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Review Article

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Artificial Intelligence for Strengthening Aquaculture Extension Systems: A Review and Conceptual Framework

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ABSTRACT

Aquaculture has become an important contributor to food security, rural livelihoods, and economic development. Despite its rapid growth, the sector continues to face challenges arising from disease outbreaks, declining water quality, climate variability, rising production costs, and limited access to timely technical information. These challenges highlight the need for responsive and knowledge-based extension systems capable of supporting informed farm-level decision-making. Recent advances in artificial intelligence (AI) provide new opportunities to strengthen extension services through intelligent advisory systems, predictive analytics, automated information management, and evidence-informed decision support. This review synthesises recent developments in machine learning, deep learning, computer vision, natural language processing, large language models, retrieval-augmented generation, and knowledge graph technologies from the perspective of aquaculture extension. Particular emphasis is placed on their potential to improve advisory services, disease surveillance, water quality monitoring, information dissemination, and stakeholder communication while complementing the expertise of extension professionals. The review also discusses major challenges associated with data quality, digital infrastructure, institutional readiness, transparency, and ethical governance that influence the effective adoption of AI-enabled extension services. A major contribution of this paper is the proposed Intelligent Aquaculture Extension Ecosystem (IAEE), a conceptual framework designed to guide the integration of validated scientific knowledge, AI-enabled analytical tools, and professional extension expertise for transparent, context-specific, and farmer-centred advisory services. The review concludes that artificial intelligence should be viewed as a complementary resource that can enhance, rather than replace, conventional extension systems and has potential to contribute to more responsive, inclusive, and sustainable aquaculture development.

INTRODUCTION

Aquaculture has become one of the fastest-growing food production sectors worldwide and now contributes more than half of the aquatic food consumed globally (FAO, 2024). Beyond increasing fish production, the sector plays an important role in improving food and nutritional security, generating rural employment, supporting livelihoods, and contributing to economic growth. In India, aquaculture has expanded rapidly over the past two decades and has emerged as a key component of agricultural diversification and the Blue Economy. Despite these achievements, sustained growth is constrained by recurrent disease outbreaks, deteriorating water quality, climate variability, increasing input costs, and fluctuations in market demand (Boyd et al., 2022; Naylor et al., 2021). Overcoming these challenges requires timely access to reliable scientific information and responsive advisory support. Well-functioning extension systems play a central role in facilitating technology dissemination, strengthening farmers' decision-making capacity, and promoting innovation within agricultural and aquaculture production systems (Anderson & Feder, 2007; Swanson & Rajalahti, 2010).

Extension systems serve as an important link between research organisations, educational institutions, policymakers, and farming communities. Their role extends beyond the dissemination of technologies to facilitating learning, strengthening farmers' decision-making capacity, encouraging innovation, and promoting sustainable production practices. Contemporary extension therefore emphasises participatory approaches, continuous capacity building, and knowledge sharing rather than one-way technology transfer (Swanson et al., 1997; Swanson & Rajalahti, 2010; Anderson & Feder, 2007). However, many aquaculture extension programmes continue to face operational constraints, including shortages of trained personnel, inadequate technical updating, fragmented communication channels, and limited outreach to geographically dispersed farming communities. These limitations can reduce the effectiveness and timeliness of advisory services, particularly for small-scale producers.

Rapid advances in digital agriculture have created new opportunities to strengthen extension delivery. Mobile applications, cloud computing, remote sensing, geographic information systems, Internet of Things (IoT) devices, and digital communication platforms have substantially improved the collection and exchange of farm-related information. At the same time, the increasing volume, diversity, and complexity of production data create new demands on extension personnel, who must interpret information from multiple sources and translate it into practical recommendations for farmers. These developments have increased interest in intelligent systems capable of transforming complex datasets into reliable, location-specific advisory information.

Artificial intelligence (AI) has emerged as a promising technology in this context. Machine learning, deep learning, computer vision, and natural language processing can analyse large and heterogeneous datasets to support prediction, pattern recognition, classification, and evidence-informed decision-making (Russell & Norvig, 2021). In aquaculture, empirical studies have demonstrated applications in areas including disease detection, water-quality prediction, biomass estimation, feeding management, and farm-level decision support (Ahmed et al., 2022; Zambrano et al., 2021; Eze et al., 2023; Zhang et al., 2020; Ubina et al., 2021). Machine-learning approaches have also been applied to management decisions in shellfish farming, including prediction of precautionary closures associated with harmful algal blooms and lipophilic biotoxins (Molares-Ulloa et al., 2022). Together with broader reviews of AI applications in aquaculture (Vo et al., 2021), these studies demonstrate the expanding technical capabilities of AI for aquaculture monitoring, prediction, and management. However, the implications of these capabilities for the organisation and delivery of extension services remain comparatively less developed. The potential value of AI in this context therefore extends beyond automating farm operations to improving the quality, accessibility, and responsiveness of advisory services.

Recent developments in generative artificial intelligence further broaden the scope of digital extension. Large Language Models (LLMs) can process scientific and technical information and generate user-oriented responses, whereas Retrieval-Augmented Generation (RAG) can connect generated responses with external knowledge sources (Lewis et al., 2020). Knowledge graph technologies can organise relationships among concepts and support structured information retrieval and decision support (Kejriwal, 2022; Peng et al., 2023). When combined with validated scientific knowledge and professional expertise, these technologies may provide additional mechanisms for developing context-specific and accountable digital advisory systems.

Although recent reviews have examined the application of artificial intelligence in aquaculture, their principal emphasis has been on production-oriented and technological applications. Vo et al. (2021), for example, reviewed artificial intelligence applications across aquaculture, with emphasis on disease diagnosis, water-quality assessment, biomass estimation, feeding, production forecasting, and farm monitoring. More recently, Aung et al. (2025) systematically reviewed AI methodologies used in aquaculture and synthesised evidence from 57 studies published between 2020 and 2024, with major application areas including disease detection, feeding behaviour, environmental monitoring, aquaculture-area extraction, and other production and management functions. These reviews provide important evidence on the technological capabilities and operational applications of AI in aquaculture, but their primary analytical focus remains on farm production, monitoring, automation, and decision-support applications rather than on the organisation and delivery of extension and advisory services. Consequently, comparatively limited attention has been given to how AI can be integrated into broader extension functions, including knowledge management, farmer advisory services, communication, capacity building, institutional learning, and professional validation of digital recommendations. This distinction represents an important research gap because technological innovations in aquaculture can contribute meaningfully to development only when scientific information is translated into recommendations that are credible, context-specific, accessible, and usable by farming communities.

Against this background, the present review examines the role of artificial intelligence in strengthening aquaculture extension systems. Specifically, the review addresses four questions: (1) Which artificial intelligence technologies and approaches are relevant to aquaculture extension, and what are their principal technical capabilities and aquaculture applications? (2) What evidence is available regarding the effectiveness and practical value of these technologies for improving the delivery, accessibility, and reliability of aquaculture extension services? (3) What technical, infrastructural, institutional, ethical, and socio-economic factors constrain the adoption and responsible use of AI-enabled extension systems? and (4) How can artificial intelligence, validated scientific knowledge, and professional extension expertise be integrated into a coherent, farmer-centred extension ecosystem? To address these questions, the review synthesises evidence on AI technologies relevant to aquaculture extension, examines their applications across major extension functions, critically evaluates barriers and governance considerations, and proposes the Intelligent Aquaculture Extension Ecosystem (IAEE) as a conceptual framework for integrating digital technologies with established extension practice. By positioning artificial intelligence as a complementary resource rather than a substitute for extension professionals, the review seeks to provide a framework for strengthening farmer-centred, evidence-based, and sustainable aquaculture extension.

SCOPE AND SEARCH STRATEGY

This paper adopts a narrative review approach to examine the application of artificial intelligence in aquaculture from an extension systems perspective. The review focuses on how emerging digital technologies can strengthen advisory services, knowledge management, farmer learning, communication, decision support, and related institutional functions rather than on engineering or production technologies alone.

Relevant literature was identified through searches of major bibliographic databases and scholarly literature platforms, including Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore, Wiley Online Library, and Google Scholar. Publications from international organisations and recognised institutions, particularly the Food and Agriculture Organization (FAO), were also consulted to provide background information on global aquaculture and extension development. The literature search focused primarily on publications from 2015 to 2025, while earlier seminal publications were retained where necessary to explain foundational concepts in artificial intelligence, agricultural extension, and digital knowledge systems.

The search strategy combined terms related to artificial intelligence and aquaculture extension, including “artificial intelligence”, “aquaculture extension”, “digital extension”, “machine learning”, “deep learning”, “computer vision”, “natural language processing”, “large language models”, “retrieval-augmented generation”, “knowledge graphs”, “decision support systems”, and “precision aquaculture”. Combinations of these terms were used to identify literature addressing both the technological and extension dimensions of the review topic.

Inclusion and exclusion criteria

Literature was considered eligible when it addressed artificial intelligence, machine learning, deep learning, computer vision, natural language processing, large language models, retrieval-augmented generation, knowledge graphs, or related digital decision-support technologies in aquaculture, agricultural extension, fisheries advisory systems, digital agriculture, or closely related knowledge and advisory contexts. Particular emphasis was placed on publications providing evidence relevant to advisory services, knowledge management, farmer learning, communication, decision support, capacity building, or institutional strengthening. Both primary research studies and relevant review articles were considered. Primary studies were used preferentially when evidence was available for specific applications or performance claims, whereas review articles and authoritative institutional reports were used to provide broader conceptual and contextual information.

The review was limited to literature published in English, with peer-reviewed journal articles constituting the principal evidence base. Relevant reports and publications from recognised international organisations and institutions, particularly the Food and Agriculture Organization (FAO), were also considered where they provided important information on aquaculture, agricultural extension, digital transformation, or policy and institutional development. Conference proceedings, preprints, unpublished manuscripts, and other non-peer-reviewed sources were not used as primary evidence for claims concerning the effectiveness or performance of AI applications. Authoritative institutional documents were retained where they provided policy, sectoral, or contextual information not adequately represented in the peer-reviewed literature.

Studies were excluded when they dealt exclusively with engineering design, automated production systems, robotics, or algorithm development without a clear connection to aquaculture management, advisory services, knowledge dissemination, decision support, technology transfer, or extension functions. Studies focused solely on non-aquaculture applications were also excluded unless their findings provided directly relevant evidence for understanding AI adoption, digital advisory systems, or extension processes. Where several publications addressed similar applications, greater weight was given to empirical studies with clearly described datasets, methods, validation procedures, and measurable outcomes.

No formal numerical quality-assessment or risk-of-bias scoring system was applied because the present study is a narrative review rather than a systematic evidence synthesis. Instead, the relevance, methodological clarity, empirical basis, and applicability of individual studies were considered during thematic interpretation. Claims concerning specific AI applications were supported preferentially by empirical or applied studies, while conceptual papers and methodological publications were used primarily to explain underlying technologies and theoretical principles. Because the review was designed to synthesise relevant evidence across a broad and interdisciplinary literature base rather than to undertake formal systematic screening and quantitative accounting of records, a PRISMA-style numerical flow of records identified, screened, excluded, and included is not presented. The selection process was guided by the stated scope, eligibility criteria, methodological relevance, and thematic relevance to the objectives of the review.

The selected literature was analysed thematically to identify major developments, emerging trends, research gaps, and practical implications for extension systems. Particular attention was given to studies demonstrating how artificial intelligence can strengthen information exchange, facilitate evidence-based decision-making, improve advisory delivery, and enhance collaboration among researchers, extension personnel, and farming communities. This thematic synthesis informed the development of the Intelligent Aquaculture Extension Ecosystem (IAEE) as a conceptual framework for integrating AI-enabled analytical tools with validated scientific knowledge and professional extension practice.

ARTIFICIAL INTELLIGENCE TECHNOLOGIES AND THEIR APPLICATIONS IN AQUACULTURE

Artificial intelligence (AI) encompasses computational approaches that enable systems to analyse data, identify patterns, generate predictions, classify information, and support complex decision-making. In aquaculture, the application of AI has expanded with the increasing availability of sensor data, images, video, environmental measurements, farm records, and other digital information. Current applications are concentrated mainly on production monitoring, environmental assessment, fish health, biomass estimation, behavioural analysis, and feeding management (Vo et al., 2021; Aung et al., 2025). Machine learning and deep learning constitute the principal analytical approaches, while more recent developments in natural language processing, large language models, retrieval-augmented generation, and knowledge representation provide additional capabilities for processing textual, visual, numerical, and knowledge-intensive information.

Machine learning

Machine learning enables computational systems to learn patterns from data and use these patterns to generate predictions or classifications without relying exclusively on explicitly programmed rules (Jordan & Mitchell, 2015). Its application in aquaculture has expanded across areas in which production and environmental conditions generate complex and often interdependent datasets. Reviews of intelligent aquaculture applications have identified biomass assessment, fish identification and classification, behavioural analysis, and prediction of water-quality parameters among important applications of machine-learning approaches (Vo et al., 2021; Aung et al., 2025).

Empirical studies demonstrate the use of machine-learning approaches for prediction of important water-quality variables. Zambrano et al. (2021), for example, evaluated machine-learning models for predicting manually measured water-quality parameters in fish farming, including dissolved oxygen, temperature, pH, ammonia, and ammonium. Eze et al. (2023) subsequently demonstrated a hybrid neural-network approach for multivariate water-quality forecasting using data from an aquaculture production environment. These studies illustrate the capacity of machine-learning models to identify relationships among environmental variables and generate predictions that may assist the interpretation of changing production conditions.

Machine-learning approaches have also been applied to other aquaculture datasets, including production and biological measurements. Their principal technical value lies in identifying complex relationships within numerical, environmental, and observational data that may be difficult to characterise using conventional statistical approaches. The performance of such models, however, depends on the quality and representativeness of training data, appropriate model selection, validation under realistic farming conditions, and the extent to which models generalise across species, production systems, and environmental conditions. Consequently, machine-learning outputs should be interpreted in relation to biological and farm-specific knowledge rather than treated as universally transferable predictions.

Deep learning and computer vision

The increasing availability of image and video data has accelerated the application of deep learning and computer vision in aquaculture. Deep-learning approaches provide the computational basis for automated image recognition and classification, while their ability to extract features directly from complex image data has expanded applications in fish identification, species classification, behavioural analysis, feeding assessment, health monitoring, and biomass estimation (Vo et al., 2021; Aung et al., 2025).

Empirical studies provide evidence for several of these applications. Ahmed et al. (2022) demonstrated an image-based machine-learning approach for fish-disease detection, illustrating the potential of image data for automated health assessment. Zhang et al. (2020) investigated fish-mass estimation using image analysis and a neural network, demonstrating the use of visual information for non-invasive biomass assessment. Ubina et al. (2021) evaluated convolutional neural networks for assessing feeding intensity in aquaculture. Together, these studies demonstrate how image and video data can provide non-invasive information on cultured animals and production processes.

Computer-vision systems can potentially reduce the need for continuous manual observation by extracting measurable features from images and video. However, their performance remains sensitive to factors such as illumination, turbidity, camera position, fish density, species morphology, image quality, and the representativeness of training datasets. The transferability of models between farms and production conditions therefore remains an important limitation. Deep-learning systems may also require substantial labelled datasets and computational resources, which can restrict their adoption in smaller or resource-constrained aquaculture operations.

Natural language processing and large language models

Natural language processing (NLP) extends AI applications from numerical and visual data to human language. It enables computational systems to process, classify, retrieve, summarise, and generate textual information. Large Language Models (LLMs) represent a major development in NLP and can generate contextually relevant responses from natural-language prompts while processing large volumes of textual information (Brown et al., 2020).

The relevance of NLP and LLMs to aquaculture arises partly from the large volume of textual and semi-structured information associated with scientific publications, technical guidelines, disease-management documents, regulations, farm records, and institutional reports. These systems can support document classification, information extraction, semantic retrieval, summarisation, question answering, and natural-language generation across heterogeneous information sources. Such capabilities provide a potential mechanism for processing knowledge that cannot readily be represented as numerical or image-based datasets.

However, these applications should not be equated with established aquaculture AI practice. Direct evidence demonstrating the accuracy, reliability, usability, and effectiveness of LLM-based systems in real-world aquaculture settings remains limited. LLM outputs may contain inaccurate, incomplete, outdated, or unsupported information, particularly when domain-specific knowledge is poorly represented in the underlying model. Consequently, LLMs should be considered an emerging information-processing technology whose application in aquaculture requires domain-specific validation and expert oversight.

Retrieval-Augmented Generation

Retrieval-Augmented Generation (RAG) provides a mechanism for connecting language models with external knowledge sources. Rather than relying exclusively on information encoded within a language model, RAG retrieves relevant documents or information from an external knowledge repository and incorporates the retrieved material into the generation process (Lewis et al., 2020).

For aquaculture applications, a RAG architecture could retrieve information from validated scientific publications, technical manuals, government advisories, institutional databases, disease-management resources, and other curated technical documents before generating a response. This creates a potential mechanism for grounding language-model outputs in identifiable information sources and for updating the information available to an AI system without retraining the underlying language model.

The effectiveness of RAG nevertheless depends on the quality and organisation of the external knowledge repository, the accuracy of document retrieval, the currency of the information, and the ability of the language model to interpret the retrieved material correctly. RAG should therefore be regarded as a mechanism for grounding AI-generated information rather than as a guarantee that the resulting response is scientifically correct. Its application to aquaculture remains an emerging area requiring domain-specific evaluation and validation.

Knowledge graphs

Knowledge graphs provide a structured approach to representing entities and the relationships among them. They can support semantic representation, information retrieval, and integration of heterogeneous information within a defined knowledge domain (Kejriwal, 2022). In agricultural applications, knowledge-graph approaches have been explored for organising relationships among production factors, management practices, and other domain-specific information (Peng et al., 2023).

A similar approach could be adapted to aquaculture by connecting information relating to cultured species, diseases, water-quality conditions, feeds, production systems, management practices, regulations, and technical recommendations. Such a structure could enable information to be retrieved according to relationships among entities rather than through isolated keyword matching. It could also provide a structured knowledge layer that complements numerical prediction and language-based systems.

The usefulness of an aquaculture knowledge graph would depend on the completeness, accuracy, consistency, provenance, and regular updating of its underlying information. Construction and validation would consequently require participation from aquaculture scientists and other domain specialists. Knowledge graphs should therefore be viewed as a potential knowledge-organisation technology rather than as a substitute for expert knowledge.

Integration of AI capabilities in aquaculture systems

The applications described above demonstrate that different AI approaches address different forms of aquaculture information. Machine learning is particularly suited to learning predictive relationships from numerical and environmental data; deep learning and computer vision can analyse images and video; NLP and LLMs can process and generate textual information; RAG can connect language generation with external knowledge repositories; and knowledge graphs can represent relationships among domain-specific entities.

The integration of these capabilities provides a technological basis for more comprehensive intelligent aquaculture systems. Environmental and farm data could be analysed through predictive models, visual information could be assessed through computer-vision systems, relevant scientific or technical information could be retrieved from structured knowledge repositories, and information from these different sources could be combined through interoperable analytical architectures. Such integration is technically plausible, but the maturity and validation of individual components differ substantially. Recent aquaculture literature continues to identify data quality, model generalisation, interoperability, computational requirements, and real-world validation as important barriers to wider AI adoption (Aung et al., 2025).

Integration also introduces additional technical requirements. Data generated by sensors, farm records, images, environmental monitoring systems, and textual repositories may differ in format, temporal resolution, quality, and completeness. Interoperability and data-standardisation mechanisms are therefore important for combining heterogeneous information sources. Similarly, models developed for one species, geographical region, production system, or environmental range may not perform reliably when transferred to another context. Integrated systems consequently require continuous validation, monitoring, updating, and domain-specific testing rather than assuming that performance in one application will automatically transfer to another.

Accordingly, the evidence reviewed in this section should be interpreted primarily as demonstrating technical capabilities and aquaculture applications, rather than as evidence that fully integrated AI-enabled extension systems are already established. The technologies discussed here provide different analytical and knowledge-processing capabilities, but their effectiveness depends on data quality, contextual validity, technical infrastructure, and appropriate human oversight. The implications of combining these capabilities for advisory services, knowledge management, farmer learning, communication, and institutional planning are considered separately in the following section.

ARTIFICIAL INTELLIGENCE AND THE TRANSFORMATION OF AQUACULTURE EXTENSION

Effective extension depends on the generation, organisation, validation, and exchange of knowledge among researchers, extension professionals, policymakers, and farming communities. Contemporary extension systems extend beyond one-way technology transfer to include learning, communication, decision support, innovation, and institutional linkages (Anderson & Feder, 2007; Swanson & Rajalahti, 2010). Within this broader framework, artificial intelligence can potentially strengthen extension by improving the processing and organisation of heterogeneous information, supporting more responsive advisory processes, and facilitating interactions among different sources of knowledge. Its contribution should nevertheless be understood as complementary to the professional, participatory, and relational functions of extension rather than as a replacement for them.

Intelligent advisory services

One of the most direct opportunities for AI-enabled extension is the development of more responsive advisory services. Conventional aquaculture extension often relies on farm visits, training programmes, telephone communication, printed materials, farmer meetings, and other channels through which extension personnel interpret production problems and provide recommendations. AI-enabled systems can potentially complement these approaches by bringing together information from farm records, environmental observations, sensor systems, weather data, scientific resources, and previous advisory interactions.

The principal change is not simply faster information delivery but the possibility of linking a farm-level problem with relevant evidence from multiple information sources. For example, observations relating to deteriorating water quality, disease risk, feeding problems, or environmental stress could be analysed alongside available scientific and technical information before an advisory response is prepared. Extension professionals could then assess the relevance of the information in relation to the species, production system, local environmental conditions, and available resources. Such an approach is consistent with the broader role of extension in supporting farmers' decision-making rather than merely transferring technical information (Anderson & Feder, 2007; Swanson & Rajalahti, 2010).

Conversational interfaces may further facilitate access to information by allowing farmers to communicate questions and describe production problems using natural language. AI-assisted systems could support retrieval and organisation of relevant information from scientific and technical resources, while professional extension personnel retain responsibility for interpreting and validating recommendations. Such an arrangement is particularly important where advice may affect animal health, environmental management, food safety, or farm profitability.

Knowledge management and evidence-based decision support

Knowledge management is another major extension function that can potentially benefit from AI. Extension organisations must work with increasingly large and heterogeneous collections of scientific publications, technical manuals, policy documents, field observations, regulatory information, market information, and farmer-generated knowledge. The distribution of these resources across different databases and repositories can make the identification of relevant and current information time-consuming.

AI-supported retrieval and knowledge-organisation approaches can facilitate more efficient access to such information. Semantic retrieval and knowledge-graph technologies, for example, can help establish relationships among entities and concepts and support structured retrieval of domain-specific information (Kejriwal, 2022; Peng et al., 2023). In aquaculture, knowledge resources could be organised according to species, production systems, diseases, environmental conditions, feeds, management practices, geographical context, and regulatory requirements. This could assist extension personnel in locating relevant evidence and preparing more consistent technical materials.

The significance of AI-based knowledge management therefore lies in connecting previously fragmented information resources rather than simply converting paper-based information into digital form. Information repositories can potentially be linked with new scientific findings, field observations, and validated production data, allowing knowledge resources to be updated as conditions change. Earlier expert-system approaches had already demonstrated the value of computer-assisted knowledge management in agricultural and aquaculture contexts; contemporary AI expands this possibility through improved information retrieval, pattern recognition, and natural-language interaction. The reliability of such systems nevertheless depends on the quality, currency, provenance, and expert validation of the underlying information.

Farmer learning and capacity building

AI-enabled extension also creates possibilities for more flexible and context-sensitive approaches to farmer learning. Aquaculture farmers differ in species cultured, production systems, experience, educational background, language, resource availability, and access to digital technologies. Consequently, a uniform extension message may not adequately address the needs of all producers.

Digital systems can potentially assist in adapting learning materials to different production contexts and levels of technical understanding. They may support the preparation of multilingual materials, simplified explanations, interactive learning resources, and responses to routine information requests. Extension personnel can also use AI-assisted information retrieval and summarisation to identify relevant scientific developments and prepare educational materials more efficiently.

These possibilities should be viewed as complements to established learning approaches rather than substitutes for them. Demonstrations, farmer meetings, field visits, peer learning, and participatory activities remain important because aquaculture knowledge is not acquired solely through the receipt of information. Contemporary extension approaches emphasise interaction, participation, learning, and collaboration between extension personnel and farming communities (Davis & Sulaiman, 2014; Swanson & Rajalahti, 2010). The effectiveness of AI-supported learning should therefore be assessed through outcomes such as knowledge acquisition, appropriate practice adoption, farmer confidence, problem-solving ability, and improved decision-making rather than through the frequency of digital interactions alone.

Communication and two-way extension

AI can also contribute to changing extension communication from predominantly one-way dissemination towards more interactive knowledge exchange. Farmers can communicate questions, observations, photographs, and descriptions of production problems through digital platforms, while extension organisations can use aggregated interactions to identify recurring concerns and emerging information needs.

This capability may be particularly valuable when farmers face time-sensitive problems such as disease outbreaks, deterioration of water quality, extreme weather events, or other sudden production risks. Digital channels can reduce the delay between identification of a problem and access to relevant information. Language adaptation and natural-language interfaces may also improve accessibility for farmers with different linguistic backgrounds and levels of technical knowledge.

However, increased communication speed does not necessarily guarantee effective extension. Trust, contextual understanding, participation, and continuing interaction between knowledge providers and users remain fundamental to successful extension (Davis & Sulaiman, 2014). AI-supported communication should therefore be designed as a two-way process in which farmer observations and responses can influence subsequent advisory activities rather than merely increasing the volume of information delivered to farmers.

Institutional planning and extension management

The potential contribution of AI extends beyond individual advisory interactions to the planning, monitoring, and management of extension programmes. Extension organisations must identify priority production problems, determine which communities require additional support, allocate personnel and resources, monitor emerging risks, and evaluate the outcomes of interventions.

Information generated through farmer enquiries, advisory interactions, production records, environmental observations, disease reports, and regional production patterns could potentially be analysed to identify recurring problems and geographical or production-specific priorities. Such information may assist extension organisations in targeting training programmes, prioritising field visits, updating technical materials, and identifying areas requiring further research or institutional intervention.

This application represents an important shift from responding primarily to individual requests towards using aggregated information to support strategic extension planning. Nevertheless, institutional decisions involve social, economic, ecological, cultural, and policy considerations that cannot necessarily be inferred from digital datasets alone. AI-generated patterns should therefore constitute an additional evidence source for professional and institutional judgement rather than an automated basis for determining extension priorities. This perspective is consistent with agricultural innovation-system approaches that view extension as part of interconnected networks involving knowledge generation, learning, institutions, and innovation (Rivera & Sulaiman, 2009; Swanson & Rajalahti, 2010).

Human expertise, validation and responsible use

Across these functions, the effectiveness of AI-enabled extension depends on maintaining an appropriate relationship between computational capability and professional expertise. AI systems can process large volumes of information and identify patterns that may be difficult to detect manually, but they do not independently possess the contextual understanding required to determine whether a recommendation is appropriate for a particular farmer, production system, or environmental situation.

Extension professionals therefore remain important for interpreting information, assessing uncertainty, adapting recommendations to local circumstances, communicating limitations, and facilitating participatory decision-making. This is consistent with contemporary extension perspectives that emphasise trust, communication, participation, and collaboration in innovation processes (Davis & Sulaiman, 2014).

Human validation is particularly important where AI-generated information is uncertain or where incorrect recommendations could result in significant biological, economic, environmental, or food-safety consequences. Professional oversight can provide a mechanism through which questionable outputs are identified and corrected before they become operational recommendations. It can also help maintain accountability for decisions made with AI assistance.

Consequently, the transformation of extension through AI should not be understood as a transition from human-based to machine-based advisory services. Rather, it represents a potential redistribution of tasks in which computational systems assist with information-intensive activities while extension professionals retain responsibility for contextual interpretation, validation, communication, and relationship building.

From individual functions to an integrated extension system

The preceding functions demonstrate that the potential contribution of AI to aquaculture extension extends across several interconnected activities rather than being confined to a single advisory application. AI can support the organisation and retrieval of knowledge, assist in interpreting complex information, facilitate more responsive communication, support differentiated learning resources, and provide additional evidence for institutional planning. These functions are mutually reinforcing: improved knowledge organisation can strengthen advisory preparation; farmer interactions can generate information for knowledge updating; and aggregated field information can inform institutional planning.

The significance of AI therefore lies in the possibility of connecting these functions within a continuous knowledge and learning process. Research findings, technical information, institutional knowledge, farm observations, and farmer experience can contribute to an evolving information environment. AI-enabled analytical and retrieval capabilities can assist in processing these resources, while extension professionals interpret and validate relevant outputs before they are incorporated into advisory and learning processes. Feedback from farmers and field experience can subsequently contribute to further knowledge updating and refinement.

Such integration is consistent with established extension perspectives that emphasise knowledge exchange, participation, institutional learning, and innovation rather than one-way technology transfer (Rivera & Sulaiman, 2009; Swanson & Rajalahti, 2010; Davis & Sulaiman, 2014). The proposed Intelligent Aquaculture Extension Ecosystem, developed in Section 6, builds on this principle by providing a conceptual structure for connecting validated knowledge, AI-assisted analysis, professional interpretation, communication, and feedback.

The transformation described here should nevertheless be regarded as a potential rather than an established outcome. Evidence for individual AI applications in aquaculture is developing more rapidly than evidence for their sustained integration into extension systems. The practical value of AI-enabled extension will depend on data quality, knowledge curation, digital infrastructure, interoperability, professional capacity, farmer participation, institutional readiness, and appropriate governance. These constraints and considerations are examined in the following section.

CHALLENGES AND CONSIDERATIONS FOR INTEGRATING ARTIFICIAL INTELLIGENCE INTO AQUACULTURE EXTENSION

The integration of artificial intelligence into aquaculture extension involves challenges that extend beyond the technical performance of individual AI models. Reliable data, appropriate digital infrastructure, human capacity, institutional readiness, responsible governance, and equitable access all influence whether AI-enabled tools can function effectively in real-world extension environments. These considerations are particularly important in aquaculture because production systems vary widely in species, scale, environmental conditions, management practices, and technological capacity. Recent reviews of AI applications in aquaculture similarly identify data limitations, model development and validation, infrastructure, cost, and implementation capacity as important constraints to wider adoption (Aung et al., 2025; Yang et al., 2025). The practical value of AI-enabled extension will therefore depend on how effectively these interrelated challenges are addressed.

Data quality, interoperability, and digital infrastructure

Reliable data are fundamental to AI-enabled advisory systems. Predictive models, classification systems, and automated decision-support tools depend on information that is sufficiently accurate, representative, consistent, and regularly updated. Aquaculture datasets, however, may be fragmented across farms, research institutions, monitoring systems, and extension organisations. Differences in species, production systems, geographical conditions, management practices, environmental variability, and methods of data collection can further affect the quality and comparability of available information.

These limitations have direct implications for model generalisation. An AI model developed using data from a particular species, geographical region, production intensity, or environmental range may not perform equally well under substantially different conditions. Systematic evidence from aquaculture AI research has consequently highlighted data acquisition, dataset quality, environmental variability, model training, and generalisation as recurring challenges (Aung et al., 2025). Testing models under realistic farming conditions and across diverse production environments is therefore necessary before their outputs are used to support extension decisions.

Interoperability presents an additional challenge. Information may originate from sensors, farm records, images, environmental monitoring systems, scientific publications, institutional databases, and farmer observations, each using different formats, measurement procedures, terminology, and temporal scales. Integrating these heterogeneous resources requires appropriate data standards, metadata, storage systems, and information-sharing mechanisms. Without such interoperability, the potential benefits of combining different sources of information may remain limited.

Digital infrastructure is an equally important consideration. AI-enabled extension may require reliable internet connectivity, electricity, suitable mobile or computing devices, data-storage facilities, and, for some applications, substantial computational resources. Financial and technical limitations can make these requirements difficult to meet, particularly in small-scale or geographically dispersed farming communities. The infrastructure requirements and costs associated with AI deployment therefore need to be considered alongside the technical performance of the technology itself (Aung et al., 2025; Yang et al., 2025).

These constraints also create a risk of unequal access. If AI-enabled extension is designed primarily for well-connected and technologically advanced farms, farmers with limited connectivity, digital devices, or technical skills may benefit less from the transformation. Affordable deployment models, mobile-compatible systems, low-bandwidth options, and appropriate non-digital communication channels should therefore remain part of an inclusive extension strategy.

Human capacity and digital literacy

The effectiveness of AI-enabled extension depends substantially on the capacity of both extension personnel and farmers to use digital systems appropriately. Extension professionals need sufficient understanding of AI-generated information to assess its relevance, recognise uncertainty, identify potentially inappropriate outputs, and integrate computational information with scientific evidence and field observations. Farmers, in turn, require adequate digital and information literacy to access, interpret, question, and apply information obtained through AI-supported advisory systems.

This does not mean that extension professionals must become AI specialists. Rather, they require practical competencies that allow them to understand the strengths and limitations of AI tools and to judge when additional evidence or expert consultation is necessary. Such capacity building is consistent with the broader role of extension as a process of knowledge exchange, learning, communication, and facilitation rather than simple technology transfer (Anderson & Feder, 2007; Swanson & Rajalahti, 2010).

Training should therefore extend beyond technical operation of digital platforms. Extension personnel may require skills in interpreting AI outputs, identifying uncertainty, checking information against authoritative sources, communicating limitations to farmers, and recognising situations in which professional or specialist intervention is necessary. Farmers may similarly require support in evaluating digitally delivered information rather than simply accepting automated recommendations.

The human dimension remains important because farming decisions are influenced by local environmental conditions, resource availability, experience, economic circumstances, social relationships, and cultural practices that may not be adequately represented in digital datasets. Trust and participation therefore remain important components of technology adoption and effective extension (Davis & Sulaiman, 2014).

Transparency, explainability, and reliability

The credibility of AI-supported advisory services depends partly on the ability of users to understand the basis and limitations of generated outputs. Some AI models, particularly complex deep-learning systems, may provide predictions or classifications without making their reasoning readily interpretable to extension professionals or farmers. Lack of interpretability can reduce confidence in AI-generated recommendations and make it more difficult to identify inappropriate outputs.

Explainability is therefore particularly important where AI information contributes to decisions involving animal health, disease management, water quality, environmental conditions, or financial risk. A recommendation that cannot be adequately interpreted may be difficult to evaluate against field observations or established scientific knowledge. Explainable AI approaches, transparent validation procedures, and access to the evidence supporting an advisory output can help users assess whether a recommendation is appropriate.

Reliability also requires recognition of uncertainty. AI systems may generate outputs that are statistically plausible but biologically inappropriate under conditions not represented in their training data. Consequently, AI-generated information should not be presented as inherently certain or universally applicable. Clear indication of confidence, limitations, and the conditions under which a model has been validated can contribute to more responsible use.

Data governance, privacy, bias, and accountability

The increasing collection and integration of farm-level information raises important governance questions concerning data ownership, privacy, consent, access, security, and accountability. Farm records, production information, environmental observations, and other digitally collected data may contain commercially sensitive or personally identifiable information. Clear arrangements are therefore required regarding who can collect, store, access, modify, share, and use such information.

Algorithmic bias represents another concern. AI systems trained predominantly on data from particular geographical regions, species, production systems, or farmer groups may perform less effectively when applied to populations that are poorly represented in the training data. This can result in unequal quality of advisory support. Representative datasets, transparent validation, monitoring of model performance across user groups and production conditions, and mechanisms for correcting identified biases are therefore important components of responsible implementation.

Accountability must also be clearly established. When an AI-supported recommendation contributes to an inappropriate management decision, responsibility should not become obscured by the involvement of an automated system. Institutional procedures should specify how AI outputs are checked, who authorises their use as advisory information, how errors are reported, and how corrective action is taken. Human oversight is therefore an important governance mechanism rather than merely a technical safeguard.

Knowledge resources also require continuing oversight. Scientific findings, disease-management recommendations, regulations, environmental conditions, and production practices can change over time. AI-enabled advisory systems should consequently rely on knowledge resources that are periodically reviewed, updated, and appropriately curated.

Institutional readiness and policy support

The successful adoption of AI requires institutional capacity in addition to individual technical competence. Universities, research institutions, extension agencies, government departments, technology developers, and farming organisations may need to collaborate in developing knowledge resources, maintaining digital infrastructure, validating AI applications, and establishing appropriate procedures for their use. Such collaboration is consistent with the view of extension as part of wider systems of knowledge generation, learning, and innovation (Rivera & Sulaiman, 2009; Swanson & Rajalahti, 2010).

Institutional readiness includes the availability of trained personnel, financial resources, technical support, data-management procedures, maintenance capacity, and mechanisms for evaluating digital interventions. AI systems that depend on continuous data input, software maintenance, model updating, or specialist technical support may be difficult to sustain if these requirements are not incorporated into institutional planning from the beginning.

Policy support is similarly important. Appropriate policies can facilitate investment in digital infrastructure, capacity development, interdisciplinary research, data stewardship, and responsible technology adoption. At the same time, governance frameworks need to address privacy, accountability, transparency, data access, liability, and equitable participation. AI adoption should therefore be incorporated into broader digital-extension and aquaculture-development strategies rather than implemented as an isolated technological initiative.

Institutional suitability will also vary among production systems. Technologies that are practical for large commercial farms may be unsuitable for small-scale producers with limited financial and digital resources. Consequently, the selection of AI applications should be based not only on technical sophistication but also on affordability, usability, accessibility, and relevance to the intended users.

Evidence, validation, and scalability

A major challenge in translating AI research into extension practice is the difference between technical demonstration and sustained field-level effectiveness. A model may achieve high predictive accuracy under a particular experimental dataset without necessarily producing useful or reliable outcomes when deployed across different farms and environmental conditions.

AI-enabled extension applications should therefore be evaluated at several levels. Technical assessment should consider accuracy, robustness, generalisation, reliability, and computational requirements. Extension-oriented assessment should additionally consider usability, accessibility, affordability, farmer acceptance, extension-worker capacity, timeliness of advisory delivery, and the quality of decision support. Ultimately, evaluation should determine whether the technology contributes to meaningful improvements in farmer knowledge, management decisions, production outcomes, resilience, or other clearly defined extension objectives.

Pilot implementation can provide an appropriate pathway for such evaluation. Small-scale trials can identify technical and institutional problems before wider deployment and can generate evidence concerning user acceptance and practical feasibility. Successful approaches can subsequently be adapted and expanded while continuing to be monitored for performance under different production and environmental conditions.

This iterative approach is particularly important because AI applications in aquaculture are developing rapidly, whereas evidence concerning their long-term integration into extension systems remains comparatively limited. Greater emphasis on field validation, longitudinal assessment, cross-system testing, and user-centred evaluation would therefore help distinguish promising technological demonstrations from genuinely effective extension innovations.

Towards responsible and inclusive AI-enabled extension

The challenges discussed above demonstrate that the integration of AI into aquaculture extension is a systems-level process rather than a purely technological intervention. Data quality and interoperability influence the reliability of AI outputs; infrastructure and affordability influence accessibility; human capacity influences interpretation and use; governance influences trust and accountability; and institutional readiness influences sustainability and scalability.

Accordingly, AI should be implemented according to the needs and capacities of the extension system rather than introduced solely because a particular technology is available. The most appropriate applications will be those that address clearly identified extension needs, provide demonstrable value to users, and can be supported by reliable knowledge, suitable infrastructure, trained personnel, and appropriate governance.

For aquaculture extension, responsible implementation should therefore combine technological capability with professional judgement, farmer participation, transparent validation, equitable access, and continuous evaluation. This approach recognises that the effectiveness of AI depends not only on what an algorithm can calculate or generate, but also on whether the resulting information is scientifically credible, contextually appropriate, understandable, accessible, and actionable for the people who use it.

These considerations establish the requirements within which the Intelligent Aquaculture Extension Ecosystem (IAEE) proposed in the following section can operate. The framework brings together validated knowledge, AI-assisted analysis, professional interpretation, farmer interaction, and feedback while recognising the technical, institutional, ethical, and social conditions required for responsible implementation.

INTELLIGENT AQUACULTURE EXTENSION ECOSYSTEM (IAEE): A CONCEPTUAL FRAMEWORK

Effective aquaculture extension depends on continuous interaction among research organisations, extension institutions, policymakers, and farming communities through knowledge exchange, learning, feedback, and adaptation (Swanson & Rajalahti, 2010). The preceding sections show that artificial intelligence can strengthen individual extension functions, but its value depends on how computational capabilities are connected with reliable knowledge, professional judgement, appropriate communication mechanisms, and learning from field experience. Recent work on AI in aquaculture similarly emphasises the importance of human-centred design, data foundations, governance, and stakeholder participation in the development of practical AI systems (Cortes, 2026).

Against this background, the Intelligent Aquaculture Extension Ecosystem (IAEE) is proposed as a conceptual framework for integrating artificial intelligence with validated scientific knowledge, professional extension expertise, farmer participation, and continuous feedback. The IAEE is not proposed as a new AI technology or as a standalone digital platform. Rather, it provides a systems-level architecture through which the technological capabilities discussed in Section 3 and the extension functions examined in Section 4 can be brought together within an organised and accountable advisory process. Its central premise is that AI-generated information should be grounded in appropriate knowledge resources and subjected to professional interpretation before it is converted into actionable extension advice.

The IAEE comprises five interconnected components: (i) a validated knowledge foundation, (ii) an AI analytical and reasoning layer, (iii) an extension-professional validation layer, (iv) a multi-channel advisory and stakeholder interface, and (v) an adaptive feedback mechanism. These components form an iterative system rather than a set of isolated stages. Information can therefore move from scientific and field-based knowledge through computational analysis and professional interpretation to advisory delivery, while experience and outcomes from the field are returned to the system for further learning and refinement.

Validated knowledge foundation

The validated knowledge foundation provides the

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evidentiary basis of the IAEE. It may incorporate peer-reviewed scientific literature, extension manuals, technical guidelines, government advisories, institutional databases, environmental observations, farm records, and appropriately documented farmer knowledge. Its purpose is not merely to accumulate information but to ensure that information used for advisory purposes is relevant, credible, traceable, and appropriately maintained.

This foundation is particularly important for AI systems that retrieve or generate information from external knowledge resources. Retrieval-augmented approaches can connect language-model outputs with external sources, while knowledge-graph approaches can structure relationships among domain-specific concepts (Lewis et al., 2020; Kejriwal, 2022; Peng et al., 2023). Within the IAEE, however, these technologies serve to access and organise knowledge; they do not replace the scientific curation and validation required to determine whether information is suitable for extension use.

The knowledge foundation should also remain dynamic. New research findings, revised technical recommendations, regulatory changes, validated field observations, and emerging production problems should be incorporated through defined procedures for review and updating. This allows the evidence base to remain responsive to changes in aquaculture production and extension requirements.

AI analytical and reasoning layer

The AI analytical and reasoning layer provides the computational functions of the ecosystem. It incorporates the technologies discussed in Section 3, including machine learning, deep learning, natural language processing, large language models, retrieval-augmented generation, knowledge graphs, and related decision-support approaches.

Within the IAEE, these technologies can process different forms of information according to the requirements of a particular advisory problem. Numerical and environmental data may be analysed to identify patterns or predict risks; images may be examined for disease or behavioural indicators; textual resources may be retrieved and summarised; and relationships among scientific and technical concepts may be represented through structured knowledge systems. The layer can therefore generate candidate insights, alerts, explanations, or preliminary recommendations from information available within the ecosystem.

The output of this layer is not considered final extension advice. Rather, it constitutes decision-support information that requires professional assessment. This distinction maintains a clear separation between computational processing and responsibility for extension recommendations.

Extension-professional validation layer

The extension-professional validation layer is the principal human decision point within the IAEE. AI-generated outputs are reviewed by qualified extension professionals before they are communicated as actionable recommendations. The professional assesses the scientific plausibility, contextual relevance, uncertainty, and practical feasibility of the proposed information and considers local production conditions and farmer circumstances.

This process allows computational outputs to be interpreted in relation to factors that may not be adequately represented within digital datasets, including local management practices, resource constraints, farmer priorities, environmental conditions, and practical feasibility. Professional review can also identify incomplete, inappropriate, or potentially misleading AI-generated information before it reaches farmers.

The validation layer therefore performs two closely related functions: quality control and contextualisation. It also provides an identifiable point of professional responsibility within the system. AI assists the advisory process, but the transition from computational output to actionable extension recommendation remains subject to professional judgement.

Multi-channel advisory and stakeholder interface

Following professional validation, advisory information is communicated through channels appropriate to the users and the local context. These may include mobile applications, conversational interfaces, digital advisory platforms, messaging services, farmer meetings, demonstrations, field visits, producer organisations, and other established extension mechanisms.

The use of multiple channels is important because farmers differ in digital access, language, literacy, technological familiarity, and preferred modes of communication. The IAEE therefore does not assume that digital delivery should replace interpersonal extension. Instead, digital and conventional channels can operate together, allowing technological efficiency to be combined with interaction, demonstration, clarification, and direct field engagement.

The interface also extends beyond communication with individual farmers. Researchers, extension agencies, government departments, producer organisations, and other relevant stakeholders may contribute information to or obtain information from the ecosystem. The interface consequently functions as a point of interaction between the knowledge and advisory system and the wider aquaculture innovation environment.

Adaptive feedback and continuous learning

The adaptive feedback mechanism connects advisory delivery with subsequent learning. Information generated through farmer responses, field observations, implementation experiences, production outcomes, and extension activities can be returned to the knowledge foundation and used to improve subsequent advisory processes.

Feedback may indicate that a recommendation was effective, ineffective, unsuitable under particular environmental conditions, difficult to implement, or misunderstood. Such information can prompt updating of knowledge resources, renewed AI analysis, modification of advisory content, or reconsideration by extension professionals. The feedback mechanism therefore links individual advisory interactions with organisational learning.

This iterative capacity is particularly relevant to aquaculture because production conditions are dynamic. Changes in water quality, weather, disease occurrence, species performance, management practices, and market conditions may alter the relevance of previously generated information. Continuous feedback allows the advisory system to respond to such changes rather than relying on a static body of recommendations.

Integration of the IAEE components

The distinctive feature of the IAEE is the integration of these five components into a continuous advisory process. The knowledge foundation supplies validated evidence; the AI layer performs computational analysis and information retrieval; extension professionals assess and contextualise the resulting outputs; the advisory interface communicates validated information to users; and field experience provides feedback for subsequent learning.

The principal forward pathway can therefore be represented as:

Validated knowledge and field inputs → AI-assisted analysis and retrieval → extension-professional validation → multi-channel advisory delivery → farmer decision and action

The corresponding return pathway is:

Farmer experience and field outcomes → feedback → knowledge updating and system refinement → renewed analysis and advisory development

These pathways should not be interpreted as strictly linear. Feedback may lead directly to renewed analysis, professional reassessment, modification of advisory content, or updating of the underlying knowledge resources. The IAEE is consequently better understood as a recursive knowledge and advisory cycle in which information, professional judgement, and field experience continuously interact.

Governance as a cross-cutting layer

Governance operates across the entire IAEE rather than as a separate sequential component. Data provenance, privacy, access rights, transparency, accountability, model validation, knowledge curation, and professional responsibility need to be considered throughout the advisory cycle. Recent literature on AI in aquaculture highlights human-centred design, explainability, data ownership, algorithmic bias, accountability, and interoperability as important considerations for responsible implementation.

Within the IAEE, governance should define how knowledge resources are contributed, reviewed, modified, and updated; how AI-generated outputs are validated; how farm-level information is protected; how system performance is monitored; and how errors or inappropriate recommendations are identified and corrected. This cross-cutting arrangement ensures that responsible use is embedded within the architecture rather than treated as an additional step after advisory information has already been generated.

Figure 1 represents the IAEE as an integrated system with two principal input streams. The first consists of validated scientific and technical knowledge, including scientific literature, technical guidelines, institutional information, and other curated resources. The second consists of field-level information derived from farm records, environmental observations, farmer experience, production outcomes, and extension activities. These inputs converge within the validated knowledge foundation, where information is curated, organised, validated, and periodically updated.

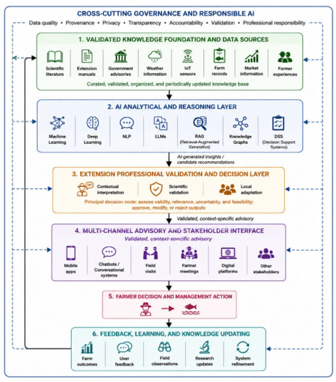

Figure 1. Conceptual framework of the Intelligent Aquaculture Extension Ecosystem (IAEE)

From the knowledge foundation, relevant information is made available to the AI analytical and reasoning layer.

The AI layer applies functions such as information retrieval, pattern recognition, prediction, classification, language processing, and decision support to generate candidate insights or preliminary recommendations. The figure therefore shows a forward directional relationship from the knowledge foundation to the AI layer.

Importantly, the AI output is not shown as moving directly to farmers. Instead, the output is directed to the extension-professional validation layer, which constitutes the principal decision node in the framework. At this point, extension professionals assess the scientific validity, contextual relevance, uncertainty, and practical feasibility of the AI-generated information. They may approve, modify, or reject a proposed recommendation before it proceeds further through the system.

Validated information then moves to the multi-channel advisory and stakeholder interface. From this interface, context-specific advisory information can reach farmers and other stakeholders through appropriate digital and interpersonal channels, including mobile applications, conversational systems, messaging services, meetings, demonstrations, field visits, and other established extension mechanisms. The immediate outcome of this pathway is information that can support farmer decision-making and management action.

Figure 1 also depicts a return feedback pathway. Farmer responses, field observations, implementation experiences, production outcomes, and extension-worker feedback move back into the knowledge component of the system. This feedback can initiate knowledge updating and, where necessary, renewed AI analysis, professional reassessment, modification of advisory information, or refinement of communication strategies. The feedback pathway therefore connects practical experience with subsequent cycles of knowledge processing and advisory development.

The resulting structure is therefore a continuous cycle rather than a one-directional information pipeline. The forward pathway is:

Knowledge and field inputs → AI-assisted analysis and retrieval → professional validation → advisory delivery → farmer decision and action

while the feedback pathway is:

Farmer experience and outcomes → feedback → knowledge updating and system refinement → renewed analysis and advisory development

The extension-professional validation layer is the principal decision node between AI-generated information and actionable extension advice. Governance forms a cross-cutting layer across the entire framework, encompassing data provenance, privacy, transparency, accountability, validation, and professional responsibility. The figure should therefore be read as showing four essential structural relationships: a forward information pathway, a human validation decision point, a recursive feedback loop, and governance operating across all components.

As illustrated in Figure 1, the architecture operates through a continuous, dynamic cycle rather than a one-directional information pipeline. The forward pathway begins by ingesting heterogeneous data—including real-time IoT sensor feeds, scientific literature, and historical farm logs—into specialized computational layers. These layers utilize advanced machine learning, GraphRAG, and explainable analytics to translate raw inputs into context-aware advisory recommendations. Before reaching the end-user, these automated outputs pass through an expert verification layer involving extension professionals or aquaculture specialists, ensuring biological relevance and socioeconomic validity.

Conversely, the return feedback pathway captures the practical outcomes of management interventions, user responses, and production metrics from the field. This returning data feeds directly back into the IAEE knowledge base and system memory, allowing predictive models to self-correct, refine their algorithms, and progressively enhance the accuracy of future guidance over time.

Expected contribution of the IAEE framework

The IAEE provides a conceptual basis for connecting AI capabilities with the organisational and human processes required for effective aquaculture extension. Its contribution lies not simply in accelerating information processing but in organising the relationship among evidence, computational analysis, professional judgement, communication, farmer experience, and institutional learning.

At the institutional level, the framework provides a structure for linking research organisations, extension agencies, policymakers, and farming communities through a shared knowledge and feedback system. At the professional level, it can assist extension personnel in locating and interpreting evidence and in developing context-specific recommendations. At the farmer level, it has the potential to improve access to timely and relevant information while retaining opportunities for interaction, clarification, and feedback.

These potential contributions should, however, be regarded as conceptual propositions rather than established empirical outcomes. The effectiveness of the IAEE will depend on the quality of its knowledge foundation, the reliability and validation of its AI components, the capacity of extension professionals, accessibility for farmers, institutional readiness, and the governance arrangements under which the system operates. Empirical evaluation will therefore be necessary to determine whether the proposed architecture improves advisory quality, farmer learning, decision-making, adoption of appropriate practices, and extension-system performance under real aquaculture conditions.

The IAEE consequently represents a human-centred extension ecosystem in which artificial intelligence functions as an enabling analytical and knowledge-processing layer within a broader system of professional validation, multi-channel communication, farmer experience, feedback, and institutional learning. Rather than presenting AI as a replacement for conventional extension, the framework positions it as a complementary capability that can be integrated with established extension principles to support more responsive, accountable, participatory, and farmer-centred aquaculture advisory systems.

FUTURE RESEARCH DIRECTIONS

Although artificial intelligence is increasingly being applied to aquaculture production and digital agriculture, its systematic integration into aquaculture extension remains comparatively underdeveloped. The next stage of research should therefore move beyond demonstrating the technical performance of individual algorithms and examine how AI-enabled advisory systems operate within real farming environments, extension institutions and farming communities. The central questions are no longer simply whether AI can generate accurate predictions or recommendations, but whether these systems are contextually appropriate, trusted by users, inclusive, economically viable and capable of producing measurable improvements in extension and farming outcomes. This requires greater attention to the institutional, social and knowledge dimensions of AI-supported extension alongside computational performance (Anderson & Feder, 2007).

Field validation and context-specific AI

A major priority is the development and rigorous field validation of context-specific AI-enabled advisory systems. Aquaculture production differs considerably among species, production systems, environmental conditions, geographic regions, farm scales, resource availability and farmer experience. Consequently, models developed from narrowly defined datasets may not retain their performance when transferred to different production environments. Research should establish the extent to which AI models can be generalised across species, regions and production systems, identify the factors responsible for performance deterioration, and determine when local adaptation, recalibration or retraining is required.

This issue is particularly important because aquaculture decisions are often influenced by environmental conditions and management practices that vary over relatively short spatial and temporal scales. AI systems should therefore be evaluated under realistic conditions involving seasonal variation, disease outbreaks, changing water quality, climatic disturbances and alterations in management practices. Longitudinal field studies would provide stronger evidence than short-term demonstrations by showing whether model performance, recommendation quality and user trust remain stable as production conditions change.

An additional research priority is the systematic integration of scientific evidence with farmers' experiential and locally generated knowledge. Local observations concerning water quality, disease occurrence, weather patterns, species behaviour and management responses can contain information that may not be represented in conventional datasets. Rather than treating such knowledge merely as an informal supplement to computational models, future research should investigate methods for documenting, validating, representing and incorporating it within AI-enabled advisory systems. Such approaches could improve contextual relevance while also strengthening farmer participation in the development and validation of digital advisory tools.

Knowledge architecture, retrieval reliability and continuous updating

The effectiveness of an AI-enabled extension ecosystem ultimately depends on the quality and currency of the knowledge on which its recommendations are based. The IAEE therefore requires mechanisms for curating, structuring, validating and continuously updating heterogeneous sources, including scientific literature, extension materials, institutional guidelines, regulatory information, farm records and validated local knowledge. Research is needed to establish robust approaches for maintaining provenance and traceability as information moves through different components of the advisory system.

Retrieval-augmented generation, semantic search and knowledge-graph approaches warrant particular investigation in this context. Their value should be assessed using aquaculture-specific knowledge bases rather than relying solely on generic benchmarks. Evaluation should consider factual accuracy, relevance, consistency, completeness, source traceability and the system's ability to distinguish established evidence from uncertain or context-dependent information. Importantly, studies should quantify unsupported, outdated or erroneous responses and develop mechanisms for detecting and correcting them before recommendations reach farmers.

Continuous knowledge updating is equally important. Information concerning disease management, environmental thresholds, production practices, food safety requirements and regulations may change over time. Future research should therefore investigate systems capable of identifying potentially outdated information while retaining expert oversight for validation and controlled updating. Such mechanisms would help prevent knowledge drift and maintain the scientific reliability of AI-enabled extension services over extended periods.

Human–AI collaboration and participatory extension

The future role of AI in aquaculture extension should be examined within the broader framework of human–AI collaboration. Established extension approaches—including demonstrations, farmer field schools, producer organisations, peer learning, participatory technology development and direct interaction with extension professionals—continue to play important roles in knowledge acquisition, behavioural change and relationship-building. AI is therefore more appropriately investigated as an additional decision-support and communication resource rather than as an automatic replacement for these mechanisms.

Empirical studies should compare different combinations of digital and interpersonal extension. For example, the effectiveness of AI-supported mobile advisories combined with field visits could be compared with digital-only and conventional extension approaches. Outcomes should be examined across farmers with different levels of digital access and literacy, education, age, gender, production scale and socioeconomic resources. Such comparisons would help establish where AI provides genuine added value and where interpersonal engagement remains essential.

The role of extension professionals also requires closer examination. Research should investigate how practitioners interpret AI-generated recommendations, identify errors, incorporate local knowledge, communicate uncertainty and modify advice before delivering it to farmers. It should also assess whether AI changes the allocation of extension workers' time between information retrieval, administrative tasks, diagnosis, training, field interaction and relationship-building.

The key research question is therefore one of human–AI complementarity: which extension tasks can be automated reliably, which require professional judgement, and which are most effective when performed collaboratively? Evidence from such research could inform extension workflows in which AI reduces routine information-processing demands while professionals retain responsibility for complex diagnosis, contextual interpretation, communication and participatory learning.

Adoption, effectiveness and measurable outcomes

A major limitation of the emerging literature is that AI-enabled aquaculture applications are frequently evaluated using technical indicators such as classification accuracy, prediction error or computational efficiency, with comparatively limited evidence on their actual contribution to extension and farming outcomes. Technical performance is necessary but does not, by itself, demonstrate extension effectiveness.

Future evaluations should therefore adopt multidimensional outcome frameworks encompassing knowledge acquisition, understanding of recommendations, decision quality, adoption of management practices, response time to emerging problems, farmer satisfaction, trust, extension-worker workload and institutional effectiveness. Where appropriate, longer-term indicators such as productivity, profitability, resource-use efficiency, environmental performance and farm resilience should also be incorporated.

Comparative and longitudinal evaluations will be particularly valuable. AI-supported, conventional and hybrid extension approaches should be assessed under comparable production conditions and followed over sufficiently long periods to determine whether observed improvements are sustained. Economic evaluation is equally important because technically successful systems may not be cost-effective once data collection, model development, infrastructure, training, maintenance and updating requirements are considered.

Evaluation should also account for unintended consequences. AI-enabled extension may improve access to information while simultaneously creating new forms of exclusion, increasing dependence on particular technology providers, reducing interpersonal interaction or encouraging excessive reliance on automated recommendations. Research should therefore assess not only the benefits of AI adoption but also its distributional and behavioural consequences.

Governance, institutional responsibility and responsible scaling

As AI-enabled advisory systems move from experimental applications towards wider deployment, governance and institutional responsibility will become increasingly important. Research should examine practical mechanisms for data ownership, privacy, informed consent, transparency, algorithmic accountability, model validation and responsibility for erroneous or inappropriate recommendations. These issues should be investigated within actual extension institutions rather than treated solely as abstract ethical considerations.

Institutional arrangements may also determine whether AI systems can be sustained beyond pilot projects. Comparative research across regions and countries could examine how extension structures, regulatory environments, digital infrastructure, workforce capacity and existing advisory traditions influence the adoption and effective use of AI. Such studies could help identify institutional models that encourage innovation while retaining professional accountability and farmer protection.

Scalability requires particular attention. A system that performs satisfactorily in a small, controlled pilot may encounter technical, financial, organisational and social constraints when introduced across districts, states or national extension networks. Research should therefore examine interoperability, data infrastructure, maintenance and updating requirements, financing models, workforce training, institutional ownership and long-term operational sustainability. Scaling should be viewed not simply as increasing the number of users, but as maintaining reliability, contextual relevance and accountability as the system expands.

Towards an evidence-based IAEE

Taken together, these research priorities indicate a shift in the central question for AI-enabled aquaculture extension. The objective is no longer simply to establish whether artificial intelligence can be applied to aquaculture extension, but to determine under what conditions, for whom, through which institutional and human–AI arrangements, and with what measurable outcomes AI can improve extension effectiveness.

Addressing this question will require interdisciplinary collaboration among aquaculture scientists, extension specialists, computer scientists, social scientists, economists, policymakers and farming communities. Particular emphasis should be placed on longitudinal field evidence, comparative evaluation, participatory system development and transparent assessment of both benefits and risks. Such evidence is essential for testing the assumptions underlying the proposed Intelligent Aquaculture Extension Ecosystem and for determining which components provide demonstrable value in real-world extension settings.

Ultimately, the future of AI-enabled aquaculture extension will depend less on the sophistication of individual algorithms than on the ability to connect reliable knowledge, appropriate technologies, professional expertise and farmer participation within accountable institutional systems. Research that establishes these connections can help determine whether the IAEE can evolve from a conceptual framework into a practical model for more accessible, credible, adaptive and sustainable aquaculture advisory services.

CONCLUSION

Aquaculture is becoming increasingly knowledge-intensive, creating a growing need for advisory systems capable of delivering timely, reliable and contextually relevant information for farm-level decision-making. This review examined artificial intelligence from the perspective of aquaculture extension rather than solely as a production technology. The evidence indicates that AI can support information management, knowledge retrieval, advisory preparation, communication and decision support across multiple extension functions. However, technological capability alone cannot ensure effective extension. The value of AI depends on the reliability of the underlying knowledge, the competence and judgement of extension professionals, institutional capacity, farmer participation, and mechanisms for validation, feedback and continuous improvement.

The principal conceptual contribution of this review is the Intelligent Aquaculture Extension Ecosystem (IAEE), which provides a framework for integrating AI-enabled analytical and advisory capabilities with validated scientific knowledge, professional expertise, farmer experience, multi-channel communication and continuous learning. Importantly, the IAEE does not position artificial intelligence as an autonomous replacement for extension personnel. Instead, AI is conceptualised as an enabling component within a broader socio-technical extension system in which contextual interpretation, professional judgement, farmer interaction, trust and experiential learning remain essential.

The review also highlights the need to evaluate AI-enabled extension according to extension and farming outcomes rather than technological performance alone. Measures such as predictive accuracy, classification performance and computational efficiency are important for assessing system capability, but they do not establish whether AI improves farmer understanding, decision-making, adoption of recommended practices, productivity, profitability, environmental performance or resilience. Comparative and longitudinal field evaluations are therefore needed to determine whether AI-supported and hybrid extension approaches provide sustained benefits under diverse aquaculture conditions.

Overall, artificial intelligence has considerable potential to strengthen aquaculture extension when embedded within human-centred, evidence-based, participatory and institutionally supported systems. Realising this potential will require reliable knowledge infrastructures, context-sensitive system development, professional oversight, farmer participation and responsible governance. The IAEE provides a conceptual basis for bringing these elements together, but its practical validity remains to be established through empirical field research. The future of AI-enabled aquaculture extension should therefore be understood not as a transition from human to automated advisory services, but as the development of human–AI extension systems in which computational capabilities complement scientific knowledge, professional judgement and farmer experience. Such integration could contribute to more responsive, inclusive, credible and sustainable aquaculture advisory systems.

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