

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.