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Decision support in recirculating aquaculture systems (RAS): A case study of a human–AI interface in prawn hatchery operation

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ABSTRACT

The need for sustainable and responsible production in aquaculture calls for innovative implementation of recirculating aquaculture systems (RAS), which are extraordinarily complex, requiring the integration of various fields of science and technology to reach the desired productivity. In this case study, we report a four-month observation using a large language model (LLM) that – collaboratively with human expertise – analyzed and resolved complex challenges in a *Macrobrachium rosenbergii* RAS hatchery. Unacceptable larval and post-larval mortality prompted the integration into hatchery management of an AI decision-support system as a strategic management partner, enabling exploration across chemical, biological, physical, engineering, and behavioral domains. Key interventions suggested by the AI agent included mineral balance recalibration, microbial load diagnostics, behavioral pattern decoding, and lighting and flow engineering. Outcomes were evaluated in terms of a reduction in larval mortality and improved rates of larval metamorphosis to post larvae. Central to the process was the presence of a guiding human entity, steering AI's analytical power through deliberate questioning and contextual framing. This case study suggests that AI has the potential to improve intensive aquaculture systems. However, the tendency of AI agents to oversimplify complex systems requires the direction and guidance of a human expert to lead AI-human conversations. The adoption of LLMs in RAS-based aquaculture, bridging the gaps between raw data and actionable insights, has the potential to drive both the efficiency and the long-term sustainability of the aquaculture industry.

1. Introduction

The giant freshwater prawn, *Macrobrachium rosenbergii,* is a key species in aquaculture, with a growing demand worldwide [1,2]. To meet this demand, aquaculture farmers rely on a steady supply of larvae and post-larvae. Hatchery managers, in turn, must be able to reliably produce populations of larvae and post-larvae, especially monosex populations. These requirements constitute the very foundation of *M. rosenbergii* aquaculture, being the key to the production of the ever-growing amounts – and the quality – demanded by customers and producers alike. Successful and sustainable operation of a commercial-scale *M. rosenbergii* hatchery revolves around managing an intricate matrix of water chemistry, larval biology, microbial ecology, and systems engineering [3–6]. While conventional protocols provide standard parameters for water quality, feeding, and system operation, persistent larval mortality and irregular performance indicate that there are hidden stressors and dynamic interactions that cannot be improved in isolation. A more sophisticated approach to dealing with the above interrelated problems in the aquaculture of *M. rosenbergii* – and indeed for high-end aquacultural products in general – is therefore required.

As mentioned above, management of an *M. rosenbergii* hatchery is faced with multifactorial challenges. In particular, *M. rosenbergii,* being a catadromous species, requires brackish water for breeding and larval development, but fresh water for the remainder of its life cycle [7,8]. This aspect of its lifecycle adds complexity for growers and hatchery managers and introduces challenges related to the integration into hatchery procedures of the recirculating aquaculture systems (RAS) [4, 9–11] that are necessary for sustainable aquaculture. The multiple diverse variables that must be taken into consideration include water flow regimes, water chemistry, and light intensity, all of which could result in decreased survival rates, poor development, and increased stress. For example, it has been shown that improper water flow induces stress, resulting in physical damage and reduced feeding efficiency in larvae [12]; limited calcium chloride concentrations interfere with

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molting and reduce growth and survival [13]; and incorrect lighting conditions adversely affect feeding and development [14].

To address the challenges of the type described above, it has been suggested that large language models (LLMs) in the form of AI agents could be integrated into the all-encompassing management of aquacultural systems. However, despite rapid methodological advances and some proof-of-concept studies, the implementation of precision decision support is still in its infancy in aquaculture [15–19]. To date, AI interventions [15,18] have not provided pre-packed solutions to aquacultural challenges, rather they have extended human capacity to observe, test, and adjust systems across complex variables.

This article describes a human-AI interface for improving the management of an aquacultural RAS in an *M. rosenbergii* hatchery. This interface is particularly suitable for multifaceted and intensive systems of this type, which require a deep understanding of all aspects of managing RAS systems for raising aquaculture products, including physics, chemistry, biology, and engineering. Each of these aspects is multifactorial, resulting, overall, in dozens to hundreds of parameters to be monitored and controlled—a distinctively AI type of scenario. The present study serves as a unique first step aiming at the integration of AI into the management of RAS for aquaculture, specifically training such an agent to be involved in day-to-day decision support for *M. rosenbergii* aquaculture. Integrating human expertise with AI capabilities implies that RAS aquaculture can be scaled responsibly to secure the future of global blue food supplies.

2. Methodology

The study was conducted at the Enzootic Breeding RAS indoor prawn hatchery situated in Nakhon Pathom Province, Western Thailand. This facility operates as an exclusive *M. rosenbergii* all-female production center for both larvae and post-larvae. It maintains specialized maturation units designed to rear diverse broodstock lineages to sexual maturity. All stages of breeding and larval culture utilize integrated RAS technology, configured for either freshwater or brackish water environments. The facility's annual production capacity is approximately 720 million larvae and 240 million post-larvae. In total, the facility consists of fifty-five tanks divided into five lines. Each line contains eleven tanks with a volume of $3m^3$ each, as well as a collection tank. The system circulates water through a biofilter at a turnover rate of approximately once every three hours. Stocking density in each tank was fifty larvae per liter of water. Water quality was monitored routinely using commercial Red Sea Fish Company (Herzliya, Israel) test kits for ammonia, nitrite, nitrate, magnesium, calcium, alkalinity, and pH. Each parameter had a predefined acceptable operating range. Measurements within the accepted range were classified as green, measurements requiring caution were classified as orange, and measurements requiring immediate corrective action were classified as red. These classifications were used for routine hatchery management and as contextual information during human-AI interactions. Facility operational framework performed as part of this study to monitor the RAS system parameters and performance are presented in Table S2 (see supplementary materials).

To define challenges in the *M. rosenbergii* hatcheries and thereby to improve performance, a conversational, layered AI approach was used, starting with system mapping and progressing to problem mapping, specific domain deep dives, hypothesis testing, scientific cross-referencing, and integration into the system of feedback, as described below. The AI agent used in this project was ChatGPT version GPT-4o via a paid subscription. First, general data (Table S1) was fed into the AI agent inside a dedicated project, together with an initial conversation supplying the agent with all system-specific relevant data. Conversation prompts of specific domain deep dives discussed with ChatGPT to support the decision-making process are available as supplementary materials. This methodology allowed the AI agent to familiarize itself with system-relevant parameters, functions, and purposes to permit better decision-making support. In each step of this approach, a conversation was conducted with a foundation-model AI agent, which was requested to pinpoint bottlenecks and to suggest a sustainable resolution to each challenge. The conversations with the AI agent lasted for a total of four months, from the establishment of the hatchery in January 2025 to April of the same year. The first challenge, in the form of increased larval/post larval mortality, became apparent in February/March 2025 at 5 days of culture (DOC; February), at 11 DOC (February), and, again, at 16–21 DOC (February–March 2025). At these times, conversations with the AI agent were conducted to determine the cause of the problem and to request suggestions for a solution (see Section 2.2).

2.1. System mapping

For system mapping, all the system-specific parameters were summarized and presented to the AI agent as the foundation for all human-AI interactions reported in this case study. These system parameters were thus used to introduce the specific RAS system to the AI agent, aiming to allow maximum efficiency and productivity of the reported *M. rosenbergii* hatchery. The input to the AI agent for the *M. rosenbergii* larval and post-larval growth stages comprised: physical and engineering parameters, such as the tank sizes and the specifications and directionality of the water flow system; filtration mechanisms; chemical parameters, such as water chemistry and temperature; nutrients; and added feed. Additionally, all relevant biological parameters, such as numbers of breeders (males and females), egg laying rate, and amounts of embryos in hatcheries and larvae in nurseries, were provided to the AI agent, allowing the creation of a comprehensive picture of the system and facilitating the analysis of the various challenges. Prawn density in every section of the system (i.e. breeding tanks, hatcheries, and nurseries) and continuous monitoring of changes occurring throughout all growth and production stages were constantly fed into the AI agent to enable the optimized utilization of its capabilities for integrating challenges and pinpointing possible problems or bottlenecks in the RAS systems. All the steps listed below were analyzed in accordance with the system-specific parameters to ensure their suitability for our specific RAS.

2.2. Problem mapping

Problem mapping was the first stage involving conversations with the AI agent. In this step, a categorized list of all observable symptoms related to the failure of larval growth and development and increased mortality was generated. These symptoms included reduced water quality measured as described above. Developmental and molting problems were assessed primarily through subjective observation throughout the rearing period. Population survival was estimated by volumetric counting, i.e., determining the number of larvae or post-larvae present within a standardized volume, while final production and successful larval-to-post-larval transition were used as indicators of developmental performance. Accordingly, the term "molt failure" is used here as an operational descriptor of impaired developmental progression rather than as a direct individual-level measurement of failed ecdysis. This distinction was maintained throughout the study: volumetric counting was used to estimate population survival, whereas developmental impairment and metamorphosis success were evaluated from the observed progression of the population and final production outcome. Abnormal larval behavior (i.e., vertical migration or edge-hugging [20], whereas larvae swim in groups and clusters along the tank walls), and impediments to larval development (determined through subjective assessment throughout the rearing period, with final production results and survival rate used as performance indicators) caused by fluctuations of magnesium ion concentrations in the water [13,21,22]. In practice, the list comprised a summary of the main problems known to hinder *M. rosenbergii* growth in aquacultural ponds [23,24]. We thus asked the AI agent specific questions about the factors possibly adversely affecting the chemical, biological, physical, and engineering setups of our RAS system. For example, we asked the AI agent to determine whether the salt composition of the water, the lighting intensity, and the water flow regimes optimally fulfilled the demands of *M. rosenbergii* larvae and post-larvae in our hatcheries. Each item on the list was thoroughly covered in conversations with the AI agent, which was requested to pinpoint key challenges, provide protocols for tackling problems, and support decision-making based on system properties and past records in our *M. rosenbergii* large-scale hatcheries.

2.3. Domain deep dives

To further determine specific factors related to hatchery failure, AI-assisted literature reviews were conducted regarding four domains related to water characteristics, namely, chemical, biological, physical, and systems engineering, and one domain comprising the behavioral characteristics of *M. rosenbergii*, as follows. For the chemical domain, key water factors affecting *M. rosenbergii* larval survival and development [25–27] were assessed once or twice a day. These included ion concentrations (especially calcium, magnesium, sodium, and potassium) and total hardness, together with water alkalinity and pH. Biological water properties, such as the make-up of the microbial community, *Artemia*-borne bacterial load, and biofilm developmental processes, were assessed once a week or once a fortnight to monitor any possible disease-inflicting water contamination [24]. Biological water properties and microbial contamination were monitored through periodic tank-specific assessment and external laboratory bacteriological testing. Samples were submitted primarily for detection of pathogenic bacteria. When required, tanks were disinfected with chlorine, and infected animals were treated with formalin at 25 mg/L for 30 min to one hour. These procedures formed part of routine hatchery management and were not implemented as an independently controlled microbiological experiment. Finally, the water's physical properties (which are often neglected in comparison to its chemical and biological properties) were monitored to ensure proper clarity, flow rates, and aeration patterns (dissolved oxygen). Although these values are nominally fixed for a given tank in the hatchery, they were monitored weekly in terms of previously acquired knowledge for different aeration techniques [28, 29]. Chemical water parameters, including ion concentrations, total hardness, alkalinity and pH, were assessed once or twice daily as part of routine hatchery monitoring. Biological water properties, including microbial contamination and Artemia-associated bacterial loads, were assessed weekly or biweekly when required. Physical properties, including water clarity, flow and aeration/dissolved oxygen, were monitored periodically, generally weekly. Because these measurements were primarily manual operational measurements rather than continuously logged sensor data, they provide snapshots of system conditions and may not capture short-term fluctuations. The information for the above three domains related to water properties was finally integrated into a list detailing all systems engineering parameters, together dictating the overall structure and design of the system.

The final deep-dived domain comprised the behavioral aspects of *M. rosenbergii* larvae and post larvae. For larval stages, vertical migration, edge-hugging [20], and response to water turbulence and light conditions were discussed with the agent with the aim to prevent edge-hugging. In addition, for both larval and post larval stages, conversations were conducted with the AI agent regarding stocking density, feeding quantities, and oxygen levels, aiming to prevent stress and mortality [20].

2.4. Human-AI conversation-generated hypotheses to improve M. rosenbergii hatcheries

Human-AI conversations leveraged the unique ability of LLMs to process, cross-check, and confirm significant amounts of information in short periods of time. Based on a literature review and known physiological benchmarks (e.g., hatching, larval development, post-larval metamorphosis), we requested the AI agent to provide premises relating to potential sources of harmful effects on *M. rosenbergii* larvae and to synthesize recommendations for optimizing *M. rosenbergii* aquaculture. In doing so, we were able to explore new information sources through the implementation of the AI agent's recommendations, thereby adding a unique layer to our methodology of relevant scientific literature search.

2.5. System feedback integration

The human-AI conversations held as part of this study were translated into specific action items applied to the RAS facility, and empirical field data (e.g., ion concentrations, mortality curves) were incorporated into the system to refine conclusions. In this way, AI inputs were integrated with empirical data, farm properties (e.g., water source, pond size, production rate, prawn population densities) and our goals to sustainably produce *M. rosenbergii* in RAS aquaculture, thereby assisting us to form a comprehensive workplan. The integration of the AI agent with human expert knowledge and goals allowed us to obtain the desired outputs derived from the AI agent's detailed recommendations for optimal growing conditions, including the specifications for the water and the environment. Furthermore, in real time, the AI agent proposed adjustments to the farm management parameters and suggested structural changes to the RAS system.

3. Results

At any given moment, real-time information on our RAS was continuously fed to the AI agent as a general background for human-AI conversations (as detailed in the Materials and Methods section). It was assumed that the data provided to the AI agent was sufficient to allow the agent to form and suggest problem-solving paradigms for specific bottlenecks in the *M. rosenbergii* production process. In each conversation session with the AI agent, increased larval mortality and metamorphosis failure (manifested as molt failure events) were the initial discussion points, and the agent was requested to suggest reasons for these events. Based on an analysis of the data, the AI agent suggested management changes to improve aquaculture yields, where yield improvement was regarded as an increase in larval metamorphosis occurrences and reduced mortality.

Conversations with the agent led to specific steps for solving problems and hence to improving the RAS, as reported below. In the diagrams presented below for each aspect of improving the system, we state the challenge or the question to the AI agent (in the left red circle), the suggestions of the AI agent (middle yellow circle), and the responsive action and/or the outcome (right green circle), where the outcomes comprised successful metamorphosis from larvae to post-larvae (measured as decreased molt failure), improved survival rates, and, in some cases, the return of *M. rosenbergii* larvae to normal behavior and swimming patterns. Summarizing the chronological intervention process in a table (Table 1) presents interventions order in both dates and DOC values, together with their outcomes.

3.1. Mineral interactions and ion competition during the post-larval rearing stage

The first sign of stress was noted on 15 February 2025, at about 5 DOC, manifested as increased mortality of larvae and post-larvae, without any apparent reason. Regular tests determined that the immediate suspect factors (i.e., dissolved oxygen, CO_2 concentrations, water pH, or pathogens) failed to explain the increased mortality. The AI agent initially suggested changing the composition of salts, but no clear improvement in survival or metamorphosis was observed during the initial implementation. Challenging the agent with this fact and conducting a common-sense guided conversation revealed a lack of calcium

Table 1
Chronology and operational characteristics of human-AI-supported interventions.

Date/ DOC	Operational problem	AI-generated recommendation	Intervention	Scale	Duration	Observed outcome	Interpretive limitation
15 Feb 2025; ~DOC 5	Increased mortality	Alteration of salt composition	Gradual $CaCl_2$ addition	Three tanks	5 days	Mg: Ca ratio lowered; short-term changes in observed mortality and molt synchronization were reported	Response was not sustained and individual intervention effects could not be isolated
21 Feb 2025; ~DOC 11	Abnormal swimming	High aeration may produce turbulence	Reduced aeration and redistribution of airlift systems	Entire system	N/A	More typical swimming patterns were observed	Contribution of aeration/ flow modification could not be isolated from concurrent system changes
25 Feb 2025; ~DOC 15	Mortality recurrence	Clear water may contribute to larval stress	Water coloration and light diffusion	Eleven tanks / one line initially	5 days initially	30–40 cm visibility; improved survival and metamorphosis were observed operationally	Contribution of water coloration versus optical modification could not be separated; quantitative survival record was not retained
3 Mar 2025; ~DOC 21	Metamorphosis delay recurrence	High light intensity may contribute to stress	Light intensity reduced	Entire system	N/A	Improved metamorphosis was observed operationally	Contribution of light intensity could not be isolated from preceding interventions
5 Mar 2025; ~DOC 23	Persistent mortality	Microbial load from live feed considered as a factor	Microbial diagnostics and disinfection measures	Initially one line; subsequently whole facility when necessary	When necessary	Mortality was reported to decrease from approximately 50% to approximately 20%	Quantitative microbiological results were unavailable; causal contribution of microbiological measures could not be established

in the system as a possible cause for molt failure in the larval and post-larval prawns. Water analysis showed that calcium levels remained within the literature-recommended range (200–280 ppm) [30] but that magnesium concentrations were elevated, in some cases to >700 mg/L, which exceeded the target range and therefore indicated possible ionic interference with calcium uptake. Through ion modeling and synthesis of literature data from various sources, the AI agent suggested that high Mg: Ca ratios (>2.5:1) could inhibit calcium absorption and disrupt exoskeleton development. It is therefore recommended that this ratio be changed by gradually adding calcium chloride to the system (Fig. 1). The intervention was initially implemented for five days in three tanks as a preliminary trial. Under these limited operating conditions, a short-term improvement in molt synchronization and a reduction in observed mortality were reported. However, when the intervention was extended to a larger portion of the system operating at higher capacity, the improvement was not maintained and mortality recurred. Retrospectively, hatchery personnel considered that the response may have depended on the degree of water dilution associated with water exchange and system loading. This interpretation is based on operational experience rather than a controlled test and therefore remains a post hoc hypothesis. The observation nevertheless illustrates the context dependence of management interventions in a high-volume RAS and the difficulty of extrapolating a response observed in a small number of tanks to the full system.

3.2. *Aeration and flow dynamics in the larval rearing stage*

Following the initial mineral intervention, poor larval metamorphosis and survival were again recorded on 21 February 2025, around DOC 11. This recurrence prompted another session of conversations with the AI agent regarding aeration and flow conditions in the tanks, which aimed, at that time, to achieve a dissolved oxygen concentration of 1.9–2.9 mg O_2/L^{-1} [31]. To reach this target, we had designed airlift systems to produce maximum water turnover, but these led to behavioral stress of the larvae, which clung to the tank edges, jumped erratically, and appeared to experience vertical disorientation. A conversation with the AI agent produced the suggestion of changes to the aeration regime, suggesting that high aeration rate and maximum water turnover cause CO_2 evaporation and a change in the water pH. In accordance with the recommendations, aeration was substantially reduced at the early larval stages, accompanied by an even distribution of airlift systems in the tanks and a gentler flow gradient. We introduced this change for the entire system at once. Following these changes, larvae were observed to return toward more typical swimming patterns, with less edge-hugging and erratic movement (Fig. 2). However, because aeration was modified as part of a broader sequence of simultaneous operational changes, the independent contribution of aeration to this response cannot be determined.

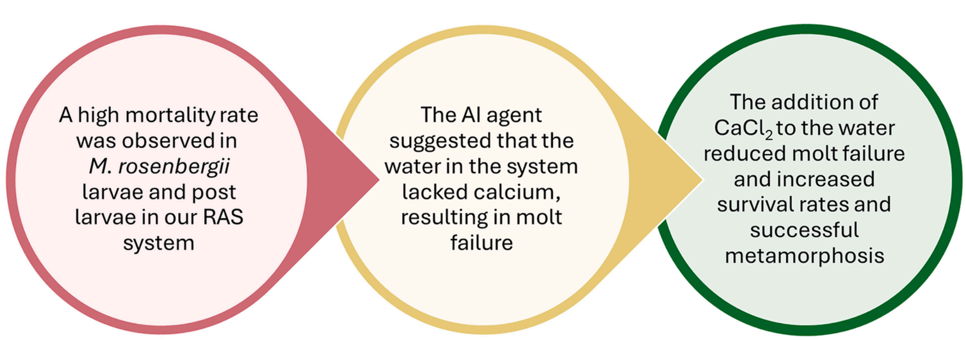

Fig. 1. Process simulation of the conversation with the AI agent on molt failure and mortality in *M. rosenbergii* larvae and post larvae, summarizing suggestions given by the agent to change the salt composition for preventing molt failure.

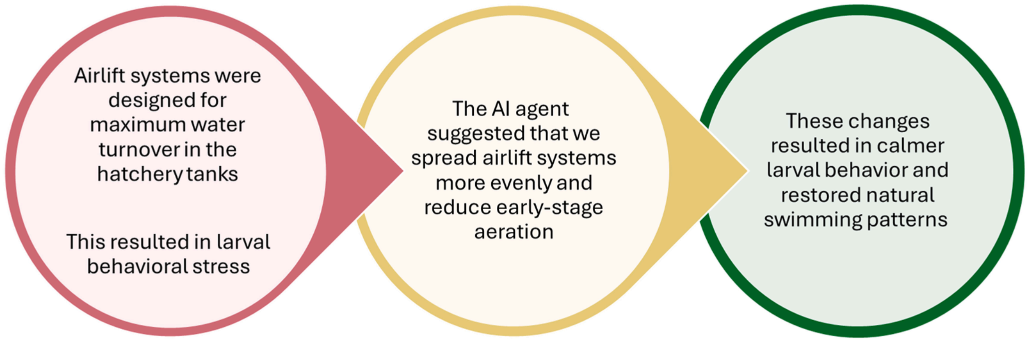

Fig. 2. Process simulation of the conversation with the AI agent on the effects of aeration and water flow on *M. rosenbergii* larvae in the RAS system; the yellow circle shows a summary of the suggestions given by the agent to alter the distribution of the airlift systems throughout the growing ponds to reduce larval behavioral stress.

3.3. Water clarity during the larval rearing stage

Several days after the preceding interventions, around DOC 15 (25 February 2025), adverse effects were again observed. Seeking additional reasons for the rise in larval mortality, we opened another conversation with the AI agent, this time focusing on water clarity. Initially, the water in the RAS system tanks remained ultra-clear, which was interpreted as a positive sign of efficient mechanical filtration. However, brainstorming with the AI agent suggested that this near perfect water clarity might be stressful for *M. rosenbergii* larvae, as integrating the literature review with the AI-led conversation revealed that in the wild *M. rosenbergii* larvae inhabit estuarine zones that are rich in suspended organic matter, which diffuses the light and contributes to visual orientation [20, 32–34]. Thus, to alleviate larval stress, the AI agent suggested the introduction of murkiness by adding vegetation to the water. We judged the working hypothesis to be logical but the solution to be problematic, as it could introduce microbial factors or plant byproducts into the RAS, potentially affecting water quality. Instead, we added artificial color to the water, dyeing them bluish green to simulate estuarine watercolor, and added optical green diffusers to the lighting system (Fig. 3), thereby maintaining water turbidity with a visibility distance of 30–40 cm, with the intention of reducing direct light exposure to the larvae. This change was initially introduced for five days on one line of tanks as a preliminary trial. The conditions were thereby modified to approximate aspects of the native estuarine environment. Following the intervention, improved larval survival and successful metamorphosis were observed in the treated line. However, a sufficiently documented quantitative survival record was not retained to support a precise numerical estimate, and the contribution of water coloration versus optical modification of the lighting system cannot be separated. The improvement was also short-lived.

3.4. Lighting intensity management in the larvae to post-larvae metamorphosis

Following the preceding interventions, a further recurrence of problems related to larval metamorphosis was observed at the beginning of March 2025, at about DOC 21 (March 3rd, 2025), triggering another conversation with the AI agent. The AI agent suggested that the lighting intensity used in our aquaculture facility could be a stressor for the larvae. In addition to the tank's coloration and the diffusers (see Section 3.3 above), AI-assisted cross-referencing of published scientific literature reporting on light penetration in aquatic systems suggested the need for further lighting adjustments, as the initial LED intensity in our system was high (1000–6000 lx), possibly inducing stress. Following the conversations with the AI agent, we reduced the light intensity in our system to 250–800 Lux, once again to resemble that of the natural habitat more closely; following the reduction in light intensity, improved metamorphosis was observed operationally (Fig. 4). Because the lighting intervention followed several preceding changes to water chemistry, flow, water appearance, and lighting diffusion, the independent contribution of light intensity to the observed developmental response cannot be determined.

3.5. Artemia and microbial load management in RAS larval systems

After the conversation about the need to change the lighting at the beginning of March, around DOC 23 (March 5th, 2025), our conversations with the AI-agent also related to larval mortality induced by the live-feed-borne microbial load. This aspect of RAS systems is known to adversely affect *M. rosenbergii*, causing stress and diseases, with the *Artemia* acting as possible trojan horses by introducing high concentrations of opportunistic pathogens into the larval environment and gut [35–37]. Since the use of live feed, such as *Artemia*, is crucial for proper *M. rosenbergii* larval development, we initiated a conversation with the

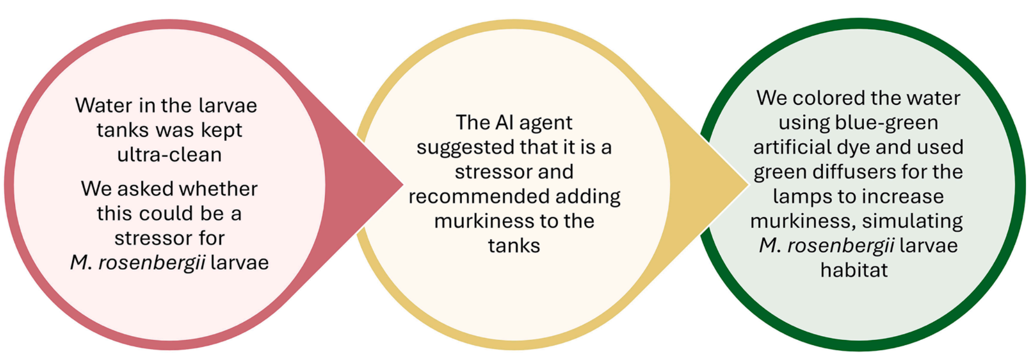

Fig. 3. Process simulation of the conversation with the AI agent on water clarity and murkiness, summarizing the suggestion given by the agent to add murkiness to the water, thereby simulating the *M. rosenbergii* larvae's natural habitat and reducing stress.

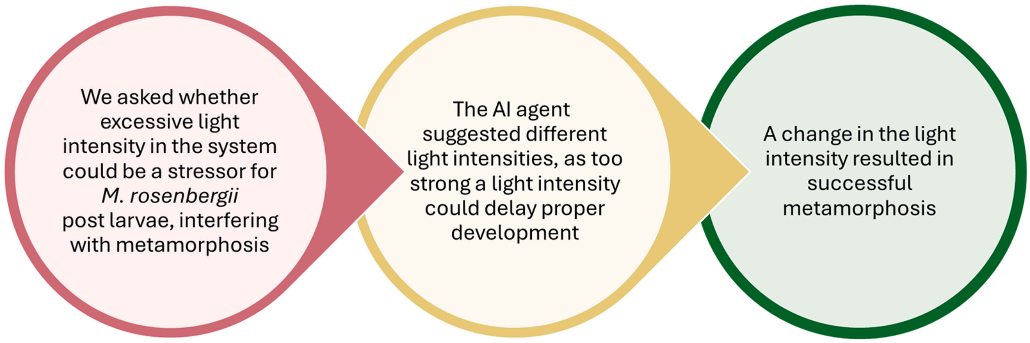

Fig. 4. Process simulation of the conversation with the AI agent on improving light conditions to reduce larval stress, summarizing the suggestions given by the agent to reduce the light intensity, thereby alleviating stress and improving larval metamorphosis.

AI agent on ways to prevent bacterial blooms in our system, as mortality persisted even when we changed the physical and chemical conditions, as discussed above. Initially, the AI agent suggested designing specific tests – via environmental PCR analyses – to determine which microorganisms were causing the adverse effects in our system. However, environmental PCR is labor intensive and not suitable for high-volume RAS systems such as ours. Feeding the AI agent with references pertaining to *Artemia*-borne bacterial load elicited two suggestions from the agent: the addition to the RAS of prebiotics and probiotics, and the use of commercially available microbial testing to monitor infections (Fig. 5). In practice, we implemented the AI-suggested disinfection protocols, performed microbial testing based on tank-specific microbial baseline maps, and ran diagnostics aimed to reduce presence of toxic bacteria in our system. Bacteriological samples were sent to an external laboratory, to test for pathogenic bacteria, and the tanks are disinfected using chlorine. In case of infection, the animals are treated with formalin at a concentration of 25 mg/L for 30 min to one hour. Following implementation of the microbiological-control measures, observed mortality was reported to decrease from approximately 50% to approximately 20%. This temporal change cannot be attributed specifically to the microbiological-control measures because other system conditions had also changed during the intervention sequence. Bacteriological testing was conducted as part of the diagnostic process; however, quantitative microbiological results suitable for retrospective statistical analysis were not available. Because quantitative microbiological laboratory results were not retained in a form suitable for retrospective analysis, the observed reduction in mortality cannot be directly linked to a quantified reduction in microbial load. Mortality rates were assessed by volumetric counting of each tank before and after disinfection. This protocol was applied first to one line of tanks followed by implementation on the whole facility, when necessary.

3.6. *Use of AI as a multidisciplinary tool (integrating biological, chemical, physical, and engineering inputs) into practical outputs*

This article presents a chronological case study of conversations with an LLM concerning various aspects of *M. rosenbergii* hatchery operation, taking into consideration parameters related to larval biology, water chemistry and physics, and systems engineering. The sequence illustrates how repeated human-AI interactions were used to identify bottlenecks, generate hypotheses, and inform subsequent management decisions in the RAS system. The AI agent's suggestions were evaluated and implemented by human personnel within the operational constraints of the commercial hatchery. Changes in mortality, survival, behavior, and metamorphosis were subsequently observed at different stages of the intervention sequence; however, because the interventions were sequential and several parameters were modified within the same period, these observations cannot be attributed to the AI agent's suggestions or to any individual intervention. The human-AI interface therefore functioned primarily as a multidisciplinary decision-support and hypothesis-generation tool. Building upon the suggestions generated during the conversations, the workflow addressed five operational challenges in *M. rosenbergii* production, as shown in Fig. 6.

4. Conclusions

This case study illustrates how a human-AI interface can support multidisciplinary hypothesis generation and decision-making in a complex commercial RAS hatchery. The AI agent did not independently diagnose or control the production system; rather, it served as a cognitive decision-support tool whose suggestions were interpreted, challenged, and implemented by human experts. The observed changes in survival, behavior, metamorphosis, and operational conditions occurred during a sequential series of management interventions and therefore cannot be attributed causally to the AI system or to any individual

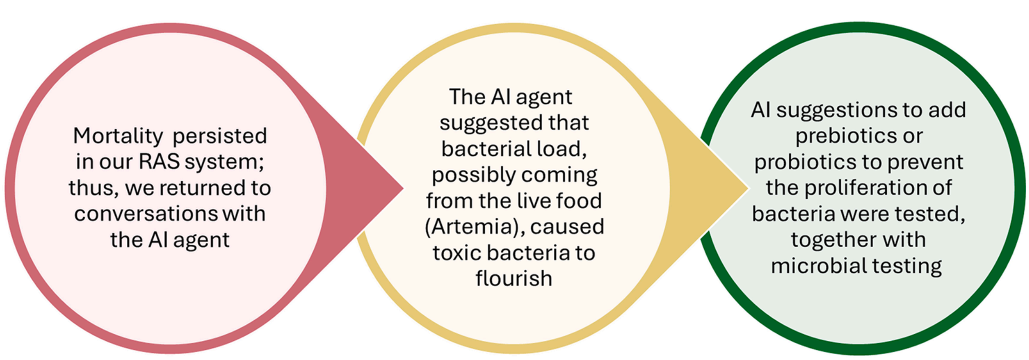

Fig. 5. Process simulation of the conversation with the AI agent on reducing mortality rates deriving from the food-related microbial load, summarizing suggestions given by the agent to add prebiotics and probiotics to the water, together with serial microbial testing to prevent bacterial blooms.

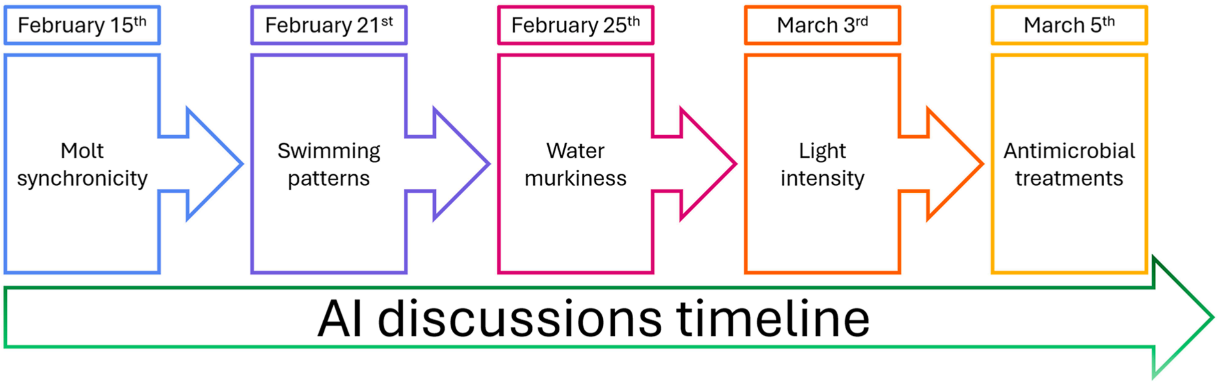

Fig. 6. Summarized timeline of the specific AI conversations in the project, chronologically presenting the process of AI-directed problem solving in our RAS system. Above each box representing each step, the date on which we first recognized the challenge is noted.

intervention. The value demonstrated here is consequently methodological: AI may provide a rapid mechanism for integrating information across biological, chemical, physical, and engineering domains and for generating hypotheses that can be evaluated by experienced hatchery personnel. Controlled, replicated comparative trials will be required to determine whether individual interventions identified through this process provide reproducible benefits. Rather than optimizing isolated parameters from each category of factors influencing productivity, the use of AI assisted us in linking possible interventions and implementing them in parallel to improve *M. rosenbergii* production, thereby minimizing ecosystem disruptions. Indeed, integration of an AI agent into our complex RAS hatchery changed the way in which we approached existing problems in the large-scale aquaculture production of *M. rosenbergii* prawns.

LLMs significantly aid in the diagnosis and isolation of faults within complex systems, often accelerating root cause analysis. The utility of AI in the form of an LLM lies in its capacity for rapid and multi-faceted (interdisciplinary) problem isolation and the subsequent integration of contextual variables to form a unified solution framework, possibly allowing farmers to easily and cost-effectively tackle challenges related to survival rates and larval development and other growth-related issues. Even though AI still has a long way to go, this study exemplifies how a responsible combination of human knowledge and brainstorming with AI agents can lead to advances in aquaculture production.

Our collaborative AI-human approach allowed us to transform a fragmented diagnostic process into a structured, multidisciplinary dialogue, actively combining human expertise with state-of-the-art knowledge into a comprehensive guide for troubleshooting *M. rosenbergii* aquaculture production in RAS systems. In a few cases, the tendency of LLMs to oversimplify complex systems came to the fore, resulting in unsuitable suggestions. These cases highlighted the necessity for conversations with the AI agent to be guided by a human expert towards framing hypotheses, raising questions, and validating AI-suggested interventions. This fact, together with the AI agent's tendency to hallucinate and aim to please the user, a behavior known as sycophancy [38,39], received special attention during chats with the AI agent. These phenomena were mainly attributed to the microbial load and light intensity domain deep dives, where ChatGPT tended to make up references fitting our original hypotheses. Persistence from our side, exemplified as the demand for additional peer-reviewed scientific manuscripts to support the agent's claim, resulted in a 'change of heart'. Such observations were of special interest in suggesting this approach's caveat, requiring careful examination of information and data provided by AI agents. To tackle sycophancy, we supplied the AI agent with all system-specific data before starting deep dive conversations to support decision-making. Larval mortality, for example, was temporarily reduced after improving the Mg: Ca ratio but has risen again after a few days. Discussion with the AI agent on this matter is prone to limitations; thus, our prompts were designed to insist on open-ended questions after feeding the AI agent with general information. In cases where the AI agent was entrenched in a specific position, going back to open-ended questions made the agent step out of its comfort zone and prevented sycophancy. Nonetheless, the AI agent offered clear advantages in terms of its ability to compare data from our system with data from dozens of different systems across multiple fields (biology, chemistry, physics, and engineering), thereby supplying us with timely decision support. In complex RAS hatchery systems, especially for sensitive species like *M. rosenbergii*, AI can serve as a cognitive co-pilot, integrating data from a body of literature, modeling scenarios, and maintaining long chains of reasoning, while being guided by human experts. As we continue to refine protocols, this integration of intuitive expertise with structured digital analysis may give rise to the next generation of hatchery innovation, providing improved hatchery protocols and hence higher yields and profits. In this case, the AI agent's broad way of thinking allowed human experts to explore possible production issues that otherwise might be overlooked. Utilization of an AI agent as a managing thinking partner facilitated high-volume literature review, and the tailored suggested solutions were guided by a human expert. The present case also demonstrates several failure modes that limit autonomous use of LLMs in hatchery management. The agent occasionally proposed technically plausible but operationally unsuitable interventions. For example, environmental PCR was initially suggested for microbial diagnosis, but this approach was considered impractical for routine use in a high-volume commercial RAS. The interactions also demonstrated the potential for contextual or sycophantic bias. Some conversations were initiated around a particular suspected factor, such as water clarity, rather than through an entirely unconditioned diagnostic query. Although system-specific information had previously been provided to the agent and open-ended questioning was subsequently used to challenge its assumptions, the possibility that the framing of a conversation influenced the generated hypotheses cannot be excluded. For this reason, the AI output was not treated as a diagnosis. Suggestions were challenged through additional questioning, comparison with available scientific literature, consideration of hatchery-specific constraints, and human expert judgment. The supplementary material provides the relevant prompts to make this decision-support process transparent.

A major limitation of this case study is that the management interventions were implemented sequentially under commercial production conditions rather than as independent controlled experiments. The hatchery was experiencing ongoing mortality and developmental problems, and operational constraints did not permit changing a single parameter and waiting for a sufficiently extended period to determine its isolated effect. Consequently, several parameters were modified within the same period. For example, the aeration intervention involved both a reduction in aeration intensity and redistribution of airlift systems, while other environmental conditions continued to change. The water-clarity intervention combined artificial water coloration with optical modification of the lighting system. The later lighting intervention was therefore introduced into a system that had already undergone several preceding modifications. Consequently, the observed temporal changes in survival, behavior, metamorphosis, or mortality cannot be attributed to any single intervention with confidence. Cumulative and interaction effects cannot be excluded, and temporal changes associated with larval development may also have contributed. The sequence should therefore be interpreted as an observational troubleshooting process rather than a series of independent treatment experiments. This limitation also applies to the role of the AI agent itself. Because the AI system generated hypotheses that were subsequently evaluated and implemented by human personnel, and because no comparison facility or non-AI control process was available, the present study cannot establish that AI use caused the observed operational changes. Instead, the study demonstrates the feasibility of integrating an LLM into an expert-supervised decision-support workflow. Prospective replicated trials in which individual interventions are independently evaluated would be required to establish their efficacy.

This case study reports that work conducted at a single commercial facility represents an observational $n = 1$ case study, thus imposing some conclusion limitations. No independent control facility or non-AI troubleshooting pathway was available. These limitations do not invalidate the operational observations, but they constrain the conclusions that can be drawn from them. In particular, the observations should be regarded as hypothesis-generating and methodologically illustrative rather than as evidence of the efficacy of individual interventions or of AI-assisted management. Future work should prospectively evaluate individual hypotheses using replicated control and treatment groups, predefined endpoints, standardized behavioral and developmental scoring, continuous water-quality monitoring where appropriate, and quantitative microbiological measurements.

In conclusion, the case study presented here illustrates a comprehensive approach to the integrative use of AI in closed RAS hatcheries, not just for farmers of prawns (such as *M. rosenbergii*), but also for those raising fish, shrimp, and other aquatic animals. In general, insights acquired from this study will be relevant to aquaculture farmers requiring interdisciplinary professional support. An AI-assisted process allows the isolation of problems, one at a time, while taking into consideration the accumulated history of changes made to the system. In the future, to include real-world considerations into AI-hatchery manager interaction, it will be essential to integrate profit-and-loss information into the framework. Profit-and-loss analysis should be integrated into the sequence of events after AI determination of the emerging challenge, followed by controlled/comparative trials and ahead of implementing the suggested intervention in the entire hatchery. This way, economic analysis of the event will permit or reject intervention based on potential profit-and-loss. A detailed evaluation of resource inputs versus resulting outputs will be critical for assessing economic efficiency and improving the outcomes of AI recommendations. AI could also be used for ample managerial tasks in the routine running of a RAS hatchery; however, in a world where the use of AI is becoming ubiquitously popular, the **responsible** use of AI tools to produce sustainable aquaculture products is important and could serve as a fresh breeze for a healthier, bluer future.

Declaration of generative AI and AI-assisted technologies in the writing process

During the writing of this work the authors used Gemini and ChatGPT for minor linguistic editing of the paper. After using those AI tools, the authors reviewed and edited the content and are fully responsible for the content of the manuscript.

Ethics declaration

This study was conducted in accordance with the following guidelines for animal welfare and/or reporting: Ethical approval was not required for this study, as *Macrobrachium rosenbergii* is an invertebrate species and is therefore not covered by national or institutional regulations governing the use of animals in scientific research. Nevertheless, all experimental procedures were conducted in accordance with generally accepted principles of animal welfare and good laboratory practice; no prawns were harmed during the study, and appropriate measures were taken to minimise stress and ensure the wellbeing of the animals throughout the experimental period. Ethics committee approval was not required. Ethical approval was not required for this study, as *Macrobrachium rosenbergii* is an invertebrate species and is therefore not covered by national or institutional regulations governing the use of animals in scientific research.

CRediT authorship contribution statement

Shai Avraham Shaked: Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis, Data curation, Conceptualization. **Assaf Shechter:** Writing – original draft, Resources, Project administration, Methodology, Conceptualization. **Amir Sagi:** Writing – review & editing, Writing – original draft, Supervision, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2026.102554.

Data availability

Data will be made available on request.

References

[1] FAO, The state of world fisheries and aquaculture. The State of World Fisheries and Aquaculture (SOFIA), FAO, 2022, p. 266, https://doi.org/10.4060/cc0461en.
[2] FAO, Global Aquaculture Production, FAO, 2025. https://www.fao.org/fishery/en/collection/aquaculture?lang=en.
[3] K. Chareontawee, S. Poompuang, U. Na-Nakorn, W. Kamonrat, Genetic diversity of hatchery stocks of giant freshwater prawn (*Macrobrachium rosenbergii*) in Thailand, Aquaculture 271 (1–4) (2007) 121–129, https://doi.org/10.1016/j.aquaculture.2007.07.001.
[4] F.S. David, F.P.A. Cohen, W.C. Valenti, Intensification of the Giant river prawn *Macrobrachium rosenbergii* hatchery production, Aquac. Res. 47 (12) (2016) 3747–3752, https://doi.org/10.1111/are.12824.
[5] F.S. David, T. Fonseca, G.W. Bueno, W.C. Valenti, Economic feasibility of intensification of *Macrobrachium rosenbergii* hatchery, Aquac. Res. 49 (12) (2018) 3769–3776, https://doi.org/10.1111/are.13844.
[6] Nhan, D. (2009). Optimization of hatchery protocols for *Macrobrachium rosenbergii* culture in Vietnam, PhD Thesis, Ghent University, Belgium. https://biblio.ugent.be/publication/2065067.
[7] S.W. Ling, The General Biology and Development of Macrobrachium Rosenbergii (de Man), FAO, 1967.
[8] Y.R. Chen, W.S. Hou, Y.H. Chen, C.Y. Chou, Study on low-energy recirculating aquaculture system (RAS) improve culture water quality in the growth and survival

rate of *Macrobrachium rosenbergii*, Taiwan Water Conserv. 70 (3) (2022) 1–10, https://doi.org/10.6937/TWC.202209_70(3.

[9] J.H. Tidwell, S. Coyle, A. Van Arnum, C. Weibel, Production response of freshwater prawns *Macrobrachium rosenbergii* to increasing amounts of artificial substrate in ponds, J. World Aquac. Soc. 31 (3) (2000) 452–458, https://doi.org/10.1111/j.1749-7345.2000.tb00895.x.

[10] J.H. Tidwell, S.D. Coyle, G. Schulmeister, Effects of added substrate on the production and population characteristics of freshwater prawns *Macrobrachium rosenbergii* in ponds, J. World Aquac. Soc. 29 (1) (1998) 17–22, https://doi.org/10.1111/j.1749-7345.1998.tb00295.

[11] J.H. Tidwell, L.R. D'Abramo, S.D. Coyle, D. Yasharian, Overview of recent research and development in temperate culture of the freshwater prawn (*Macrobrachium rosenbergii* De Man) in the South Central United States, Aquac. Res. 36 (3) (2005) 264–277, https://doi.org/10.1111/j.1365-2109.2005.01241.x.

[12] M.A. Camarin, A. Gonzaga, J. Jamis, A. Calpe, Effects of biofloc technology on water quality and growth performance of *Macrobrachium rosenbergii*, Isr. J. Aquac. Bamidgeh 75 (2) (2023), https://doi.org/10.46989/001c.88899.

[13] L.A. Fieber, P.L. Lutz, Magnesium and calcium metabolism during molting in the freshwater prawn *Macrobrachium rosenbergii*, Can. J. Zool. 63 (5) (1985) 1120–1124, https://doi.org/10.1139/z85-169.

[14] F.P. Da Costa, M.D.F. Arruda, K. Ribeiro, D.M.D.A. Pessoa, Influence of color and brightness on ontogenetic shelter preference by the prawn *Macrobrachium rosenbergii* (Decapoda: palaemonidae), Zoologia 40 (2023) e22023, https://doi.org/10.1590/S1984-4689.v40.e22023 (Curitiba).

[15] T. Aung, R. Abdul Razak, A. Rahiman Bin Md Nor, Artificial intelligence methods used in various aquaculture applications: a systematic literature review, J. World Aquac. Soc. 56 (1) (2025) e13107, https://doi.org/10.1111/jwas.13107Digital.

[16] O. Er-Rousse, A. Qafas, Artificial intelligence for the optimization of marine aquaculture, in: Proceedings of the E3S Web of Conferences 477, 2024 00102, https://doi.org/10.1051/e3sconf/202447700102.

[17] A.I. Francis, O.I. David, O.I. Fedora, Exploring the role of IoT, AI, and remote sensing in precision aquaculture: monitoring, automation, and data-driven decision-making, Magna Sci. Adv. Biol. Pharm. 14 (2) (2025) 018–033, https://doi.org/10.30574/msabp.2025.14.2.0018.

[18] M.M. Stofa, F.A.Z. Azizan, M.A. Zulkifley, A review of deep learning methods in aquatic animal husbandry, PeerJ Comput. Sci. 11 (2025) e3105, https://doi.org/10.7717/peerj-cs.3105.

[19] X. Yang, S. Zhang, J. Liu, Q. Gao, S. Dong, C. Zhou, Deep learning for smart fish farming: applications, opportunities and challenges, Rev. Aquac. 13 (1) (2021) 66–90, https://doi.org/10.1111/raq.12464.

[20] M.B. New, Farming Freshwater Prawns: A Manual for the Culture of the Giant River Prawn (*Macrobrachium rosenbergii*), 428, Food & Agriculture Organization, 2002.

[21] K. Hangsapreurke, T. Thamrongnawasawat, S. Powtongsook, P. Tabthipwon, P. Lumubol, B. Pratoomchat, Embryonic development, hatching, mineral consumption, and survival of *Macrobrachium rosenbergii* (de Man) reared in artificial seawater in closed recirculating water system at different levels of salinity, Majeo Int. J. Sci. Technol. 2 (3) (2008) 471–482.

[22] V. Srinivasan, P.S. Bhavan, G. Rajkumar, T. Satgurunathan, T. Muralisankar, Dietary supplementation of magnesium oxide (MgO) nanoparticles for better survival and growth of the freshwater prawn *Macrobrachium rosenbergii* post-larvae, Biol. Trace Elem. Res. 177 (2017) 196–208, https://doi.org/10.1007/s12011-016-0855-4.

[23] L.R. D'Abramo, W.H. Daniels, P.D. Gerard, W.H. Jun, C.G. Summerlin, Influence of water volume, surface area, and water replacement rate on weight gain of juvenile freshwater prawns, *Macrobrachium rosenbergii*, Aquaculture 182 (1–2) (2000) 161–171, https://doi.org/10.1016/S0044-8486(99)00258-6.

[24] M.A. Islam, S.S. Islam, J. Bir, P. Debnath, M.R. Ullah, K.A. Huq, Effect on water quality, growth performance and economics of giant freshwater prawn, *Macrobrachium rosenbergii* with partial feed in biofloc system, Aquac. Fish Fish. 3 (5) (2023) 435–446, https://doi.org/10.1002/aff2.126Digital.

[25] K. Hangsapreurke, T. Thamrongnawasawat, S. Powtongsook, P. Tabthipwon, P. Lumubol, B. Pratoomchat, Effect of salinity on embryonic development of *Macrobrachium rosenbergii* (De Man), J. Fish Technol. 2 (2010) 1–11.

[26] H.J. Liew, S. Rahmah, P.W. Tang, K. Waiho, H. Fazhan, N.W. Rasdi, S.I.A. Hamin, S. Mazelan, S. Muda, L.S. Lim, Low water pH depressed growth and early development of giant freshwater prawn *Macrobrachium rosenbergii* larvae, Heliyon 8 (7) (2022) e09989, https://doi.org/10.1016/j.heliyon.2022.e09989.

[27] M.C. Miglio, B. Zaga, J.C. Gastelu, W. Severi, S. Peixoto, Survival and metamorphosis of giant river prawn *Macrobrachium rosenbergii* larvae in a commercial recirculation system with artificial seawater, Aquac. Res. 52 (12) (2021) 6063–6073, https://doi.org/10.1111/are.15468.

[28] W.H. Li, X.J. Cheng, J. Xie, Z.L. Wang, D.G. Yu, Hydrodynamics of an in-pond raceway system with an aeration plug-flow device for application in aquaculture: an experimental study, R. Soc. Open Sci. 6 (7) (2019) 182061, https://doi.org/10.1098/rsos.182061.

[29] P. Ramesh, A. Jasmin, M. Tanveer, R.U. Roshan, P. Ganeshan, K. Rajendran, S. M. Roy, D. Kumar, A. Chinnathambi, K. Brindhadevi, Optimizing aeration efficiency and forecasting dissolved oxygen in brackish water aquaculture: insights from paddle wheel aerator, J. Taiwan Inst. Chem. Eng. 156 (2024) 105353, https://doi.org/10.1016/j.jtice.2024.105353.

[30] K.R. Tavabe, G. Rafiee, M. Frinsko, H. Daniels, Effects of different calcium and magnesium concentrations separately and in combination on *Macrobarchium rosenbergii* (de Man) larviculture, Aquaculture 412 (2013) 160–166, https://doi.org/10.1016/j.aquaculture.2013.07.023.

[31] R. Rasid, A.L. Tajuddin, M.A.A. Abu Zarim, S. Thanakodi, S.B. Rahayu, N. D. Kamarudin, A.A. Omar, M.F.H.A. Aziz, A. Habib, Tolerance limit of physicochemical water parameters in giant freshwater prawn (*Macrobrachium rosenbergii*) in a captive condition, Turk. J. Zool. 47 (5) (2023) 291–298, https://doi.org/10.55730/1300-0179.3142.

[32] G. Kawamura, T.U. Bagarinao, A.S.K. Yong, A.B. Faisal, L.S. Lim, Limit of colour vision in dim light in larvae of the giant freshwater prawn *Macrobrachium rosenbergii*, Fish. Sci. 84 (2) (2018) 365–371, https://doi.org/10.1007/s12562-018-1179-4.

[33] P.A. Sandifer, T.I. Smith, Freshwater prawns. Crustacean and Mollusk Aquaculture in the United States, Springer, 1985, pp. 63–125.

[34] C.T. Tao, T.N. Khoa, P.M. Truyen, N.V. Hoa, C.M. An, T.N. Hai, Effects of light intensity on growth and survival rate of freshwater prawn (*Macrobrachium rosenbergii*) at larvae and postlarvae stages in biofloc system, Aquac. Aquar. Conserv. Legis. 14 (6) (2021) 3556–3565.

[35] B. Kennedy, M. Venugopal, I. Karunasagar, I. Karunasagar, Bacterial flora associated with the giant freshwater prawn *Macrobrachium rosenbergii*, in the hatchery system, Aquaculture 261 (4) (2006) 1156–1167, https://doi.org/10.1016/j.aquaculture.2006.09.015.

[36] Z. Lu, W. Lin, Q. Li, Q. Wu, Z. Ren, C. Mu, C. Wang, C. Shi, Y. Ye, Recirculating aquaculture system as microbial community and water quality management strategy in the larviculture of *Scylla paramamosain*, Water Res. 252 (2024) 121218, https://doi.org/10.1016/j.watres.2024.121218.

[37] M.A. Monghit-Camarin, E.R. Cruz-Lacierda, R. Pakingking Jr, M.L. Cuvin-Aralar, R. F. Traifalgar, N.C. Añasco, F. Austin, M. Lawrence, Bacterial microbiota of hatchery-reared freshwater prawn *Macrobrachium rosenbergii* (de Man, 1879), Asian Fish. Sci. 33 (2020) 241–248, https://doi.org/10.33997/j.afs.2020.33.3.005.

[38] M. Cheng, C. Lee, P. Khadpe, S. Yu, D. Han, D. Jurafsky, Sycophantic AI decreases prosocial intentions and promotes dependence, Science 391 (6792) (2026), https://doi.org/10.1126/science.aec8352.

[39] L. Malmgvist, Sycophancy in large language models: causes and mitigations, Intell. Comput. 1426 (2025) 61–74, https://doi.org/10.1007/978-3-031-92611-2_5.