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Applying Generative AI for Knowledge Translation in Aquaculture: An Empirical Study

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Abstract: This study examines the feasibility and effectiveness of using Generative Artificial Intelligence (Generative AI) as a knowledge translation tool for aquaculture. Existing technical materials in the field are often presented in complex, domain-specific terminology, making them difficult for grassroots farmers and non-specialists to apply, thereby creating barriers to technology transfer. To address this issue, the research adopts a mixed-methods approach that combines document analysis, system development, and user evaluation. A prototype system was built using a Retrieval-Augmented Generation (RAG) framework, providing plain-language translation, contextual Q&A, and localized indigenous language support. The study involved 20 non-specialist users and 5 aquaculture or education experts who participated in testing and review. Data were collected through questionnaires, paired-sample t-tests, and interviews to assess the system's impact. Results show that participants' knowledge comprehension improved significantly after using the system ($p < 0.05$). Additionally, 85% of users expressed high satisfaction with the system's readability and responsiveness, and most agreed that the indigenous language feature enhanced their learning experience. Experts acknowledged the system's value in simplifying technical knowledge but highlighted the need to improve the accuracy of technical terms and detailed content. They also recommended adding glossary explanations and visual step-by-step guides. Overall, the findings demonstrate that Generative AI can effectively lower the comprehension threshold for aquaculture knowledge and promote its application, with potential to expand into other agricultural domains. However, improving content accuracy and reducing AI hallucinations remain critical to ensuring the system's reliability and long-term adoption in practice.

Keywords: Generative Artificial Intelligence, Knowledge Translation, Aquaculture

1. Introduction

Aquaculture is one of the key pillars of Taiwan's agricultural sector, having long provided stable support for local economies. In recent years, however, the industry has faced increasingly complex technical and managerial challenges due to climate change, environmental pressures, and market fluctuations [1]. Taiwan's aquaculture sector is highly technical, requiring expertise in water quality monitoring, disease prevention, feed management, and environmental adaptation (Huang, S., et al., 2022). Although government agencies and academic institutions have produced technical documents, training materials, and digital platforms to help farmers acquire essential knowledge in water quality management, disease control, and feed regulation, most grassroots farmers still encounter barriers. Problems such as overly technical terminology, data complexity, inconsistent formats, and ambiguous expressions make these resources difficult to understand and apply. As a result, knowledge gaps and bottlenecks in technology transfer persist, limiting both comprehension and practical application [13].

Meanwhile, rapid advances in generative AI, especially in natural language processing, have introduced new possibilities for knowledge translation. Such systems can simplify complex content, restate technical knowledge in plain language, and provide personalized, conversational support. Large Language Models (LLMs), such as ChatGPT, Claude, and LLaMA, generate natural language responses that adapt to logic, grammar, and context, enabling non-specialists to grasp complex material more quickly. Applied in aquaculture, this technology could bridge information gaps, reduce communication barriers, improve comprehension and application among grassroots farmers, and support the broader popularization and sustainable development of smart aquaculture. This study therefore investigates the feasibility of applying generative AI for translating aquaculture technical information and develops a prototype system to evaluate its impact on comprehension and accuracy among non-specialist users.

2. Method

This study aims to examine the feasibility and effectiveness of generative AI as a knowledge translation and technical support tool in aquaculture, particularly for users without a professional background (e.g., aquaculture farmers, youth returning to rural areas). The main objectives are as follows:

1. Analyze barriers: Identify the professional and linguistic challenges that hinder aquaculture knowledge transfer.
2. Build a prototype system: Use generative AI models (e.g., ChatGPT or open-source LLMs) to translate professional materials (such as manuals and technical documents) into plain, understandable language.
3. Explore application strategies: Propose future pathways for promoting and scaling this tool among aquaculture practitioners.

3. Literature Review

3-1. Challenges in Aquaculture Knowledge Transfer

Most aquaculture technical documents are highly specialized and theoretical. Small-scale farmers often struggle to fully understand and apply them due to limited education, language proficiency, and resources [4],[6] . While information technologies have expanded opportunities for knowledge dissemination, the lack of tools specifically designed for semantic simplification and contextual adaptation continues to limit effective knowledge transfer and widespread adoption. Consequently, many practitioners rely on personal experience or peer consultation to solve problems, underscoring the absence of a convenient, professional Q&A channel for aquaculture knowledge [20].

3-2. Applications of Generative AI in Education

Generative AI, a technology capable of producing new content (text, images, audio) from trained data, has gained momentum with Transformer-based LLMs such as GPT-5, Claude, and LLaMA. These models excel in text generation, summarization, translation, and conversational systems [3]. The rise of prompt engineering has further enabled users to control outputs and tones with precision [15]. Generative AI has been widely applied across education (e.g., tutoring assistants), healthcare (e.g., symptom analysis and explanation), law (e.g., contract interpretation), and agriculture (e.g., pest and disease consultations). In communities with limited resources, such as rural farming and fishing villages, it plays a crucial role in bridging knowledge gaps and facilitating knowledge dissemination. Moreover, its capabilities in restating technical documents, simulating contextual scenarios, and enabling multilingual Q&A have already been applied in fields such as healthcare [21] , education (Holmes et al., 2023), and agricultural extension [9]. Its strengths lie in generating plain and accessible language, visual explanations, and interactive responses. In the field of educational technology, generative AI enables teachers to adopt more diverse digital teaching methods, and its effectiveness has already been demonstrated. For example, Jauhiainen and Guerra (2023) evaluated the use of ChatGPT in real classroom settings through both qualitative and quantitative methods. Their findings showed that incorporating generative AI tools into courses significantly enhanced student engagement and improved teaching quality. Rowland (2023) found that introducing generative AI into academic writing instruction provided students with structured frameworks, enabling them to improve the quality of their writing while maintaining academic integrity - highlighting AI's potential to support academic development. Khosravi, Viberg, Kovanovic, and Ferguson (2023) further examined how generative AI can optimize learning pathways and provide real-time feedback to enhance the learning experience. [14] conducted a bibliometric analysis of recent applications of generative AI in education, not only summarizing existing case studies but also emphasizing that the integration of AI and education represents a key future trend.

3-3. Theoretical Foundations of Knowledge Translation

Straus et al. (2013) describe knowledge translation as a bridging process that links knowledge production to practical application. It involves phases such as translation, adaptation, dissemination, and validation, while emphasizing the central role of language and culture in the dissemination of knowledge. Graham et al. (2006) proposed the knowledge-to-action conceptual framework, which divides knowledge translation into two parts: knowledge creation and the action cycle-application. The knowledge creation stage includes knowledge inquiry, synthesis, and tool development. It focuses on distilling insights from primary research, systematic reviews, and meta-analyses into practical tools for aquaculture technology, management, and disease prevention. The action cycle-application stage consists of identifying gaps between knowledge and practice, adapting knowledge to local contexts, assessing barriers and facilitators of knowledge applications, selecting, tailoring, and implementing interventions, monitoring knowledge use, evaluating outcomes, and ensuring sustained application. This stage emphasizes applying evidence-based knowledge to real-world aquaculture settings while evaluating the effectiveness of knowledge translation [18]. In summary, the knowledge creation stage emphasizes the construction of knowledge, while the application stage highlights its practical use. Only by completing both stages can high-quality scientific knowledge be effectively incorporated into decision-making and practice, thereby improving aquaculture productivity [19].

4. Research Methods

4-1. Research Design

This study adopts a mixed methods research approach, combining qualitative and quantitative analyses to evaluate the effectiveness of generative AI in knowledge translation within aquaculture.

4-2. Research Participants

The research participants include two groups: (1) professional users, including grassroots fish farmers, returning youth, and Indigenous community members, with 20 participants expected to join user testing, and expert reviewers, including aquaculture technology specialists and educators, comprising a total of five reviewers.

4-3. Data Collection Methods

(1) Document analysis: Based on the official website of the Fisheries Research Institute, Ministry of Agriculture, collecting and analyzing materials such as the aquaculture digital archive, aquaculture knowledge briefs, fisheries Q&A, aquaculture thematic portals, aquafarm updates, food safety sections, aquaculture technologies, research projects and results, key research achievements, patents and technology transfers, newsletters, aquaculture research, special issues, technical manuals, annual reports, and experimental reports.

(2) System outputs: Recording generative AI outputs under different prompt configurations.
(3) Questionnaire survey: Using comprehension and satisfaction scales to evaluate user feedback.
(4) In-depth interviews: Collecting qualitative opinions from users and experts.

4-4. System Development Process
(1) Knowledge base construction: Aquaculture technical documents are vectorized and stored in a database.
(2) Adoption of the RAG architecture: Combining document retrieval and generative models to provide knowledge translation functions.
(3) Prompt design: Setting multiple prompt templates for different user needs (e.g., plain Chinese, scenario-based Q&A, data analysis).

4-5. RAG Architecture and Prompt Design
Retrieval-Augmented Generation (RAG) is an AI technique that combines information retrieval and language generation models. The technology retrieves relevant information from the aquaculture knowledge base and uses it as prompts for large language models (LLMs) to enhance their ability to handle knowledge-intensive tasks such as Q&A, text summarization, and content generation. The RAG model was first proposed by the FAIR (Facebook AI Research) team in 2020 and quickly became a widely adopted approach in large model applications. Its main steps can be divided into three stages: the first is retrieval. Retrieval is the initial step of the RAG process, extracting information related to the query from the pre-built aquaculture knowledge base. The purpose of this step is to provide useful contextual information and knowledge for the subsequent generation process. The second step is augmentation. In RAG, augmentation means feeding the retrieved information into the generative model (i.e., large language models, LLMs) as contextual input, thereby improving the model's ability to understand and answer specific questions. The purpose of this step is to integrate aquaculture knowledge into the generation process, making the generated text richer, more accurate, and better aligned with user needs. Through augmentation, LLMs can fully utilize the information stored in the aquaculture knowledge base. The third step is generation. Generation is the final stage of the RAG process. The purpose of this step is to use the retrieved information as contextual input and, together with a large language model (LLM), generate responses that meet user needs [2].Applying RAG-enhanced LLMs can effectively address the hallucination problem in native LLMs - namely, the tendency of models to produce false or fabricated information; address timeliness issues - namely, the inability to answer highly time-sensitive questions; and address data security concerns - namely, that users do not need to upload their information to the internet. The RAG architecture allows AI models to retrieve relevant information from a knowledge base and then generate answers, thereby reducing the risk of generative AI hallucinations and providing an essential foundation for professional knowledge Q&A and technical content applications. (Lewis et al., 2020).

5. Research Conclusions

5-1. System Development and Model Construction
This study collected and analyzed 1,783 aquaculture knowledge documents from the official website of the Fisheries Research Institute, MOA and built a RAG-based vector database. Claude 4 Sonnet was used as the LLM model, Cohere Embed 4.0 as the embedding model, and Cohere Rerank v3.5 as the reranker model.

5-2. Prompt Content Design
To enhance the accuracy and completeness of responses generated by the AI, the prompts were designed as follows: "You are an AI assistant at the Fisheries Research Institute (FRI), specialized in assisting researchers, fish farmers, and members of the public interested in aquaculture. You provide answers to professional questions related to aquaculture science, fisheries management, and marine ecology. Your responses must be based solely on the FRI internal knowledge base, ensuring accuracy, and should be presented in a bullet-point format to avoid unnecessary length or deviation from the question. Each response should be limited to 300 words to ensure clarity and conciseness." The main responsibilities of the FRI AI assistant include:
(a) Professional Q&A: 1. Answer questions regarding research methods, experimental design, and data analysis in aquaculture science. 2. Provide the latest research findings and recommendations on fisheries management and policies. 3. Explain the status, challenges, and conservation measures of marine ecosystems.
(b) Research Resource Support: 1. Provide relevant research reports, experimental data, and technical guidelines.2. Guide researchers in using the internal database to locate required research resources.
(c) Data Analysis Assistance: 1. Assist in analyzing research data, offering trend observations and recommendations.2. Provide interpretation of statistical data to support scientific decision-making.
(d) Project Management Support: 1. Track research project progress and provide progress reports.2. Coordinate cross-department collaborations to ensure smooth project execution.
(e) Response Principles: 1. Source Limitation: All responses must rely solely on the FRI internal knowledge base; no external websites, personal experience, or speculative information may be used. 2. Accuracy First: Ensure the information aligns with the knowledge base and is up to date. 3. Bullet-Point Responses: Use bullet points to present answers clearly, concisely, and directly addressing the question. 4. Handling Unknown Questions: If relevant information is not found in the knowledge base, respond with "Sorry, please contact the Fisheries Research Institute," and remind users to verify answers with FRI. 5. Objectivity and Neutrality: Provide only factual information and

professional advice, without personal opinions or value judgments. 6. Clarity and Conciseness: Each response should not exceed 300 words to ensure it is easily understandable.
(f) Workflow: 1. Receive Request: Users submit professional questions or requests related to aquaculture research. 2. Information Retrieval: Search the internal knowledge base for relevant data to ensure accuracy. 3. Response Generation: Generate concise, concrete responses in bullet-point format based on retrieved information.4. Feedback Confirmation: Verify user satisfaction and provide options for further assistance.

5-3. System Development Outcomes
Through document collection and analysis, the establishment of a RAG-based vector database, and prompt engineering, this study successfully developed a prototype generative AI system for aquaculture knowledge translation based on the RAG framework. The system supports text-based Q&A, contextual explanations, and multilingual translation. It can transform specialized content into easily understandable language and, in some scenarios, provide visual aids.

5-4. User Evaluation Results
(1) Improved Comprehension: The quantitative analysis showed that participants' average test scores significantly increased after using the system ($p < 0.05$).
(2) High Satisfaction: Survey results indicated that 85% of users were highly satisfied with the system's readability and immediacy.
(3) Language Adaptability: Most users found the system's vocabulary and phrasing easy to understand. Its localized translation feature helped facilitate the learning of aquaculture knowledge.

5-5. Expert Review Results
Experts agreed that the system performs well in simplifying knowledge, though there is room for improvement in detail accuracy and precision of professional terminology. Key expert review comments include:
(1) Technical Advantages: Generative AI effectively lowers the barrier to understanding professional knowledge, particularly in communities with significant information gaps. Experts suggested adding explanations for technical terms and visual step-by-step guidance to enhance learning outcomes.
(2) Limitations and Challenges: The model occasionally produces hallucinations, which should be mitigated through knowledge base retrieval and expert review.
(3) Future Applications: The system could be extended to other agricultural domains and integrated with mobile apps and voice assistants to improve usability and reach.

5-6. Promotion Strategies
Generative AI has significant potential as a knowledge translation tool in aquaculture, improving knowledge accessibility and facilitating learning. However, continued optimization of content accuracy and contextual adaptation is necessary to ensure reliability and long-term value in real-world applications. The generative AI aquaculture knowledge translation prototype system developed in this study can be promoted using the following strategies:
(1) User Adoption Strategies: 1. Demonstration Sites and Seed Users: Select several indoor and outdoor aquaculture farms as demonstration sites to allow local farmers to experience the convenience of AI-assisted guidance firsthand. 2. Cultivate "AI Aquaculture Advisor" Demonstration Farms to share practical benefits and case studies. 3. Digital Training for Farmers: Collaborate with local agricultural and fisheries associations and Indigenous organizations to offer courses on mobile apps and AI Q&A usage. 4. Provide online instructional videos and quick-start guides. 5. Interactive Community Management: Create dedicated communities on LINE, Facebook, and YouTube to share farming tips, success stories, and real-time consultation services. 6. Launch "Ask AI, Get Rewards" campaigns, e.g., users who answer AI-provided aquaculture questions correctly can receive related gifts.
(2) Government Policy Collaboration Strategies: 1. Integrate with government projects: Seek inclusion in digital transformation or smart aquaculture subsidy programs under the Fisheries Agency and the Ministry of Agriculture. 2. Combine with smart aquaculture sensor subsidy programs, integrating AI with IoT data, and link with climate adaptation projects to provide climate-smart aquaculture recommendations. 3. Collaborate with FAO, ICRISAT, and other organizations to adopt international smart agriculture and fisheries standards.
(3) Commercial and Sustainable Development Strategies: 1. Tiered Pricing Model: For example, allow 3 free questions per day; paid monthly subscriptions offer unlimited queries. 2. Data-Driven Added Value: Provide advanced analyses of farmers' aquaculture data to help them monitor market trends and risk alerts. 3. Collaborate with feed and equipment suppliers to provide precision marketing and exclusive offers based on AI recommendations. 4. Publish real-world case reports demonstrating that the AI system can increase yields, reduce mortality, or cut costs.

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