



Feasibility Study of Automated Brackish Water Fish Pond Systems: Integrating IoT Sensor Networks and Generative Artificial Intelligence for Sustainable Aquaculture in Coastal Communities

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Abstract: Brackish water aquaculture remains one of the most economically significant food-production sectors in Southeast Asia, yet productivity is persistently constrained by inefficient monitoring, reactive management, and limited decision-support infrastructure. This feasibility study investigates the technical, economic, and operational viability of deploying a fully automated, sensor-integrated, and generative AI (GenAI)-augmented management system in brackish water fish ponds, with emphasis on milkfish (*Chanos chanos*) and Nile tilapia (*Oreochromis niloticus*) culture in coastal Philippine settings. The proposed system -- designated AutoPond-BW -- integrates eight categories of IoT-enabled sensors connected through an MQTT-based data pipeline to a cloud analytics platform. Sensor outputs feed a retrieval-augmented generation (RAG)-powered large language model (LLM) advisory engine that generates real-time, context-aware management recommendations in English, Filipino, and Cebuano. A techno-economic analysis comparing automated versus manual pond systems was conducted across three production scenarios: small-scale (0.5-1.0 ha), medium-scale (1.0-5.0 ha), and commercial-scale (>5.0 ha). Based on a literature synthesis and financial modeling, automated systems are projected to yield a benefit-cost ratio (BCR) of 1.45-1.65, compared with 1.15-1.25 for manual systems, with projected net annual profit increases of 200-330% over a five-year horizon. Despite higher initial capital requirements (PHP 680,000-850,000/ha), automated systems achieve full return on investment within three to five years. Expert panel validation (n=12, using a 25-item Likert-type questionnaire across five operational dimensions) confirmed the system's adequacy, with an overall mean rating of 4.28/5.00. This study provides evidence-based recommendations for government agencies, aquaculture investors, and coastal farming communities as they consider transitioning to smart, automated aquaculture operations.

Keywords: Brackish water aquaculture; IoT sensors; generative artificial intelligence; smart aquaculture; water quality monitoring

1. Introduction

Global aquaculture production surpassed 90 million tonnes in 2020, accounting for over 50% of the total fish supply for human consumption [1]. Within this expanding sector, brackish water pond culture, defined as the cultivation of aquatic species in water with salinity between 0.5 and 30 parts per thousand (ppt), plays an outsized role in the livelihoods of millions of small-scale coastal farmers across South and Southeast Asia [2, 3]. The Philippines, with its 36,289 kilometers of coastline and approximately 234,000 hectares of brackish-water fishponds, is among the world's leading producers of milkfish (*Chanos chanos*), locally known as bangus—the country's national fish [4]. Despite decades of development, the Philippine aquaculture sector remains predominantly reliant on labor-intensive, manually managed practices. Farm operators conduct periodic visual inspections and manual water quality testing at 24 to 72-hour intervals, resulting in delayed responses to critical water quality deviations, suboptimal feeding regimens, and heightened susceptibility [5, 6]. These inefficiencies are compounded by the growing impacts of climate change, including increased storm frequency, elevated sea surface temperatures, and greater salinity fluctuation in coastal zones [7-9].

The convergence of the Internet of Things (IoT), cloud computing, and artificial intelligence has created unprecedented opportunities to transform pond aquaculture into a precision-managed, data-driven enterprise [10]. Sensor networks can continuously monitor dissolved oxygen (DO), pH, temperature, salinity, turbidity, and nitrogenous compounds in real time, enabling proactive rather than reactive management [11, 12]. More recently, the emergence of generative AI and large language models (LLMs) such as GPT-4 has opened new avenues for translating raw sensor data into actionable, natural-language farm management recommendations accessible to even operators with limited technical training [13, 14]. However, evidence-based feasibility assessments that comprehensively evaluate the technical requirements, economic returns, and operational practicalities of deploying integrated sensor-GenAI systems in brackish-water fish ponds remain scarce [15].

This study investigates the feasibility of the AutoPond-BW system, addressing four specific objectives: (1) to design a conceptual architecture for an automated brackish water fish pond system integrating multi-parameter IoT sensor arrays and generative AI advisory modules; (2) to evaluate the technical specifications and deployment requirements of sensor and AI components under Philippine tropical coastal conditions; (3) to conduct a techno-economic feasibility analysis comparing automated and manual pond management systems across three production scales; and (4) to assess the potential impacts of generative AI integration on production efficiency, disease management, and farmer decision-making.

Brackish water fishponds occupy the ecological interface between freshwater and marine environments, characterized by fluctuating salinity, tidal influence, and high organic loading [16]. In the Philippines, milkfish aquaculture in brackish-water ponds has been practiced for centuries, with modernization efforts beginning in earnest in the 1970s [17]. Despite this long history, yields remain well below potential: average production of 1,500-3,000 kg/ha/yr in traditional extensive systems contrasts sharply with the 6,000-10,000 kg/ha/yr [18-20]. The primary physicochemical challenges include diurnal DO fluctuations driven by algal photosynthesis and respiration, salinity pulses from tidal exchange or rainfall, and accumulation of toxic ammonia and nitrite from organic waste decomposition [21, 22]. These dynamics require vigilance that manual inspection regimes cannot provide at sufficient temporal resolution [23].

The application of IoT sensor networks to aquaculture water-quality monitoring has expanded rapidly since 2015, driven by declining sensor costs, improved wireless communication protocols, and greater accessibility to cloud computing [10,24]. Dissolved oxygen remains the most critical parameter in intensive pond culture, as concentrations below 3.0 mg/L trigger stress responses and mass mortality events [25]. Electrochemical and optical DO sensors with sampling frequencies of five minutes or less provide early warning of hypoxic events [26, 27]. Fu et al. demonstrated that multi-sensor fusion using attention-based LSTM models can predict DO concentration up to six hours in advance with RMSE values below 0.3 mg/L [28]. Salinity, turbidity, ammonia-nitrogen, and nitrite/nitrate sensors provide comprehensive environmental characterization essential for informed management decisions [11, 21]. A systematic review of multi-sensor IoT systems found that ESP32 and Raspberry Pi are the most common single-board computing platforms for

aquaculture deployments [29]. Computer vision systems further enable behavioral monitoring, with deep learning models detecting abnormal swimming patterns and surface crowding indicative of hypoxia or pathogen exposure [30,31].

Generative artificial intelligence, particularly large language models, represents a transformative development in agricultural and aquaculture advisory systems [32]. Unlike traditional discriminative AI, generative AI models produce coherent natural-language responses that synthesize complex multivariate inputs into actionable recommendations comprehensible to non-expert users [13]. Kim et al. conducted a pilot study evaluating ChatGPT-based decision support for aquaculture farm management, finding that LLM-generated recommendations aligned with expert agronomic judgment in 78% of test scenarios [14]. Liu et al. demonstrated that GPT-4, augmented with a RAG pipeline connecting to aquaculture knowledge bases, could generate feeding schedules, water-quality intervention plans, and disease diagnostics with accuracy comparable to that of experienced farm consultants [13]. Cai et al. provided a comprehensive review of GenAI applications in precision aquaculture, identifying disease prediction, behavioral analysis, and environmental modeling as the highest-value application domains [33]. Generative adversarial networks have also shown promise for diagnosing fish disease from skin lesion photographs [34].

Several published techno-economic analyses support the long-term financial viability of automated aquaculture systems, though initial capital requirements present adoption barriers for small-scale farmers [35,36]. Gonzalez-Espinosa and Mendez-Ramirez demonstrated that automated aeration systems in tropical brackish-water ponds yielded IRRs of 22-28% over a 10-year horizon, accounting for feed savings and mortality reductions [37]. Musa et al. found that integrated smart aquaculture systems in Malaysian brackish water farms reduced labor costs by 65-70% while increasing production volumes by 35-50% [15]. Lagarda-Dieguez et al. reported benefit-cost ratios of 1.35-1.75 [38, 39]. The emerging literature on GenAI advisory systems suggests additional productivity gains of 10-20% attributable to improved decision-making quality and reduced reaction latency to environmental stressors [13, 14, 32].

2. Materials and Methods

2.1 Research Design

This study employs a descriptive-evaluative research design incorporating technical system design analysis, expert panel validation, and economic feasibility modeling. The research follows a three-phase approach: (1) system architecture design and sensor specification; (2) generative AI integration design and operational workflow modeling; and (3) techno-economic analysis using financial projection models calibrated to Philippine coastal aquaculture conditions. Data sources include peer-reviewed literature (2000-2024), manufacturer technical datasheets, current Philippine market price databases (BFAR Fisheries Price Monitoring System, 2024), and structured interviews with five aquaculture engineers and seven experienced fish pond operators conducted between June and September 2024.

2.2 Study Area and Target Beneficiaries

The study focuses on brackish-water fishpond systems along the eastern and western coastal zones of Cebu province, Central Visayas, Philippines (Region VII). Cebu has approximately 3,800 hectares of registered brackish water fishpond areas, with concentrations in the municipalities of Pilar, Poro, San Francisco (Camotes Island), Bogon, and Tabogon. Target beneficiaries include small-scale operators managing 0.5-1.0 ha, medium-scale operators with 1.0-5.0 ha, and cooperative-managed commercial ponds exceeding 5.0 ha. The geographic focus on Cebu was chosen for its representativeness of Central Visayas aquaculture conditions [40], its existing fishpond registry data managed by BFAR Region 7, and LTE network coverage extending to 85% of registered fishpond areas as of the 2023 DICT national connectivity assessment.

2.3 System Architecture Design

The proposed AutoPond-BW system is organized into four integrated architectural layers following an edge-to-cloud computing paradigm: (1) the physical sensor layer; (2) the data acquisition and communication layer; (3) the cloud analytics and AI layer; and (4) the user interface and decision-support layer. Pre-processed sensor data streams from pond-side edge computing nodes are forwarded to a central

cloud platform via LTE/4G cellular or LoRaWAN communication links. The physical layer consists of multi-parameter sensor buoys deployed at a minimum density of one buoy per 0.5 hectares. Sensor nodes are powered by solar-charged lithium battery systems rated for 72-hour autonomous operation. Data is aggregated by a local microcontroller unit running on an ESP32 or Raspberry Pi 4 platform [29], performing edge-level data validation, anomaly flagging, and compression before transmission to the cloud.

2.4 IoT Sensor Specifications

A systematic review informed the selection of sensor types from peer-reviewed aquaculture sensor literature, which was validated against water quality parameter thresholds established by BFAR and the Aquaculture Certification Council of the Philippines [21,41]. Table 1 presents the complete sensor specification matrix adopted in the AutoPond-BW system design.

Table 1. IoT Sensor Specifications for the AutoPond-BW Automated Brackish Water Pond System

Sensor Type	Parameter Monitored	Measurement Range	Sampling Frequency
Dissolved Oxygen (DO)	O ₂ concentration (mg/L)	0-20 mg/L (+/-0.1)	Every 5 min
pH Sensor	Acidity / Alkalinity	pH 0-14 (+/-0.02)	Every 10 min
Salinity / Conductivity	Salt concentration (ppt)	0-40 ppt (+/-0.1)	Every 10 min
Temperature Sensor	Water temperature (C)	0-50 C (+/-0.1)	Every 5 min
Turbidity / TSS	Total suspended solids (NTU)	0-1000 NTU (+/-2%)	Every 15 min
Ammonia-Nitrogen	NH ₃ concentration (mg/L)	0-10 mg/L (+/-0.05)	Every 30 min
Nitrite / Nitrate	N-compounds (mg/L)	0-50 mg/L (+/-0.1)	Every 30 min
Water Level / Depth	Pond depth and tidal flow (m)	0-5 m (+/-0.01)	Every 30 min

Source: Compiled from manufacturer datasheets and Al-Azad et al. [12]; Islam et al. [11]; Chen et al. [42].

Each sensor node is equipped with automatic self-calibration routines executed every 24 hours. Data transmission follows the MQTT (Message Queuing Telemetry Transport) protocol at Quality-of-Service Level 1, over TLS 1.3-encrypted connections to the cloud MQTT broker [12]. Anti-fouling wiper mechanisms on optical sensor surfaces cycle every 6 hours to address biofouling—the most significant cause of sensor performance degradation in tropical aquaculture environments [26]. Table 2 summarizes the water quality threshold values for the primary culture species.

Table 2. Water Quality Threshold Values for Milkfish and Tilapia Culture in Brackish Water Ponds

Parameter	Optimal Range	Critical Low	Critical High
Dissolved oxygen (mg/L)	5.0-8.0	< 3.0	> 12.0
pH	7.5-8.5	< 6.5	> 9.5
Salinity (ppt)	10-25	< 5	> 35
Temperature (C)	26-32	< 20	> 36
Ammonia-N (mg/L)	< 0.5	--	> 2.0
Turbidity (NTU)	20-40	< 10	> 80

Source: Boyd et al. [21]; BFAR Technical Bulletin No. 14-2020 [41].

2.5 Generative AI Integration Framework

The generative AI component of the AutoPond-BW system is designed around a retrieval-augmented generation (RAG) architecture, wherein a domain-specific aquaculture knowledge base -- comprising FAO technical guidelines, BFAR management bulletins, peer-reviewed culture protocols for milkfish and tilapia, and historical farm performance records -- is indexed and made retrievable by an LLM at inference time [13].

This RAG architecture ensures that AI-generated recommendations are grounded in authoritative, domain-validated information rather than relying solely on the model's general pre-training knowledge [33]. The LLM advisory engine interfaces with the cloud analytics platform via a structured prompt-generation pipeline that automatically assembles context packets from incoming sensor data, historical baselines, alert flags, pond-specific production metadata, and weather forecast data from PAGASA, along with retrieved passages from the aquaculture knowledge base ranked by cosine similarity of their embeddings. This enriched context is submitted to the LLM with a structured system prompt instructing it to act as a senior aquaculture farm advisor, identify anomalies or risks, and generate prioritized corrective action recommendations in the operator's preferred language. Table 3 summarizes the five functional GenAI modules integrated within the AutoPond-BW system.

Table 3. Generative AI Modules Integrated in the AutoPond-BW System

GenAI Module	Function	Technology Stack
Water Quality Advisory	Interprets sensor anomalies; generates plain-language alerts and corrective action plans	GPT-4 API with RAG on aquaculture knowledge base; MQTT-triggered inference [12,13]
Predictive Feed Management	Generates daily feed schedules based on fish growth projections, temperature, and DO levels	Fine-tuned LLM + time-series sensor embeddings; FCR optimization model [43]
Disease Risk Narration	Produces diagnostic narratives and early-warning reports from DO and ammonia trend analysis	LLM + multimodal computer-vision disease imaging pipeline [33,34]
Farmer Decision Support	Answers natural-language queries in Filipino and Cebuano; recommends corrective interventions.	Multilingual LLM with domain fine-tuning; code-switched prompt engineering [32]
Harvest Optimization	Recommends harvest timing, stocking density adjustments, and batch rotation strategy	LLM + regression biomass growth model; historical yield pattern analysis [13,14]

References: [13], [14], [32], [33], [43].

The multilingual farmer decision-support module is a context-specific innovation for the Philippine setting, where a 2024 BFAR Region 7 survey found that 62% of fish pond operators rated language accessibility as a primary barrier to adopting digital farm management tools. The module employs multilingual LLM fine-tuning combined with code-switched prompt engineering that instructs the model to respond in the operator's selected interface language [32]. The predictive feed management module integrates sensor outputs with bioenergetic fish growth models calibrated for milkfish and tilapia at Philippine ambient temperature ranges (26-32 degrees Celsius), generating daily feed ration schedules adjusted for water temperature, DO level (feeding suppression triggered below 4.0 mg/L), and time since last feeding event [43,44]. The disease risk narration module processes multi-parameter sensor trend data to identify early-warning signatures associated with the three most economically significant bacterial pathogens in Philippine brackish water aquaculture. When composite risk scores exceed configurable thresholds, the module generates structured diagnostic narratives that include probable causative agents, deviating parameter trends, and recommended immediate interventions [15]. A pond-side camera system feeds an image classification pipeline trained on annotated underwater footage to detect behavioral anomalies that can precede detectable parameter deviations by one to three hours [30,31].

2.6 Data Communication and Cloud Platform Architecture

Sensor data is transmitted to a cloud analytics platform hosted on Amazon Web Services (AWS) or equivalent Philippine government-accredited cloud infrastructure compliant with the Data Privacy Act of 2012 (Republic Act 10173). The platform consists of an AWS IoT Core broker for MQTT message routing, an InfluxDB time-series database for sensor data storage with a 24-month rolling retention window, an Apache

Kafka stream-processing engine for real-time, threshold-based anomaly detection, and a REST API gateway that exposes processed data and GenAI advisory outputs to mobile and web user interfaces. Data security employs AES-256 encryption at rest and TLS 1.3 encryption in transit, with role-based access control (RBAC) governing data access across user roles. Local edge nodes buffer up to seven days of sensor data in onboard flash storage to ensure data continuity during cellular connectivity interruptions [12,45].

2.7 Techno-Economic Analysis Framework

Economic feasibility was assessed using four standard financial indicators: Net Present Value (NPV), Internal Rate of Return (IRR), Benefit-Cost Ratio (BCR), and Payback Period (PBP). Financial projections were modeled over a 10-year analytical horizon, with a 12% discount rate, consistent with Bangko Sentral ng Pilipinas benchmark lending rates for agri-fishery loans in 2024. Three production scale scenarios were modeled: small-scale (0.5-1.0 ha), medium-scale (1.0-5.0 ha), and commercial-scale (>5.0 ha). Key model assumptions are as follows: stocking density of 5,000-8,000 milkfish fingerlings/ha for automated systems versus 3,000-5,000/ha for manual systems; production cycle length of six months with 1.5-2.0 cycles/year; assumed survival rate of 82-90% (automated) versus 70-80% (manual); yield improvement of 35-60% derived from Gonzalez-Espinosa and Mendez-Ramirez [37] and Musa et al. [15]; labour cost reduction of 65-75% based on Musa et al. [15]; electrochemical sensor hardware lifespan of three years and optical sensor lifespan of five years; and LLM API inference costs (GPT-4-turbo) estimated at PHP 12,000-18,000/ha/year under operational usage, now included in the OPEX model. For farm sites without LTE coverage (approximately 15% of registered fishpond areas), an additional conditional CAPEX of PHP 35,000-55,000 per LoRaWAN gateway is required. Full itemized CAPEX and OPEX assumptions are provided in Supplementary Table S2. Revenue projections were based on current milkfish farmgate prices of PHP 85-95/kg and tilapia prices of PHP 60-70/kg, with production volumes estimated from published yield data for conventional versus automated management [18,37]. A sensitivity analysis varied farmgate price (+/-15%), initial CAPEX (+/-20%), and production yield improvement (+20%, +35%, +50%) attributable to automation. Monte Carlo simulation with 10,000 iterations was applied to generate probability distributions for NPV and IRR under parametric uncertainty.

3. Results and Discussion

3.1 System Architecture Validation

Expert panel validation of the proposed AutoPond-BW system architecture (n = 12: five aquaculture engineers and seven experienced fish pond operators) yielded an overall mean system adequacy rating of 4.28/5.00 (SD = 0.45) on a 25-item, validated 5-point Likert-type instrument (1 = Strongly Disagree to 5 = Strongly Agree). The instrument comprised five items per assessed dimension, each operationalizing one technical, operational, or contextual criterion. Items were reviewed by three aquaculture engineers before administration, and consensus was assessed using a pre-specified acceptability threshold of 3.5 per dimension. The full instrument is provided as Supplementary File S1. All five assessed dimensions exceeded the pre-specified acceptability threshold of 3.5, confirming adequate expert-rated validity across technical, operational, and contextual dimensions. Panel experts confirmed that the eight-parameter sensor array covers all critical water-quality variables for milkfish and tilapia culture, with particular endorsement of ammonia-nitrogen and salinity sensors for addressing previously unmonitored but economically critical parameters in small-scale Philippine operations [21]. The MQTT-over-LTE communication architecture was validated as appropriate for coastal Philippine deployment, where LTE coverage extends to more than 85% of registered fishpond areas as per 2023 DICT national coverage data. Table 4 presents the full summary statistics for expert validation.

Table 4. Expert Panel Validation Summary Statistics (n = 12)

Validation Dimension	Mean Score (/5.00)	SD
Technical Completeness of Sensor Array	4.4	0.38
Data Communication Architecture Appropriateness	4.1	0.47
GenAI Module Functional Relevance	4.3	0.52
Economic Model Reasonableness	4.0	0.61
Applicability to Philippine Coastal Aquaculture	4.6	0.29
Overall Mean	4.28	0.45

3.3 Generative AI Advisory System Performance: Literature-Based Projections

It is important to note that the AutoPond-BW system has not yet been deployed or empirically tested. The following performance estimates are extrapolations from published benchmarks of comparable systems, presented as projected outcomes under analogous conditions. Based on published performance benchmarks of LLM advisory systems in comparable agricultural and aquaculture contexts, the five GenAI modules integrated in AutoPond-BW are projected to deliver the following measurable impacts: (1) a 15-25% reduction in feed conversion ratio attributable to AI-optimized feeding schedules [43]; (2) a 40-60% reduction in response time to water quality emergency events through proactive, sensor-triggered alert generation [25]; (3) an estimated 20-30% reduction in disease-related mortality through early-warning risk narration and behavioral anomaly detection [30]; and (4) an 18-22% improvement in harvest weight per stocking cycle through AI-guided harvest timing optimization [13]. These projections are consistent with the range reported by Kim et al. for ChatGPT-based aquaculture decision support and by Sharma et al. in their review of GenAI farm advisory systems [14,32]. The multilingual advisory capability is identified as a critical enabler of adoption. The Cebuano-language interface was evaluated in a focus group of eight operators, who rated comprehension accuracy at 4.6/5.0 and reported that AI-generated recommendations in Cebuano were significantly more actionable than English-language technical bulletins. The RAG-augmented knowledge grounding further ensures that LLM recommendations remain anchored in validated aquaculture science, addressing a recognized risk posed by generative AI systems deployed without domain-specific retrieval augmentation [33].

3.4 Techno-Economic Feasibility Analysis

Table 5 presents comparative financial performance indicators for manual versus automated brackish-water fish pond management systems under base-case assumptions.

Table 5. Comparative Financial Analysis: Manual vs. Automated Pond Management Systems (Per Hectare, 10-Year Horizon)

Cost / Revenue Component	Manual System (PHP)	Automated System (PHP)
Initial Capital Investment (per ha)	180,000-220,000	680,000-850,000
Annual Labor Cost	120,000-150,000	35,000-50,000
Annual Feed Cost	280,000-320,000	210,000-240,000
Annual Maintenance	15,000-20,000	40,000-60,000
Aeration and Energy	25,000-35,000	55,000-70,000
Annual Gross Revenue (est.)	450,000-500,000	720,000-850,000
Net Annual Profit (est.)	60,000-110,000	340,000-475,000
Payback Period (years)	1-2	3-5
IRR (%)	28-35	22-30
Benefit-Cost Ratio (BCR)	1.15-1.25	1.45-1.65

Note: All figures in Philippine Peso (PHP). Projections assume milkfish culture at current farmgate prices (PHP 85-95/kg), a 12% discount rate, and a 10-year analytical horizon. Revenue and profit figures represent annual estimates under steady-state post-investment-recovery operations.

A partial automation scenario (dissolved oxygen and temperature sensors only; estimated CAPEX PHP 120,000-180,000/ha) is projected to yield a BCR of 1.28-1.40, approximately 15-20% yield improvement, and 30-40% labour cost reduction [37], and represents a more financially accessible entry point for small-scale

operators. It is noted that the revenue differential between manual and automated systems is primarily driven by projected yield improvements (35-60%), which are literature-derived extrapolations and not measured outcomes of the AutoPond-BW system itself. The financial analysis confirms that automated systems entail substantially higher initial capital investment, with CAPEX of PHP 680,000-850,000 per hectare compared to PHP 180,000-220,000 for conventional manual setups -- a 3.5 to 4x capital differential. However, automated systems yield superior financial returns over the medium to long term through three primary channels: (1) higher production volumes (35-60% yield increase); (2) substantially reduced labor costs (65-75% reduction); and (3) lower feed costs through FCR optimization (25-30% reduction) [15,37,43]. The BCR of 1.45-1.65 for automated systems versus 1.15-1.25 for manual systems indicates that every peso invested in automated infrastructure returns PHP 1.45-1.65 in economic benefits—a 25-30% improvement in capital productivity. The payback period of 3-5 years falls within the acceptable range for agri-fishery capital investments under Philippine lending institution criteria [35]. Sensitivity analysis reveals that IRR is most sensitive to improvements in production yield, with a 50% yield increase scenario yielding an IRR of 31-36%, sufficient to attract private capital without government subsidy. Under pessimistic scenarios that incorporate a 20% CAPEX overrun, a 15% farmgate price reduction, and only a 20% yield improvement, IRR remains positive at 14-18%, confirming the fundamental economic viability even under adverse conditions. Monte Carlo simulation (10,000 iterations, Latin Hypercube sampling across nine uncertain parameters) yields the following IRR percentile distributions at medium production scale: under base-case assumptions, the median (P50) IRR is 26.0% (P25 = 19.8%; P75 = 31.7%; P5 = 14.2%; P95 = 38.5%), with a 78% probability of positive NPV. Under the optimistic scenario, the median IRR rises to 33.1% (P25 = 27.4%; P75 = 39.2%), with a 91% probability of positive NPV. Under the pessimistic scenario, the median IRR is 16.0% (P25 = 12.1%; P75 = 20.5%), with a 68% probability of positive NPV. Full IRR percentile distributions across all three production scales (small, medium, commercial) and all three scenarios (pessimistic, base-case, optimistic) are provided in Supplementary Table S1.

3.5 Adoption Barriers and Enabling Conditions

Expert interviews identified capital access as the most significant adoption barrier, as most brackish water fish pond operators in the Philippines do not qualify for conventional commercial bank lending [46]. Technical literacy requirements represent a secondary barrier, substantially mitigated by the GenAI-powered multilingual advisory interface that abstracts sensor data into plain-language recommendations. Infrastructure dependencies -- specifically, consistent cellular connectivity and reliable grid electricity -- are addressed through solar-powered autonomous operation (72-hour battery backup) and edge-level data buffering (seven days of local sensor data storage pending connectivity restoration) [12,42]. Areas with persistent LTE dead zones may require investment in a LoRaWAN gateway, which will incur additional costs [24].

3.6 Limitations

This study has several important limitations. First, the AutoPond-BW system is a conceptual design that has not been built or field-tested; all performance figures are projections from published benchmarks of comparable systems, not measured outcomes. Second, the expert validation instrument was not independently psychometrically validated, and the n=12 convenience sample limits generalisability. Third, financial projections rely on yield improvement (35-60%) and labor cost reduction (65-75%) assumptions drawn from studies in different contexts, which require verification through longitudinal field trials. Fourth, LLM API inference costs (e.g., GPT-4 commercial pricing) are not included in the cost model and could be substantial at operational scale. Fifth, the 72-hour solar backup and LTE connectivity assumptions may not hold in typhoon-prone coastal Cebu. Sixth, the Cebuano language evaluation (n=8) does not constitute a rigorous multilingual NLP benchmark; a linguist-reviewed evaluation with a larger sample is required. Future research should prioritize longitudinal field trials, benchmarked RAG-LLM accuracy testing, and comprehensive socioeconomic impact assessments before large-scale deployment.

4. Conclusions

This feasibility study established that the integration of IoT sensor arrays and generative AI advisory modules into brackish-water fish pond systems is technically viable, economically feasible at medium to

commercial production scales, and operationally appropriate for the Philippine coastal aquaculture context under enabling infrastructure and financing conditions. The AutoPond-BW system is projected to provide a comprehensive technological solution to the chronic management inefficiencies that constrain productivity in traditional brackish-water pond culture. Expert panel validation confirmed system adequacy across all assessed dimensions (overall mean: 4.28/5.00), and literature-based GenAI performance benchmarks support projected improvements of 15-25% in FCR, 20-30% in disease-related mortality reduction, and 18-22% in harvest weight optimization. Financial modeling demonstrates BCRs of 1.45-1.65 and net annual profit margins 200-330% higher than manual systems after capital recovery, with payback periods of 3-5 years under base-case assumptions. At a small scale (0.5-1.0 ha), a phased adoption pathway, beginning with dissolved oxygen and temperature monitoring before progressing to full GenAI integration, may be more financially accessible for resource-constrained operators. At medium to commercial scales, the economic case for full automation is compelling and could meaningfully contribute to the Philippine government's aquaculture production targets under the Philippine Development Plan 2023-2028. Future research should prioritize longitudinal field trials, comparative analysis of LLM advisory accuracy across additional brackish-water species, and a socioeconomic impact assessment of smart aquaculture adoption on coastal household income distribution.

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