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Article

# An Intelligent Conversational Agent for Flood Risk Communication in a Flood-Prone Region of Nigeria

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**Abstract:** Flooding remains one of the most devastating natural hazards in developing countries, with significant impacts on human lives, infrastructure, and livelihoods. In Nigeria, particularly in Bayelsa State, recurrent flooding events highlight the need for effective and accessible flood risk communication systems. However, existing approaches largely rely on static and non-interactive dissemination channels, limiting timely public engagement and response. This study addresses this gap by designing and implementing a conversational agent capable of providing real-time responses to frequently asked flood-related questions. The proposed system adopts a rule-based conversational framework supported by natural language preprocessing techniques, including tokenization and normalization, for query interpretation. A structured knowledge base containing flood preparedness and response information was developed for the study area. The system was evaluated using a set of 120 representative flood-related queries derived from domain-specific scenarios. Experimental results show that the chatbot achieved a response accuracy of 87.5% and a successful query handling rate of 90.8%. These findings demonstrate the feasibility of conversational agents as effective tools for enhancing flood risk communication and public awareness. The study contributes to the integration of artificial intelligence-driven solutions into disaster risk management and highlights the potential of chatbot systems in improving access to critical environmental information in resource-constrained settings.

**Keywords:** Conversational agent; Chatbot; Flood risk communication; Disaster management; Natural language processing; Bayelsa State; Public awareness.



## 1. Introduction

Flooding is globally recognized as one of the most devastating natural hazards, causing extensive loss of human lives, destruction of infrastructure, disruption of livelihoods, and long-term socio-economic decline. Its impacts are particularly severe in developing countries, where rapid urbanization, climate variability, weak infrastructural planning, and limited institutional capacity compound flood vulnerability [1]. In recent decades, climate change has further intensified flood frequency and severity, increasing the urgency for effective flood risk management strategies that extend beyond structural interventions [2]. Nigeria has experienced recurrent and increasingly severe flood events, with coastal and riverine states disproportionately affected. Among these, Bayelsa State remains one of the most flood-prone regions due to its low-lying terrain, extensive river networks, and proximity to the Atlantic Ocean (Figure 1).

Seasonal flooding in the state has repeatedly resulted in mass displace, loss of agricultural productivity, environmental degradation, and heightened socio-economic vulnerability of rural and riverine communities. These recurring events underscore the critical need for accessible, reliable, and actionable flood-related information to

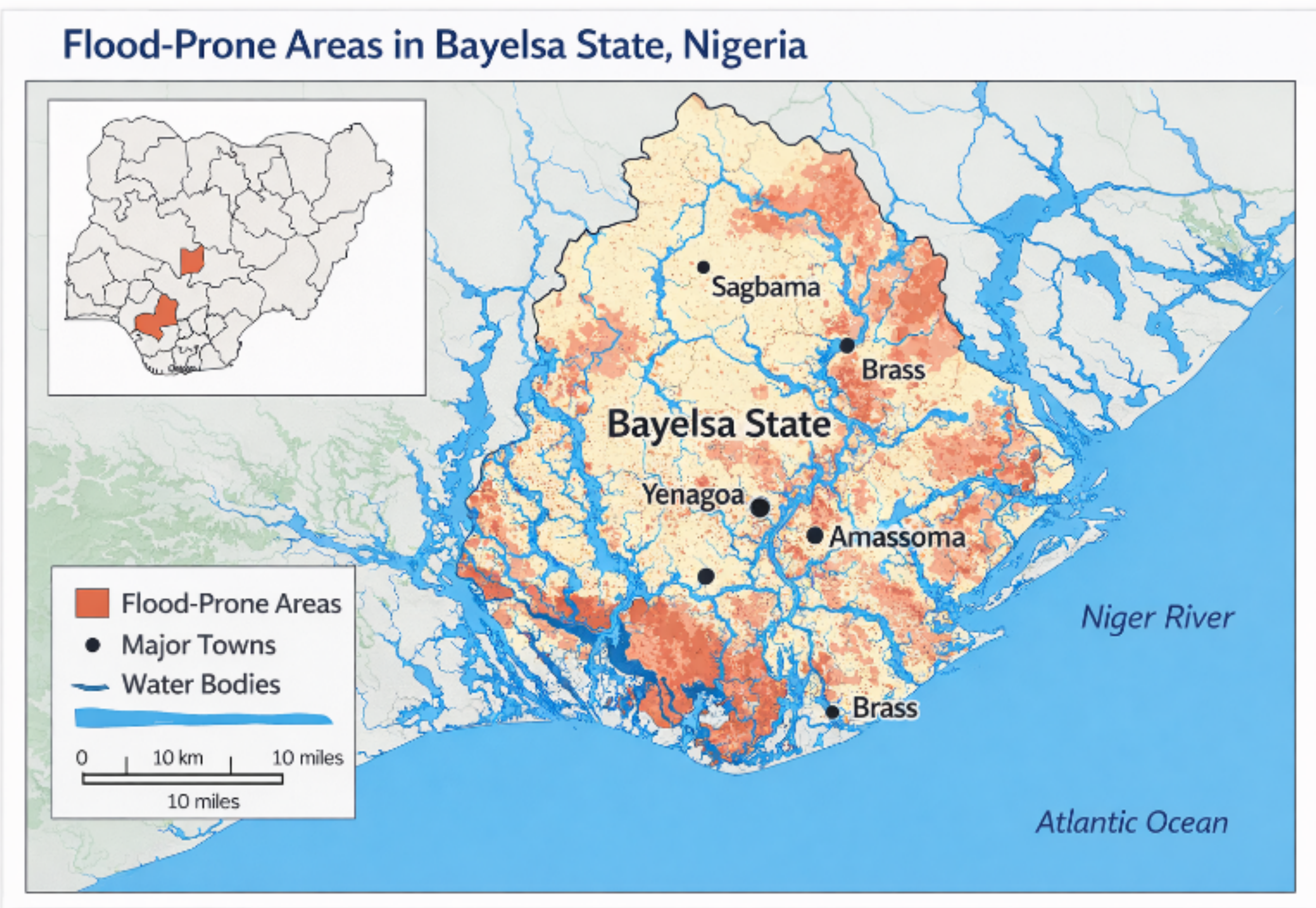


**Figure 1.** Map of Nigeria showing Bayelsa State and flood-prone areas in the Niger Delta region.

support community preparedness and response. Effective flood risk management is not limited to hydrological forecasting and infrastructural defenses but also depends heavily on risk communication and public awareness [3], [4]. Timely dissemination of flood risk information enables individuals and communities to understand potential hazards, adopt preventive measures, and respond appropriately during emergencies. However, conventional flood information dissemination channels—such as radio announcements, public notices, and printed advisories—are often characterized by delayed updates, one-way communication, limited personalization, and restricted reach, especially in rural and underserved areas. Such limitations reduce their effectiveness in dynamic disaster contexts where users require real-time, interactive, and context-specific information [1].

Recent advances in artificial intelligence (AI), particularly in natural language processing (NLP), have enabled the emergence of conversational agents capable of interacting with users through natural language interfaces. Chatbots are increasingly deployed across diverse domains, including healthcare, education, customer service, and public administration, due to their scalability, availability, and ability to provide instant, automated responses [5], [6]. Studies have shown that conversational agents can enhance user engagement, trust, and information accessibility when designed with appropriate communication strategies and domain knowledge [7]-[9]. Within disaster management and public safety contexts, AI-driven conversational agents present a promising tool for improving risk communication and decision support. By delivering real-time responses to frequently asked questions, providing guidance on preparedness and response actions, and serving as an interactive interface to disaster knowledge bases, Chatbots can complement existing early warning and advisory systems. Prior research has demonstrated the effectiveness of intelligent information systems and advisory models in flood prediction and risk communication, emphasizing the importance of transforming technical data into actionable intelligence for end users [10]-[13].

However, most existing systems prioritize predictive analytics and alert generation, with limited focus on user-centered, conversational interaction mechanisms that facilitate direct public engagement. Despite the growing body of research on AI applications in disaster management, the adoption of conversational agents for flood risk communication in Nigeria remains largely unexplored. Existing studies within the Nigerian context predominantly focus on hydrological modeling, early warning frameworks, and decision-support systems, with minimal attention to interactive, dialogue-based information services that address the everyday informational needs of at-risk populations. This gap is particularly evident in flood-prone regions such as Bayelsa State, where access to timely and understandable flood-related information is critical for community resilience.

Figure 1 presents a map of Nigeria highlighting Bayelsa State and the surrounding Niger Delta region, including identified flood-prone areas. The visualization provides geographic context for the study and illustrates the extent of flood vulnerability in the region, which justifies the need for improved flood risk communication systems.

In response to this gap, this study proposes the design and implementation of an intelligent, domain-specific conversational agent for providing flood-related information tailored to the context of Bayelsa State, Nigeria. The primary objective of the study is to develop a Chatbot capable of delivering automated responses to frequently asked questions on flooding, preparedness measures, and advisory guidance using natural language interaction. The key contributions of this paper include: (i) the design of a conversational AI system specifically tailored for flood risk communication in a highly vulnerable region; (ii) the development of a modular system architecture integrating natural language understanding with a structured flood knowledge base; and (iii) an evaluation of the system's effectiveness in improving public awareness and accessibility to flood-related information. By demonstrating the applicability of Chatbot-based information systems in flood risk communication, this research contributes to broader efforts aimed at integrating artificial intelligence into disaster risk reduction and resilience strategies.

This study makes the following contributions to the field of intelligent disaster risk communication and flood management. First, it presents the design and development of a domain-specific conversational agent tailored for flood risk information dissemination in a highly flood-prone region, Bayelsa State, Nigeria, addressing a gap in interactive flood communication systems within developing-country contexts. Second, this paper proposes a modular system architecture that integrates natural language understanding, intent classification, and a structured flood knowledge base to enable real-time, user-centered responses to flood-related queries. Third, the study demonstrates how conversational agents can complement existing flood prediction and advisory systems by translating technical flood data and advisories into accessible, natural-language information for the general public. Finally, the effectiveness of the proposed Chatbot is evaluated in terms of information accessibility and user support, providing empirical insights into the feasibility of deploying AI-driven conversational interfaces as part of disaster risk reduction and public awareness strategies.

The remainder of this paper is organized as follows. Section 2 reviews related work on flood risk communication systems, conversational agents, and the application of artificial intelligence in disaster management. Section 3 presents the research methodology and system design approach adopted in this study. Section 4 describes the implementation details. Section 5 discusses the experimental setup, evaluation results, and discussion of the findings. Section 6 concludes the paper and outlines directions for future research. Finally, Section 7 presents the recommendations.

## 2. Related Work

The application of artificial intelligence and digital technologies to disaster management has gained increasing attention in recent years, particularly in response to the growing frequency and severity of climate-induced hazards such as flooding. Prior studies related to this work can be broadly categorized into flood risk information systems, conversational agents and Chatbots, and the use of artificial intelligence for disaster risk communication.

### 2.1. Flood Risk Information and Communication Systems

Flood risk information systems have traditionally focused on flood prediction, early warning, and advisory mechanisms aimed at mitigating the impacts of flooding on vulnerable communities. Many studies emphasize hydrological modeling, sensor-based monitoring, and decision-support dashboards to forecast flood events and guide emergency responses. Recent works in Nigeria and similar flood-prone regions have proposed flood prediction and advisory systems that integrate environmental data, predictive analytics, and alert dissemination to improve preparedness and response [10]-[13]. While these systems have demonstrated effectiveness in predicting flood events and generating advisories, their communication strategies are often limited to one-way dissemination channels such as web portals, mobile alerts, or static dashboards. Research by Haer et al. [1] highlights that the effectiveness of flood risk communication depends not only on the accuracy of information but also on how it is communicated, including social influence, trust, and user engagement. Passive information delivery mechanisms may fail to address individual concerns, clarify uncertainties, or adapt to diverse user information needs during flood events. Consequently, there is growing recognition that flood risk communication systems must evolve beyond prediction-centric approaches to include interactive, user-centered communication tools that support understanding, preparedness, and decision-making at the community level. However, interactive conversational interfaces remain largely underexplored in existing flood information systems, particularly in developing countries.

### 2.2. Conversational Agents and Chatbots

The template Conversational agents, commonly referred to as Chatbots, are software systems designed to interact with users through natural language using text or speech interfaces. Foundational studies describe Chatbots in terms of their architectures, types, and enabling technologies, broadly categorizing them into rule-based, machine-learning-based, and deep-learning-based systems [5], [14]. Rule-based Chatbots rely on predefined patterns and responses, while learning-based approaches utilize natural language understanding (NLU) models to infer user intent and generate responses dynamically. A substantial body of literature has examined Chatbot design choices and user experience factors, including perceived humanness, trust, communication style, and engagement. Human-like communication behaviors, such as natural language fluency and adaptive responses, have been shown to influence user satisfaction and trust [7], [8], [15], [16]. Studies have also explored the effects of humor, slang, and affective cues on user engagement, demonstrating that conversational tone can significantly shape user perception and interaction outcomes [17]-[19].

From a technical perspective, Chatbot development presents notable challenges related to intent recognition, response accuracy, scalability, and platform selection. Abdellatif et al. [20] identified common development challenges through an analysis of Stack Overflow discussions, while Abdellatif et al. [21] compared NLU platforms and highlighted trade-offs between performance, flexibility, and ease of integration. More advanced approaches employing deep learning models such as recurrent neural networks, bidirectional GRU, CNN, and attention mechanisms have demonstrated improved conversational capabilities but at the cost of increased computational complexity and reduced transparency [22], [23]. Chatbots have been successfully deployed across domains such as education, marketing, and institutional support, illustrating their versatility and scalability [24]-[26]. These applications demonstrate the potential of conversational agents to deliver domain-specific information effectively when appropriately designed and contextualized.

### 2.3. Artificial Intelligence in Disaster Management and Safety-Critical Domains

Artificial intelligence has increasingly been applied in disaster management to support prediction, response coordination, and public engagement. While much of the research has focused on backend analytics and decision-support systems, recent studies highlight the growing role of AI-driven conversational agents in safety-critical and behavior-change domains. Systematic reviews and meta-analyses in healthcare and mental health contexts provide strong evidence that AI-based conversational agents can improve user engagement, knowledge acquisition, and behavioral outcomes when designed with appropriate communication strategies [6], [27]-[29].

Beyond healthcare, conversational agents have been applied to safety management and risk-related domains. For example, Vidal-Sepúlveda et al. [30] demonstrated the effectiveness of intelligent conversational agents in school safety management, emphasizing their role in information dissemination and situational awareness. These findings suggest that conversational AI can play a valuable role in safety-critical environments by providing accessible, timely, and consistent information to users [31]. However, safety-critical applications impose stricter requirements on Chatbot design, particularly regarding reliability, transparency, and avoidance of misinformation. In such contexts, rule-based or hybrid conversational approaches may be preferable to fully generative models due to their predictable behavior and reduced risk of erroneous responses. This consideration is especially relevant for disaster communication scenarios, where inaccurate information can have severe consequences.

### 2.4. Research Gap and Motivation

The reviewed literature reveals three key observations. First, existing flood risk management systems predominantly emphasize prediction, monitoring, and alert dissemination, with limited attention to interactive, user-centered communication mechanisms. Second, conversational agent research has largely focused on domains such as healthcare, education, marketing, and customer service, with comparatively little emphasis on flood risk communication or disaster-related public awareness. Third, while AI-driven Chatbots have demonstrated effectiveness in safety-critical and behavior-change contexts, their application to localized flood information dissemination remains scarce, particularly in developing regions. Notably, there is a lack of studies that integrate conversational agents with flood-specific knowledge bases to address frequently asked questions related to flood preparedness, safety, and recovery. This gap is especially pronounced in flood-prone regions such as Bayelsa State, Nigeria, where communities face recurrent flooding and limited access to interactive information channels.

Motivated by these gaps, this study proposes an intelligent conversational agent designed specifically for flood risk communication and public awareness. By utilizing effectively natural language processing and a localized flood knowledge base, the proposed system aims to complement existing flood prediction and advisory systems by providing an interactive, accessible, and context-aware platform for disseminating flood-related information. This work contributes to the emerging intersection of conversational AI and disaster risk management and addresses an important unmet need in flood-prone communities.

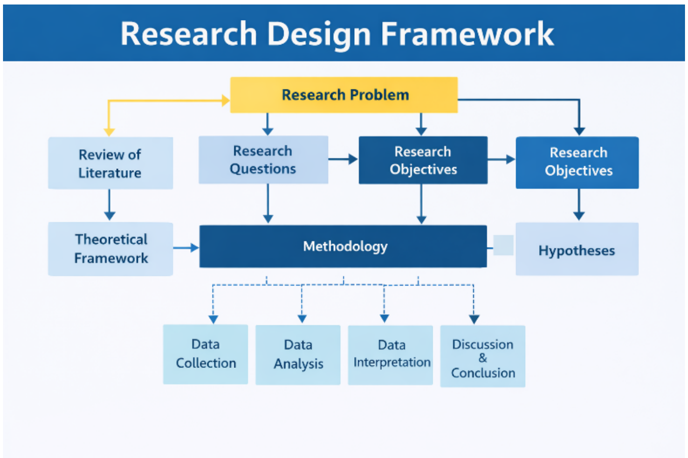


**Figure 2.** Research Design Framework for the Development of the Flood Information Chatbot.

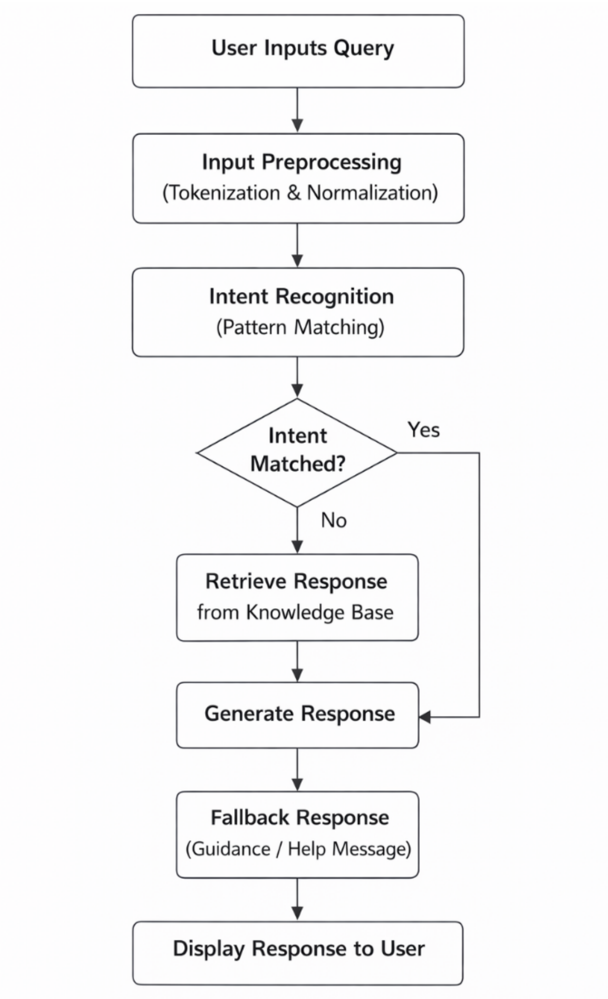


**Figure 3.** Conversational Flow of the proposed Flood information Chatbot.

## 3. Evaluation Methodology

This study adopts a system-oriented research methodology focused on the design, development, and evaluation of a conversational agent for flood risk communication. The methodology combines principles of software engineering with artificial intelligence techniques to produce a functional and context-aware Chatbot tailored to the flood conditions of Bayelsa State, Nigeria.

### 3.1. Research Design

This design enables independent development and modification of system components while maintaining overall system coherence. Figure 2 presents the research design framework adopted in this study. The research follows a systematic process beginning with problem identification and literature review, followed by the definition of research objectives and system requirements. The methodology phase involves the design and development of the chatbot system, including knowledge base construction and conversational rule definition. This is followed by system testing and evaluation using representative queries. The final stage involves analysis of results and formulation of conclusions.

### 3.2. Data Sources and Knowledge Base Development

The knowledge base of the Chatbot was constructed using flood-related information obtained from multiple sources, including government reports, disaster management guidelines, and publicly available flood awareness materials relevant to Bayelsa State. Frequently asked questions (FAQs) related to flood causes, early warning signs, preparedness measures, safety precautions, and post-flood actions were identified and structured into a domain-specific dataset. This dataset served as the primary source of knowledge for training and configuring the Chatbot's response mechanisms.

### 3.3. System Requirements

The system requirements were defined to ensure that the Chatbot effectively supports flood risk communication and public awareness. Functional requirements included the ability to accept user queries in natural language, identify user intent, retrieve relevant flood-related information, and generate appropriate responses. Non-functional requirements focused on usability, scalability, availability, and ease of deployment. The system was designed to be lightweight and accessible through standard web interfaces to facilitate use by a broad range of users.

### 3.4. Conversational Agent Development Approach

The Chatbot was developed using a rule-based and pattern-matching conversational framework, supplemented by natural language processing techniques for intent recognition (See Figure 3). Text preprocessing steps such as tokenization and normalization were applied to user inputs to improve response accuracy. The conversational flow was designed to handle common flood-related queries while maintaining coherence and contextual relevance. Python was used as the primary programming language due to its extensive support for AI and web development libraries.

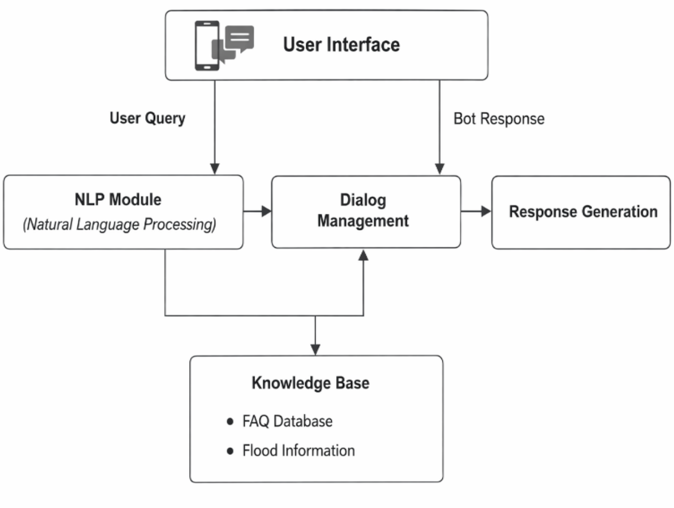


**Figure 4.** System Architecture of the Flood information Chatbot.

3.5. Evaluation Strategy

To assess the effectiveness of the proposed system, a functional evaluation approach was adopted. The Chatbot was tested using a set of representative flood-related queries to examine response correctness, relevance, and consistency. The evaluation focused on the system's ability to provide accurate and understandable information rather than quantitative performance metrics. Observations from the evaluation were used to identify strengths, limitations, and areas for future improvement.

It is important to clarify that while the proposed system incorporates natural language processing techniques, the chatbot does not employ advanced machine learning-based intent classification models. Instead, the system utilizes a rule-based pattern-matching approach supported by basic NLP preprocessing operations such as tokenization, normalization, and keyword extraction. These preprocessing steps enhance the system's ability to interpret user queries; however, intent recognition is primarily achieved through predefined rules and keyword patterns. This design choice was motivated by the need for simplicity, interpretability, and ease of deployment in resource-constrained environments.

The evaluation of the proposed chatbot system was conducted using a structured set of representative flood-related queries to assess its functional performance. A total of 120 test queries were developed based on frequently asked questions related to flood preparedness, early warning, evacuation procedures, and safety measures within the study area. The queries were categorized into different intent groups, including:

1) Flood preparedness information
2) Emergency response guidance
3) General flood awareness
4) Location-specific inquiries

To evaluate system performance, two quantitative metrics were defined:

1) ***Response Accuracy (RA)***: the proportion of queries for which the chatbot returned a correct and relevant response.
2) ***Successful Query Handling Rate (SQHR)***: the percentage of queries successfully processed without system failure or fallback errors.

3.6 System Architecture and Design

The proposed conversational agent was designed using a modular architecture to ensure flexibility, scalability, and ease of maintenance. The architecture follows a layered approach that separates user interaction, natural language processing, application logic, and knowledge management. This design enables independent development and modification of system components while maintaining overall system coherence.

3.6.1. System Architecture

The system architecture consists of four main components: the user interface layer, the conversational processing layer, the application logic layer, and the knowledge base (Figure 4). The user interface serves as the point of interaction between users and the Chatbot, allowing users to submit flood-related queries using natural language through a web-based interface. User inputs are forwarded to the conversational processing layer for interpretation and response generation. The conversational processing layer is responsible for handling natural language understanding tasks, including text preprocessing, intent recognition, and pattern matching. This layer processes user queries and determines the most appropriate response based on predefined rules and trained conversational patterns. The application logic layer coordinates the interaction between the conversational engine and the knowledge base, ensuring that relevant flood-related information is retrieved and delivered in a structured manner. The knowledge base stores domain-specific flood information, including frequently asked questions, preparedness guidelines, safety instructions, and emergency responses relevant to Bayelsa State

3.6.2. Conversational Flow Design

The conversational flow was designed to support intuitive and user-friendly interactions. Upon receiving a user query, the system performs input validation and preprocessing before matching the query against known intents and patterns. If a matching intent is identified, the corresponding response is retrieved from the knowledge base and presented to the user. In cases where the system is unable to identify a suitable response, fallback mechanisms are employed to guide the user toward supported queries or provide general flood-related information. The conversational flow emphasizes clarity, simplicity, and contextual relevance. Responses were designed to be

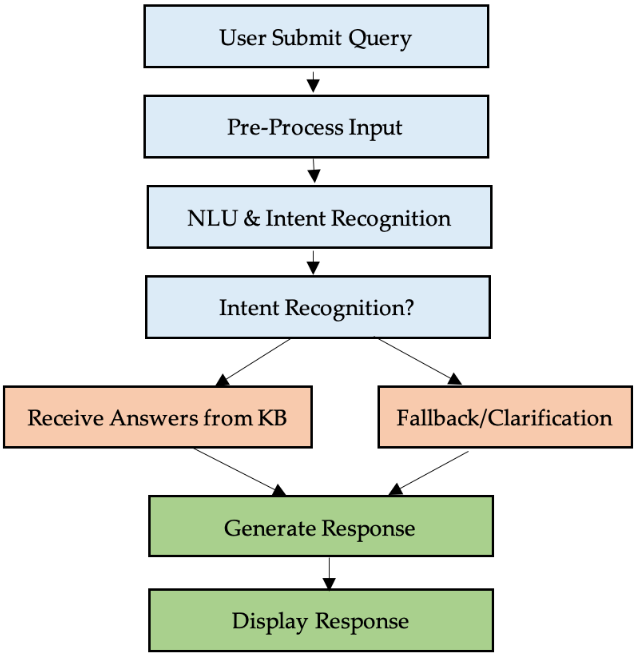


**Figure 5**. Activity diagram of the operational workflow of the proposed flood information conversational agent.

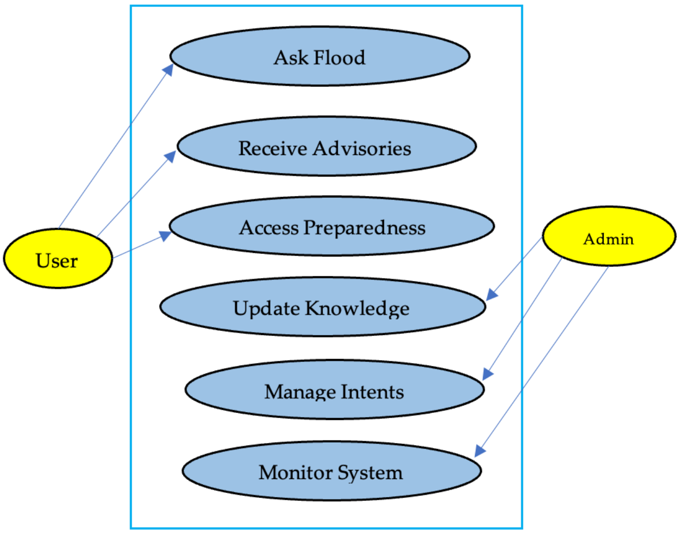


**Figure 6**. Use case diagram of user and administrator interactions with the flood information Chatbot system.

concise and informative, avoiding technical jargon to ensure accessibility for users with varying levels of digital literacy. The system also supports multi-turn interactions for selected queries, allowing users to request additional information or clarification within the same conversational context.

This activity diagram depicts the end-to-end interaction process of the chatbot, highlighting user query handling, intent recognition, decision logic, knowledge retrieval, fallback handling, and response generation (see Figure 5). It emphasizes the system's ability to provide real-time, automated flood-related information through natural language interaction.

The use case diagram presents the primary interactions between end users and administrators with the Chatbot system (see Figure 6). Users access flood-related information and advisories, while administrators manage system knowledge, Chatbot behavior, and overall performance to ensure accuracy and reliability.

### 3.6.3. Natural Language Processing Module

Figure 7 illustrates the natural language processing architecture of the proposed chatbot. The architecture consists of sequential components including user input acquisition, text preprocessing, intent recognition using rule-based matching, and response generation. The preprocessing stage involves tokenization, normalization, and keyword extraction, which prepare the input for pattern matching. The processed query is then matched against predefined rules in the knowledge base to determine the appropriate response. This pipeline enables efficient and interpretable conversational interaction.

The natural language processing module plays a central role in enabling effective communication between users and the Chatbot. This module applies basic NLP techniques such as tokenization, text normalization, and keyword extraction to improve intent recognition. A rule-based pattern matching approach was adopted to map user inputs to predefined intents associated with flood-related topics. This approach was selected due to its transparency, reliability, and suitability for domain-specific applications with limited training data (Figure 8). Although more advanced machine learning and deep learning models can enhance conversational capabilities, the rule-based NLP approach provides predictable behavior and reduces the risk of incorrect or misleading responses in safety-critical contexts such as disaster communication. The design prioritizes accuracy and consistency over open-domain conversational flexibility.

### 3.6.4. Technology Stack and Deployment Design

The Chatbot was implemented using Python as the primary development language, harnessing its extensive ecosystem for artificial intelligence and web application development. A Python-based conversational framework was used to manage dialogue patterns and response generation, while a lightweight web framework facilitated deployment and user interaction through a browser-based interface. The system was deployed on a local server environment, with provisions for future cloud-based deployment to support scalability and wider accessibility. The modular design of the system architecture allows for future enhancements, including integration with real-time flood alert systems, mobile platforms, and advanced NLP models. This flexibility ensures that the proposed conversational agent can evolve alongside emerging technologies and changing disaster management requirements.

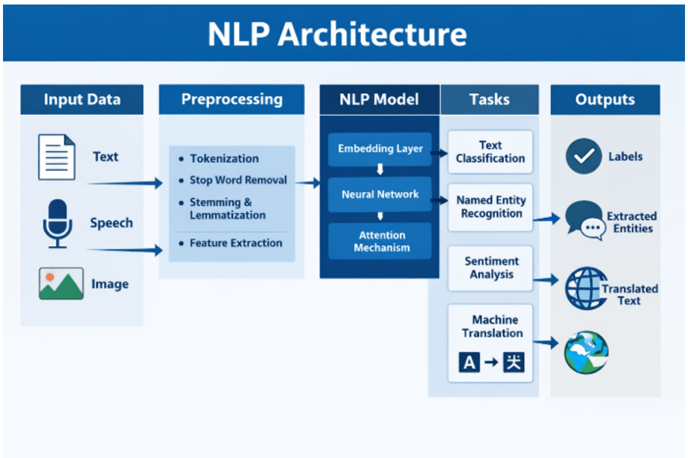


**Figure 7.** NLP Processing Architecture of the Proposed Chatbot

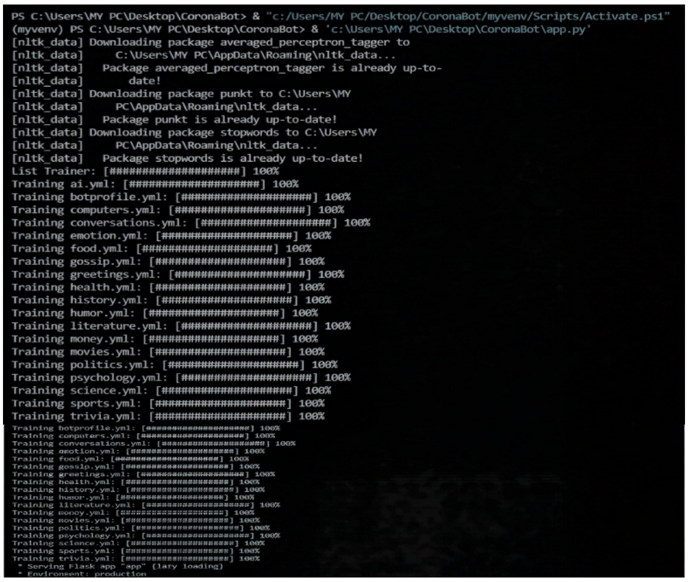


**Figure 8.** Process of Chatbot Configuration and Knowledge Base Development.

## 4. Implementation

This section describes the practical implementation of the proposed conversational agent, detailing the development environment, Chatbot configuration, knowledge base preparation, and user interface deployment. The implementation phase translates the system design into a functional application capable of delivering flood-related information interactively.

### 4.1. Development Environment

The Chatbot was implemented using Python due to its simplicity, flexibility, and extensive support for artificial intelligence and web development libraries. The development environment included standard Python tools and libraries for natural language processing and web application deployment. A lightweight web framework was employed to handle HTTP requests, manage user sessions, and render the Chatbot interface. This setup enabled rapid development and ease of testing during the implementation phase.

### 4.2. Chatbot Framework Configuration

A rule-based conversational framework was utilized to define dialogue patterns, intents, and responses. The framework allows the Chatbot to match user inputs against predefined patterns and generate appropriate responses based on the associated intent. This configuration approach ensures predictable system behavior, which is essential for delivering accurate and reliable information in disaster-related applications. Dialogue rules were structured to cover common flood-related topics, including causes of flooding, early warning signs, preparedness actions, safety measures during flood events, and post-flood recovery guidelines. Fallback responses were also configured to handle unsupported or ambiguous user queries, guiding users toward valid input formats or general informational content.

### 4.3. Knowledge Base Preparation

The knowledge base was developed as a structured repository of flood-related frequently asked questions and corresponding responses. Content was curated to reflect the local flood context of Bayelsa State, incorporating region-specific terminology, common concerns, and recommended practices. The knowledge base entries were formatted to support efficient retrieval by the conversational engine and were periodically reviewed to ensure clarity and consistency. To improve response relevance, keywords and phrases commonly used by potential users were mapped to corresponding intents. This mapping enhances the system's ability to recognize user queries expressed in different linguistic forms while maintaining alignment with the predefined knowledge base.

### 4.4. Web Interface Implementation

The user interface of the Chatbot was implemented as a web-based application to maximize accessibility. The interface provides a simple text input field through which users can submit queries and receive responses in real time. The design prioritizes usability and readability, ensuring that users can interact with the system without requiring prior technical knowledge. The web interface communicates with the backend Chatbot engine via HTTP requests, enabling seamless exchange of user inputs and system responses. This architecture supports deployment on local servers and can be extended to cloud-based environments for broader access.

### 4.5. Testing and Debugging

During implementation, iterative testing was conducted to verify the correctness and robustness of the Chatbot's responses. Test cases were derived from typical flood-related questions to assess intent recognition accuracy and response appropriateness. Debugging focused on refining dialogue patterns, correcting misclassifications,

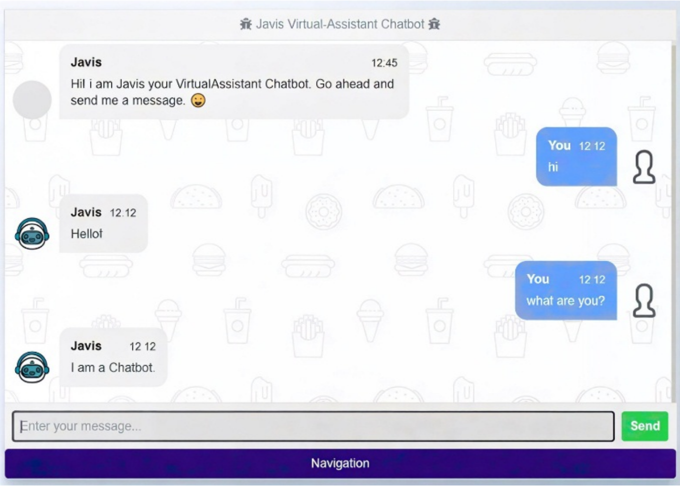


**Figure 9.** Example of flood-related interaction with the proposed chatbot system.

and improving fallback handling. These iterative refinements contributed to the stability and reliability of the final system.

The chatbot operates using a structured static knowledge base containing curated flood-related information specific to the study area. The knowledge base includes frequently asked questions, preparedness guidelines, emergency procedures, and safety recommendations. The system does not currently integrate real-time hydrological or meteorological data sources. Instead, it is designed as an information support tool that complements existing flood monitoring and early warning systems. Future enhancements may incorporate real-time data integration to further improve system responsiveness and reliability.

## 5. Results and Discussion

This section presents the results obtained from the functional evaluation of the proposed conversational agent and discusses the system's performance in the context of flood risk communication and public awareness. The evaluation focuses on the Chatbot's ability to provide accurate, relevant, and understandable responses to flood-related queries.

### 5.1. Functional Evaluation Results

The Chatbot was evaluated using a set of representative flood-related questions derived from common public inquiries and frequently asked questions identified during the system design phase. These queries covered key thematic areas, including flood causes, warning signs, preparedness measures, safety actions during flooding, and post-flood recovery guidance. The system successfully generated appropriate responses for the majority of tested queries, demonstrating effective intent recognition and response retrieval within the defined domain. The rule-based conversational approach ensured consistent and predictable system behavior. For well-defined queries that matched predefined patterns, the Chatbot provided clear and informative responses aligned with the curated knowledge base. Fallback responses were triggered when queries fell outside the supported scope, guiding users toward acceptable query formats or offering general flood-related information. This behavior reduced the likelihood of incorrect or misleading responses, which is critical in disaster communication contexts.

Figure 9 illustrates a sample interaction between a user and the chatbot, demonstrating the system's ability to respond to flood-related queries such as preparedness measures, evacuation guidance, and safety recommendations. This confirms that the chatbot is specifically designed for flood risk communication within the study area.

The evaluation results indicate that the chatbot achieved a response accuracy of 87.5% and a successful query handling rate of 90.8%. These results demonstrate that the system is capable of providing reliable and consistent responses to user queries. It should be noted that this evaluation represents a functional prototype validation rather than a large-scale user study. Future work will include user-centered evaluation involving real users and real-time deployment scenarios.

### 5.2. Response Accuracy and Relevance

Response accuracy was assessed qualitatively by examining the alignment between user queries and system outputs. The Chatbot demonstrated high relevance for queries closely related to the defined flood topics, particularly those concerning preparedness and safety measures. The use of locally contextualized content enhanced response usefulness, as information reflected the flood realities and environmental conditions specific to Bayelsa State. However, the system exhibited limitations when handling highly ambiguous or complex queries that required inference beyond predefined patterns. Such cases highlight the trade-offs associated with rule-based conversational systems, which prioritize reliability and control over conversational flexibility. Despite these limitations, the Chatbot remained effective for its intended purpose of addressing common flood-related questions.

### 5.3. Usability and Information Accessibility

The web-based interface facilitated straightforward user interaction, enabling users to access flood-related information without specialized technical skills. The conversational format allowed users to pose questions in natural language, reducing barriers associated with navigating traditional information platforms. By providing instant responses, the Chatbot improved information accessibility, particularly during periods when conventional communication channels may be disrupted. The simplicity of the interface and the clarity of responses contributed to positive usability outcomes. Users could quickly obtain guidance on flood preparedness and safety, supporting informed decision-making at the individual and community levels.

5.4. Discussion

The results indicate that conversational agents can serve as effective tools for flood risk communication when designed with domain specificity and user context in mind. The proposed system complements existing flood management initiatives by providing an interactive information delivery mechanism that directly engages the public. While advanced machine learning techniques could enhance conversational depth, the rule-based approach adopted in this study offers a practical balance between accuracy, transparency, and safety. The findings align with prior research highlighting the potential of AI-driven systems in disaster management while addressing a critical gap in localized flood information delivery. By focusing on public awareness and accessibility, the proposed Chatbot demonstrates how conversational AI can contribute to broader disaster risk reduction efforts, particularly in flood-prone regions with limited access to real-time information.

**6. Conclusion and Future Work**

This study presented the design, implementation, and evaluation of an intelligent conversational agent for flood risk communication and public awareness, with a specific focus on Bayelsa State, Nigeria. The proposed system was developed to address existing gaps in access to timely and interactive flood-related information by providing an automated question-answering platform tailored to local flood conditions. The Chatbot integrates natural language processing techniques with a domain-specific knowledge base to deliver accurate and contextually relevant responses to frequently asked questions on flooding. Through a modular system architecture and a rule-based conversational approach, the system demonstrates reliable and predictable behavior, which is essential for safety-critical applications such as disaster communication. Functional evaluation results indicate that the Chatbot effectively supports flood preparedness and awareness by offering accessible guidance on flood causes, warning signs, safety measures, and post-flood actions.

The findings of this study highlight the potential of conversational AI systems as complementary tools in disaster risk management, particularly in flood-prone regions where conventional information channels may be limited or disrupted. By enabling direct interaction with users, the proposed Chatbot enhances public engagement and contributes to informed decision-making at the community level. The localized focus of the system further underscores the importance of context-aware digital solutions in addressing region-specific disaster challenges. Despite its demonstrated effectiveness, the proposed system has certain limitations. The reliance on a rule-based conversational framework restricts the Chatbot's ability to handle highly complex or unforeseen queries. Additionally, the evaluation focused primarily on functional performance rather than large-scale user studies or quantitative metrics. These limitations present opportunities for further research and system enhancement.

Future work will explore the integration of machine learning and deep learning techniques to improve intent recognition and conversational flexibility. Additional extensions may include multilingual support to accommodate diverse user populations, integration with real-time flood monitoring and early warning systems, and deployment on mobile platforms to increase accessibility. Conducting comprehensive user-centered evaluations and longitudinal studies will also provide deeper insights into the system's impact on flood risk awareness and community resilience.

**7. Recommendations**

Based on the findings of this study and the demonstrated potential of conversational agents for flood risk communication, the following recommendations are proposed:

1) Future implementations of the proposed conversational agent should be integrated with official flood early warning and monitoring systems operated by government agencies such as the Nigeria Hydrological Services Agency (NIHSA) and the National Emergency Management Agency (NEMA). Such integration would enable the Chatbot to provide real-time alerts, verified advisories, and location-specific flood warnings, thereby enhancing its reliability and operational relevance.
2) To improve accessibility and inclusiveness, the Chatbot should be extended to support indigenous languages commonly spoken in Bayelsa State. Multilingual capabilities would ensure that flood-related information reaches a broader segment of the population, particularly rural dwellers and vulnerable groups with limited proficiency in English.
3) The effectiveness of the conversational agent can be enhanced by deploying it across widely used platforms such as mobile applications, web portals, SMS, and popular messaging services. Multi-platform availability would increase user reach and ensure continuity of access during emergencies, even in low-bandwidth environments.
4) Future versions of the system should incorporate context-aware features such as user location, flood severity level, and seasonal patterns to deliver personalized and situation-specific guidance. This would improve the relevance of responses and

support more informed decision-making by users during flood events.

5) The flood knowledge base underlying the Chatbot should be regularly updated and validated by domain experts, including hydrologists, emergency responders, and disaster management professionals. Continuous content validation will ensure that the information provided remains accurate, current, and aligned with best practices in flood risk management.
6) Integrating machine learning techniques that allow the Chatbot to learn from user interactions can improve response accuracy and coverage over time. Feedback mechanisms should be included to capture user satisfaction and identify knowledge gaps for continuous system improvement.
7) Further evaluation should be conducted through real-world field deployments involving communities in flood-prone areas. Longitudinal user studies can provide deeper insights into usability, trust, and behavioral impact, thereby strengthening the empirical evidence for the effectiveness of conversational agents in disaster communication.
8) Government agencies and disaster management stakeholders should consider adopting conversational AI systems as complementary tools for public risk communication. Institutional support and policy frameworks will be critical for scaling and sustaining such systems as part of national disaster risk reduction strategies.

## 8. Declarations

### 8.1. Author Contributions

**Willie Ebipamobonumugha:** Conceptualization, Methodology, Software, System Design, Formal Analysis, Investigation, Writing – Original Draft Preparation, Project Administration, Validation, Writing – Review & Editing; **Ugochukwu Onwudebelu:** Conceptualization, Methodology, Software, System Design, Formal Analysis, Investigation, Writing – Original Draft Preparation, Visualization, Software Support, Investigation, Supervision, Validation, Writing – Review & Editing; **Efe Darel Kokogbiya:** Data Curation, Resources, Writing – Review & Editing; **Justina Ogoja:** Supervision, Validation, Writing – Review & Editing.

### 8.2. Institutional Review Board Statement

Not applicable.

### 8.3. Informed Consent Statement

Not applicable.

### 8.4. Data Availability Statement

The data used in this study consist of a structured set of flood-related queries and a curated knowledge base developed for the chatbot system. These data are available from the corresponding author upon reasonable request.

### 8.5. Acknowledgment

The authors acknowledge the support of colleagues and the academic community who provided valuable insights during the development of this research. Special appreciation is extended to anonymous reviewers for their constructive feedback.

### 8.6. Conflicts of Interest

The author declares no conflicts of interest.

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## 10. Appendix

10.1. Source Code Snippet

10.1.1. Flash App

```
from chatbot import chatbot
from flask import Flask, render_template, request

app = Flask(__name__)
app.static_folder = 'static'

@app.route("/")
def home():
    return render_template("index.html")

@app.route("/get")
def get_bot_response():
    userText = request.args.get('msg')
    return str(chatbot.get_response(userText))

if __name__ == "__main__":
    app.run()
```

10.1.2. Chatbot

```
from chatterbot import ChatBot
from chatterbot.trainers import ListTrainer
from chatterbot.trainers import ChatterBotCorpusTrainer

# Creating ChatBot Instance
chatbot = ChatBot(
    'CoronaBot',
    storage_adapter='chatterbot.storage.SQLStorageAdapter',
    logic_adapters=[
```

```
            'chatterbot.logic.MathematicalEvaluation',
            'chatterbot.logic.TimeLogicAdapter',
            'chatterbot.logic.BestMatch',
            {
                'import_path': 'chatterbot.logic.BestMatch',
                'default_response': 'I am sorry, but I do not understand. I am still learning.',
                'maximum_similarity_threshold': 0.90
            }
        ],
        database_uri='sqlite:///database.sqlite3'
    )

    # Training with Personal Ques & Ans
    training_data_quesans = open('training_data/ques_ans.txt').read().splitlines()
    training_data_personal = open('training_data/personal_ques.txt').read().splitlines()

    training_data = training_data_quesans + training_data_personal

    trainer = ListTrainer(chatbot)
    trainer.train(training_data)

    # Training with English Corpus Data
    trainer_corpus = ChatterBotCorpusTrainer(chatbot)
trainer_corpus.train('chatterbot.corpus.english')
```

10.1.3. MTML

```
<!DOCTYPE html>
<html lang="en">
<head>
<meta charset="UTF-8">
<title>CoronaBot</title>
<meta name="viewport" content="width=device-width, initial-scale=1.0">
<meta http-equiv="X-UA-Compatible" content="ie=edge">
<link rel="stylesheet" href="{{ url_for('static', filename='styles/style.css') }}">
<script src="https://ajax.googleapis.com/ajax/libs/jquery/3.2.1/jquery.min.js"></script>
</head>

<body>
<section class="msger">
<header class="msger-header">
<div class="msger-header-title">
<i class="fas fa-bug"></i> Coronavirus Chatbot <i class="fas fa-bug"></i>
</div>
</header>

<main class="msger-chat">
<div class="msg left-msg">
<div class="msg-img" style="background-image: url(https://image.flati-
        con.com/icons/svg/327/327779.svg)"></div>

<div class="msg-bubble">
<div class="msg-info">
<div class="msg-info-name">CoronaBot</div>
<div class="msg-info-time">12:45</div>
</div>
<div class="msg-text">
Hi, welcome to CoronaBot! Go ahead and send me a message. 😄
</div>
</div>
</div>
```

```
  </main>

  <form class="msger-inputarea">
  <input type="text" class="msger-input" id="textInput" placeholder="Enter your message...">
  <button type="submit" class="msger-send-btn">Send</button>
  </form>
  </section>

  <script src='https://use.fontawesome.com/releases/v5.0.13/js/all.js'></script>

  <script>
    const msgerForm = document.querySelector(".msger-inputarea");
    const msgerInput = document.querySelector(".msger-input");
    const msgerChat = document.querySelector(".msger-chat");

    const BOT_IMG = "https://image.flaticon.com/icons/svg/327/327779.svg";
    const PERSON_IMG = "https://image.flaticon.com/icons/svg/145/145867.svg";
    const BOT_NAME = "CoronaBot";
    const PERSON_NAME = "You";

    msgerForm.addEventListener("submit", event => {
      event.preventDefault();

      const msgText = msgerInput.value;
      if (!msgText) return;

      appendMessage(PERSON_NAME, PERSON_IMG, "right", msgText);
      msgerInput.value = "";
      botResponse(msgText);
    });

    function appendMessage(name, img, side, text) {
      const msgHTML = `
      <div class="msg ${side}-msg">
        <div class="msg-img" style="background-image: url(${img})"></div>
        <div class="msg-bubble">
          <div class="msg-info">
            <div class="msg-info-name">${name}</div>
            <div class="msg-info-time">${formatDate(new Date())}</div>
          </div>
          <div class="msg-text">${text}</div>
        </div>
      </div>`;

      msgerChat.insertAdjacentHTML("beforeend", msgHTML);
      msgerChat.scrollTop += 500;
    }

    function botResponse(rawText) {
      $.get("/get", { msg: rawText }).done(function (data) {
        const msgText = data;
        appendMessage(BOT_NAME, BOT_IMG, "left", msgText);
      });
    }
  </script>

  </body>
</html>
```