Integrating Conversational AI Agents for Enhanced Water Quality Analytics: Development of a Novel Data Expert System

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Abstract
Despite advancements in environmental monitoring, the gap between data collection and user-friendly data interpretation remains a significant challenge, especially in the domain of water quality management. This paper introduces the Artificial Intelligence Data Expert (AI-DE), a novel data analytics system that is designed to facilitate on-demand analysis of time-series sensor data related to water quality using natural language queries. The AI-DE leverages features of ChatGPT, including Named Entity Recognition, geocoding, and sentiment analysis, to enable intuitive and natural language-based data analysis. This system transformation allows for immediate, ad-hoc querying and interpretation of environmental data, tailored to the needs of diverse user groups. Key features include chat controls that customize user interaction, a chat bypass enabling seamless integration with an integrated information system, and a data interpretation mode for detailed analysis. The AI-DE enhances user engagement and comprehension of water quality data, thereby supporting informed decisions and actions for environmental management. The AI-DE represents a step forward in increasing access to complex environmental data through conversational AI technologies.

Keywords: water quality, time series data, sensor network, data expert, natural language processing, artificial intelligence, large language models

1. Introduction

The effective management of water quality (WQ) is of critical importance due to its direct impact on ecosystems and human well-being (Mount et al., 2023). Nitrogen and phosphorus, essential nutrients for plant growth, are crucial components to monitor and control in water systems such as lakes, rivers, and streams. The excessive presence of these nutrients, often stemming from agricultural runoff and urban activities, can lead to nutrient pollution, causing harmful algal blooms and oxygen depletion in aquatic environments (Conley et al., 2009). Heavy rainfall exacerbates these concerns, as it can enhance the transport of pollutants into water bodies. The runoff from impervious surfaces carries contaminants, including sediments and chemicals, into rivers and bays, compromising water quality (Salerno et al., 2018).

Increase in volume and rapidity of runoff underscores the need for robust strategies to mitigate the adverse effects of heavy rainfall on water systems. Runoff from fertilized fields can introduce elevated levels of nutrients such as nitrogen, phosphorus, potassium and others into waterways, leading to the degradation of water quality and posing risks to aquatic ecosystems (Pericherla et al., 2020). Implementing improved farming techniques and adopting best management practices are vital for minimizing these impacts. Additionally, boat traffic in bodies of water introduces potential pollutants, such as oil and fuel residues, into the water (Meyers et al., 2021). The disturbance caused by boats can also contribute to sediment resuspension, further influencing water quality dynamics like turbidity and habitat preservation. Sustainable boating practices and regulations are imperative to mitigate the negative consequences of boat traffic on aquatic ecosystems. These issues highlight a small portion of the totality of threats to water quality, but nonetheless underscore the importance of managing water quality.

Since the 1920s, time series data has been used to model hydrological bodies (Ambrose et al., 2009). The storage, collection, and analysis of time series data has given us our current understanding of water quality management and has contributed to a massive amount of historical data. This extensive corpus of historical data serves as a valuable resource for understanding trends and patterns in water-related phenomena. Until the internet, the task of finding, accessing, and analyzing such data was relegated to trained professionals. Issues like volume of data, data formatting and data structure all imposed barriers (Baydaroglu et al., 2023). However, with the advent of the internet, there has been a notable evolution in our approach to handling this wealth of information. The development of information systems has played a pivotal role in transforming the landscape of data accessibility and utilization (Goodall et al., 2008). These information systems are designed to bridge the gap between raw data and the knowledge concealed within it. Unlike earlier paradigms where data analysis was confined to experts, these systems aim to democratize access, allowing a wider range of users to explore and extract meaningful insights from the vast reservoir of historical water-related data.

The emergence of more complex and powerful hardware and software in the early 2000s paved the way for information systems with user interfaces (Sit et al., 2021). These systems were now freed from basic networked data access; they could now execute limited analyses on specific sets of measurements or datasets. In some cases, models were even implemented into the system in order to forecast future data (Wang et al., 2000). Importantly, these early iterations were highly tailored for specific purposes and intended audiences, reflecting a more specialized approach to information processing.

Before Google Earth and Web-GIS the design of information systems leaned more towards a user-friendly interface for databases than comprehensive information systems (Shahid et al., 2023). These nascent systems were primarily designed for the storage and retrieval of data, serving academic and professional communities with a focus on areas like the study or management of water quality. The primary function was to facilitate data access for specific purposes within these specialized fields. This focus began to shift upon the release of Google Earth in 2007 (Jankowski et al., 2007). The advent of Google Earth introduced the general public to GIS and information systems broadly. This marked a significant departure from the constrained nature of earlier systems.

Improvements in networking, bandwidth, and software availability all contributed to the rise of Web-GIS. These platforms allowed users to interact with data in a more dynamic and visually intuitive manner (Wang et al., 2005; Sermet and Demir, 2022). Users have the ability to create data layers, enabling analysis and a deeper understanding of spatiotemporal trends in the information at hand. This transition represented a substantial leap towards versatility, making these systems more applicable to a broader user base. With these benefits in mind, there were still limitations such as server-side processing capabilities, massive data volume, and poor networks that limited the scope of these systems (Ramirez et al., 2024).

Due to the rigidity of pre-ChatGPT chatbots, conversational agents (CA) research was largely conducted in laboratory settings, leading to a disconnection from practical applications. This leaves a gap in knowledge which must be addressed in order to deliver the best experience to users. To effectively advance CA development, a shift towards user-centered investigations is essential in order to align CA capabilities with real-world needs and enhance their integration within Information Systems (Diederich et al., 2019; Sermet et al., 2018).

Historically, the biggest challenges that have limited the use of conversational agents in the field are challenges with natural language processing (NLP) and named entity recognition (NER), each of which are crucial in providing a cohesive and coherent chat experience. Natural Language Processing (NLP) is a branch of artificial intelligence which deals with the interactions between machines and humans, more specifically, it pertains to the creation of algorithms which can understand and respond meaningfully to human language inputs. NER is a subset of NLP which aims to identify named entities such as names, places, quantities, monetary values, and others from unstructured text in order to extract valuable information.

With the release of ChatGPT in 2022, these challenges have been reduced dramatically (Wei et al., 2023). With this new technology, NER and NLP are handled by ChatGPT itself, and natural language prompting can be used as instructions for the agents (Sajja et al., 2023a). The standard function of ChatGPT accomplishes what previously could have been the entire focus of conversational agent development, freeing up development resources to enhance agent capabilities, such as giving contextual knowledge, access to factual documentation, or limitation of question scoping (limiting what agents can talk about) in order to create more capable agents (Sajja et al., 2023b).

This research presents the development and deployment of the Artificial Intelligence Data Expert (AI-DE), a conversational AI system tailored for dynamic water quality analytics. By integrating AI capabilities such as NER, geocoding, and real-time data interpretation, the AI-DE system represents a significant evolution from traditional informational tools, aiming to revolutionize how users interact with and understand complex environmental data. Our work seeks to bridge the gap between data accessibility and user engagement, making it easier for a diverse audience to make informed decisions regarding water quality management.

The paper is organized into several sections. Section 2 delineates the methods employed, encompassing the purpose and scope, system architecture, data sources, AI background, and enhancements implemented for this system. Following this, Section 3 features a showcase of results, while Section 4 engages in a discussion of these results. Section 5 addresses conclusions and future opportunities.

2. Methods

The focus of this study is the design, implementation, and evaluation of the AI-DE system. The goal of this AI agent is to serve as an interface between the user and the vast amount of water quality data and support natural language queries to interact and analyze the data.

2.1. Purpose and Scope

Blue-Green Action Platform (BlueGAP) is a project, funded by US National Science Foundation, that aims to increase the number of people working to reduce nitrogen pollution through storytelling, access to reliable water quality information, and evidenced-based actions for improving water quality at the watershed scale (BlueGAP, 2024). The organization is primarily concerned with information dissemination, community building, and translating evidence into action. To accomplish these goals, BlueGAP seeks to develop an information system which can support all three goals, blending water quality data with knowledge of community stakeholders to humanize nitrogen pollution. Currently, BlueGAP is providing data and services in Iowa, the Tampa Bay area in Florida, and the US Virgin Islands.

The BlueGAP Information System constitutes a web-based data visualization tool designed to facilitate user access to historically challenging data sources. Its functionality is rooted in the combination of publicly available data repositories, including but not limited to the United States Geological Survey (USGS) and the Environmental Protection Agency (EPA). The system utilizes a map-based user interface with data layers and enables further analysis using graphs and tables for specific locations of interest. This strategic approach allows users to gain insights into the prevailing water quality conditions in their geographic area. Moreover, the information system goes beyond mere map-based analysis by offering users the opportunity to delve into the narratives of authentic water quality advocates, referred to as Champions. This inclusion serves to contextualize the significance of water quality within a given geographic area, adding a human dimension to the understanding of environmental concerns.

To optimize the educational capacity of the BlueGAP Information System, a series of Intelligent Agents, denoted as BlueGAP AI Agents, have been developed to enhance the user experience and facilitate learning on diverse water quality topics (Samuel et al., 2024a). Each agent is purposefully designed to fulfill a specific role within the platform, contributing to a comprehensive and tailored educational journey for users. To provide a detailed understanding of the roles each agent plays within the BlueGAP Information System, we introduce the following agents: (i) Virtual Champions, who are virtual representations of real-life water quality advocates allowing users to interact with and learn from their experiences and insights; (ii) Nitrogen Expert, specializing in providing comprehensive information about nitrogen's effects on water quality, aiding in both general and in-depth understanding; (iii) Local WQ Expert, focused on region-specific water quality issues, offers tailored advice and data relevant to users' local environments; (iv) Action Planner, a pragmatic agent designed to help users formulate and implement actionable plans to address water quality issues in their communities; and (v) Data Expert, primarily responsible for providing information on how to interpret technical terms and concepts regarding water quality data.

This study introduces a novel system focused on advanced data analytics to enhance real-time decision-making and insights. Within the context of this study, the AI-DE caters to a diverse audience of curious users, ranging from academics seeking a rapid overview of water quality in an unfamiliar area to amateur analysts eager to engage with data, and even children keen on deciphering the meaning behind colors on a graph. To meet the needs of these target users, various methods for accessing and comprehending data have been implemented, like controlling chat length and vocabulary level, data analysis mode for follow up questions, data summary and data download all aim to serve the unique needs of user groups from school children to WQ professionals.

The AI-DE boasts a new data retrieval method that prioritizes user convenience as opposed to the previous method which prioritized the ability to access a specific site for a specific time range. This enhancement is geared towards providing a seamless experience for users who may have minimal information, such as a location, but still desire relevant data. The agent takes the guesswork out for the user, and automatically finds the data from the closest monitoring site. These capabilities also empower users with the ability to ask questions about retrieved data in a manner that aligns with their specific needs and level of expertise.

2.2. System Architecture

The AI-DE system is configured in a multi-faceted architecture (Figure 1). First, data is aggregated into private drinking water, public drinking water, recreational waters (surface), and recreational waters (ocean). These datasets serve as the baseline data for the entire information system, and their creation and source data are outlined in a later section. By creating various AI services, intelligent agents are given an array of capabilities. Some features are must-haves, like sentiment analysis and embeddings creation, but other services were created to improve the user experience, such as model selection and tone customization. Users are able to get a more detailed response (which utilizes OpenAI’s gpt-4 model) or a faster response (which utilizes OpenAI’s gpt-3.5 model). A basic tone can be used, or a tone suitable to professionals. A vector database houses the embeddings that each agent uses to generate their response. A flask application runs all bots excluding AI-DE, which runs on a node application. Finally, the user interface features a ReactJS based user interface. This allows the users to input their questions to the agent and facilitates the data interpretation mode and response length selection. Users who do not speak English can also enter their question in another language and will get a response in that language as well. This is a crucial aspect to the usability and accessibility of the platform and remains a strength of LLM based chatbots.

The frontend is developed using ReactJS, a JavaScript library known for its robust features. ReactJS facilitates the creation of reusable components, fostering a modular design that promotes easy customization. The declarative syntax of React enhances the code's readability and maintainability, contributing to a streamlined development process. NodeJS serves as the frontend runtime environment for the application, leveraging its capabilities for asynchronous input/output (I/O) operations. This choice enhances the responsiveness and overall performance of the application. The use of JavaScript for both frontend and backend code introduce consistency and reduces the learning curve for developers, streamlining the development workflow.

Python serves as the primary development language for the AI backend, housing the majority of the code for intelligent services. The selection of Python for the backend is underpinned by several considerations. Python boasts a wealth of libraries and frameworks, including Langchains, Chroma, and tokenizers. These resources greatly facilitate the development of practical applications, offering a rich ecosystem that supports the implementation of sophisticated features. The robust Python community and comprehensive documentation contribute to a smooth and rapid development process. The availability of resources and support within the community enhances the efficiency of the development workflow.

Python's ongoing development and the continuous emergence of new technologies and libraries align well with the dynamic nature of AI applications. This ensures that the system can leverage the latest tools and capabilities as they become available over time. Chroma, an AI-friendly vector database solution, plays a crucial role by storing embeddings that serve as the informational foundation for chatbots. This method is seamlessly compatible with standard libraries such as Langchains, enhancing conversational fluidity within the system. Flask, a lightweight web framework for Python, powers the backend of the intelligent agent system. Flask is chosen for its flexibility, ease of learning and use, and compatibility with selected frontend frameworks such as Node and ReactJS. Its adaptability makes it an ideal choice for efficiently managing the backend operations of the system.

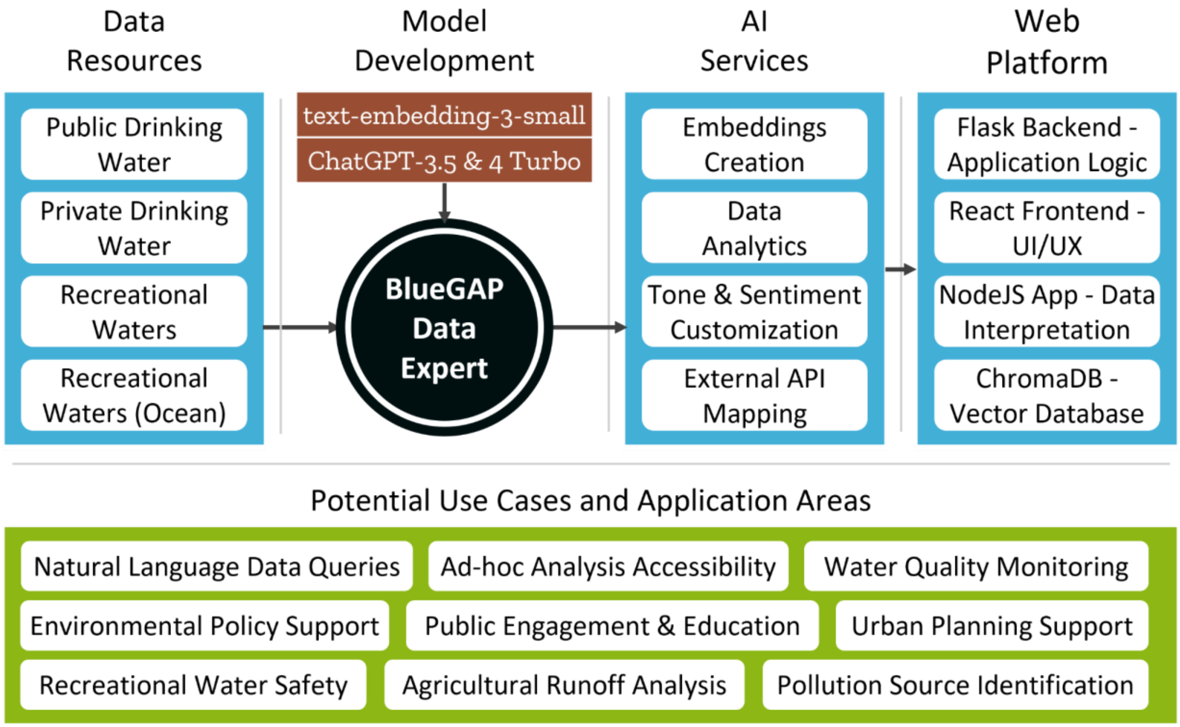


Figure 1: System architecture, components and functionality summary

2.3. Data Sources

The data utilized within the proposed system is sourced from a diverse array of state and national data repositories renowned for their credibility as accepted water quality monitoring sources (Table 1). These sources have been chosen based on their ubiquity and comprehensive coverage of water quality data. These data sources are classified into the type of water quality that they measure: (i) public drinking water; (ii) private drinking water; (iii) recreational waters; and (iv) ocean recreational waters.

Table 1: Overview of key data resources used by the AI-DE system.

Data Source	**Description**
National Water Information System (NWIS)	*Managed by the U.S. Geological Survey, NWIS serves as a data source offering comprehensive information on water resources. It covers aspects such as streamflow, water quality, and groundwater, providing a foundational dataset for water quality assessment.*
Storage and Retrieval of Environmental Data (STORET)	*Administered by the EPA, STORET functions as a centralized repository for a diverse range of environmental data, prominently featuring water quality data. Its inclusivity makes it a vital source for aggregating information critical to understanding environmental conditions.*

Safe Drinking Water Act (SDWA)	*Enacted as a federal law, SDWA regulates the quality of drinking water. Data sources associated with SDWA furnish valuable insights into compliance, monitoring results, and details on water systems.*
Iowa Water Quality IS (IWQIS)	*IWQIS acts as an integrative platform for water quality data derived from various sources in Iowa. Its role in storing and managing data facilitates a holistic understanding of water quality issues.*
Iowa Department of Natural Resources (IADNR) (PWTS)	*The Iowa Department of Natural Resources (IADNR) is a regional contributor, providing specific data on water quality in the state of Iowa. This regional focus enhances the granularity of information to address localized water quality concerns effectively. The private well tracking system (PWTS) is used to monitor private drinking water.*
EPC of Hillsborough County (EPC)	*The Hillsborough County Environmental Protection Commission (EPC) is committed to safeguarding the county's environment and ensuring exceptional service, guided by values of environmental stewardship and accountability. They collect data on water quality in Tampa Bay.*
FDEP: Public Water Supply Plants (PWS)	*The Florida Department of Environmental Protection (FDEP) curates numerous open datasets. It uses the Public Water Supply Plants (non-federal) dataset to show the quality of public drinking water in Tampa Bay.*

2.4. AI Integration to Information System

In order to improve the functionality and usability of the AI-DE, there were numerous changes made, each aimed at improving a different aspect of the chat experience. By seamlessly integrating the AI-DE into the Information System mapping interface, allowing users to control their chat experience (length, tone, detail), and using ChatGPT's innate abilities for NER, geocoding, and multilingual responses, the chat experience meets users at their level of understanding.

2.4.1. Chat Controls

A significant challenge encountered in the initial iterations of the AI-DE pertained to the time required for queries. The default configuration of the AI-DE necessitated two calls to the OpenAI API, leading to potential delays in response time. This delay was contingent on various factors, including the length of the retrieved data, the length of the response text, and the choice of the underlying OpenAI model (gpt-3.5-16k vs gpt-4-1106-preview). Notably, the default behavior of the GPT model often resulted in verbose outputs that could have been more succinctly conveyed.

To address this issue and ensure a more consistent user experience across all agents, the introduction of chat controls has become imperative. These controls offer users the flexibility to tailor their experience based on their preferences, accommodating diverse user groups. Each control choice involves tradeoffs, as elucidated below. However, these tradeoffs are designed to empower distinct user groups to optimize their interactions. The available chat controls are conveniently presented in a hidden panel with dropdowns and include the following options:

Response Length: The default setting for response length is 'Brief,' with options including Brief (30 words or less), Concise (60 words or less), Medium (150 words or less), and Long (300 words or less). This feature was primarily implemented to mitigate wait times for users, as shorter responses (e.g., 30 words) significantly expedite the interaction compared to lengthier ones (e.g., 300 words). Beyond addressing time considerations, these controls also afford users the ability to regulate the complexity of the topics discussed. Shorter responses, such as those within the 'Brief' category, enhance accessibility, catering even to younger audiences.

Response Speed: The Response Speed option provides two choices: 'Fastest' and 'Most Detailed.' This feature, operating on the backend, dictates the model used to generate responses—either gpt-3.5-16k (Fastest) or gpt-4-1106-preview (Most Detailed). The default prioritization is speed, ensuring a consistent user experience across the AI-DE and other non-technical experts. This decision optimizes efficiency and responsiveness.

Conversational Tone: The final option empowers users to select the conversational tone and vocabulary employed by the Agent. The default choice is a 'General' conversational tone, which, on the backend, translates to responding in a manner understandable to a high-school student. Alternatively, users can opt for a tone appropriate for a professional audience. This control significantly influences not only the specific vocabulary utilized but also the manner in which concepts are explained. The versatility of this feature allows users to tailor the conversational style to align with the intended audience, whether it be a broad audience or a more specialized, professional group.

The integration of these chat controls collectively enhances the versatility of the AI-DE, rendering it valuable across a spectrum of scenarios and user profiles. The AI-DE becomes not only faster but also adept at tailoring its communication style to diverse user groups. To mitigate cognitive overload, these controls are discreetly tucked away by default but can be effortlessly revealed by users in the chat interface. This design choice prioritizes a clean and uncluttered user interface while providing users with the option to access advanced controls when needed.

2.4.2. Geocoding Process

To ascertain the appropriate data source, the AI-DE employs NER by utilizing prompts. This NER process helps identify the location specified by the user. Once the location is determined, the system instructs ChatGPT to estimate coordinates and retrieve the corresponding county FIPS (Federal Information Processing Standards) through a OpenAI API call. Leveraging ChatGPT's advanced Natural Language Processing (NLP) capabilities, the prompt also guides the bot to discern, if specified, the type of water data the user intends to access. The internal response is then tailored based on this determination, with three possible sources identified and processed by the system. This intricate interplay of NER and NLP ensures accurate and context-aware data retrieval based on the user's inquiry.

It's noteworthy that the geocoding estimates generated by ChatGPT exhibit a degree of non-determinism. Even with a temperature setting of zero, which is considered the most deterministic configuration, slight variations in coordinates may occur upon multiple estimates for a single location. In the context of this Information System's purpose, this variability does not impede its ability to achieve its objectives.

Subsequent to obtaining the geographic estimates, a cross-referencing process is initiated to pinpoint the closest water quality monitoring site to the specified location. The user is then presented with a concise summary of this data. This summary serves as an informative snapshot, allowing users to delve deeper into the analysis if they wish to explore more detailed insights.

2.4.3. Data Interpretation Mode

In the initial implementation of the AI-DE, users faced a constraint where they needed to inquire about all desired information in a single interaction, as the chatbot would 'forget' previously retrieved and summarized data. Recognizing the importance of enabling users to explore and comprehend data iteratively, the Data Interpretation Mode was introduced.

Within this mode, users encounter a new chat interaction option after the bot responds to a request. Clicking this button or requesting entry into Data Interpretation Mode triggers the site's transition into this mode. Upon entry, a call is initiated to the summary statistics API for the county corresponding to the monitoring site under consideration. While in Data Interpretation Mode, users can engage with the bot through four specific intents, in addition to a generic intent:

Site Interaction: When a user poses a question about site-level data, the AI-DE directs its attention to the monitoring site level data while formulating responses. In cases where the user's question lacks specificity regarding county or site, the assumption defaults to the site.

County Interaction: When users inquire about county-level data, the AI-DE retrieves comprehensive statistical information. This data encompasses metrics such as minimum, maximum, standard deviation, sample size (n), and variance. The specific statistics included in this data are [min, max, stdev, number of sites, variance] for all measured analytes from all data sources.

Greet User: A general greeting function is available for user interactions, providing a courteous and welcoming response to initiate conversations with sample questions users can ask to the system.

Exit Data Interpret: In response to a user request to exit interpretation mode, the AI-DE facilitates a smooth transition out of Data Interpretation Mode, accommodating the user's preferences.

The user's queries are strategically directed to backend processes based on their intent. The Site and County Interaction types trigger an OpenAI API call, instructing the agent to address the user's question while taking into account either a) site-level data initially retrieved (via chat query or bypass) or b) county-level summary data. This ensures a tailored and context-aware response to the user's specific inquiry.

The *Greet User* intent is managed through a set of predefined responses designed to minimize latency, offering a prompt and courteous initiation to user interactions. On the other hand, the *Exit Data Interpret* intent efficiently updates the state of the site and clears saved data, allowing users to seamlessly transition to obtaining different data without unnecessary complications. This approach optimizes the user experience by streamlining processes and minimizing delays.

2.4.4. Chat Bypass Functionality

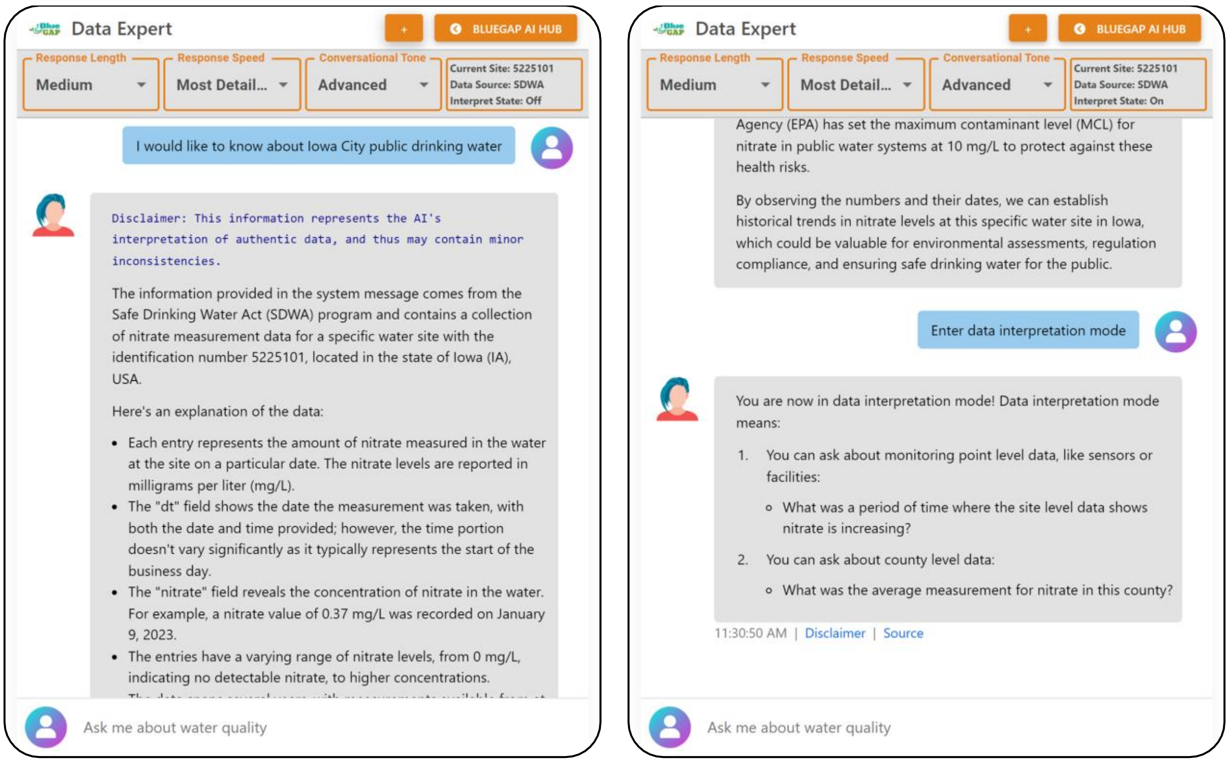
One function implemented to enhance user experience is the 'chat bypass' feature within the AI-DE. This feature empowers users to seamlessly transition from an information system interface to the AI-DE interface, by passing the dataset from an information system to the AI-DE directly. This allows for immediate follow-up questions about the data site that appears on the map. Upon visualizing data on a map, users often formulate questions based on their observations. To streamline this process, the AI-DE function, when selected while viewing a specific site in the Information System, transfers the site data directly to the AI-DE. This functionality allows users to inquire about specific details, such as whether there were instances in the data where nitrate levels exceeded safety thresholds.

Furthermore, by bypassing the data retrieval query through the information system, the county level summary API is automatically invoked. This integration empowers users to seek insights from the AI-DE not only about site-specific data but also about county-level summary statistics. An additional merit of the chat bypass functionality lies in the reduction of user latency. By bypassing the chat data query, the need for a call to the OpenAI API is obviated, leading to a notable decrease in the lag time between selecting the AI-DE and posing a question.

3. Results

This section presents the features implemented in the information system which improve usability for a diverse set of users. Some features are platform-wide and extend to all AI agents, such as the chat controls and example question generation. Many features are specific to the AI-DE and achieve the goal of overhauling this expert to make it a useful interface between users and water quality data sources. These features include: a) geocoding user responses to ensure the data accessed is relevant to the location in their query, b) a data interpretation mode which enables detailed Q and A over specific WQ data, and c) chat bypass functionality allowing seamless integration of the AI-DE with the information system's front end.

Data Interpretation Mode: The Figure 2 represents the "typical" method of querying for data using the AI-DE. The user's message is interpreted, and the data from the closest matching water quality measurement site is given to the OpenAI API with the instructions to explain the data so that a person who's never worked with data before can understand what it means. Here is an example of such a summary. From this point, the user is given the choice of how they'd like to interact with the data: 1) they can download the data in JavaScript Object Notation (JSON); 2) be redirected to the IS to see the data as either a map or a graph; 3) enter data interpretation mode for further questions about this data.

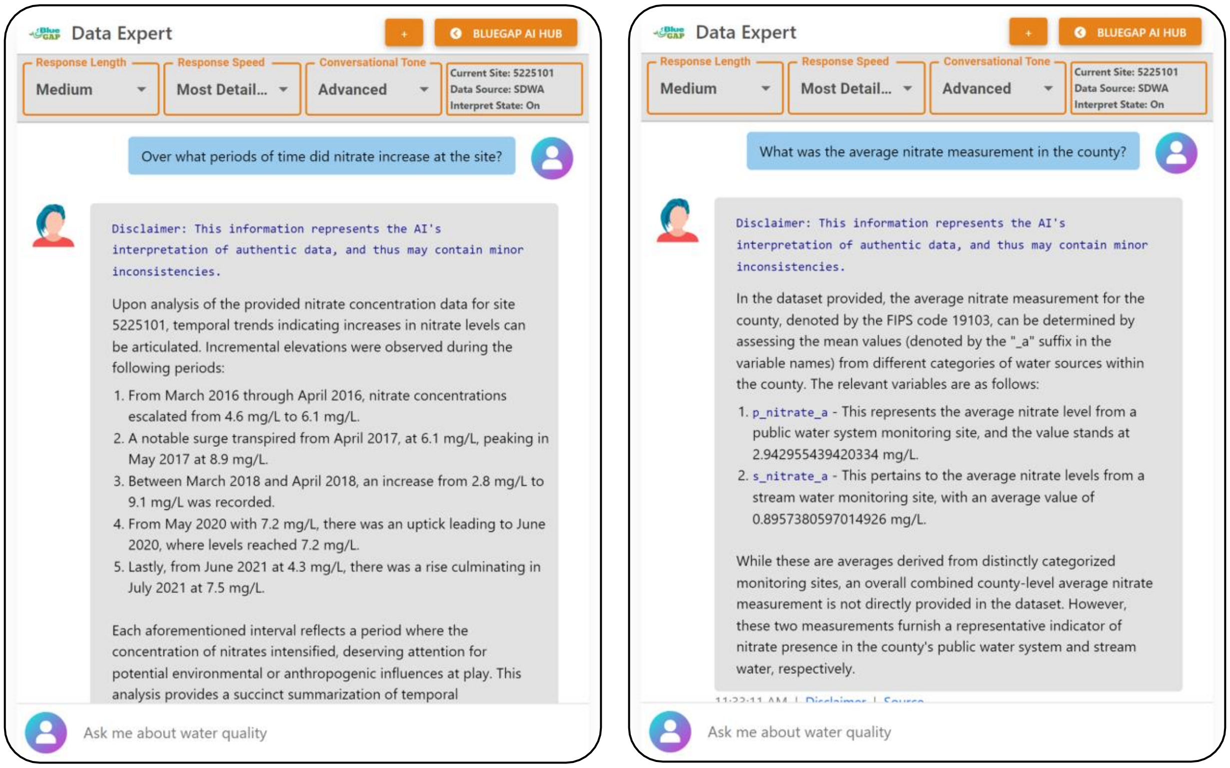


(a) (b)

Figure 2: (a) User enters data interpretation mode conversationally; (b) User is presented with example questions upon entering interpretation mode.

Figure 2a shows the user entering the data interaction mode after receiving some water quality site data. After entering this state, the user is prompted with example questions about both site level and county level data, enabling the user to have their follow up questions addressed, and put into the context of a larger geographic area. Site level questions are related to the data fetched in the initial query, and county level questions draw from summary statistics for WQ analytes.

Figure 2b represents the data interaction mode of the AI-DE. The data interaction mode enables data analysis by allowing repeated questioning of the previously fetched site level information as well as the introduction of county level aggregate analyte statistics. Figure 3a is an example of what a typical site level interaction question might look like. The user is curious about trends in the data, specifically in the context of nitrate. The AI-DE addresses this question seamlessly and delivers a data driven answer which indicates not only periods of time where the nitrate levels were increasing, but also tells the maximum recorded value. The prompt used for site interactions encourages the chatbot to look into the data and answer the user's question most appropriately, and in cases where they are unable to address the question, to tell the user.



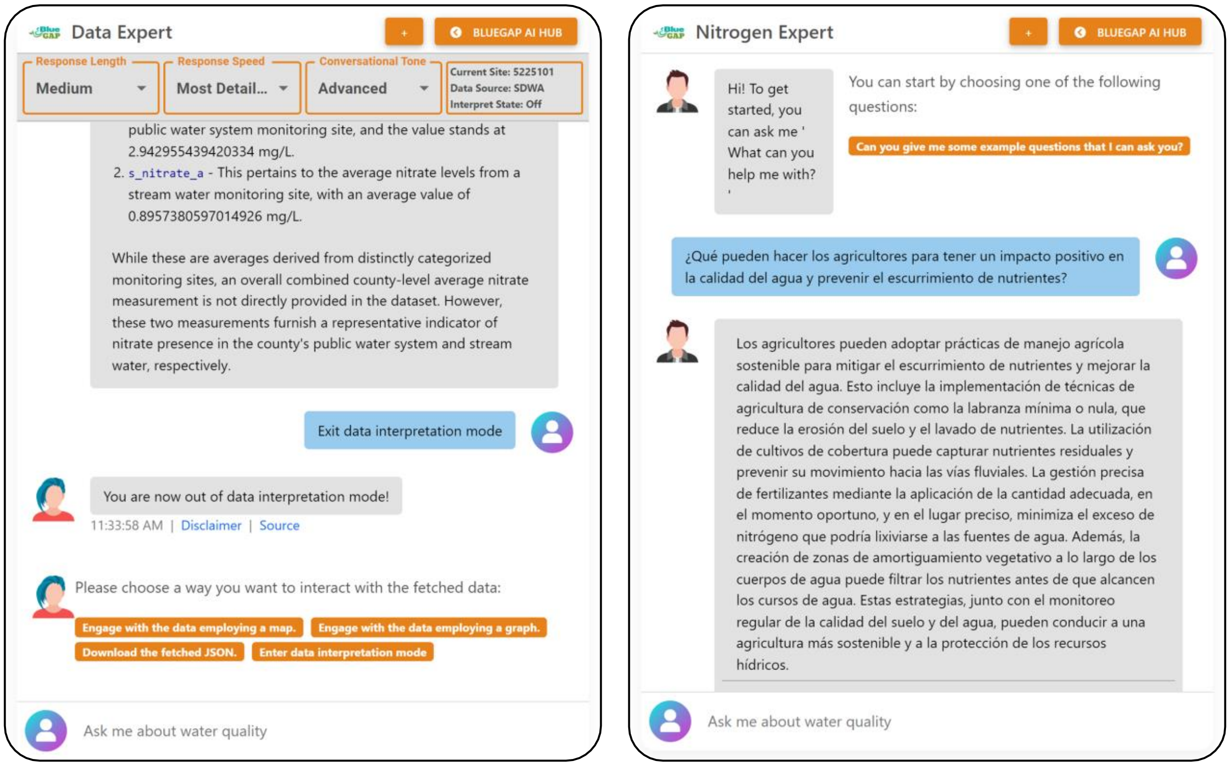
(a) (b)

Figure 3: (a) User asks AI-DE about collection site level data; (b) User asks AI-DE about county level aggregate statistics.

The county interaction type allows users to query an array of summary statistics that are generated for the mapping side of the information system (Figure 3b). These summary statistics include: 1) number of sites for each data source in a county; 2) minimum and maximum datetimes for the county; and 3) count, minimum, maximum, average, standard deviation for all analytes across all data sources for the county. By allowing the user to query this information, they can contextualize the localized WQ situation at the specific site they are looking at. By giving the user access to this summary data, the aim is to empower users to have their 'so what?' questions answered.

Figure 4a demonstrates the user leaving data interpretation mode, which updates the interpret state and gives the users options for how they'd like to continue using the AI-DE. This action can be taken either by selecting the "Exit Interpretation Mode" or asking the bot to leave the mode.

Geocoding Process: Figure 5 represents the output of the geocoding performed by ChatGPT when the user makes a request of the AI-DE: 1) data source desired; 2) coordinate estimation from location in input; 3) state that specified location exists within; 4) county FIPS code for the location in the input.



(a) (b)

Figure 4: (a) User exits data interpretation mode via chat interface; (b) Explanation of water quality concepts in Spanish.

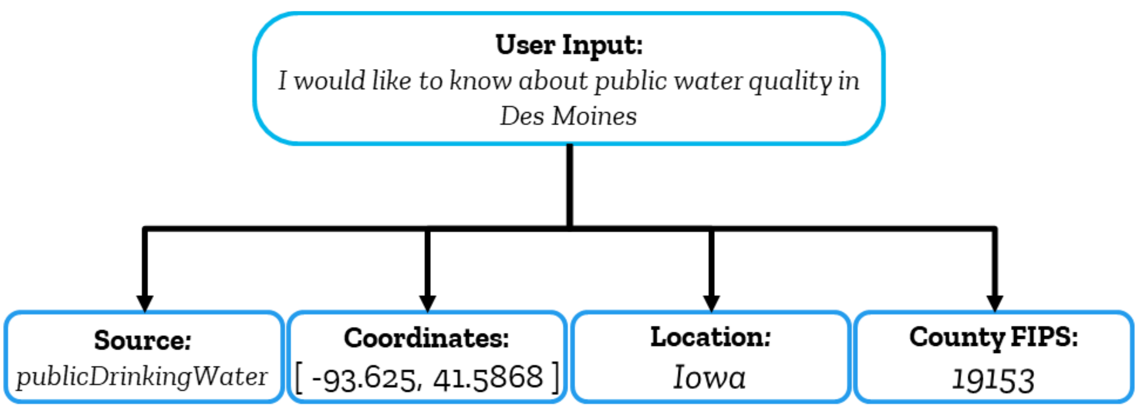


Figure 5: Geocoded outputs as a result of NER and NLP from user input.

Chat Controls: Figure 6a is how the site looks in its base state. Initially the chat controls are hidden. This was a conscious design choice that enables the user to choose the complexity level at which they'd like to interface with the system. Figure 6b shows the interface after expanding the chat controls. This presents the user with the ability to customize their experience based on what they aim to get from it. By presenting this interface with familiar UI pieces, the user will automatically understand how to use these controls. Figure 6c shows the informational panel exclusive to the AI-DE. This is a crucial piece of the AI-DE's interface, and improves the user experience by displaying the current site, its source, and the state of the AI-DE's interpretation mode. As users interact with a variety of data from many sources, it is important that they are able to tell at a glance the current state of the site.

(a)
(b)
(c)

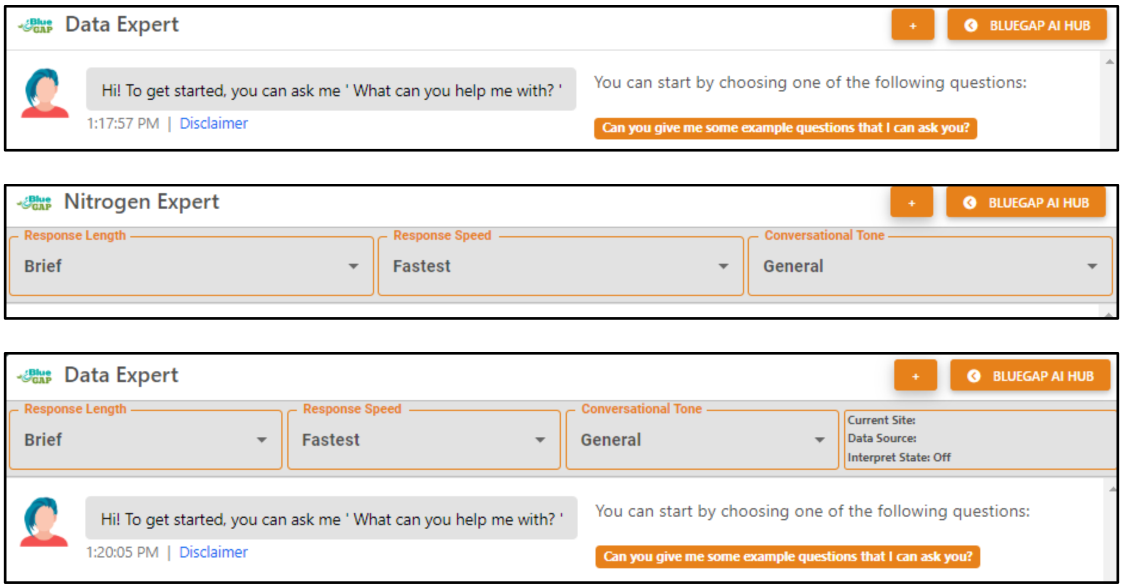
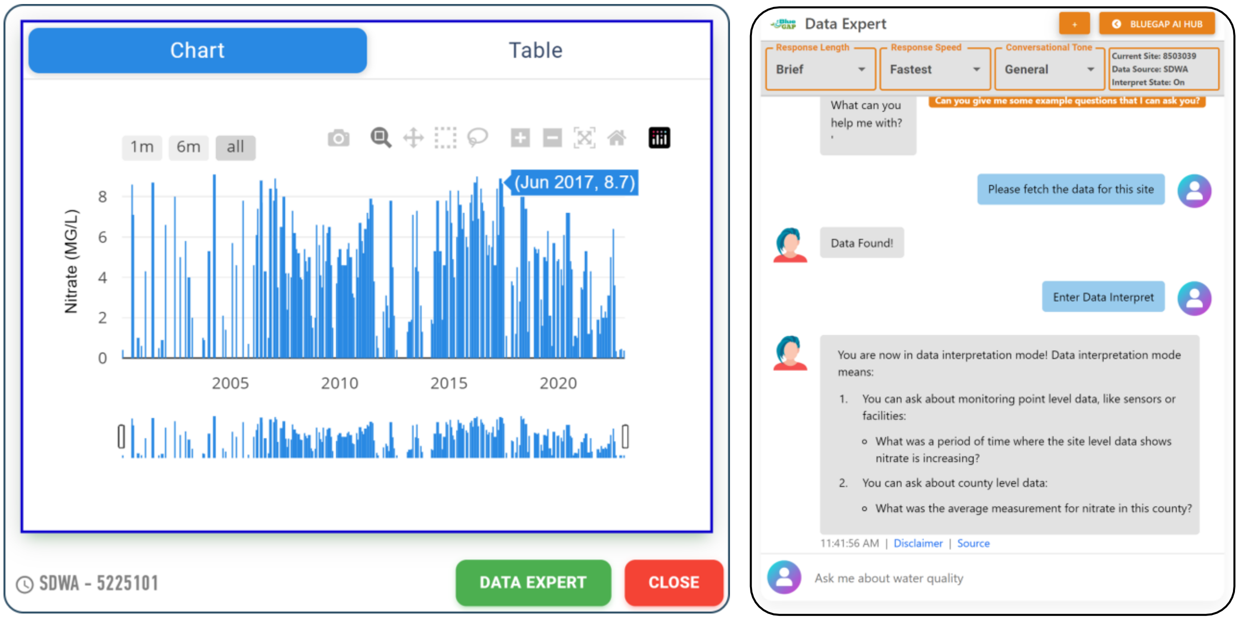


Figure 6: Variations to chat controls based on system state.

Accessibility: Since ChatGPT can by default understand and translate to languages other than English, the intelligent agent is multilingual (Figure 4b). This capability opens these experts to be used by almost any person who has access to a computer and network. By meeting users at their communication level and language, the AI-DE has the potential to be a dynamic teacher regarding water quality issues.

Chat Bypass: When the user selects a particular WQ measurement location, they can choose to view the observations and visualize the analyte measurements at this site over time. There is the ability to choose which analytes, temporal period, and the resolution of the data shown (Figure 7a). If the user has more questions, or would simply like to get ahold of the data, they can activate the AI-DE which will then take the user directly to the AI-DE with the appropriate site and county data preloaded (e.g., SDWA - ID 8503039).

After the AI-DE button has been enabled, the regular chat interface for the AI-DE appears, with the correct site and interpret state shown in the top right information panel (Figure 7b). When the user enters the AI-DE interface via the observation panel in the information system, they are able to immediately begin to ask questions of the data. If the user is unsure or clicked the AI-DE button out of curiosity, there are two example questions which show how you can ask about site level or county level data. These questions are basic and meant to be accessible, but more advanced user queries will return more detailed results.



(a) (b)

Figure 7: (a) IS-Side view of the AI-DE bypass button; (b) Entry to AI-DE using the bypass method.

4. Discussion

Centralizing ChatGPT at the core of the AI-DE presents a powerful model where a single underlying codebase can drive multiple AI-assisted bots. This versatility is achieved by modulating the embeddings (i.e., previous knowledge) accessible to the bot, along with modifying the bot's underlying system message that imparts instructions and defines its personality. This modular approach empowers the continuous development and refinement of a centralized framework, ensuring an enhanced user experience across all agents. Furthermore, specific agents requiring additional functionality can have bespoke features developed without necessitating a complete overhaul of the core framework. This strategic balance between a unified foundation and tailored enhancements allows for scalability, adaptability, and ongoing improvements in delivering a seamless and effective user experience.

ChatGPT demonstrates remarkable proficiency in tasks such as NER, geocoding, coordinate estimation, and sentiment analysis. This versatility enables natural language prompting to effortlessly address challenges that were once difficult (Pursnani et al., 2023). The combination of these capabilities into a single prompt empowers the system to operate with efficiency, maximizing the accuracy of responses aligned with the user's inquiries. The model showcases a commendable ability to interpret string-formatted, non-cleaned water quality sensor data, providing all users with a fundamental summary of the data. Beyond this, well-crafted prompts from users allow the AI-DE to transcend basic data summaries and can adeptly respond to advanced questions, aiding users in comprehending intricate water quality data in diverse locations such as Iowa, Tampa, and the US Virgin Islands. Through careful system prompts and embeddings, an application leveraging the ChatGPT API is crafted to engage users and elucidate complex water quality topics. These explanations are not only tailored to the user's vocabulary and response style but also dynamically generated based on individual user input, ensuring a personalized and informative interaction.

Empowering users with enhanced control over their chat experience through the use of chat controls establishes a consistent baseline that users can customize according to their specific requirements. This approach accommodates a diverse user base, ensuring a tailored experience that aligns with individual preferences and purposes. By offering control over chat length, users with straightforward questions can avoid cognitive overload, steering clear of excessive technical jargon. Simultaneously, academic and professional audiences find their needs met by the ability to engage with technical language, leverage the advanced capabilities of gpt-4 for high-quality answers, and access responses of up to 300 words. This flexibility allows for the effective explanation of complex water quality topics, catering to users with varying levels of expertise and interest.

4.1. GPT Paradigm

The integration of ChatGPT and its API facilitates the swift development of water quality chatbots. The paradigm of providing the model with appropriate embeddings and prompting has proven effective in the water quality domain, enabling the creation of conversational agents that accurately explain complex topics to users of varying ages, expertise levels, and linguistic backgrounds. Conversational agents, acting as moderators or docents within Information Systems, play a crucial role. Positioned as auxiliary entities, these agents naturally engage users, providing them with avenues to explore and delve deeper into the subject area (Sit et al., 2020). Whether driven by curiosity or happenstance, users can have their questions addressed, and these agents serve to answer the 'so what' questions that may arise during the use of the information system. The ChatGPT + prompting + embedding paradigm streamlines development efforts by allowing a focus on elements that enhance the usability and practicality of water quality intelligent agents. This approach significantly reduces development time, enabling projects to either incorporate additional features or be deployed to users more expeditiously.

4.2. Limitations

While the approach to intelligent agent development outlined has significant strengths and advantages, there are areas where further refinement can enhance the capabilities of such agents:

AI-DE Context: The AI-DE's current ability to perform ad-hoc data retrieval and analysis is confined to the context of a specific site. While this limitation is acceptable for the current project's objectives, future information systems could benefit from agents with increased contextual awareness. Expanding the scope of contextual understanding would enable agents to provide more comprehensive and nuanced analyses beyond individual sites.

Limited Niche Knowledge: Conversational agents excel in responding to a broad spectrum of questions about water quality and management. However, their capacity to address queries related to niche topics or delve deeply into specific water quality questions is constrained by the embeddings provided to the agent. Enhancements in embedding methodologies could broaden the agent's knowledge base, allowing it to tackle more specialized and intricate inquiries.

Reliance on Data Quality: The effectiveness of the bot's responses is contingent upon the quality of the underlying data. Outdated, incomplete, or inaccurate data may result in responses that mirror these shortcomings. Ensuring data accuracy, completeness, and timeliness is crucial to optimizing the bot's ability to furnish the most accurate and reliable answers to user queries. Continuous efforts to maintain and improve data quality are essential for sustained efficacy.

Addressing these areas for improvement can contribute to the evolution of conversational agents, enhancing their utility and effectiveness in providing valuable insights and information to users.

5. Conclusions

The integration of conversational AI into environmental information systems marks a significant advancement in the accessibility and usability of complex data. Through the development of the AI-DE, users can engage with water quality data through intuitive, real-time analytics and interaction, enhancing informed decision-making. This system demonstrates the potential of AI-driven platforms in environmental management by simplifying the interpretation of intricate data sets, thus democratizing access and fostering a greater understanding of crucial water quality issues. The modular design of the agents within the system further ensures adaptability and scalability, suggesting a robust framework for future enhancements and applications in various domains.

While the pursuit toward environmental education and protection is extensive, conversational agents exhibit a unique ability to establish connections with users, effectively communicating important and complex topics. Their continuous engagement supports users in pursuing their curiosity, enabling them to make more informed decisions about how their actions impact the environment. This represents a promising step toward fostering environmental awareness and empowering users to contribute to environmental conservation efforts.

5.1. Future Research

Future research in the domain of conversational agents, as integral components of environmental information systems, stands to benefit significantly from a user-centric focus. Historically, developing and studying chatbots within the broader context of environmental information systems presented challenges due to the complexity of creating effective chatbots and deciphering meaning from language. The emergence of ChatGPT and its API has transformed this aspect of chatbot development, making it notably more accessible. This newfound accessibility opens the door to an increased proliferation of chatbots serving as information liaisons. Future research endeavors can now shift their focus from questions like 'how do we design a chatbot' to more user-oriented inquiries such as 'what would our users want an intelligent agent for?'. This shift in perspective allows for a deeper exploration of how chatbots can enhance communication and facilitate the seamless delivery of information within the broader scope of Information Systems.

Another intriguing avenue for exploration involves the potential of WQ agents that can consume and analyze multimodal data, including videos and images. By integrating machine learning models capable of interpreting visual and auditory data (Samuel et al., 2024b), these agents could offer insights into water quality and public health issues (Sermet et al., 2021). For instance, analyzing video data from near water or underwater cameras could help identify sources of pollution, track the spread of algal blooms, or monitor the health of aquatic ecosystems with greater precision. An additional dimension of data enables a better picture of the real world. These advanced agents could leverage a formalized WQ ontology, ensuring alignment with subject matter and facilitating a deeper understanding of water quality dynamics. The development of a comprehensive WQ ontology would provide a structured framework for these agents, enabling them to categorize and analyze data more effectively, and offer users rich, contextually relevant information that goes beyond traditional data formats (Sermet et al., 2019). Use of other domain specific ontologies would enable future similar systems to be adapted to other fields of geosciences, such as hydrology.

Furthermore, the utilization of intelligent agents as tutors for water quality concepts presents a promising direction for educational outreach and engagement. These WQ tutor agents could employ adaptive learning techniques to tailor educational content to the user's knowledge level, learning pace, and interests (Sajja et al., 2023c). By providing interactive lessons, quizzes, and real-world problem-solving scenarios, these agents could significantly enhance users' understanding of water quality issues, management practices, and conservation strategies. This approach not only democratizes access to specialized knowledge but also fosters a more informed and engaged public ready to take action on water quality issues. The development of these tutor agents could leverage the existing capabilities of conversational AI, augmented with educational methodologies and content validation by water quality experts, to ensure accuracy and effectiveness.

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