Sustainable Urban Water Decisions using Generative Artificial Intelligence

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***Abstract*— Urban water systems are increasingly strained by the impacts of climate change, growing populations, and resource constraints, driving the need for more integrated and sustainable management solutions. Small and Medium-sized Enterprises (SMEs) are central to driving this transformation, leveraging their adaptability and significant impact on the industry. However, many SMEs lack access to comprehensive Information Systems (ISs) that combine data on government policies, industry trends, and water management initiatives, limiting their ability to implement sustainable practices. This study introduces *SustainWaterBot*, a Chatbot powered by Generative Artificial Intelligence (GenAI), including Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG). *SustainWaterBot* bridges this information gap by seamlessly integrating data from diverse sources such as news outlets, government publications, industry reports, scientific studies, and social media platforms into a unified IS. It enhances decision-making by providing timely and relevant insights into Sustainable Urban Water Initiatives (SUWIs) through an interactive Question Answering (QA) framework. By leveraging open-source technologies, *SustainWaterBot* offers SMEs an affordable, scalable, and sustainable tool to adopt eco-friendly water practices while improving operational efficiency and informed decision-making.**

Keywords—Sustainable Urban Water Management, Generative Artificial Intelligence, Large Language Models, Retrieval-Augmented Generation

I. INTRODUCTION

In 2019, the UK became the first major economy to legally pledge to achieve net-zero emissions by 2050 [1, 2]. Achieving this goal requires not only a transition to nearly zero greenhouse gas emissions but also offsetting any residual emissions. Strategies [3] include water conservation, leakage reduction, and the development of efficient urban water systems, which face increasing demands from climate change, growth of population, and resource constraints. These factors are driving a shift toward integrated, sustainable management to address water security, flood risk, urban heat islands, and waterway degradation while enhancing urban quality of life.

Sustainable Urban Water Transitions (SUWTs) are essential at multiple levels [4 - 6]; individual, community, SME, and government. SMEs, representing over 99% of the UK's businesses and impacting both resource use and emissions, play a crucial role in these transitions. By adopting practices like water-efficient technologies, greywater recycling, and stormwater management, SMEs can encourage urban water resilience and set standards that promote sustainability. Supporting SMEs in this shift are government policies, subsidies, and information resources available in structured and unstructured formats. However, SMEs face challenges in organizing and accessing this diverse data effectively. This study addresses these gaps by exploring:

1. How an IS can integrate diverse data to support SMEs in urban water management using open-source technologies.
2. In what ways can this system enhance decision-making within SUWTs for SMEs?
3. How to ensure the system's adaptability and sustainability for evolving needs.

To address these challenges, we introduce *SustainWaterBot*, a GenAI-powered Chatbot that consolidates information from diverse sources such as news outlets, government documents, and industry reports, offering SMEs a centralized and current resource for SUWIs and emerging trends. The Chatbot offers three key benefits:

- *Comprehensive Data Integration: SustainWaterBot* combines information from multiple sources, delivering a broad view of SUWIs.
- *Enhanced Decision-Making:* It supports SMEs with timely data for effective and data-driven choices in sustainable water management.
- *Adaptable and Cost-Effective:* The system is designed to be easily upgradeable and customizable, ensuring its relevance and sustainability over time.

The paper is ordered as follows: Section 2 presents the background, setting the foundation for the research context. Section 3 outlines the proposed system, followed by an analysis of its advantages and limitations in Section 4. Finally, Section 5 presents concluding insights.

II. BACKGROUND

Urban water systems encompass the management and disposal of city water, covering supply, treatment, and stormwater management [7]. Sustainable urban water management faces challenges from resource scarcity, climate change, urbanization, technology shifts, and governance demands for global cooperation [7]. Effective management requires reliable water supply, flood risk control, and the protection of environmental and social resources [8]. Various approaches include centralized water supply and treatment, stormwater management for flood prevention, natural waterway restoration, and adaptive urban-rural water strategies [8].

Recent studies propose innovative models to improve urban water management. For instance, a knowledge management system using web technology integrates data management and smart metering for water insights [9]. Other systems include the dynamic water simulation system to analyse urbanization and climate impact [10], the integrated water system to forecast demand and assess conservation strategies [11], and an intelligent water management system that uses granular data to optimize efficiencies [12]. Additional advancements include an Urban Building Database (UBD) for urban energy simulations [13], a dashboard with indicators for urban water security [14], a geospatial tool for optimizing relief posts [15], an IoT-based environmental monitoring approach [16], and a decision support system based on knowledge for water supply planning [17]. These innovations enhance urban water sustainability and efficiency through data-driven insights and strategic planning tools.

The studies highlighted above make significant strides in advancing urban water management systems and promoting sustainable practices. However, most rely on a single data type or source, are not open-source, and lack well-documented information. Given the evolving nature of urban water management, it is essential to continually update these systems with the latest information on water and related areas. SMEs, which are crucial in this sector, often face resource constraints that hinder their ability to test and implement existing urban water systems tailored to their needs. They require solutions that are open-source, customizable, and adaptable to their specific organizational requirements. Currently, there is no comprehensive IS available for SMEs to access up-to-date information on SUWIs and the broader urban water landscape. This gap can be effectively addressed using LLMs combined with RAG based on GenAI principles.

GenAI encompasses advanced algorithms that create new content like text by training patterns from various large datasets [18, 19]. This technology allows machines to produce original outputs that resemble human creativity and problem-solving. A key application of GenAI is LLMs, which are pre-trained on extensive datasets with billions of parameters. Utilizing deep learning techniques, LLMs can identify complex language patterns [18]. However, LLMs often struggle with domain-specific queries due to their general training, leading to inaccuracies. To mitigate these issues, RAG [20] has been introduced, which enhances LLMs by retrieving related information from external sources before producing responses (see Fig. 1).

This integration enhances the precision and relevance of the generated content. RAG's versatility enhances QA systems across different domains like biomedical, financial, technical, and humanitarian sectors [21]. This is exemplified by the development of QA assistants, including Chatbots, which demonstrate how RAG facilitates seamless interactions with complex systems. However, its integration with LLMs in the urban water sector remains largely unknown. Integrating RAG with LLMs allows organizations to access and analyze diverse data sources, enabling the creation of robust QA systems. This approach streamlines data aggregation and uncovering key insights for informed decision-making. In the subsequent section, we will detail how we use LLMs and RAG to develop a comprehensive IS that offers SMEs an up-to-date repository of SUWI information.

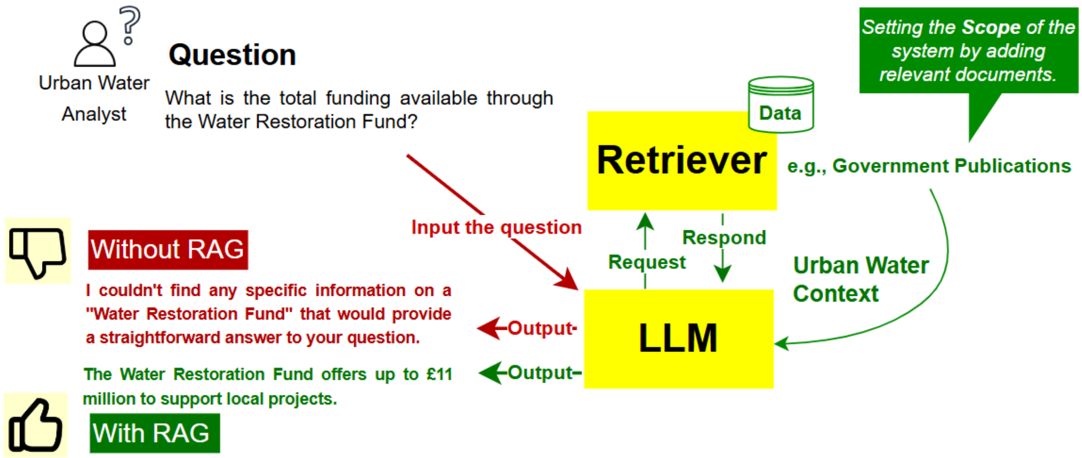

Fig. 1. Benefits of RAG in improving LLMs for domain-specific queries through external relevant data: A case study using recent government publications.

III. Proposed System

This section outlines the creation of a specialized dataset aimed at enhancing *SustainWaterBot*, an IS powered by a LLM integrated with RAG technology. Designed as a QA Chatbot for the urban water sector, the selection of a QA Chatbot is backed by research [21], which demonstrates its effectiveness in fostering better user interaction and engagement with ISs. Chatbots enable efficient querying and information retrieval, delivering quick responses and enhancing accessibility, especially in complex domains like water management, where clear and concise information is essential. After discussing the dataset construction process, we will outline the system's implementation using current tools and technologies, concluding with an evaluation of its performance in generating user responses.

A. *Dataset Development*

We performed an extensive literature review to create a dataset for an IS utilizing RAG and LLMs, aimed at enhancing decision-making in SUWTs. This review identified key topics relevant to SUWIs and the urban water landscape essential for promoting sustainability. These topics include Trends and Emerging Issues, Case Studies, Public Opinion and Awareness, Regulatory Guidelines, Policy Frameworks, Funding Opportunities and Incentives, Best Practices and Standards, Technological Innovations, Market Trends, Scientific Evidence and Data, Innovative Approaches and Theories, Long-Term Projections, Public Engagement and Sentiment, Community Initiatives, and Real-Time Feedback.

To keep the information current, we utilized six main sources: News publications, governmental reports, industry papers, scholarly research, and social media platforms. This data comes in various formats like HTML, PDFs, CSVs, and spreadsheets, providing valuable insights for informed decision-making in sustainable urban water management. For our proof-of-concept, we focused on specific sources for each topic: BBC News - Science & Environment for Trends [22], UK Water Industry Research (UKWIR) for Case Studies [23], and YouGov for Public Opinion [24]. Regulatory Guidelines come from Ofwat [25] and the Environment Agency [26], while Policy Frameworks are from DEFRA [27]. Funding Opportunities are provided by UK Research and Innovation (UKRI) [28], and Best Practices are from the British Standards Institution (BSI) [29]. Market Trends are analysed through IBISWorld UK [30], and Scientific Evidence is provided by the UK Centre for Ecology & Hydrology (CEH) [31]. Other sources include the Met Office for Long-Term Projections [32] and Groundwork UK for Public Engagement [33]. In the next section, we will discuss the development of *SustainWaterBot*, an IS that serves as a QA tool for analysts using this curated urban water dataset.

B. *Implementation of SustainWaterBot*

To provide SMEs with a powerful system for exploring SUWIs, we developed an advanced *SustainWaterBot* (see Fig. 2) utilizing LLMs. After evaluating several leading LLMs, we selected Llama3.1 [34] for its superior performance, freely accessible Application Programming Interface (API) and extensive training on diverse datasets. While developers can choose from these models based on their specific needs and availability, we tailored Llama3.1 specifically for the water sector. This process integrated RAG technology, equipping the Chatbot to accurately interpret and respond to urban water-related queries by utilizing data from diverse formats, including structured and semi-structured sources like CSVs,

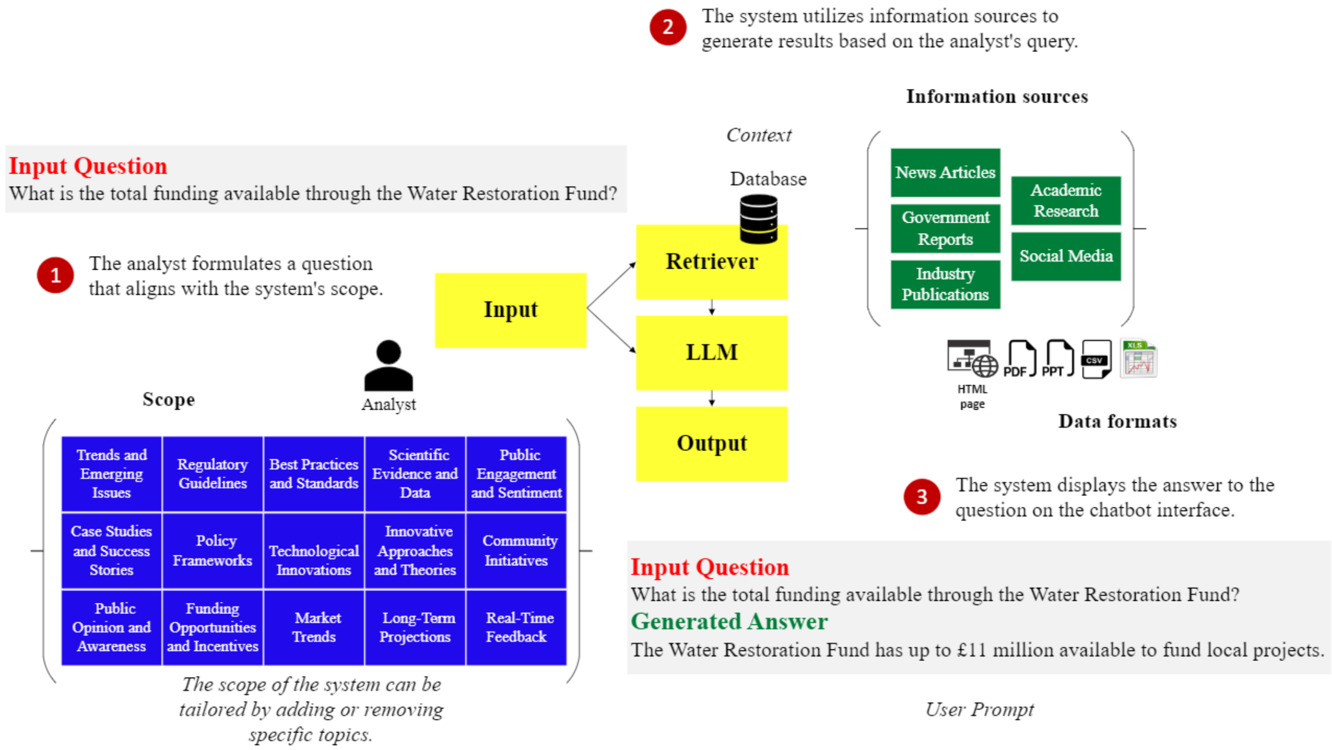

Fig. 2. *SustainWaterBot* using RAG with LLM-based QA system

spreadsheets, and HTML pages. The efficiency of the Chatbot in addressing a wide range of urban water-related questions depends on the comprehensiveness of the water dataset, which serves as the contextual foundation for the water domain. To tailor Llama3.1 for urban water-specific QA, we implemented a structured approach designed to extract and process relevant information effectively. This methodology leverages Llama3.1 alongside Hugging Face models (huggingface.co), renowned for their advanced NLP capabilities, to optimize performance in addressing urban water-related queries.

The implementation process begins with installing essential packages like Transformers [35], langchain [36], and llama_index [37], which are critical for model deployment and data handling. We import key modules such as VectorStoreIndex and HuggingFaceLLM (https://docs.llamaindex.ai/) to support efficient indexing and model integration. System prompts and query wrapper prompts are defined to ensure that the model receives the proper context and structure for generating accurate responses. After logging into Hugging Face to access the model hub, we initialize HuggingFaceLLM due to its excellent performance and comprehensive model repository. LangchainEmbedding is used to convert text into vectors [38] through embedding models like HuggingFaceEmbeddings, improving semantic search and context management via the creation of a ServiceContext. Documents are loaded from a specified directory using SimpleDirectoryReader, and a VectorStoreIndex is created to generate embeddings and ensure rapid, precise information retrieval. The query_engine then uses these embeddings to query the index with specific questions, leveraging Llama3.1 to deliver accurate answers. The responses generated are then presented to users, thereby enhancing interaction and information accessibility within the urban water domain.

C. *Evaluation of SustainWaterBot*

To evaluate the accuracy of the Chatbot's responses, we used Precision and Recall, two key metrics commonly applied to LLM-based systems [39]. These metrics evaluate the quality of the Chatbot's output, focusing on how effectively it retrieves and presents relevant information. Information Components (ICs) were defined as the basis for evaluation, which include organizational names, individuals, keywords, geographic locations, and timestamps [40, 41]. Precision measures the proportion of relevant ICs among all retrieved components, highlighting the system's ability to eliminate irrelevant data [39]. Recall, on the other hand, measures the proportion of relevant ICs retrieved out of the total available, reflecting the system's capability to capture all pertinent information [39]. Moreover, F1-Score is the harmonic mean of precision and recall, providing a single metric that balances both [39]. Together, these metrics provide a robust framework for evaluating the Chatbot's performance in terms of relevance and completeness.

For evaluation, we constructed 150 water-related questions based on the water dataset, with some questions listed in Table I. Table II evaluates the *SustainWaterBot*, showing a Precision of 88%, Recall of 90%, and an F1-Score of 89%. These scores demonstrate the effectiveness of the RAG with LLM (i.e., Llama3.1) system in delivering precise and comprehensive responses, highlighting its capability to handle urban water-related queries effectively.

TABLE I. A SUBSET OF QA PAIRS FOR CHATBOT EVALUATION

No.	Question	Answer
1	How does the Water Restoration Fund support biodiversity targets in the Environment Act?	The Fund supports biodiversity by aiming to halt species decline by 2030 and restore or create 500,000 hectares of wildlife habitats by 2042.
2	What is the maximum grant amount available through Swansea Council's Carbon Reduction Grant, and what is required from applicants?	The Swansea Council Carbon Reduction Grant offers up to £10,000, requiring 50% match funding and a business plan with a 12-month cash flow forecast.
3	Which grant is designed to help SMEs in BANES and South Glos with purchasing and installing new equipment for reducing greenhouse gas emissions?	The Green Business Grants for BANES and South Glos assist SMEs in purchasing and installing equipment to reduce greenhouse gas emissions, lower utility costs, and enhance energy efficiency.

TABLE II. EVALUATING CHATBOT PERFORMANCE.

Model	Precision (%)	Recall (%)	F1-Score (%)
SustainWaterBot	88	90	89

IV. DISCUSSION

We propose *SustainWaterBot* as a centralized hub for urban water-related insights, aggregating data from diverse sources, including news outlets, government publications, industry reports, and other platforms. It supports both structured and unstructured data formats, providing a comprehensive and relevant knowledge base for users. The Chatbot's response generation relies heavily on the datasets available to it, which are currently updated manually by developers. Without these manual updates, the Chatbot may not reflect the latest developments or niche findings in urban water management. The update process is simple, requiring only the replacement of outdated files, which streamlines maintenance and reduces the environmental impact associated with additional development, making the system more sustainable. However, the performance of the *SustainWaterBot's* responses depends on the quality of the data from reliable and authentic sources. The article does not address how the information is filtered for retrieval purposes. Additionally, the system's query handling mechanism varies based on the complexity of the information provided to the Retriever. For general queries, the Chatbot generates general responses, while for complex topics, it manages more detailed answers. This system does not require resource-intensive fine-tuning of the LLMs but only the replacement of files with updated content, further enhancing the sustainability of *SustainWaterBot*.

Despite its benefits, the research has several limitations. First, the evaluation was based on a limited set of manually selected questions and the use of Precision, Recall, and F1 metrics. While these metrics are valuable, they may not fully capture the nuanced aspects of Chatbot performance, such as response relevance, coherence, and adaptability in complex scenarios. Moreover, the set of questions used may not cover the full breadth of urban water topics. A more comprehensive evaluation, utilizing advanced metrics and a broader range of queries, is essential to assess accuracy and relevance more thoroughly. Another limitation is that *SustainWaterBot* was tested with a single user interface. In high-demand environments, such as when multiple SMEs analysts access the system simultaneously, latency and data handling issues may arise, leading to delayed responses. This potential challenge should be explored in future research. Furthermore, the use of RAG technology for information retrieval may lead to slower response times as more data sources are incorporated [20, 43]. Future studies should evaluate query acquisition times for both simple and complex queries and investigate strategies to optimize data extraction processes. Lastly, the current system relies on a single LLM, the Llama 3.1 model. While effective and open-source, future research should explore other models, such as Generative Pre-trained Transformer (GPT) [42], to identify the most suitable option for urban water applications. Expanding the range of tested LLMs could provide valuable insights into improving urban water-related ISs.

V. CONCLUSIONS

SMEs are vital to the UK's net-zero goals, especially in developing efficient urban water systems. However, many lack crucial knowledge about sustainable water practices, leading to inefficiencies and increased costs. Timely access to information on SUWIs, including policies, technologies, and trends, is essential for informed decision-making. Existing systems often struggle to integrate diverse data due to their reliance on proprietary technologies that lack the flexibility of open-source solutions and the ability to dynamically customize according to evolving organizational needs. This restricts SMEs' capacity to adapt their systems to specific requirements and undermines their efforts to implement sustainable practices. Moreover, these systems typically lack upgrade options, making it difficult to incorporate or remove datasets as priorities shift. The time and resources required for new developments further contribute to their unsustainability. To address these challenges, our study introduced *SustainWaterBot*, an LLM-based tool with RAG technology, designed to provide SMEs with timely insights into the urban water sector. Built on open-source technologies, *SustainWaterBot* enables dynamic customization and system upgrades, helping SMEs align their systems with evolving needs while supporting responsible investments and reducing the carbon footprint of development.

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