Feature Review Open Access

Computational Analysis of Growth Performance and Feeding Efficiency in Aquaculture Species

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International Journal of Marine Science, 2026, Vol.16, No.4 doi: 10.5376/ijms.2026.16.0018
Received: 25 Jun., 2026
Accepted: 31 Jul., 2026
Published: 12 Aug., 2026

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Preferred citation for this article:
Chen L., and Mai R.D., 2026, Computational analysis of growth performance and feeding efficiency in aquaculture species, International Journal of Marine Science, 16(4): 231-242 (doi: 10.5376/ijms.2026.16.0018)

Abstract The rapid expansion of aquaculture production has increased the demand for efficient approaches to optimize growth performance and feeding management. Computational analysis provides powerful tools for understanding complex interactions among biological traits, nutritional factors, and environmental conditions in cultured aquatic species. This review summarizes recent advances in mathematical modeling, statistical analysis, machine learning, and artificial intelligence applications for evaluating growth dynamics and feeding efficiency in aquaculture systems. Key production indicators, including weight gain, specific growth rate, feed conversion ratio, and nutrient utilization efficiency, are analyzed through computational frameworks integrating feeding records, environmental monitoring, and physiological responses. Growth prediction models, nonlinear growth simulations, and machine learning algorithms are discussed for their ability to identify critical factors affecting production outcomes and improve management decisions. A case study of Pacific white shrimp (*Litopenaeus vannamei*) demonstrates the application of computational models in predicting growth performance and optimizing feeding strategies under different culture conditions. Furthermore, the integration of computational technologies with IoT-based monitoring and precision aquaculture systems provides new opportunities for reducing feed waste, enhancing production efficiency, and promoting sustainable aquaculture development. Future research should focus on developing more accurate, interpretable, and adaptive models that integrate multi-source biological and environmental data.

Keywords Computational analysis; Aquaculture species; Growth performance; Feeding efficiency; Machine learning models

1 Introduction

Aquaculture has become a central component of the global food system and is now expected to shoulder much of the future increase in aquatic food supply. Over the past two decades, the sector has expanded through intensification, improved feeds, stronger production management, and better biosecurity, while inland aquaculture in Asia has contributed especially strongly to global food security (Naylor et al., 2021). This growth has been driven in part by the limits of capture fisheries and by rising demand for nutrient-dense aquatic foods, making aquaculture one of the fastest-growing food production sectors worldwide and a key pathway for narrowing the global protein supply gap. Yet expansion alone is not sufficient. As fed aquaculture becomes a larger share of production, improving growth performance and feeding efficiency has become one of the industry's most important technical and economic priorities. Feed commonly represents the largest operating cost in many fish production systems, and inefficient feed use increases waste outputs, raises environmental burdens, and reduces profitability. For this reason, indicators such as growth rate, feed conversion ratio, and feed efficiency are no longer viewed simply as farm-level performance measures, but as strategic indicators linking biological productivity with sustainability, resource use, and the long-term resilience of aquaculture systems.

The biological basis of growth performance and feeding efficiency in aquaculture species is complex because these traits emerge from interactions among genetics, physiology, nutrition, environment, and behavior. At the molecular level, fish growth is strongly regulated by the hypothalamic-pituitary-somatotropic axis, particularly through growth hormone and insulin-like growth factor-I, while external variables such as diet, temperature, salinity, photoperiod, pollutants, and stocking density can alter gene expression within this pathway and thereby modify growth outcomes. Growth regulation also depends on broader integrated networks that include epigenetic mechanisms, developmental plasticity, and signaling pathways beyond GH-IGF, which helps explain why growth responses differ across species and culture environments (Şerban et al., 2025). Nutrition further shapes these outcomes by influencing digestive efficiency, metabolic allocation, gut health, and appetite regulation. Early nutritional programming can produce persistent effects on nutrient utilization, enzyme activity, immunity, and later growth, while specific dietary interventions can improve protein deposition and resilience to environmental stress. In addition, recent work has shown that feeding behavior itself is closely tied to growth performance, with faster feeding activity, stronger appetite signaling, and altered brain expression of orexigenic factors associated with improved growth in cultured carp. Taken together, these findings indicate that feeding efficiency is not a single isolated trait, but rather the phenotypic expression of interconnected biological processes operating across multiple organizational levels.

A further layer of complexity arises because feeding efficiency is also mediated by the digestive and microbial environment, the quality and acceptability of formulated diets, and dynamic responses to husbandry conditions. In practical aquaculture, the transition from traditional feeds to compound diets often exposes major differences in feed acceptance and performance, and these differences can substantially alter production cost and culture duration. In one marine species, poor acceptance of formulated feed was associated with slower production progress, whereas integrating microbiome and metabolome data revealed key microbial-metabolite signatures linked to better feed conversion and growth performance. Similar evidence from systems-level prediction studies shows that feed efficiency is difficult to measure directly in individual fish and cannot be adequately explained by single biomarkers alone; instead, integrated models using proteomic, metabolomic, microbiomic, and clinical covariates provide better predictive power than single-layer data (Young et al., 2023). These results support the view that growth and feed utilization are emergent traits arising from many weakly and strongly interacting factors. They also reveal why conventional empirical management, although still useful, is often insufficient for optimizing modern aquaculture systems in which biological regulation, feed formulation, animal behavior, and environmental variability must all be considered simultaneously.

Against this background, computational analysis provides a necessary framework for transforming complex aquaculture data into actionable knowledge on growth performance and feeding efficiency. Recent studies show that machine learning, deep learning, and adaptive statistical modeling can predict growth trajectories, feed intake, and feed conversion outcomes with useful accuracy when they integrate biological, environmental, and management data. Transformer-based growth models trained on Monte Carlo-generated datasets have reported low prediction errors for fish weight and growth rate, while algorithmic feeding systems combining visual monitoring and multimodal reasoning have improved feed conversion ratio and specific growth rate in recirculating systems (Lan et al., 2025). Likewise, automated feeder research in barramundi has shown that nonlinear and multimodel approaches can explain daily feed intake accurately by combining environmental, fish, feed-composition, and pellet-characteristic variables, reinforcing the value of integrated computational frameworks for precision feeding. Therefore, the objective of this paper is to develop a computational perspective on how growth performance and feeding efficiency can be analyzed across aquaculture species using multidimensional biological and production data. The research framework focuses on three linked tasks: identifying the major biological and environmental determinants of growth and feed utilization, evaluating quantitative indicators and predictive variables associated with performance, and summarizing computational methods capable of supporting precision feeding, selective improvement, and sustainable production management. In this way, computational analysis is positioned not merely as a technical tool, but as a bridging framework that connects biological understanding with practical decision-making in modern aquaculture.

2 Data Acquisition and Computational Framework for Aquaculture Growth Analysis

2.1 Sources and characteristics of aquaculture production datasets

Aquaculture growth analysis relies on datasets that combine biological, environmental, and management information collected at different temporal and spatial scales. At the farm level, production datasets often include fish weight, feeding decisions, and pond- or workshop-specific operating conditions, because differences in environment, equipment, and operator behavior can cause substantial deviations in growth characteristics across culture units (Li et al., 2021). More recent smart-aquaculture studies have expanded these records by linking real-world growth observations to IoT monitoring systems and open weather datasets, allowing probability-based modeling of key growth drivers under variable environmental conditions (Lan et al., 2025).

The main characteristic of these datasets is their heterogeneity, which makes both data integration and model selection critical. Some studies are based on long historical production series and external covariates such as climate variables, as shown by forecasting work that used 20 years of fish production and climatic data for model training and testing (Rahman et al., 2021). Other studies emphasize that aquaculture development can only be fully explained when production data are integrated with broader social, economic, governance, and environmental indicators, as demonstrated by cross-country datasets containing 42 indicators across 150 countries.

2.2 Computational methods for growth performance evaluation

Growth performance evaluation in aquaculture still begins with classical growth indicators, but computational analysis increasingly favors models that can represent the full growth trajectory. Common descriptive measures such as absolute, relative, and specific growth rates remain useful for basic reporting, yet they simplify growth because they rely mainly on stocking and harvest values and often ignore intermediate observations. For this reason, nonlinear growth functions and species-fitted models are preferred when the goal is realistic prediction of stock development, harvest planning, feeding cost calculation, and production scheduling.

More advanced evaluation methods are designed to handle practical limitations in aquaculture datasets, especially incomplete sampling and farm-level variation. A Bayesian hierarchical approach applied to shrimp growth showed that incomplete or limited aquaculture data can bias nonlinear growth parameters, and that hierarchical correction improved predictive accuracy to 95.76% at pond level and 85.71% at production-cycle level (Zarzar et al., 2023). At the same time, multi-omics work on feed efficiency showed that complex performance traits are better predicted when multiple biological data layers are integrated, with combined random-forest models outperforming any single data layer for feed-efficiency prediction (Young et al., 2023).

2.3 Advanced computational tools for aquaculture production prediction

Advanced prediction tools in aquaculture increasingly combine machine learning, deep learning, and simulation to forecast growth, feeding demand, and production outcomes. Comparative forecasting studies show that time-series methods such as ARIMA, linear regression, random forest, LSTM, and Prophet can all be applied to production prediction, but simpler statistical or machine-learning models sometimes outperform deep learning on univariate aquaculture time series (Nazmi et al., 2023). In parallel, neural-network forecasting for regional aquatic production found that nonlinear methods are well suited to this problem, with an RBF neural network outperforming BP, GA-BP, and LSTM models in prediction accuracy (Hu et al., 2025).

A second major direction is the use of intelligent sensing, vision systems, and simulation-based digital tools for real-time decision support. Computer-vision feeding systems can quantify fish appetite and support automatic feed control, and a near-infrared neuro-fuzzy method achieved 98% feeding-decision accuracy while reducing feed conversion rate by 10.77% compared with a feeding table. Beyond sensing alone, simulation frameworks now incorporate schooling behavior, dynamic energy budgets, and feeding-distribution rules to predict growth trajectories, evaluate the effects of feeding strategies on feed efficiency, and identify management options before live trials are conducted (Takahashi and Komeyama, 2023; Takahashi et al., 2026).

3 Computational Modeling of Growth Performance in Aquaculture Species

3.1 Mathematical modeling of growth dynamics

Mathematical modeling of aquaculture growth has moved from simple descriptive indices toward dynamic functions that can represent organism development over time. Traditional indicators such as absolute, relative, and specific growth rate remain widely used because they are easy to compute, but they simplify growth by relying mainly on stocking and harvest values and by ignoring intermediate observations. For this reason, nonlinear growth functions are preferred when the goal is realistic prediction across life stages, and the von Bertalanffy growth function remains one of the most commonly used formulations because it links observed size change to an underlying bioenergetic interpretation.

More mechanistic approaches seek to model growth as the result of energy acquisition and allocation rather than curve fitting alone. Bioenergetic formulations can incorporate environmental drivers into growth equations and help explain density-dependent and time-varying growth patterns, which makes them more informative than purely empirical trend models for scenario analysis. Dynamic energy budget models extend this logic by representing ingestion, assimilation, maintenance, and growth as connected metabolic processes, and recent aquaculture applications have shown that such models can predict measurable outputs such as weight gain, respiration, and waste production under different temperatures, feeding levels, and diet compositions (Stavrakidis-Zachou et al., 2025).

3.2 Environmental and physiological drivers affecting growth prediction

Growth prediction in aquaculture depends strongly on environmental variables because fish and crustaceans respond directly to changes in water quality and culture conditions. Temperature, dissolved oxygen, pH, ammonia, nitrite, nitrate, stocking density, and feeding regime all influence body weight, feed intake, feed conversion, survival, and health, so growth models that omit these covariates are likely to lose predictive accuracy (El-Hack et al., 2022). In intensive systems such as recirculating aquaculture, these factors must be controlled within appropriate ranges, and even light environment can alter feeding behavior, growth rate, survival, and feed conversion, showing that growth prediction must be built on multivariable environmental monitoring rather than on temperature alone (Li et al., 2021).

Physiological regulation adds another layer of complexity because growth is not only environmentally constrained but also biologically mediated. The GH-IGF-I axis is a central regulatory system for fish growth, and its expression changes with diet, photoperiod, salinity, pollutants, and stocking density, which means that environmental effects on growth often operate through endocrine and metabolic pathways rather than through direct physical stress alone. Temperature is especially important because it acts as a master abiotic factor that controls development and physiology, while extreme thermal events can alter metabolism, immunity, osmotic balance, and overall physiological fitness, thereby changing growth trajectories in ways that are species- and context-dependent.

3.3 Machine learning-based prediction of growth performance

Machine learning models are increasingly used to predict aquaculture growth because they can integrate many interacting predictors without requiring a fixed mechanistic structure. Review evidence shows that machine learning has become an important tool in intelligent aquaculture for biomass evaluation, behavioral analysis, and water-quality prediction, while more recent deep-learning reviews identify growth prediction as one of the main application areas alongside health monitoring and intelligent feeding (Wu et al., 2025). These methods are especially useful when production data include nonlinear interactions among age, temperature, mortality, flow conditions, and culture duration that are difficult to capture with classical regression alone.

Empirical studies now show that machine learning can achieve strong predictive performance across different aquaculture settings, although its success depends on data quality and generalizability. In land-based abalone culture, an ensemble of random forest, gradient boosting, support vector machine, and neural network models predicted weight increase well and identified stable warm temperature and animal age as important growth determinants. In open-sea fish farming, transformer-based models trained on Monte Carlo-expanded datasets parameterized by IoT and weather observations achieved low prediction errors for weight and growth rate, but their performance still depended on reliable input distributions and robustness across different farming environments (Lan et al., 2025).

4 Computational Analysis of Feeding Efficiency and Nutrient Utilization

4.1 Modeling feed intake and feed conversion efficiency

Computational analysis of feeding efficiency in aquaculture begins with accurate estimation of feed intake, because intake directly shapes growth, feed conversion, and waste output. Mathematical and data-driven models are now central to this task, especially because overfeeding increases economic loss and effluent release, whereas underfeeding suppresses growth and reduces production efficiency. At the same time, conventional feed conversion ratio (FCR) remains useful but incomplete, because it measures feed input relative to biomass gain without accounting for feed composition, edible yield, or the nutritional quality of harvested product.

Recent modeling approaches increasingly combine biological realism with predictive accuracy. Mechanistic and nutrient-based frameworks can simulate fish growth, composition, and nutrient utilization under varying feeding levels, feed composition, and environmental conditions, making them useful as decision-support tools for precision farming (Soares et al., 2023). In parallel, newer nutritional bioenergetic models based on dynamic energy budget theory explicitly incorporate digestion and macronutrient composition, allowing prediction not only of weight gain but also of oxygen consumption, ammonia production, and waste outputs under different feeding schedules (Stavrakidis-Zachou et al., 2025).

4.2 Nutritional factors affecting feeding performance

Nutritional factors affect feeding performance through both requirement matching and physiological regulation. Precision nutrition frameworks argue that optimal feeding cannot be defined only by feed amount, because nutrient supply must also align with genetic background, metabolism, environmental conditions, and production goals to minimize waste while sustaining performance (Zhang et al., 2020). Likewise, feed efficiency depends on meeting qualitative and quantitative nutrient requirements simultaneously, while digestibility remains a key determinant because better nutrient digestibility generally improves FCR and nutrient utilization (Hancz, 2020).

Feed composition also influences performance by altering intake regulation, health status, and metabolic use of nutrients. Adequate nutrition is necessary not only to prevent deficiency but also to maintain health and productive performance, and strategic supplementation above minimum requirement for selected amino acids, fatty acids, vitamins, or minerals can improve disease resistance and functional status. More recent work further shows that intake regulation in fish reflects coordinated behavioral and physiological control, and that feed intake is shaped not only by nutrients themselves but also by ingredient inclusion, environmental stressors, ontogeny, and other biological factors that must be represented in advanced predictive models (Soengas et al., 2024).

4.3 Intelligent feeding strategies based on computational prediction

Intelligent feeding strategies increasingly rely on sensors, machine vision, and machine learning to translate fish behavior and environmental data into real-time feeding decisions. Review evidence shows that intelligent feeding control can automatically determine feeding demand by integrating mathematical models, acoustic methods, and computer vision, although practical deployment still depends on improvements in accuracy and robustness under farm conditions. This transition is important because fixed-time or fixed-quantity feeding often fails to reflect dynamic appetite, creating avoidable risks of overfeeding, underfeeding, and water quality deterioration (Zhang et al., 2023).

Applied studies demonstrate that computational prediction can improve feeding precision and production outcomes. A near-infrared computer vision system coupled with a neuro-fuzzy model achieved 98% feeding-decision accuracy and reduced FCR by 10.77% relative to feeding-table management, while also lowering water pollution. More advanced predictive systems have expanded this logic by using optimized neural networks, support vector machines, and dynamic control architectures to infer biomass, uneaten pellets, and feeding endpoints, thereby enabling adaptive rationing in fish and shrimp culture and supporting more efficient smart aquaculture operations (Chen et al., 2022; Wang et al., 2022).

5 Integration of Environmental, Nutritional, and Biological Data for Predictive Aquaculture

5.1 Multivariate analysis of factors affecting aquaculture production

Aquaculture production is governed by interacting environmental, nutritional, and biological variables, so predictive analysis requires multivariate rather than single-factor evaluation. In intensive production systems, growth, survival, feed conversion, and health are simultaneously influenced by stocking density, feeding rate, water temperature, dissolved oxygen, pH, ammonia, nitrite, and tank system conditions, which makes isolated interpretation inadequate for management (El-Hack et al., 2022). This same logic is reflected in recirculating systems, where principal component analysis has been used to convert many correlated water-quality variables into a smaller set of interpretable components that reveal internal data structure and support early prediction of critical events (Silva et al., 2021).

The value of multivariate analysis lies not only in dimensionality reduction but also in discriminating among production environments with different ecological signatures. Comparative pond studies using discriminant analysis showed that fourteen physicochemical variables could clearly separate intensive and less intensive production systems, with dissolved oxygen, temperature, nutrient-related variables, and solids contributing most strongly to classification accuracy (Figure 1) (Delgado-Villafuerte et al., 2026). At the same time, endocrine evidence indicates that growth itself is biologically multicausal, because GH and IGF-I expression responds jointly to diet, temperature, photoperiod, salinity, pollutants, and stocking density, linking external farm conditions with internal physiological regulation.

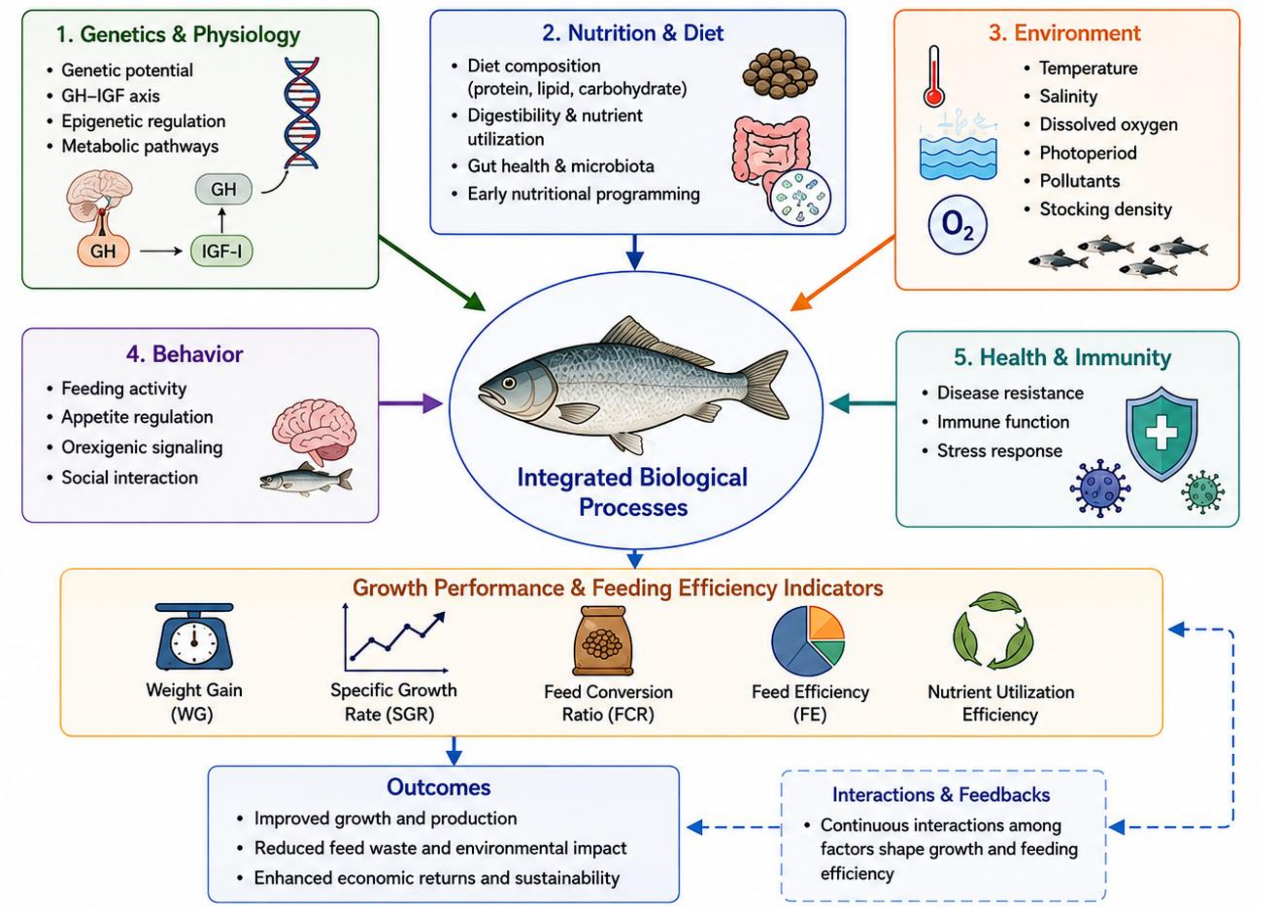

Figure 1 Aquaculture growth performance and feeding efficiency: key biological and environmental determinants

5.2 Digital twin and simulation approaches in aquaculture management

Digital twin approaches extend multivariate analysis by coupling real-time data streams with mechanistic or hybrid models that reproduce the behavior of aquaculture systems in virtual form. In aquaculture, this technology is still at an early stage, but it is increasingly viewed as a solution to the industry's difficulty in observing underwater biological and physical processes continuously and safely. Land-based case studies further show that digital twins under the Precision Fish Farming framework can integrate sensors, IoT infrastructure, and predictive mathematical models to support feeding control, oxygen management, and fish population management in real time.

The main management value of digital twins is that they enable simulation of present and future scenarios rather than passive monitoring alone. Review evidence shows that digital twin systems can support predictive analytics for risk mitigation, feeding optimization, and system-performance improvement, although interoperability and data handling remain major challenges (Huang and Khabusi, 2025). More specialized frameworks such as FishMet demonstrate how a digital twin can incorporate appetite, feeding decisions, feed intake, energetics, and growth into a modular computational service, allowing autonomous model execution and integration with broader farm management platforms.

5.3 Artificial intelligence-driven precision aquaculture systems

Artificial intelligence-driven precision aquaculture systems use integrated sensor and production data to automate monitoring, prediction, and decision-making across feeding, health, and environmental control. Recent reviews describe AI as a transformative force in aquaculture because it improves production efficiency and environmental sustainability through predictive analytics, optimized feeding protocols, and better biomass output, while also exposing persistent barriers in data quality and system integration (Yang et al., 2025). A parallel review focused on AIoT shows that continuous sensing of temperature, pH, dissolved oxygen, salinity, and fish behavior allows AI models to generate real-time insights for water-quality management, species monitoring, and feeding optimization (Huang and Khabusi, 2025).

The most advanced precision aquaculture systems are now moving beyond standalone prediction toward coordinated digital ecosystems that combine AI, IoT, edge computing, and digital twins. Current reviews indicate that machine learning, deep learning, hybrid algorithms, federated learning, and explainable AI are being used to improve predictive control in dynamic aquaculture environments, while digital twins are increasingly framed as the simulation layer that links these tools into proactive management systems (Ratan et al., 2026). At the same time, broader sustainability analyses emphasize that the transition from empirical management to data-driven operations will depend on overcoming sensor reliability problems, data heterogeneity, and the digital divide between high-tech and resource-constrained farms.

6 Case Study: Computational Prediction of Growth Performance and Feeding Efficiency in Pacific White Shrimp (*Litopenaeus vannamei*)

6.1 Experimental design and data collection

Computational prediction in Pacific white shrimp is typically built on production datasets that link growth records with operational and environmental measurements collected across real farming cycles. Industrial and farm-scale studies show that these datasets can include pond-level growth observations, culture duration, stocking density, cumulative feed, and water-quality indicators, and can span either controlled experimental campaigns or multi-year farm operations with thousands of cleaned records (Mujahid et al., 2025). This is important because shrimp body weight prediction is directly relevant to harvest timing, feed management, and stocking decisions, so the design of the dataset determines both model accuracy and management value (Mujahid et al., 2025; Chen et al., 2022).

Experimental design in this species also varies substantially by production system, which affects both the structure and interpretability of the collected data. Controlled recirculating and biofloc studies have used replicated tanks or ponds with specified stocking densities, commercial diets, fixed feeding frequencies, and routine monitoring of temperature, dissolved oxygen, salinity, pH, ammonia, and nitrite, while final biomass, weight gain, survival, and feed conversion ratio are measured as core response variables. In feeding-frequency experiments, data resolution becomes even finer because shrimp are weighed repeatedly during the trial and daily feed inputs are recorded for later calculation of growth, yield, cost, and feed conversion, making these designs particularly suitable for computational feeding analysis (Figure 2) (Liang et al., 2025).

6.2 Computational modeling and prediction analysis

Modeling approaches for L. vannamei growth range from empirical growth equations to machine-learning systems and mechanistic feed-conversion models. A Bayesian hierarchical comparison of six nonlinear growth equations found that the Weibull model performed best overall and achieved validation accuracies of 95.76% at pond level and 85.71% at production-cycle level, showing that hierarchical correction can reduce bias from incomplete farm data (Zarzar et al., 2023). Complementing this, growth-trajectory analysis across 15 commercial datasets identified two distinct growth stanzas separated at about 7.5 g, and adapted thermal-unit growth coefficients fit the data better than traditional TGC or SGR formulations.

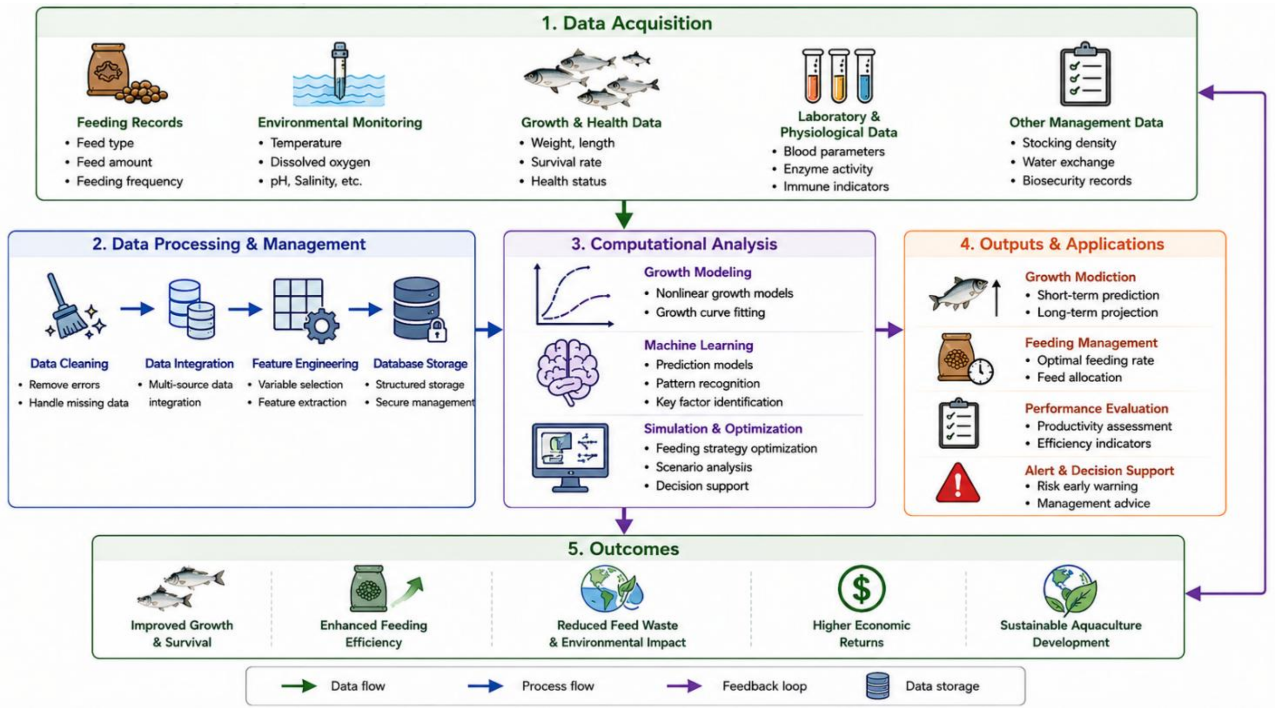

Figure 2 Computational analysis framework for growth performance and feeding efficiency in aquaculture species

Machine-learning studies show that predictive performance improves when models incorporate management and sensor variables rather than relying on water quality alone. In recirculating shrimp culture, support vector machines outperformed multiple linear regression and artificial neural networks for biomass prediction, reaching 90.91% accuracy and enabling real-time feeding decisions from sensor inputs (Chen et al., 2022). In industrial outdoor production, a weighted ensemble reached $R^2 = 0.829$, while SHAP analysis showed that days of culture, stocking density, and cumulative feed contributed more strongly to body-weight prediction than temperature, pH, or dissolved oxygen in a well-managed system (Mujahid et al., 2025).

6.3 Application of computational results in feeding management

The practical value of computational prediction lies in converting growth forecasts into feeding strategies that improve production efficiency without excessive feed waste. Mechanistic modeling has shown that shrimp growth prediction can be linked directly to feed consumption, ammonia excretion, and oxygen demand, creating a basis for stage-specific adjustment of dissolved oxygen supply and feed availability. This management logic is consistent with nutrient-budget evidence from intensive ponds showing that poor feed management raises environmental loading, and that improving feed conversion from 2.0 to 1.8 could reduce total feed use by 147 kg and save $1027 per crop (Chaikaew et al., 2019).

Computational outputs are also valuable when they identify operational optima rather than simply maximizing feed input. In high-density biofloc culture, growth increased as feed rates approached the standard ration, but feed conversion worsened beyond an inflection point near 101% of the standard feeding rate, indicating that maximum biomass gain and maximum nutrient efficiency are not the same target (Weldon et al., 2021). Similarly, automatic-feeding studies found that moderate feeding frequencies were most effective: quadratic regression identified an optimum near 7.83 feedings per day, and the A8 treatment produced the highest profitability, supporting the use of predictive systems to balance growth, feed utilization, and economic return (Liang et al., 2025).

7 Challenges and Future Perspectives of Computational Aquaculture Analysis

7.1 Limitations of current computational models

Current computational models in aquaculture are limited first by the quality, quantity, and representativeness of available data. Reviews of AI applications consistently identify restricted access to representative datasets, environmental variability, and data-quality maintenance as central obstacles to robust model development and deployment, especially when models are expected to operate across different farms and culture systems. Deep-learning models face an additional bottleneck because they often require large labeled datasets that are difficult to obtain in aquatic environments, where turbidity, occlusion, and biofouling reduce image quality and complicate annotation (Rather et al., 2024).

A second limitation is that many current models remain difficult to generalize, scale, or interpret in real production settings. Recent reviews note that traditional machine-learning approaches show limited semantic understanding and insufficient scalability in high-dimensional environments, while deep-learning systems still struggle with real-time performance, cross-domain adaptability, and robustness under changing field conditions (Wu et al., 2025). These technical issues are compounded by practical barriers such as high setup costs, computational demands, and the risk of over-automation in systems that still require human observation and judgment, particularly in small or resource-constrained farms (Ratan et al., 2026).

7.2 Future development of ai and data-driven aquaculture technologies

Future development in computational aquaculture is moving toward more integrated and adaptive digital systems rather than isolated prediction models. Emerging reviews emphasize multimodal data fusion, lightweight and edge-deployable models, synthetic data generation, and digital twin-based virtual farming platforms as key next steps for improving model adaptability and operational use (Wu et al., 2025; Ratan et al., 2026). In parallel, integrated frameworks that combine IoT sensing, AI analytics, and blockchain-supported traceability are being positioned as a pathway toward more resilient, transparent, and scalable aquaculture data infrastructures.

The next generation of systems is also likely to depend on distributed and resource-aware computing architectures that can work beyond high-bandwidth commercial farms. Edge-cloud and federated-learning approaches are being developed to reduce latency, protect farm-level data privacy, and enable local processing for real-time monitoring and growth estimation without continuous cloud dependence (Cheng et al., 2022). At the same time, IoT-ML platforms designed for constrained environments suggest that low-cost sensing, local processing, and more efficient training pipelines can make predictive aquaculture more accessible in rural settings rather than restricting advanced analytics to technologically intensive operations (Baena-Navarro et al., 2025).

7.3 Potential contributions to sustainable aquaculture development

The main long-term contribution of computational aquaculture is its potential to improve sustainability by increasing production efficiency while reducing waste and environmental pressure. Reviews of sustainable aquaculture technologies consistently report that AI-supported feeding, growth prediction, and environmental monitoring can reduce human intervention, improve resource utilization, and strengthen traceability and production control across the aquaculture value chain (Yang et al., 2025). These gains matter because improved production efficiency is already recognized as a core pathway toward lower carbon footprint, better feed management, and more sustainable intensive aquaculture systems.

Computational systems may also contribute to sustainability through more proactive management of water quality, pollution, and system resilience. Integrated IoT and machine-learning monitoring has been associated with substantial reductions in losses from water-quality problems and can support survival above 90% under tropical production conditions, showing the practical value of continuous predictive control (Baena-Navarro et al., 2025). Beyond production efficiency alone, AI-enabled precision feeding and effluent-treatment frameworks are increasingly framed as tools for pollution reduction and green fisheries development, provided that implementation economics and system-coupling challenges are addressed.

8. Conclusions

A major advance in computational aquaculture is the shift from descriptive monitoring to integrated prediction of growth, feeding, health, and environmental conditions. Recent reviews show that deep learning and broader AI methods now support growth prediction, intelligent feeding, water-quality forecasting, biomass estimation, and behavioral analysis within the same digital framework, which marks a clear expansion beyond single-purpose models. This transition is important because computational systems are increasingly expected not only to describe farm status but also to generate predictive, real-time decision support for more efficient and sustainable production.

A second advance is the growing use of hybrid computational architectures that combine sensing, simulation, and machine learning to improve prediction under dynamic farming conditions. AIoT reviews now identify smart feeding, biomass estimation, growth estimation, automation, and water-quality management as core application domains, while newer studies highlight digital twins, federated learning, and other next-generation tools for predictive control and process optimization. Together, these developments show that aquaculture analytics is moving toward connected, adaptive systems rather than isolated statistical models, with increasing emphasis on scalability and resilience across diverse environments.

In production management, the strongest practical applications are in feeding control, water-quality monitoring, and autonomous farm supervision. Smart aquaculture systems can now integrate real-time sensing with predictive models so that fishpond conditions are monitored remotely, growth can be forecast from multiple system parameters, and autonomous feeding can reduce leftover feed. Reinforcement-learning control in recirculating aquaculture extends this further by optimizing feeding rates together with water-quality management, improving tracking accuracy, reducing feed consumption, and increasing long-term system stability compared with conventional control methods.

Commercial and field-oriented reviews also indicate that AI-based management delivers measurable operational benefits when deployed at farm scale. Reported applications include automated and adaptive feeding schedules, early disease detection, biomass estimation, and predictive resource management, with commercial systems showing feed-cost reductions, lower mortality, and improved compliance with environmental standards. More broadly, AI-assisted farm management improves resource efficiency, reduces labor demands, and supports better decisions on fish health, nutrition, and product quality, which makes computational tools increasingly relevant to everyday aquaculture operations rather than only experimental settings (Ragab et al., 2024).

Future research should focus on making computational aquaculture models more transferable, data-efficient, and interoperable across species and production systems. The most consistent priorities are multimodal data fusion, edge computing, lightweight model design, synthetic data generation, and digital twin-based virtual farming, all of which aim to address persistent problems in real-time performance, generalization, and limited labeled datasets. Other reviews reach the same conclusion from a deployment perspective, arguing that broader geographic datasets, standardized data-collection protocols, and integrated AI frameworks are necessary if predictive systems are to become more robust and comparable across studies and farms.

A second priority is ensuring that future innovation remains economically and socially deployable, not only technically advanced. Several recent reviews emphasize that high implementation costs, infrastructure gaps, regulatory constraints, and the digital divide still limit adoption, especially in small-scale and resource-constrained settings. Accordingly, the most promising direction is the development of scalable, adaptive, and standardized AI systems that combine IoT, edge intelligence, blockchain, or robotics where useful, while remaining practical enough to support sustainable aquaculture growth and global seafood security.

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