Application of Large Language Models in Developing Conversational Agents for Water Quality Education, Communication and Operations

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Abstract

The rapid advancement of Large Language Models (LLMs), such as ChatGPT, has opened new horizons in the field of Artificial Intelligence (AI), revolutionizing the way we can engage with and disseminate complex information. This paper presents an innovative application of ChatGPT in the domain of Water Quality (WQ) management, through the development of an AI Hub. The Hub encompasses a suite of conversational agents, each designed to address different aspects of water quality management, including nitrogen pollution, local water quality issues, and actionable planning for water conservation. These agents utilize the advanced natural language processing capabilities of ChatGPT, complemented with water quality-related data, to provide users with accurate, up-to-date, and contextually relevant information. The objective is to empower communities with the knowledge necessary to understand and address water quality challenges effectively. Our comprehensive evaluation of these agents demonstrates their proficiency in delivering valuable insights, with an overall performance accuracy exceeding 89%. This paper underscores the potential of AI-enabled platforms in enhancing public understanding and engagement in environmental conservation efforts. By bridging the gap between complex environmental data and public awareness, the AI Hub sets a precedent for the application of AI in sustainable environmental management.

Keywords: water quality, intelligent systems, artificial intelligence, large language models, ChatGPT, chatbots, operational agents

1. Introduction

The challenge of maintaining and improving water quality is a pivotal concern in environmental science, directly impacting ecological balance, public health, and economic sustainability [Merwade et al., 2024]. Nutrients such as nitrogen and phosphorus are essential for the growth of aquatic life; however, their excessive presence, primarily due to human activities like agriculture and urban runoff, leads to nutrient pollution. This form of pollution has escalated into a global crisis, fostering conditions such as eutrophication and harmful algal blooms in water bodies, from streams and rivers to oceans and lakes. These environmental phenomena not only disrupt aquatic ecosystems but also pose serious health risks to humans and economic challenges to communities dependent on these water resources [Rolton et al., 2022; Driscoll et al., 2003].

The adverse effects of nutrient pollution extend to the degradation of drinking water sources, with nitrates, a common form of nitrogen found in fertilizers, presenting significant health concerns. Recent assessments have shown that nitrates exceed safe levels in a substantial percentage of monitoring wells, affecting both agricultural and urban areas. The resultant water quality issues highlight the urgent need for effective management strategies that can address the complex, multi-dimensional nature of water pollution [Moss et al., 2008; US Geological Survey, 2010].

In response to these challenges, the advent of Large Language Models (LLMs) like ChatGPT offers a transformative approach to water quality management. These models' capacity for processing vast datasets, coupled with their advanced natural language processing (NLP) capabilities, presents an opportunity to enhance decision-making processes, public engagement, and educational efforts in environmental science [Qin et al., 2023; De Angelis et al., 2023]. The application of LLMs in creating intelligent, conversational agents can revolutionize the way information on water quality is disseminated and understood by the public, fostering a more informed and proactive community engagement.

This study aims to leverage the potential of LLMs to develop a suite of conversational agents tailored for water quality management. These agents are designed to provide up-to-date, accurate, and accessible information on various aspects of water quality, focusing particularly on combating nitrogen pollution. By integrating scientific evidence with storytelling, creating inclusive educational materials, and establishing a platform for sustainable management and community action, this work endeavors to address the pressing challenges of nutrient pollution. Through a comprehensive exploration of the design, functionality, and impact of these conversational agents, the study contributes to the broader discourse on employing AI-driven technologies for environmental conservation and sustainable water management [Gozalo-Brizuela et al., 2023; OpenAI 2023; Altman et al., 2023; Khowaja et al., 2023].

The utilization of ChatGPT in this study underscores a transformative shift towards integrating advanced AI-driven technologies in environmental conservation efforts. The creation of the various conversational agents serving community and operational roles like Virtual Champion, Nitrogen Expert, Local WQ Expert, Action Planner, and Data Expert represents a multidimensional approach to tackling water quality issues, offering users tailored, accessible, and up-to-date information. These agents are designed not only to inform but also to engage users in a meaningful dialogue about water quality management, particularly focusing on the mitigation of nitrogen pollution. The benefits of the proposed agents underscore the innovative application of AI in environmental science:

Location-Specific Agents: By developing agents with the capability to provide localized water quality information for regions such as Iowa, Tampa Bay, and the Virgin Islands, this study addresses the need for region-specific water quality management strategies.

Comprehensive Data Retrieval: The agents' ability to access and analyze a wide array of water quality-related data, from quantitative metrics to statistical analyses, through a JSON format API, exemplifies the use of RestAPI in facilitating efficient data retrieval.

Multilingual Capability: Recognizing the importance of inclusivity, the multilingual functionality of these agents ensures that language barriers do not impede access to crucial water quality information, allowing users to receive responses in their preferred language.

Empathetic Responses: The study advances the empathetic capabilities of conversational agents, ensuring that interactions are not only informative but also cognizant of the users' emotional and contextual nuances.

Efficient Filtering: Through the implementation of sophisticated prompting techniques, the agents effectively filter out irrelevant queries and inappropriate language, maintaining a focus on providing relevant and constructive water quality information.

These benefits collectively highlight the study's role in enhancing the effectiveness, accessibility, and user engagement of water quality management practices through AI technologies. By bridging the gap between complex environmental data and actionable insights, this work sets a precedent for future endeavors in the application of AI for sustainable environmental management. Through the detailed exploration of the design, functionality, and impact of these conversational agents, the study not only contributes to the scientific discourse on AI and environmental science but also paves the way for innovative solutions to global water quality challenges.

The remainder of this article is organized as follows: Section 2 offers an overview of existing literature on chatbots, intelligent assistants, ontologies, and language models within hydrology and water management, identifying the knowledge gap this study addresses. Section 3 outlines the methodology, including the design and development of ChatGPT-powered agents, their technical foundations, and evaluation criteria for ensuring information accuracy and relevance. Section 4 presents study results, including agent performance in practical scenarios, impact on user engagement, and the efficacy of multilingual and empathetic responses. Section 5 discusses the findings' implications, AI's role in water quality management, limitations of the current study, and directions for future research. Section 6 concludes by summarizing the study's contributions to AI in water quality management and its significance for environmental conservation and sustainable management.

2. Background

Artificial Intelligence (AI plays a vital role in the field of water quality management. It helps with different aspects of the WQ management, such as collecting, understanding, predicting, planning, and solving water-related issues such as pollution and resource use. Lately, AI has increased its application to various fields, such as hydraulic engineering, hydrology, agriculture, ecology, nitrogen pollution, and the blue economy, using data-based knowledge to promote progress [Yang et al., 2022].

2.1. Previous Work

The integration of artificial intelligence (AI) within the domain of environmental sciences, especially concerning water resources management [Sermet and Demir, 2023], hydrology, and water quality, has increasingly garnered attention [Sit et al., 2020]. This burgeoning interest aligns with the global imperative to harness innovative technologies for sustainable environmental stewardship [Erazo et al., 2023]. Among the diverse AI applications, chatbots, intelligent assistants, ontologies, and language models have emerged as significant tools, offering novel approaches to water-related challenges.

In the realm of water resources management, the deployment of chatbots and intelligent assistants has revolutionized stakeholder engagement and information dissemination [Sermet and Demir, 2018]. These AI-driven interfaces facilitate real-time interaction with users, providing instant access to critical water quality data, advisories, and conservation tips [Sermet and Demir, 2021]. For instance, conversational agents have been developed to guide individuals through water-saving practices or to alert communities about potential water contamination events. The utility of these systems extends to disaster management, where chatbots offer immediate guidance and support during water-related emergencies, such as floods or waterborne disease outbreaks [Sermet and Demir, 2020].

In the context of knowledge bases, ontologies, which provide a structured framework for organizing information, have been instrumental in enhancing data interoperability and sharing within the water science community [Baydaroglu et al., 2023]. By establishing a common vocabulary and set of relationships among key concepts, ontologies enable more effective integration and analysis of disparate data sources. This approach has proven particularly valuable in water resources management, where data from various sensors, databases, and studies must be harmonized to inform decision-making processes. Ontological models have supported the development of comprehensive water quality monitoring systems, facilitating a holistic understanding of watershed health [Sermet and Demir, 2019].

The advent of sophisticated language models, such as GPT (Generative Pretrained Transformer) variants, has opened new avenues for analyzing textual data in hydrology and water quality research [Sajja et al., 2024]. These models can extract insights from vast corpora of scientific literature, policy documents, and online discussions, identifying emerging trends, knowledge gaps, and consensus within the scientific community [Pursnani et al., 2023]. Language models have also been applied to automate the generation of reports and summaries, making complex hydrological data more accessible to non-expert audiences [Sajja et al., 2023b].

Despite the promising applications of AI in addressing water-related challenges, the field is still navigating several hurdles. The accuracy and reliability of chatbots and intelligent assistants depend heavily on the quality and scope of the underlying data and models [Sajja et al., 2023a]. Additionally, the effectiveness of these tools in engaging diverse user groups hinges on their ability to provide contextually relevant, understandable, and linguistically inclusive responses [Sajja et al., 2023c]. Moreover, the development of ontologies and the application of language models in hydrology require ongoing collaboration between domain experts and AI specialists to ensure that the generated insights are scientifically sound and practically useful.

Previous work in leveraging AI tools like chatbots, intelligent assistants, ontologies, and language models has demonstrated considerable potential to enhance water resources management, hydrology, water quality monitoring, and disaster response. These technologies offer innovative solutions for data analysis, stakeholder engagement, and information dissemination, contributing to more informed and effective water management practices [Demiray et al., 2023]. As the field continues to evolve, interdisciplinary research and development efforts will be crucial to overcoming existing challenges and fully realizing the benefits of AI in water science.

2.2. Knowledge Gap

The evolution of technology and its application in environmental science have significantly advanced our understanding and management of water quality issues. However, despite these strides, a noticeable knowledge gap persists, particularly in the realm of nutrient pollution and its comprehensive management. This gap is not merely a limitation in technological capabilities but extends to the integration of community engagement, educational outreach, and sustainable solution development within water quality initiatives. Traditional approaches often overlook the critical role of human-centered design, storytelling, and inclusivity in fostering meaningful interaction and engagement with water quality data and conservation efforts.

The development of intelligent agents in water quality management presents an opportunity to bridge this knowledge gap by focusing on several key objectives that align technology with human and environmental needs. These objectives underscore the necessity of creating solutions that are not only technologically advanced but also deeply integrated with the community's fabric, ensuring that the solutions are accessible, engaging, and effective in promoting sustainable water management practices.

Advancing Human-Centered Design: The first objective emphasizes the importance of placing individuals and communities at the core of solution development. This involves understanding the specific needs, challenges, and contexts of those affected by water quality issues and designing intelligent agents that cater to these requirements. A human-centered approach ensures that the technology developed is not only functional but also relevant and adaptable to the users' changing needs.

Integrating Storytelling and Scientific Evidence: By combining the art of storytelling with the rigor of scientific evidence, intelligent agents can more effectively communicate the complexities of water quality issues. This objective aims to leverage personal narratives and real-life experiences as powerful tools for education and motivation, making the scientific data on nutrient pollution relatable and actionable. Storytelling can bridge the emotional and cognitive gaps, enabling communities to grasp the significance of the data and its implications on their lives and the environment.

Creating Inclusive Educational Materials: Addressing the knowledge gap requires making water quality information and management strategies accessible to a broad audience. This objective focuses on developing educational materials that are inclusive and understandable by people from diverse backgrounds, ages, and educational levels. Ensuring that the language, format, and dissemination channels of these materials are inclusive amplifies the reach and impact of water quality management efforts, empowering more individuals to participate in conservation activities.

Establishing a Sustainability Plan: For intelligent agents to have a lasting impact on water quality management, they must be supported by a robust sustainability plan. This involves securing ongoing support, identifying sustainable funding mechanisms, and implementing strategies for continuous improvement and adaptation. A sustainability plan guarantees that the intelligent agents remain relevant, up-to-date, and effective in addressing both current and future water quality challenges.

By targeting these objectives, the development of intelligent agents in water quality management can significantly contribute to closing the existing knowledge gap. Such agents are envisioned to not only provide technological solutions but also to foster a culture of awareness, education, and active participation in water quality conservation, ensuring that efforts to combat nutrient pollution are sustained and effective.

2.3. Characterizing ChatGPT

In the quest to address the multifaceted challenges of water quality management, particularly nutrient pollution, the role of advanced technological interventions cannot be overstated. Among the plethora of innovations, ChatGPT, a Large Language Model (LLM) developed by OpenAI, emerges as a particularly promising tool. Its exceptional ability to process natural language, generate coherent and contextually relevant responses, and engage users in meaningful interactions sets it apart as a valuable asset in environmental science applications.

The effectiveness and versatility of ChatGPT can be attributed to several key factors, including its data sources, architectural design, and the process of fine-tuning that tailors its capabilities to specific tasks. These elements collectively contribute to ChatGPT's success in various domains, including water quality management [Daull et al., 2023; Carlini et al., 2021; Vaswani et al., 2017].

The foundation of ChatGPT's performance lies in the diversity and quality of its training data. Comprising a wide array of sources such as articles, interviews, books, reports, and websites, the dataset ensures comprehensive coverage of language usage and content diversity. However, the mere collection of vast data is insufficient; meticulous curation is imperative to enhance the model's language comprehension and generation capabilities [Carlini et al., 2021]. This rigorous process of data selection and refinement enables ChatGPT to achieve a deeper understanding of human language, facilitating the generation of responses that are not only accurate but also contextually appropriate.

At the core of ChatGPT's functionality is its architecture, built upon advanced neural networks known as transformers [Vaswani et al., 2017]. This innovative design significantly improves the model's ability to understand the nuances and complexities of natural language. Transformers utilize attention mechanisms, allowing the model to emphasize relevant parts of the input text during information processing. Such a feature enables ChatGPT to capture long-range dependencies and intricate patterns within the language, thereby providing a more profound understanding of context and meaning. The multi-layered architecture, comprising attention and feed-forward neural network layers, is instrumental in handling a broad spectrum of language tasks, further enhancing ChatGPT's effectiveness.

Fine-tuning represents a critical phase in the development of LLMs like ChatGPT. This process involves training the model on a smaller, task-specific dataset, enabling it to adapt to particular objectives, ranging from text completion to question answering [Malladi et al., 2023; Jin et al., 2024]. Through fine-tuning, ChatGPT becomes specialized, improving its performance on designated tasks by leveraging prior knowledge gained from the initial training on extensive datasets. This adaptability and precision in response generation underscore ChatGPT's utility in practical applications, including those in environmental monitoring and communication.

Ongoing research and development efforts are dedicated to enhancing ChatGPT's capabilities, addressing potential biases, and ensuring ethical and responsible AI usage. These endeavors aim to expand the boundaries of what LLMs can achieve, making tools like ChatGPT increasingly effective in tackling complex issues such as water quality management. The integration of ChatGPT into the development of intelligent water quality agents represents a forward-thinking approach, combining technological sophistication with strategic objectives to address the pressing challenges of nutrient pollution and water resource management effectively.

3. Methodology

The crucial component of the water quality intelligent agent is the user-friendly and interactive interface that enables seamless interaction with users. This is achieved through the integration of five distinct agents, with ChatGPT serving as the backbone. In this section, we will delve into the agent design and workflow, chatbot's core engine, architecture, parameter optimization and prompt tuning to ensure optimal performance and user satisfaction.

3.1. Scope and Purpose

The BlueGAP initiative, funded by National Science Foundation Convergence Accelerator program, is at the forefront of combating nitrogen pollution by harnessing the collective power of community engagement, scientific research, and innovative technology [BlueGAP, 2024]. This mission is to empower communities, particularly those at the frontlines of environmental challenges, with the knowledge and tools necessary to effect meaningful change in water quality management. Through the BlueGAP AI Hub, we aim to bridge the gap between data and action, making complex information about nitrogen pollution accessible and actionable for all. At the core of our approach is the blend of human-centered storytelling with cutting-edge scientific evidence. The approach is rooted in the power of stories to inspire action and the necessity of rigorous science to guide those actions towards effectiveness and sustainability.

To actualize this vision, we have developed a suite of conversational agents, powered by the ChatGPT, each designed to cater to distinct aspects of water quality management (Figure 1). These agents form the backbone of the BlueGAP platform, offering users an interactive and personalized experience:

- *Virtual Champion*: Serves as a conduit for local expertise, drawing upon the insights of human champions from specific regions to provide advice and information tailored to the local context.
- *Nitrogen Expert*: Specializes in delivering detailed information on nitrogen pollution, equipping users with the knowledge needed to understand and address this critical issue.
- *Local WQ Expert*: Offers localized data and solutions, focusing on the unique water quality challenges faced by specific communities.
- *Action Planner*: Supports users in devising actionable strategies for water quality management, aiding in the translation of knowledge into concrete steps for improvement.
- *Data Expert*: Provides users with statistical insights into water quality, leveraging dedicated API endpoints to present comprehensive data analyses.

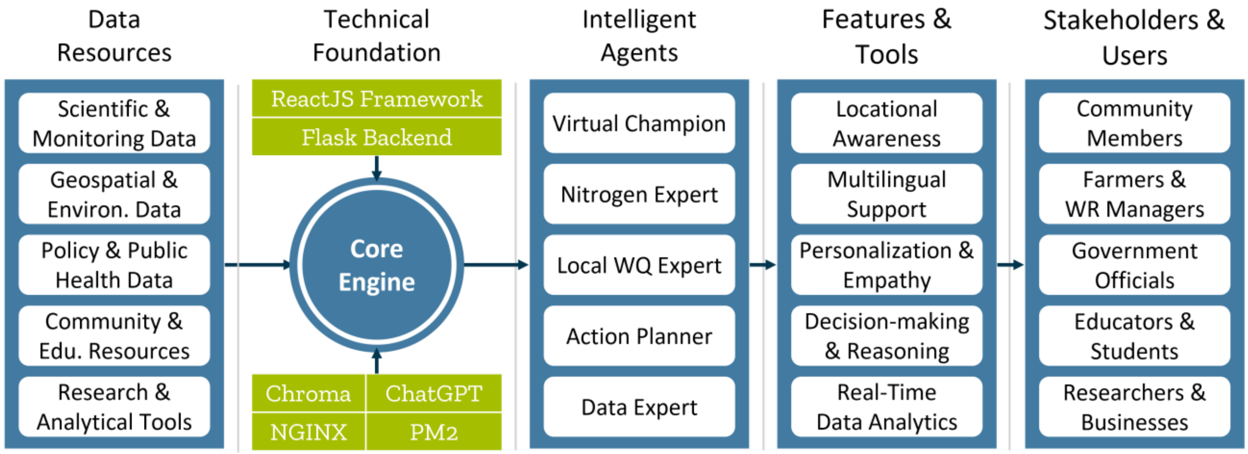


Figure 1: BlueGAP intelligent agents' workflow and the ability of human intelligence and reasoning in answering user questions through LLMs.

These agents are integral to the strategy of making scientific data and community wisdom readily available and understandable. By engaging users in meaningful conversations, the platform aims to demystify complex topics, encourage informed decision-making, and inspire collective action towards a healthier, more sustainable water ecosystem.

The BlueGAP project is driven by the conviction that informed communities are empowered communities. The multifaceted approach combines the depth of scientific research with the breadth of community knowledge, all facilitated by cutting-edge AI technology. Whether through the engaging narratives of the Virtual Champion, the detailed analyses of the Data Expert, or the strategic guidance of the Action Planner, BlueGAP is dedicated to equipping individuals and communities with the tools they need to combat nitrogen pollution effectively.

3.2. Agent Design and Workflow

The trained ChatGPT model is made accessible to users through an API service, enabling developers and applications to leverage its capabilities for various tasks. In our work, we have utilized the ChatGPT API and further fine-tuned the model with our water quality dataset, incorporating specific WQ data and prompts. This process has enabled us to develop intelligent agents tailored for the BlueGAP project. The ChatGPT API allows developers to interact with the ChatGPT model programmatically by making HTTP requests to the API endpoint.

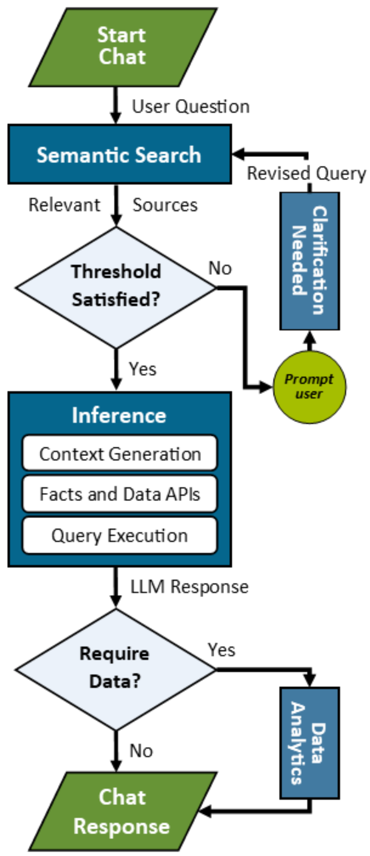


Figure 2: Flowchart of question answering via BlueGAP Intelligent Agents

The API serves as a bridge between the developer's application and the powerful language model, enabling the integration of ChatGPT's capabilities into various applications, including the development of conversational agents [Kojima et al., 2023]. The conversational agent can utilize

API calls to ChatGPT at each turn of the conversation, allowing it to provide real-time responses to user queries. The agent can maintain context by remembering previous interactions and incorporating that information into the subsequent queries, creating a more natural and engaging conversation. Figure 2 describes the generalized workflow of the agents.

3.3. Data Sources

The water quality dataset serves as a crucial foundation for providing accurate and relevant responses from the BlueGAP intelligent agents. This dataset is sourced from diverse sources, including interviews, reports, US government surveys, reliable internet sources, government bills, and input from volunteers and community members. By collating this collective data, a comprehensive data corpus is created to empower the BlueGAP intelligent agents.

For the Virtual Champion chatbot, data is collected through interviews with local water quality enthusiasts (champions) from the community. These interviews are video recorded, and the transcripts are utilized to build the data corpus. The information obtained from the champions includes details about pollution levels, sources of pollution, actions taken, and voluntary activities focused on improving water quality. The collected data is location-specific, covering areas like Iowa, Tampa Bay, and US Virgin Islands.

The Nitrogen Expert has data from reports and reliable internet sources. The collected data encompasses generic terms of water pollution, nitrogen pollution, and the impact of water pollution on ecology, economy, and human life. The Local WQ Expert, in addition to the above data sources, obtains location-specific data. This data includes information on green infrastructure practices, local wastewater management, contamination concerns, fishing, and wildlife, catering to the specific needs of the respective location. Additionally, both the Nitrogen Expert and Local WQ Expert have incorporated resources from BIMS Bytes, an initiative by Black in Marine Science, which enriches their database with educational content on Nature-Based Solutions, mangrove forests, and coral reefs, making complex environmental concepts accessible to all [Moore, 2022].

The Action Planner's dataset is gathered from government surveys and reports on action planning to reduce water pollution. It includes strategies for water nutrient management, combating algal blooms, minimizing nitrogen runoff from urban landscapes, and initiatives for creating awareness.

The Data Expert provides statistical insights based on location and time-specific data. Custom APIs are created in JSON format, and data is sourced from government agencies like NWIS, STORET, PWTS, and SDWA. Users can access this data through the chatbot and gain valuable insights for their respective dates and locations.

Overall, the comprehensive water quality dataset forms the backbone of the BlueGAP intelligent agents, enabling them to provide well-informed and accurate responses, tailored to the unique needs and queries of users across various locations.

3.4. Core AI Engine

The Core AI Engine is the foundational element of the BlueGAP Intelligent Agent, designed to harness the power of LLMs for the nuanced field of water quality management. It integrates sophisticated NLP and Named Entity Recognition (NER) capabilities, underpinned by the advanced architecture of ChatGPT. This engine is tasked with the critical functions of interpreting user queries, processing water quality data, and generating accurate, contextually relevant responses. Through its comprehensive design, the Core AI Engine ensures that the BlueGAP agents can effectively engage with users, providing them with valuable insights into water quality issues.

System Architecture: The BlueGAP Intelligent Agent system architecture is a multifaceted structure designed to optimize the delivery of water quality information through conversational AI. At its core, the system leverages the advanced capabilities of ChatGPT specifically fine-tuned for interactive applications such as chatbots. This model excels in processing sequential data and understanding complex context-based queries, making it an ideal foundation for BlueGAP agents.

Backend Application: The system's backbone is a Flask Backend application, serving as the Core AI Engine that interfaces with the ChatGPT model. Flask, a lightweight and flexible Python web framework, facilitates rapid development and deployment, enabling seamless integration with LLM services provided by OpenAI's API.

Database for Embeddings: For efficient data handling and retrieval, the architecture incorporates ChromaDB, a database specifically designed for storing and managing embeddings. This allows for quick access to pre-processed textual data, enhancing the system's responsiveness and accuracy in information retrieval.

Search and Source Retrieval: Langchain, a library designed for enhancing LLM applications, is employed for advanced search and source retrieval operations. It augments the system's capability to sift through extensive data sets, ensuring that users receive the most relevant and up-to-date information.

Frontend Application: The user interface is powered by ReactJS, a widely used JavaScript library for building dynamic and responsive UIs. The ReactJS-based frontend application presents a user-friendly chat interface, allowing for intuitive interaction with the BlueGAP agents.

Server Management: Nginx, a robust web server, is utilized for server management, ensuring efficient handling of requests and static content delivery. This component plays a critical role in maintaining the system's stability and scalability.

Process Management: To minimize downtimes and enhance system reliability, PM2, a process manager for Node.js applications, is integrated for process management. It ensures that the system remains operational and responsive, even under high load conditions.

Logging: The architecture also incorporates comprehensive logging mechanisms, enabling ongoing monitoring and optimization of the system's performance. This aspect is crucial for identifying and addressing potential issues, ensuring a smooth user experience.

Data Storage: Within the foundational structure of the BlueGAP platform, the Core AI Engine employs a methodical approach to data storage, centralizing all data resources within Chroma DB.

This database is a crucial component, serving as the repository for embeddings. Each embedding is a high-dimensional representation of data points, crafted to encapsulate the intrinsic characteristics of the information in a 1536-dimensional vector space. These embeddings are generated using OpenAI's text-embedding-3-small model, renowned for its ability to produce detailed and nuanced embeddings that significantly enhance the retrieval process. The implementation of this model, orchestrated through the use of Langchain in Python, allows for a seamless integration of advanced AI techniques within the BlueGAP platform. Moreover, a distinctive feature of this data storage approach is the transparency and accessibility it offers to users. For every response generated by the platform, the source documents from which the information was derived are provided. This not only facilitates validation of the information presented but also encourages users to delve deeper into the sources for further exploration and understanding. Through this meticulous organization and presentation of data, the BlueGAP platform ensures that users are equipped with reliable and verifiable information, reinforcing the credibility and utility of intelligent agents in water quality management.

NLP Techniques: The Core AI Engine employs a suite of sophisticated Natural Language Processing (NLP) techniques, facilitated by an LLM, to enhance its interaction capabilities with users. These techniques, which include tokenization, sentence segmentation, part-of-text tagging, and Named Entity Recognition (NER), are integral to the nuanced understanding and processing of user queries related to water quality management.

Tokenization serves to decompose complex user inputs into discrete tokens, allowing the Core AI Engine to efficiently analyze inquiries at a granular level. This process is crucial for managing the diversity and complexity of user queries. Sentence segmentation complements this by identifying and isolating individual sentences within multi-sentence queries, ensuring that each is interpreted within its unique context. This is particularly valuable for deciphering compound questions that require detailed, contextually relevant responses.

Moreover, Named Entity Recognition (NER) is employed to detect and categorize essential elements within the user's input, such as specific water quality parameters, geographical locations, and temporal references. Utilizing an LLM, NER enables the Core AI Engine to tailor its responses based on the identified entities, ensuring that information provided is directly relevant to the user's specific inquiry. For example, when a query involves a particular contaminant and region, NER ensures the response focuses on water quality issues pertinent to that region.

Water Quality Data Processing: The Core AI Engine, customized for each of the five agents (Virtual Champions, Nitrogen Expert, Local WQ Expert, Action Planner and Data Expert), plays a vital role in processing water quality data to provide accurate responses to user queries. Depending on the context and expertise of each chatbot, the Core AI Engine accesses specific data sources or text files related to the respective area of focus. For the Virtual Champions chatbot, the Core AI Engine may access water quality information shared by champions relevant to specific regions, such as Iowa and Tampa. This data could include details about hydrological conditions, water resources, agricultural patterns, nitrogen pollution and other water quality factors pertinent to the mentioned regions. On the other hand, for the Nitrogen Expert and Local WQ Expert chatbots, retrieves water quality-related information encompassing various water quality parameters, such as nitrogen levels, pH values, dissolved oxygen, and other relevant indicators. The data processing allows the chatbots to analyze and interpret water quality information, providing insightful advice and recommendations to users.

Contextual Understanding: The contextual understanding allows the chatbot to comprehend the ongoing conversation and consider the user's previous inputs when formulating its answers. By taking into account the conversation history, the chatbot can maintain continuity and coherence in its responses. It can refer back to earlier queries, understand the context of current questions, and tailor its answers accordingly. This contextual understanding enhances the user experience, as the chatbot can engage in more natural and fluid interactions, simulating human-like conversation. For instance, if a user asks a series of questions related to water quality in a specific region, the chatbot can remember and refer back to previous information shared during the conversation. The ability to retain context throughout the conversation allows the chatbot to better understand complex queries that involve multiple related topics or require contextual knowledge. As a result, the responses generated by the Core AI Engine feel more coherent, relevant, and connected to the ongoing interaction, fostering a more satisfying and immersive user experience.

Error Handling and Fallback Mechanism: It is an essential component of the Core AI Engine, designed to ensure smooth interactions and user satisfaction. These mechanisms come into play when the chatbot encounters ambiguous queries or lacks sufficient context to provide accurate responses.

- *Ambiguous Query Handling*: When the chatbot receives a query that is unclear or ambiguous, the error handling mechanism is triggered. Instead of providing inaccurate or irrelevant responses, the Core AI Engine takes a proactive approach by seeking clarification from the user. It may ask follow-up questions to better understand the user's intent and context, ensuring that the subsequent response is accurate and meaningful.
- *Lack of Context Fallbacks*: In cases where the chatbot lacks sufficient context to generate a precise answer, the fallback mechanism comes into play. The chatbot can gracefully handle such situations by suggesting alternative options or providing general information related to the topic. This prevents the chatbot from being stuck or providing incorrect answers, enhancing the user experience.
- *Suggesting Alternative Options*: The error handling and fallback mechanisms also enable the Core AI Engine to suggest alternative options or related topics when it is uncertain about the user's specific intent. By offering these alternatives, the chatbot ensures that users receive valuable information, even if the original query was not entirely clear.

By incorporating error handling and fallbacks, the Core AI Engine demonstrates a robust and user-friendly behavior. It strives to minimize frustration for users by actively seeking clarity and providing helpful information, even when faced with ambiguous queries or limited context.

3.5. Prompting and Parameter Tuning

In BlueGAP agents, customized prompts are carefully designed and tailored to extract specific information and identify semantic roles from user queries effectively [Sun et al., 2023]. These prompts are strategically crafted to guide the ChatGPT model's responses, ensuring the agents deliver accurate and contextually relevant information [Zhou et al., 2023, Hebenstreit et al., 2023].

Information Extraction Prompts: For the Virtual Champion agent, prompts are designed to ask users for precise details about their location or the region they are interested in. This information extraction prompt helps the agent focus on providing localized insights from the human champions in that particular area, ensuring personalized and relevant responses [Cao et al., 2023].

Semantic Roles Identification Prompts: In the Nitrogen Expert agent, prompts are formulated to identify semantic roles related to nitrogen pollution. These prompts prompt users to ask specific questions about nitrogen levels, sources of pollution, and potential mitigation strategies. By guiding users to provide well-structured queries, the agent can efficiently identify and address relevant semantic roles, enhancing the accuracy of its responses.

Local Community Data Collection Prompts: For the Local Data Expert agent, customized prompts seek data specific to the local community. Users are encouraged to input information regarding local water quality parameters, pollution sources, and community-specific challenges. These prompts facilitate the extraction of data that aligns with the agent's expertise, allowing it to provide tailored solutions for the local community.

Action Planning and Monitoring Prompts: The Action Planner agent employs prompts that informs users to define their water quality management and monitoring needs. These prompts help the agent extract essential information to develop effective action plans and recommendations, supporting users in their decision-making process.

Statistical Data Insights Prompts: For the Data Expert agent, customized prompts are geared towards extracting relevant statistical data from users. Users may input specific water quality measurements, data points, or data parameters through these prompts. By collecting focused data inputs, the agent can generate insightful statistical analysis and data-driven insights.

By utilizing well-crafted customized prompts, BlueGAP agents uses the power of the ChatGPT model to extract targeted information and understand the semantic roles of user queries accurately. This approach ensures that the agents provide valuable and contextually appropriate responses, enhancing the overall effectiveness and user experience of the BlueGAP platform in the field of water quality management. Figure 3 illustrates the prompt generation process that encompasses three key components: Agent Dynamics, Response Mechanics, and Informational Core, each contributing to the intelligent dialogue capabilities of conversational agents.

In the BlueGAP AI Hub, the diverse array of conversational agents necessitates the adjustment of the temperature parameter to suit their varied roles and objectives. Temperature, a critical factor in determining the randomness and creativity of responses generated by these agents, plays a pivotal role in tailoring interactions to meet specific informational and engagement needs. For instance, the Nitrogen Expert, tasked with providing precise, scientific information on nitrogen pollution, may operate with a lower temperature setting, ensuring responses are direct and factbased. Conversely, the Virtual Champion, designed to inspire and educate through engaging narratives, might employ a higher temperature, allowing for a broader, more creative range of responses. Adjusting the temperature for each agent within the BlueGAP AI Hub ensures that the balance between randomness and determinism in text generation is finely tuned to the agent's purpose, whether it be delivering factual data, offering expert advice, or narrating compelling stories on water quality management.

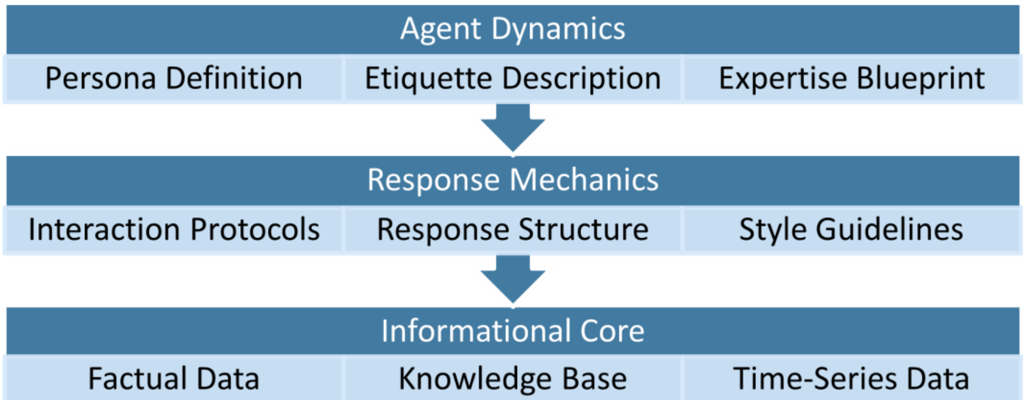


Figure 3: Structure of prompt generation: agent dynamics, response mechanics, and informational core.

4. Results

This section delineates the results derived from deploying the BlueGAP platform, focusing on its architectural framework, user interaction experience, and the comprehensive evaluation metrics applied to assess the agents' performance. By scrutinizing these facets, we aim to illuminate the functional capabilities and the value proposition of the BlueGAP AI Hub in fostering informed decision-making and enhancing public engagement in water quality initiatives.

4.1. BlueGAP AI Hub

The BlueGAP AI Hub exemplifies the convergence of advanced artificial intelligence with the essential field of water quality management, providing a platform where users can engage with sophisticated chatbots to acquire insights, recommendations, and data concerning water quality issues. This interface adeptly combines the capabilities of LLMs with principles of user-centric design to offer an engaging and informative user experience. At its core, the AI Hub seamlessly integrates cutting-edge technological frameworks with practical applicability, aiming to broaden access to water quality information across diverse user demographics. Below is an overview of the AI Hub's Landing Page, serving as the entry point to this comprehensive experience (Figure 4).

Virtual Champion: Designed to mirror the expertise of local water quality specialists, the Virtual Champion Agent provides region-specific guidance and updates (Figure 5). This agent is engineered to deliver personalized content, making the domain of water quality management accessible and actionable for users. Its responses encompass practical advice and in-depth analyses of local water conditions, reflecting the overarching goal of promoting community involvement in water conservation endeavors.

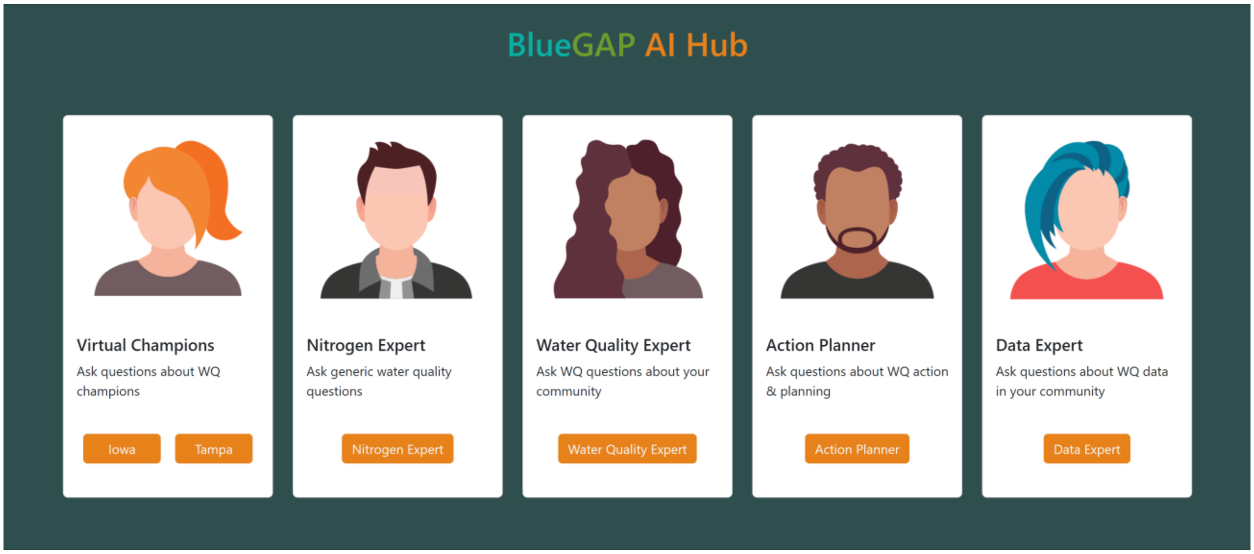
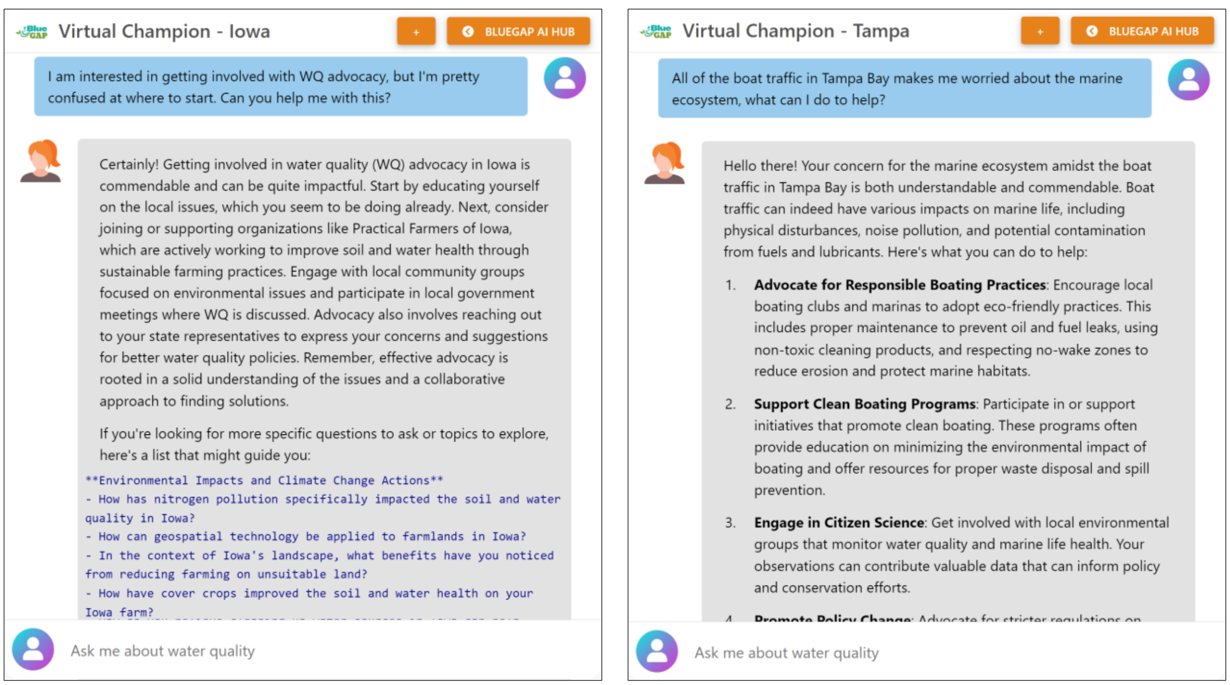


Figure 4: User interface for BlueGAP intelligent agents



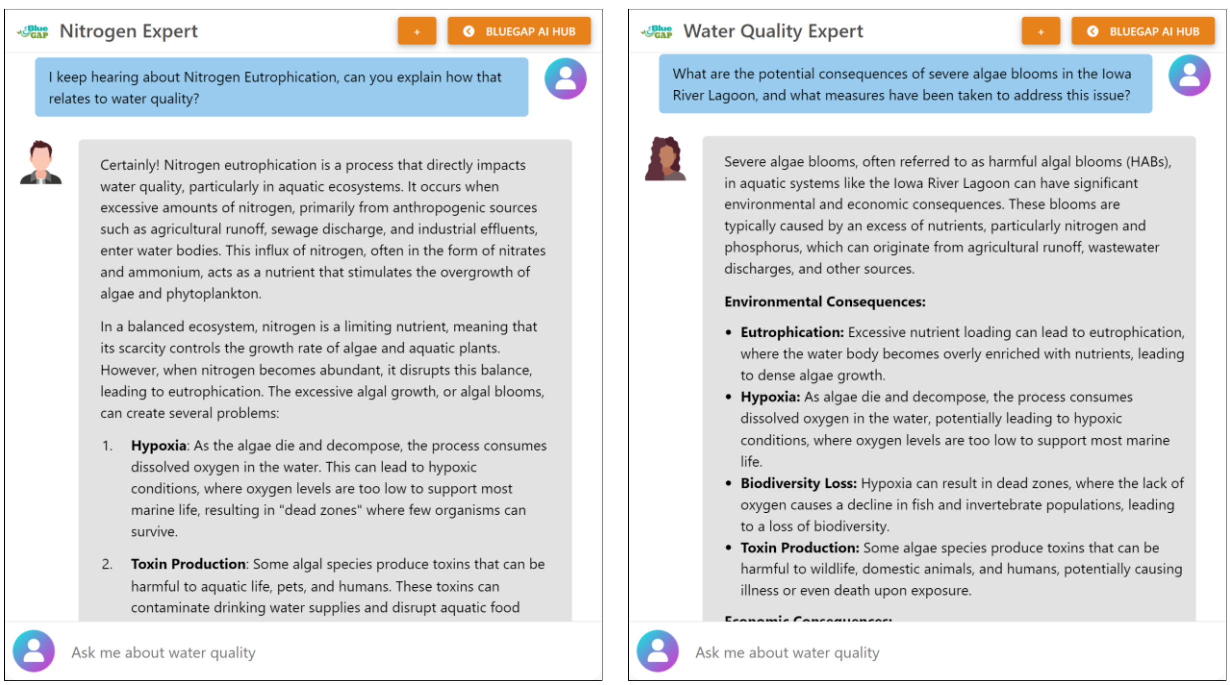
(a) (b)

Figure 5: Screenshots from the Virtual Champion; (a) inquiring local resources, and (b) stressful situations.

Nitrogen Expert: The Nitrogen Expert Agent focuses on delivering exhaustive information about nitrogen pollution, a critical issue in the context of water quality management (Figure 6a).

It educates users about the sources, impacts, and mitigation strategies related to nitrogen pollution, employing a blend of data-driven insights and specialized knowledge to inform and empower the user base. This agent emphasizes the significance of comprehending and tackling nutrient pollution for ecological sustainability.

Local WQ Expert: Concentrating on localized water quality challenges, the Local WQ Expert Agent offers advice and data specific to distinct geographical regions (Figure 6b). It utilizes regional data and community input to furnish users with actionable insights and updates on local water quality trends and issues. The objective is to arm users with pertinent information to make informed decisions and engage in local water quality improvement initiatives.

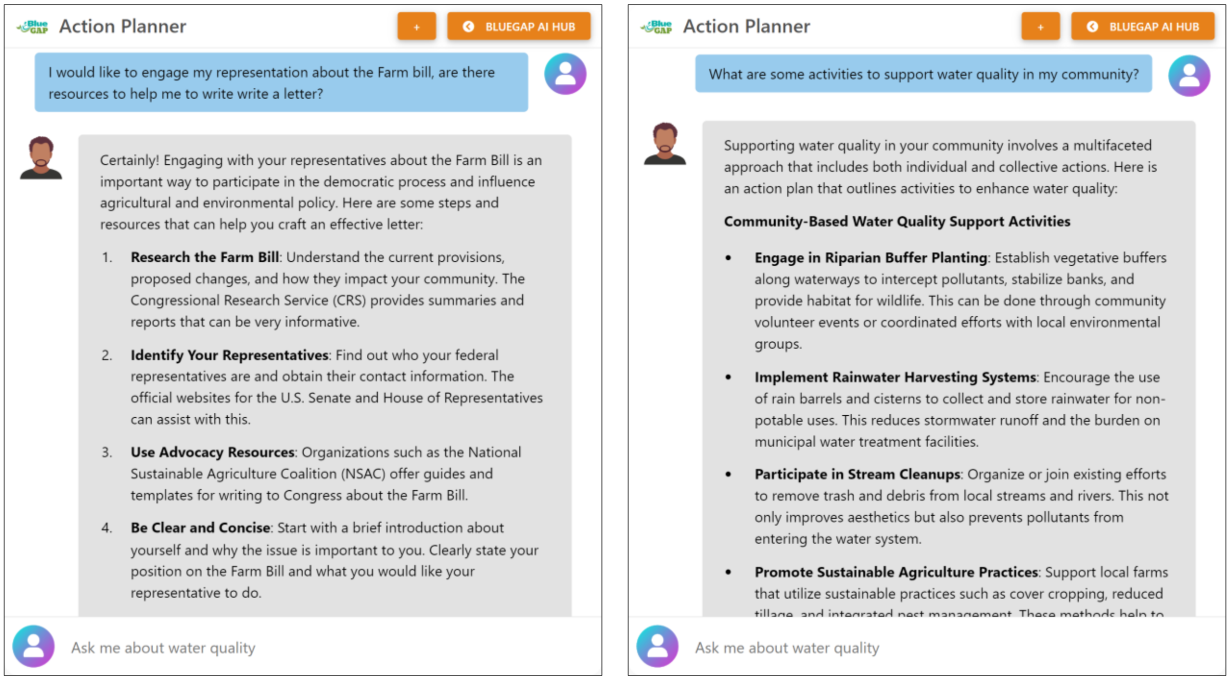


(a) (b)

Figure 6: Screenshots from the; (a) Nitrogen Expert, and (b) Local WQ Expert.

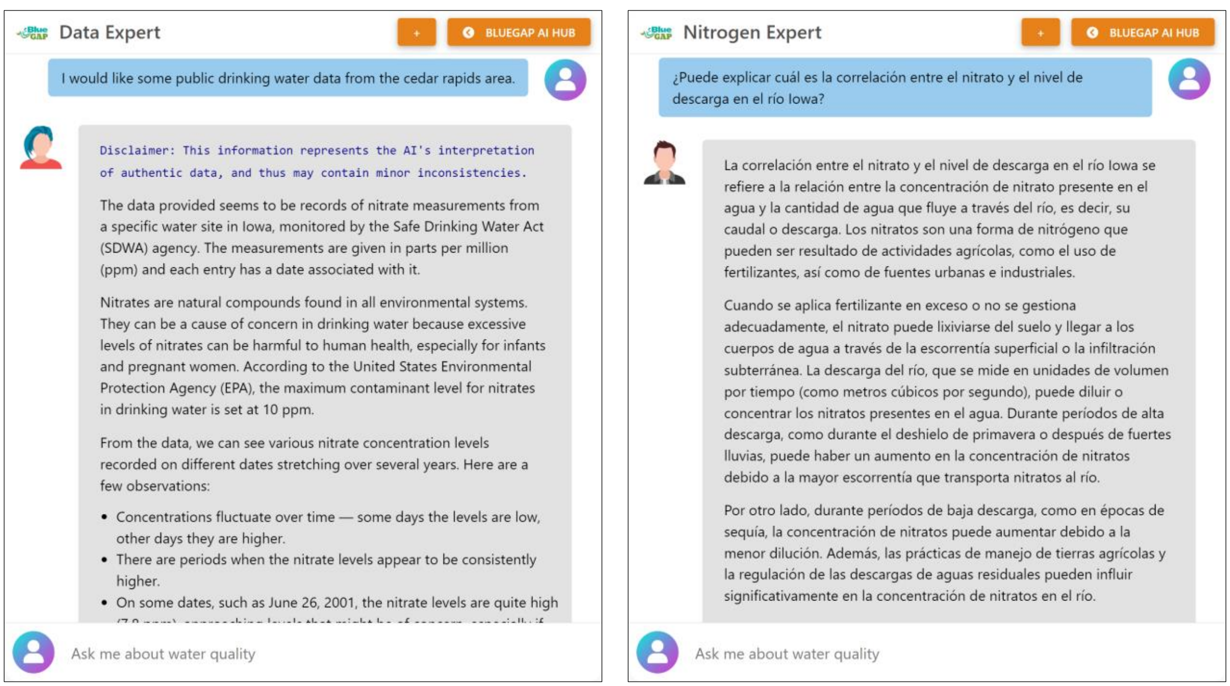
Action Planner: The Action Planner Agent is conceptualized to assist users in formulating practical strategies for water quality management (Figure 7). It facilitates the transition from awareness to action, enabling users to devise individual and communal initiatives aimed at enhancing water quality. This agent serves as a conduit between knowledge acquisition and tangible engagement with water conservation efforts.

Data Expert: Providing access to extensive water quality data, the Data Expert Agent demystifies complex information, rendering it comprehensible and accessible (Figure 8). Users can interactively query specific data points, trends, and analyses, making this agent an essential tool for researchers, policymakers, and the general public. Its primary function is to clarify the data landscape of water quality, fostering informed discourse and decision-making.



(a) (b)

Figure 7: Screenshots from the Action Planner; (a) legislative actions, and (b) community scenarios.



(a) (b)

Figure 8: Screenshots from (a) the Data Expert in English, and (b) NitrogenExpert in Spanish.

Collectively, the agents within the BlueGAP AI Hub are meticulously crafted, each with a distinct utility and objective, addressing various facets of water quality management from educational outreach to data analysis. These agents transform the platform from merely a repository of information to a catalyst for informed action and community participation in water quality conservation initiatives.

4.2. Evaluation

The evaluation of the BlueGAP AI Hub was meticulously designed to ensure the chatbot's responses were not only accurate but also relevant and effective for users seeking information on water quality management. For the purpose of a detailed evaluation, five referees with expertise in water quality management were enlisted to review the responses generated by the BlueGAP agents. Each referee was presented with a set of questions designed to cover a broad spectrum of topics within water quality management. A Quality Likert Scale, with response anchors ranging from "very poor" to "excellent" and quantified as 1 to 5, was employed to measure various dimensions of the agents' performance. This scale allowed for a nuanced assessment of the chatbots, providing insights into areas of strength and opportunities for improvement.

Table 1: Key aspects of agent evaluation.

Metric	**Description**
Accuracy	Evaluated the responses of each agent to determine if they provide accurate information and insights. Cross-checked the information with reliable sources to validate its correctness.
Relevance	Assess the relevance of the responses to user queries. The chatbots address the specific questions asked by users and avoid providing irrelevant or off-topic information.
Contextual Understanding	Evaluated the chatbot's ability to understand the context of the conversation. The agents should consider previous user inputs and maintain a coherent dialogue with users.
Completeness	Ensured that the chatbots provide comprehensive answers to user queries. The responses should cover all relevant aspects of the topic and not leave critical information out.
Natural Language Fluency	Evaluated the fluency and coherence of the chatbot's responses. The language used should be natural and human-like, fostering a seamless conversation with users.

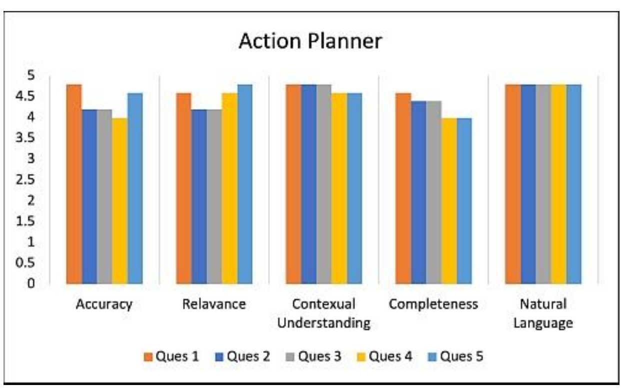
The key metrics evaluated included Accuracy, Relevance, Contextual Understanding, Completeness, and Natural Language Fluency (Table 1). Each of these metrics was carefully chosen to capture the essential attributes of effective chatbot communication. Accuracy ensured the information provided was correct, while Relevance assessed how well the responses aligned with the users' queries. Contextual Understanding evaluated the chatbots' ability to maintain coherent dialogue by considering previous interactions, and Completeness measured whether the responses covered all aspects of the query. Lastly, Natural Language Fluency assessed the chatbots' ability to communicate in a manner that was natural and engaging.

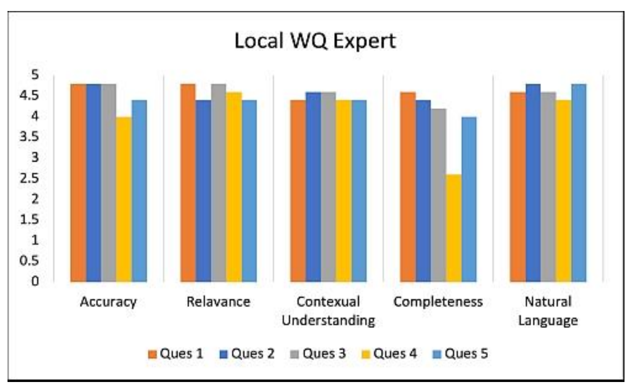
As a demonstration of the evaluation process, Table 2 showcases the responses for a single agent, the Virtual Champion, to illustrate how the survey was conducted. This table is representative of the grading provided by the referees for the Virtual Champion chatbot, reflecting its performance across various interactions. The grading process utilized the Quality Likert Scale, with each metric rated based on the level of quality observed in the chatbot's responses.

Table 2: Sample grading for Virtual Champion chatbot with rubric elements and questions

	Question 1	***Question 2***	***Question 3***	***Question 4***	***Question 5***
Accuracy	Good	Excellent	Excellent	Fair	Good
Relevance	Good	Excellent	Excellent	Good	Good
Contextual Understanding	Good	Excellent	Excellent	Excellent	Good
Completeness	Good	Good	Good	Good	Fair
Natural Language Fluency	Excellent	Excellent	Excellent	Good	Excellent

It's important to note that the complete survey results, encompassing all agents and the full set of questions, are detailed in Figure 9 through a series of charts. These charts provide a comprehensive visual representation of the performance of each BlueGAP agent across the evaluated metrics.





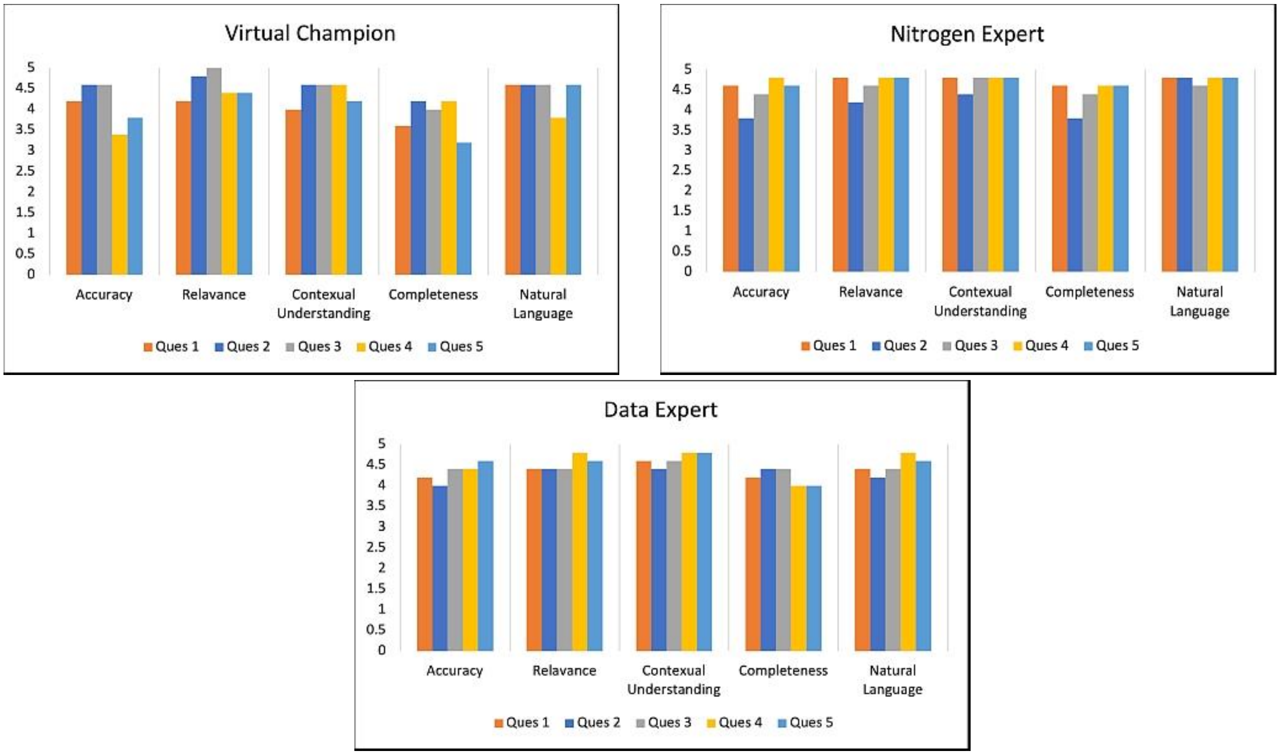


Figure 9: Graphs illustrates the grading provided by the referees for the BlueGAP agents.

The overall performance of the BlueGAP Intelligent Agents, as determined by the evaluation, highlighted their effectiveness in delivering timely and contextually relevant responses. The agents demonstrated an impressive response time of approximately 4.87 seconds, coupled with a success rate of 89.52% in providing definitive answers to a wide range of user queries (Table 3). This high level of performance underscores the BlueGAP agents' potential as a reliable source of water quality management information, capable of engaging users in meaningful and informative interactions.

Table 3: Overall performance score for BlueGAP Intelligent agents

	Accuracy	*Relevance*	*Contextual Understanding*	*Completeness*	*Natural Language Fluency*	**Overall Score - M**
Virtual Champion	84	88	92	76	96	***87.2***
Nitrogen Expert	92	96	96	92	100	***95.2***
Local WQ Expert	88	88	84	80	96	***87.2***
Action Planner	88	92	100	82	100	***92.4***
Data Expert	84	88	92	80	84	**85.6**

The evaluation process, through its comprehensive and detailed approach, provided valuable insights into the strengths and areas for improvement of the BlueGAP Intelligent Agents. By leveraging the Quality Likert Scale and the expertise of referees in water quality management, this study ensured a rigorous assessment of the chatbots' capabilities, laying a foundation for future enhancements to further refine and improve the user experience.

5. Discussion

The BlueGAP AI Hub emerges as an innovative and powerful chatbot application specifically designed for the realm of water quality management. This sophisticated tool offers a plethora of advantages, positioning itself as an invaluable resource for individuals seeking insights into water quality. Among its notable strengths is the provision of comprehensive water quality information. The array of chatbots within the BlueGAP framework, including the Virtual Champion, Nitrogen Expert, Local WQ Expert, Action Planner, and Data Expert, draws from diverse and reliable data sets to furnish users with accurate and relevant insights. This extensive knowledge base empowers users to make well-informed decisions regarding water quality management, thereby enhancing their capacity to effectuate positive environmental outcomes.

Additionally, the BlueGAP AI Hub boasts a user-friendly interface, meticulously constructed using ReactJS. This interface facilitates real-time conversations between users and chatbots, with messages presented in a conversational format that mimics human interaction. The intuitive and visually appealing design of the frontend significantly enhances the user experience, making the process of obtaining water quality information both engaging and accessible.

The accuracy and relevance of the chatbots' responses are further bolstered by expert evaluation. The integration of manual assessments conducted by domain experts lends credibility to the information provided by the chatbots. The involvement of five referees, all specialists in water quality management, underscores the reliability of the chatbots' responses, ensuring users receive trustworthy information.

Moreover, the BlueGAP chatbots are characterized by their fast response time, averaging approximately 4.87 seconds, and a high success rate of 89.52% in delivering definitive answers. These attributes underscore the efficiency and effectiveness of the chatbots in addressing user queries, thereby reinforcing the utility of the BlueGAP AI Hub as a resource for water quality insights.

Despite these strengths, the BlueGAP AI Hub is not without its limitations. One such limitation is the chatbots' limited domain expertise. While adept at handling a broad spectrum of water quality management topics, the chatbots may not provide in-depth coverage of highly specialized or niche areas. In instances involving complex and specific queries, the intervention of human experts may be necessary to furnish more nuanced insights. Additionally, the chatbots' accuracy and reliability are contingent upon the quality of the underlying data sources. Inaccurate, incomplete, or outdated data could potentially compromise the veracity of the chatbots' responses. Furthermore, the chatbots, as language models, exhibit limited emotional intelligence, which may hinder their capacity to fully comprehend or appropriately respond to emotionally charged or sensitive queries.

Therefore, the BlueGAP AI Hub stands as a formidable instrument in the domain of water quality management, offering a comprehensive suite of information, an engaging user interface, and expertly evaluated responses. However, it is crucial to recognize and address its limitations, including the need for human expertise in specialized domains, the dependence on the quality of data sources, and challenges associated with emotional intelligence. By capitalizing on its strengths and mitigating its limitations, the BlueGAP AI Hub can continue to serve as a pivotal asset in advancing water quality management efforts.

6. Conclusion

The BlueGAP AI Hub has demonstrated significant potential in the realm of water quality management, offering a novel approach to accessing, interpreting, and utilizing water quality data. Through the integration of an LLM, the platform facilitates interactive and informative exchanges, underpinned by a user-friendly interface that enhances the overall user experience. The deployment of a Quality Likert Scale for evaluation, involving domain experts, has substantiated the agents' capability to provide timely, accurate, and relevant responses, showcasing an impressive response time and a high degree of success in addressing a wide array of user queries.

Despite its promising attributes, the BlueGAP Intelligent Agent's current iteration does present limitations, including a finite scope of domain expertise and reliance on the quality and currency of underlying data sources. Additionally, the inherent challenge of imbuing chatbots with emotional intelligence suggests an area for further refinement, emphasizing the need to augment AI capabilities with nuanced human understanding and empathy.

In contemplating the trajectory of future enhancements for the BlueGAP Intelligent Agent, several key areas emerge as pivotal for its evolution. One such area is the development of advanced data visualization tools. The creation of interactive and intuitive tools for visualizing water quality data holds the potential to significantly aid users in comprehending complex datasets. By making intricate data more accessible and understandable, these tools can facilitate a deeper engagement with water quality issues and foster a more informed dialogue around management strategies.

Furthermore, expanding the domain expertise of the chatbots represents a critical avenue for future work. Broadening the knowledge base to encompass more specialized areas of water quality management, particularly through collaboration with a diverse range of domain experts, will enable the platform to address a wider spectrum of user inquiries with greater depth and accuracy. Additionally, adapting the platform to incorporate information and guidelines from various international water quality standards will enhance its applicability and relevance to a global user base, acknowledging the international nature of water quality challenges.

Enhancing user engagement also stands out as a crucial area for future development. Implementing AI-driven personalization to tailor interactions and information delivery according to individual user preferences and history can significantly elevate the user experience. This personalized approach promises to make interactions more relevant and engaging for each user, thereby increasing the utility and appeal of the platform. Moreover, integrating voice recognition and response technologies introduces an alternative, hands-free interaction mode, expanding accessibility and convenience for users. This expansion into voice interaction capabilities not only broadens the platform's accessibility but also aligns with evolving user interaction trends, marking a significant step forward in making water quality management knowledge more readily available to diverse audiences.

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