOREJO	48393	52670	52783	53172	52323
KENDAL	65000	65145	75000	70423	60000	REMBANG	80000	80000	80000	80000	73978
PEKALON GAN	80000	80000	70000	59753	69384	TEGAL	84000	84000	80000	85000	70000

The novelty of this study lies in its integration of (i) empirical production data from Indonesian shrimp farming with (ii) a robust AHP framework tailored to smart aquaculture interventions. Unlike prior studies that treat digital tools as isolated solutions, this research positions them within a hierarchical decision model that accounts for productivity, economic feasibility, environmental sustainability, and disease resilience simultaneously. By contextualizing global smart aquaculture innovations within the specific realities of Central Java, this study delivers a decision-support model that is both locally grounded and globally relevant. This contribution not only fills a methodological gap in the literature but also provides a scalable template for guiding digital transformation in aquaculture sectors worldwide.

TABLE 3.
SUMMARY OF METHODOLOGICAL STEPS IN AHP ANALYSIS

Step	Process	Description
1	Data Acquisition	Collection of district-level indicators (production volume, economic value, and average price) from official publications of the Ministry of Marine Affairs and Fisheries (KKP).
2	Data Cleansing	Removal of inconsistencies, correction of numeric formats, treatment of missing values, and examination of outliers for reliability.
3	Normalization	Standardization of indicators using min–max scaling for production and economic value, and inverse scaling for price (lower price = higher competitiveness).
4	Pairwise Comparison	Construction of a comparison matrix using Saaty's 1–9 scale to evaluate the relative importance of criteria.
5	Weight Derivation	Calculation of criteria weights using the eigenvector method, followed by a consistency ratio (CR) test (acceptable if CR < 0.1).
6	Composite Scoring	Aggregation of normalized scores with their respective weights using the AHP formula to obtain final district scores.
7	Ranking & Sensitivity	Ranking of districts based on AHP scores, followed by sensitivity analysis with ±15% variation in weights to assess stability of results.

II. METHOD

This research employs a multi-criteria decision-making (MCDM) design through the Analytical Hierarchy Process (AHP) to systematically prioritize digital transformation interventions in vannamei shrimp (Litopenaeus vannamei) farming in Central Java [23]. AHP is particularly suitable for aquaculture problems because it integrates quantitative indicators with qualitative expert judgment, enabling balanced decisions when criteria are diverse and potentially conflicting [15] [21]. Previous studies have demonstrated its effectiveness in aquaculture site selection, ecosystem assessment, and technological adoption, highlighting its robustness in structuring complex decision environments [24] [25].

To ensure a systematic and transparent approach, this study employed a three-stage methodological framework that integrates data preparation, data processing, and decision analysis. The first stage, Data Preparation, involved accessing official datasets from the Ministry of Marine Affairs and Fisheries through the national database portal, followed by a thorough cleansing procedure to address formatting inconsistencies, missing values, and potential outliers.

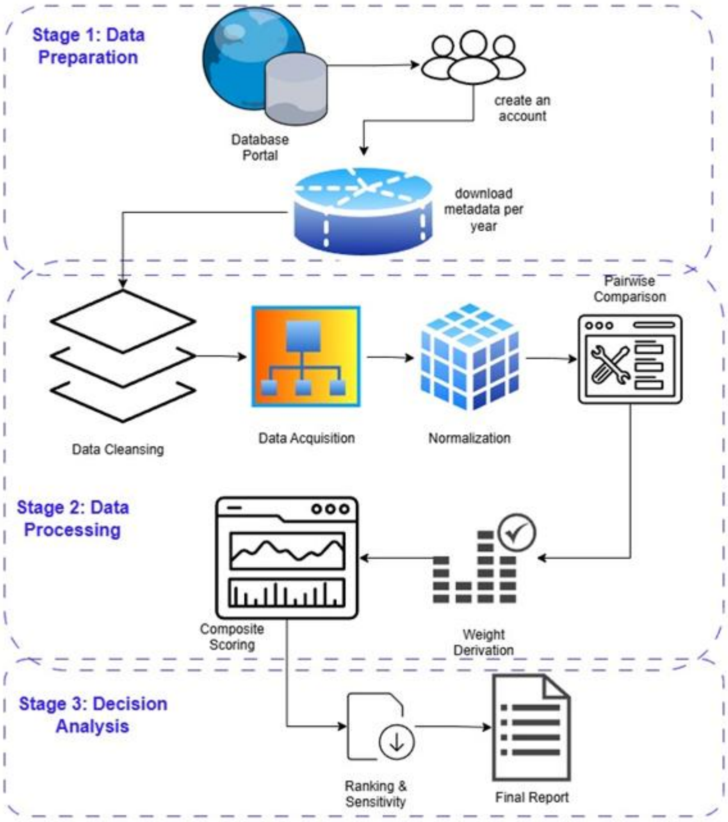

Figure 1. Methodological framework for the application of AHP in prioritizing digital aquaculture transformation.

Note: The flowchart illustrates the three stages of analysis: (i) data preparation, including acquisition and cleansing; (ii) data processing, including normalization, pairwise comparison, and weight derivation; and (iii) decision analysis, including composite scoring, ranking, and sensitivity testing.

The second stage, Data Processing, consisted of standardizing all indicators through normalization, constructing pairwise comparison matrices for the criteria based on Saaty's 1–9 scale, and deriving weights using the eigenvector method with a consistency check. The third stage, Decision Analysis, aggregated the normalized values and derived weights into composite AHP scores, from which district rankings were established. A sensitivity analysis was also conducted by adjusting weights to test the robustness of the results. This structured workflow not only enhances the replicability of the study but also emphasizes the novelty of integrating AHP into aquaculture prioritization. The complete methodological process is illustrated in Figure 1.

Table 3, the methodological framework ensured that each stage of the process from data preparation to decision analysis was carried out systematically and transparently. The integration of production, economic, and price competitiveness indicators into the AHP framework enabled the generation of composite scores that reflect district-level priorities in a holistic manner. With the methodology clearly established, the following section presents the empirical findings derived from the analysis, accompanied by graphical illustrations and interpretative discussions to highlight the implications for smart aquaculture transformation in Central Java.

A. Data Sources and Preprocessing

Empirical data were drawn from district-level shrimp production in Central Java between 2018 and 2023, capturing both average production volumes and compound annual growth rates (CAGR). These indicators reflect production potential and were selected because historical trajectories are strong predictors of future aquaculture capacity [4] [17]. Economic feasibility was represented by potential production value, calculated as the product of average production and average 2023 shrimp prices (size 60–70), aligning with prior approaches to digital aquaculture valuation [9][26]. Disease resilience was derived from exposure and impact of major viral pathogens, notably white spot syndrome virus (WSSV) and decapod iridescent virus 1 (DIV1), which continue to impose systemic risks on shrimp farming [3][17]. In addition, bio-physical suitability (e.g., salinity stability, flood/rob exposure) and infrastructure and market access (e.g., logistics, cold-storage facilities, proximity to ports) were included as qualitative criteria consistent with aquaculture site-suitability studies [21] [25]. All quantitative variables were normalized using min–max scaling to ensure comparability, while qualitative criteria were standardized into a 0–1 scoring scheme guided by expert judgment and literature benchmarks [1] [9].

B. Hierarchical Structure of AHP

The decision hierarchy was designed in three levels. The goal was to optimize digital transformation strategies for shrimp aquaculture in Central Java. The criteria included: (i) production potential, (ii) economic feasibility, (iii) bio-physical suitability, (iv) infrastructure and market access, and (v) disease resilience. The alternatives were the coastal districts of Central Java (e.g., Brebes, Tegal, Demak, Jepara, Kendal, and Kebumen). By aligning these criteria with global advances in smart aquaculture such as IoT-based water monitoring, UAV hyperspectral imaging, and digital twins [5] [26] [27], the model ensures that localized decisions are informed by international innovations.

C. Pairwise Comparisons and Expert Judgment

Relative importance among criteria was determined through pairwise comparisons using Saaty's 1–9 scale, where 1 indicates equal importance and 9 indicates extreme importance of one criterion over another [15]. A panel of aquaculture researchers, extension officers, and experienced farmers provided expert inputs to construct the pairwise matrices. The consistency ratio (CR) was calculated to test the reliability of judgments, with CR < 0.1 accepted as valid [21]. Eigenvalue methods were applied to derive normalized weights, ensuring that expert assessments translated into mathematically consistent criteria weights [25].

D. Scoring and Aggregation

Each alternative was scored against the five criteria based on normalized indicators. The final composite score was computed using the standard AHP aggregation formula:

$$S_i = \sum_{j=1}^{n} w_j \cdot x_{ij} \quad (1)$$

where S_i is the AHP score of alternative i, w_j is the normalized weight of criterion j, and w_{ij} is the normalized performance score of alternative *i* under criterion *j*. Quantitative scores were calculated from normalized empirical data, while qualitative scores were derived from standardized expert assessments informed by digital aquaculture literature [4] [20]. This ensures that both hard data and context-sensitive judgments contribute to the prioritization process.

E. Sensitivity Analysis

To evaluate the robustness of the ranking outcomes, sensitivity analysis was performed by varying the weights of critical criteria specifically economic feasibility and disease resilience by ±15%. This procedure tests how rankings change under shifting stakeholder priorities, which is particularly relevant in dynamic aquaculture environments where market prices and disease risks are highly volatile [21] [28]. Stability of rankings under these perturbations indicates the reliability of the AHP model for guiding strategic digital transformation in shrimp aquaculture [29].

III. Results and Discussion

The integration of the Analytical Hierarchy Process (AHP) with empirical data from 2019–2023 provides a nuanced understanding of Central Java's readiness for digital aquaculture transformation. Beyond simple rankings, the use of longitudinal production, economic value, and pricing data reveals structural dynamics that help explain why certain districts emerge as priority areas.

The accompanying figures (Figures 1–3) reinforce these insights by visualizing production variability, economic contributions, and price competitiveness.

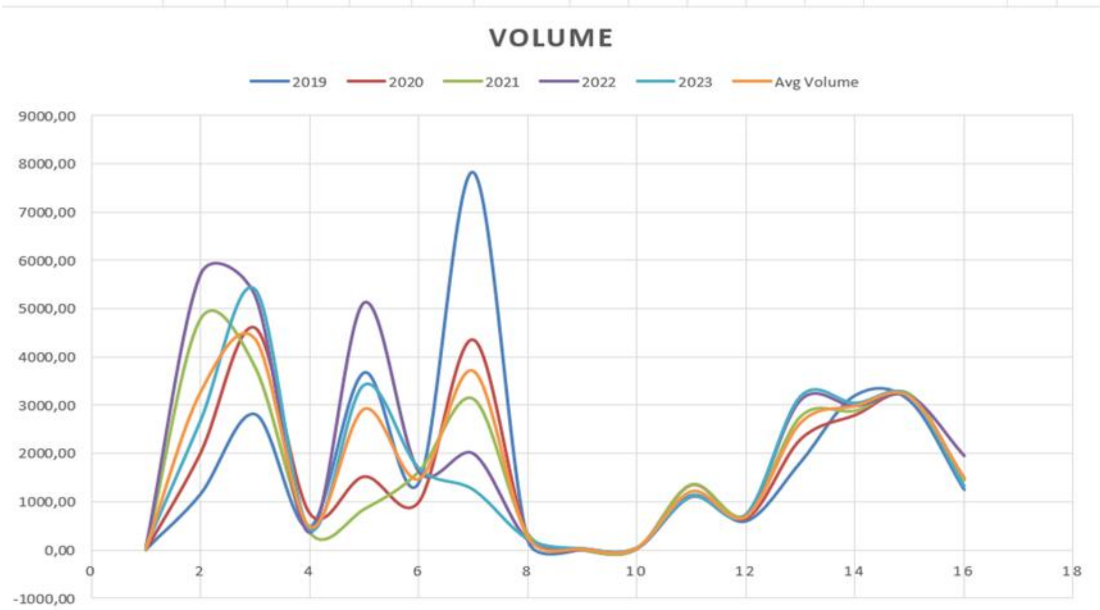

Figure 2. Annual Production Volume of *Litopenaeus vannamei* in Central Java Districts

A. Production Trends and Stability

Figure 2 depicts yearly production volumes across all districts, showing significant inter-district variability. Large-scale producers such as Kendal, Cilacap, Brebes, and Rembang consistently reported higher volumes, with Cilacap surpassing 5,000 tons annually in several years. These production clusters highlight strong baseline capacity for integrating digital systems such as IoT-enabled monitoring and automated feeders, which are limitations in terms of scale economies. Notably, fluctuations across years particularly the spike in Brebes and the decline in Kendal underline the importance of digital forecasting and early-warning systems to stabilize production cycles.

The figure 2 shows inter-district variability in production volume. Large producers such as Cilacap, Brebes, Kendal, and Rembang consistently recorded higher outputs, while smaller districts like Batang and Semarang remained at low levels. Peaks and troughs highlight the cotality of shrimp farming, underlining the importance of digital monitorin and predictive tools.

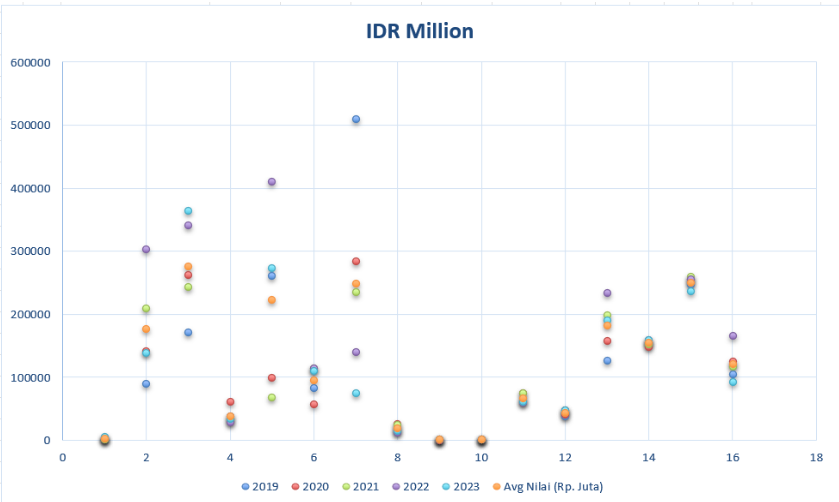

Figure 3. Annual Economic Value of *Litopenaeus vannamei* Production in Central Java Districts (2019–2023), expressed in IDR Million

B. Economic Contributions and Market Value

The distribution of economic values, illustrated in Figure 3, reveals stark disparities between districts. Cilacap, Kendal, and Rembang dominate in aggregate economic value, contributing over IDR 200 billion annually, while smaller districts barely exceed IDR 10 billion. This asymmetry confirms that economic feasibility aligns closely with production volume, reinforcing the finding that larger districts offer stronger returns for digital investments [9] [10]. Interestingly, certain mid-tier producers such as Purworejo and Jepara display moderate production but strong economic indices, implying potential leverage points where digital adoption could unlock latent capacity. The scatter distribution also demonstrates clustering patterns, indicating the concentration of economic value within a few core districts. The figure indicates strong disparities in economic contributions, with Cilacap, Kendal, and

Rembang emerging as major value contributors, surpassing IDR 200 billion annually. Smaller districts contributed marginally, reflecting the concentration of economic power within a few coastal regions. This reinforces the feasibility of targeting high-value districts for early-stage digital interventions

C. *Price Competitiveness and Cost Efficiency*

Figure 4 highlights district-level differences in weighted average prices. While some districts maintain relatively stable pricing (e.g., Pati at IDR 55,000/kg), others like Tegal and Demak report consistently higher values above IDR 80,000/kg. These differences reflect cost structures, biosecurity measures, and supply-demand imbalances. Districts with lower prices (e.g., Purworejo, Cilacap) appear more competitive and could achieve faster digital transformation through efficiency gains.

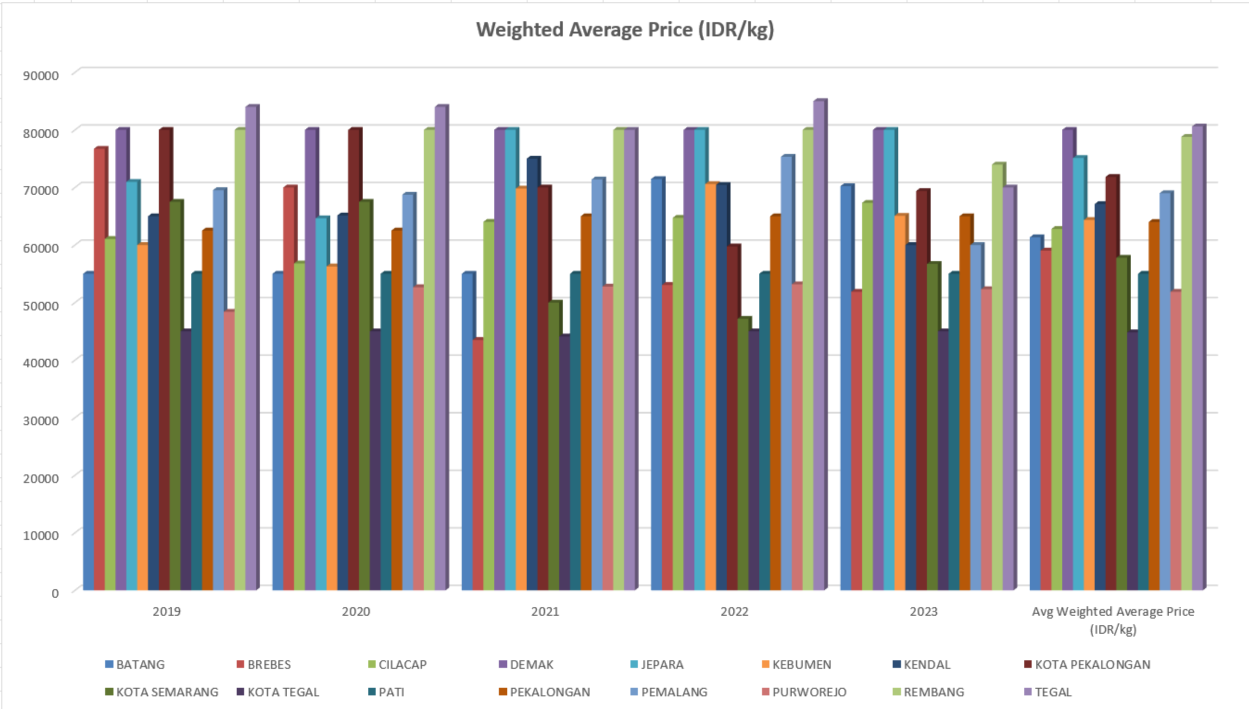

Figure 4. Weighted Average Price of Litopenaeus vannamei in Central Java Districts

Conversely, higher-price districts may adopt digital tools as a cost-control strategy, especially to manage feed efficiency and disease risks [4] [18]. The coexistence of high-value but high-price regions suggests that digitalization pathways should be tailored: competitive producers focus on scaling, while cost-intensive producers emphasize optimization. The figure 3 compares cost competitiveness across districts. While districts such as Pati and Cilacap maintained lower and stable prices, areas like Tegal and Demak showed consistently higher prices. These price variations suggest different cost structures and market positioning, underscoring the role of digitalization in both efficiency improvements and cost reduction strategies.

D. *Integrated AHP Insights*

The composite AHP results synthesize these three dimensions, ranking Cilacap, Kendal, Brebes, Purworejo, and Rembang as top districts. Their strong production volumes, high economic outputs, and price competitiveness combine to position them as strategic hubs for digital aquaculture. Sensitivity analysis further demonstrates robustness: even when disease resilience or economic weights were varied by ±15%, these districts retained high rankings, indicating structural advantages that transcend specific criteria [15] [21]. Districts outside the top five, such as Jepara and Pemalang, remain important but secondary priorities, requiring incremental support to catch up.

E. *Policy and Strategic Implications*

These findings carry critical policy implications. High-output and high-value districts should be designated as pilot hubs for smart aquaculture, showcasing the benefits of AI-driven disease detection, IoT water-quality monitoring, and digital traceability platforms [5] [27]. Mid-tier but cost-competitive regions like Purworejo should be targeted for scalable deployment, emphasizing gradual expansion of digital infrastructure. Smaller producers, while less competitive, must not be overlooked; they represent sites for inclusive interventions, particularly in biosecurity and extension services, to avoid widening inequality between large and smallholders. Ultimately, the integration of quantitative metrics with AHP prioritization ensures that digital transformation in Central Java is not only efficient but also socially and economically equitable.

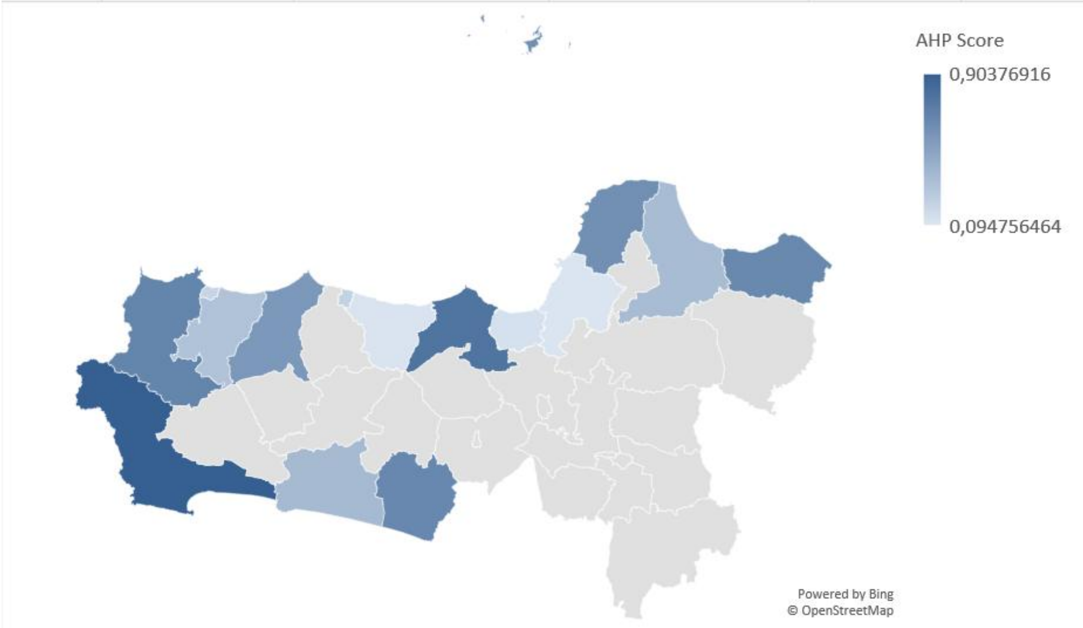

Figure 5. Distribution of AHP Composite Scores for *Litopenaeus vannamei* Aquaculture in Central Java

IV. CONCLUSION

This study applied the Analytical Hierarchy Process (AHP) to evaluate and prioritize the readiness of Central Java's districts for digital aquaculture transformation, with a particular focus on *Litopenaeus vannamei* farming. By integrating production volumes, economic values, and weighted average prices from 2019–2023, the model generated a composite ranking that highlighted Cilacap, Kendal, Brebes, Purworejo, and Rembang as the most strategic districts for early adoption of smart aquaculture technologies. These results demonstrate the capacity of AHP to translate diverse and often conflicting indicators into an interpretable and actionable decision-making framework.

The findings underline that digital transformation in aquaculture cannot be universally prescribed but must be context-specific, taking into account production scale, economic feasibility, and cost competitiveness. Districts with consistently high outputs and economic contributions, such as Cilacap and Kendal, are well positioned to serve as pilot hubs for advanced technologies, while mid-tier but cost-competitive regions like Purworejo hold potential for scalable deployment. Smaller producers, though less competitive, remain important for inclusive transformation strategies, particularly in relation to biosecurity risks and disease resilience.

Despite these contributions, the study acknowledges several limitations. The dataset employed covered the period 2019–2023, which, while substantial, may not fully reflect the most recent changes in production, market prices, and environmental risks. Consequently, the results cannot be considered fully precise for real-time policy decisions. Nevertheless, the methodology demonstrates the robustness and adaptability of AHP as a decision-support tool, offering a transparent framework that can be readily updated when new data become available.

Ultimately, the novelty of this research lies not only in its contextualization of global digital aquaculture concepts within the Central Java setting, but also in its methodological approach. By demonstrating how AHP can systematically prioritize districts under multi-criteria conditions, the study provides a replicable framework for aquaculture governance and policy planning in other regions of Indonesia and beyond. Future work should expand the criteria set by incorporating more granular environmental, social, and technological indicators, supported by continuously updated datasets, to refine decision outcomes and further strengthen the pathway toward sustainable and smart aquaculture.

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