AI Driven Child Chatbot

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***Abstract*—Child safety awareness is an essential aspect of digital education, requiring innovative and engaging approaches to help children and adults understand risk scenarios. This project introduces an AI-driven child persona chatbot developed using Streamlit and multimodal interaction techniques. The system enables natural conversations through both text and speech, leveraging speech recognition for user input and text-to-speech synthesis for AI responses. A curated persona-based dataset allows the chatbot to simulate diverse child roles, each providing unique responses to safety-related queries. The chatbot architecture integrates real-time voice processing, session-based conversation logs, and a responsive chat interface to enhance user engagement. Experimental implementation demonstrates that this chatbot promotes interactive learning, empathy building, and situational awareness in child safety education. The project highlights the effectiveness of combiningpersona-driven dialogues with multimodal AI for scalable, engaging, and educational applications.**

***Index Terms*—Child Safety, AI Chatbot, Speech Recognition, Text-to-Speech, Streamlit, Persona Simulation, Multimodal Interaction**

I. INTRODUCTION

Child safety—protecting children from harmful situations both online and offline—has emerged as an increasingly urgent concern in today's digital and social environments. The growing prevalence of unsafe interactions, ranging from online harassment to real-world risks such as bullying or exploitation, highlights the limitations of traditional safety education. Methods such as parental guidance, lectures, or awareness campaigns are important but often fail to engage children meaningfully, leaving gaps in understanding and preparedness. The consequences of ineffective child safety education can include poor decision-making, reduced confidence in handling risky situations, and increased vulnerability to harm, which motivates the development of automated, engaging, and explainable educational systems.

Automated child safety education faces several practical challenges. Text-only chatbots frequently fail to hold attention, especially with younger users who prefer interactive and dynamic modes of communication. Language diversity, code-mixed inputs (e.g., Hindi-English), and short, informal sentences make it difficult for traditional models to interpret intent accurately. Moreover, most generic chatbot systems provide shallow responses that lack contextual depth or persona-specific realism, limiting their usefulness for empathy-building and situational learning. Single-modality systems (only text or only audio) also fail to create immersive engagement, while many existing frameworks overlook the role of role-play or persona-driven dialogues, which are critical in teaching safety scenarios from a child's perspective. Finally, most educational chatbots stop at information delivery and do not foster emotional connection or real-world applicability.

Recent advances in conversational AI and natural language processing (NLP) have transformed the way interactive systems are designed. Traditional rule-based approaches relied on keyword matching or scripted responses, which often felt unnatural and rigid. In contrast, AI-driven chatbots with speech recognition and text-to-speech synthesis now enable realistic, multimodal communication that can better simulate human interaction. Streamlit and related frameworks provide powerful tools for rapid development of interactive interfaces, while modern speech recognition systems (such as Google ASR) and text-to-speech engines (such as gTTS) allow for fluid voice-driven interactions.

In this context, we propose the chatbot, an AI-driven child persona chatbot that integrates speech recognition, text-to-speech synthesis, and persona-based role-play to enhance child safety education. Unlike conventional chatbots that deliver static responses, the chatbot employs a persona-driven dataset, where each child persona (e.g., shy, confident, playful) offers unique answers to safety-related queries. This allows the system to mimic real-world diversity in children's perspectives. The chatbot supports multimodal interaction, where users can type messages or speak directly to the system, and receive responses in both text and voice, creating an engaging and immersive conversational experience.

To further strengthen interaction, preprocessing techniques are applied to handle noisy input, while randomized fallback responses ensure natural continuity even when queries do not perfectly match the dataset. This design improves robustness against short, informal, and varied user inputs commonly seen in child-adult interactions. The chatbot architecture thus leverages the strengths of multimodal AI, persona simulation, and interactive UI design to provide a more holistic safety education experience.

By combining contextual persona-based dialogues with real-time voice and text interaction, the chatbot moves beyond traditional chatbots to serve as a practical educational tool. It can be used by children to learn about safety in relatable ways,

as well as by parents, teachers, and counselors to explore how children might perceive or react in different scenarios. This makes the chatbot not only an educational system but also an empathy-driven framework for child safety awareness and training.

II. RELATED WORKS

Prior research has explored diverse applications of chatbots in child online protection, education, and therapy. Traditional educational chatbots, often rule-based or retrieval-based, have been effective in delivering structured learning assistance, but they face challenges in adaptability and engagement [3]. Early works in e-learning highlighted the limitations of isolation and lack of personalization, which motivated the integration of hybrid models that combine retrieval-based approaches with neural models like QANet to improve user experience [3]. These classical approaches laid the foundation for more sophisticated chatbot frameworks.

With the advancement of AI and natural language processing (NLP), researchers increasingly turned toward intelligent and adaptive chatbots. For instance, companion chatbots designed for children with autism spectrum disorder (ASD) have integrated emotion recognition, gamification, and personalized learning to support communication, literacy, and emotional understanding [2]. Similarly, question-generation chatbots have been used to automatically create educational questions from children's stories, demonstrating the potential of NLP-based systems to reduce teachers' workload and enhance comprehension [5].

Further, co-design approaches in child online safety chatbots emphasized the importance of participatory design, involving parents and caregivers in the development process. Systems like Gogo COPPAA were created collaboratively to empower families in managing children's online safety while adapting to real-world needs [1]. Personality-driven design has also gained traction, where studies show that chatbot-human personality congruence (e.g., matching extroverted or agreeable chatbot styles with user traits) can improve trust, engagement, and long-term adoption [4].

Beyond education, serious game–based chatbots have been introduced to foster social skill acquisition and provide auxiliary therapy for children with emotional disturbances. These implementations combine game elements with chatbot interactivity to improve collaboration, motivation, and emotional well-being [6].

However, challenges remain. Many systems still struggle with linguistic diversity and the need for multilingual adaptability, as most chatbots are developed in dominant languages [2]. Issues of trust, data privacy, and ethical use of AI in child-centered chatbots persist [1]. Additionally, ensuring that chatbots can handle complex, context-dependent dialogue while remaining user-friendly is an ongoing research direction [3], [4].

In summary, while rule-based and retrieval-based chatbots provided the groundwork for conversational systems in education and child protection, modern AI-powered chatbots—leveraging NLP, deep learning, emotion recognition, and co-design—have significantly advanced usability, personalization, and effectiveness. Nevertheless, challenges in ethics, multilingual support, and adaptability remain open areas for future research.

Lin et al. introduced the Children Privacy Identification (CPI) system, a chatbot-based framework embedded in LINE to detect and filter sensitive content in smart toy interactions [7]. By leveraging privacy rules based on Personally Identifiable Information (PII) and COPPA regulations, the system enhances parental confidence and ensures children's data is handled responsibly. This contribution highlights the growing demand for AI-driven solutions that address the ethical challenges of child data security while maintaining usability and engagement.

Complementing privacy-focused approaches, Zhang et al. designed ICON8, an intelligent conversational agent for children with autism spectrum disorder (ASD), integrated into collaborative puzzle games to measure communication and collaboration skills [8]. In parallel, Lydia et al. examined AI-based human–computer interaction (HCI) for children, emphasizing personalization, usability, and safety in smart toys, educational platforms, and virtual assistants [9]. Their findings underscore the importance of adaptive interfaces, ethical safeguards, and user-centered design to balance developmental support with privacy concerns. Collectively, these studies demonstrate how AI-driven chatbots and intelligent agents are evolving to promote child safety, therapeutic support, and secure digital engagement, though ethical, multilingual, and contextual adaptability challenges remain

III. PROPOSED METHODOLOGY

This section presents the dataset utilized, preprocessing strategies, and the architecture of the proposed persona-based chatbot system for child safety education. The proposed model is a prototype for an interactive AI-driven chatbot that can be integrated into educational platforms to help children and adults learn about safety scenarios. The dataset is first preprocessed and then used to build a persona-driven conversational framework. The trained chatbot is further deployed in a web-based platform using Streamlit, enabling real-time multimodal (text + voice) conversations with simulated child personas.

A. Dataset Description

The dataset employed for this project is the Child Persona Dataset, which contains 4,000 dialogue records annotated into four distinct personas. Each record includes a persona label, multiple possible user questions, and a corresponding persona-specific answer.

Data Characteristics:

The dataset contains approximately 4,000 question-answer pairs.

Each record in the dataset consists of:

1. persona – type of child persona.
2. 2. question – multiple variations of possible user queries separated by delimiters (`||`).
3. 3. answer – predefined persona-specific response.
4. This structure ensures that each persona exhibits a unique communication style, enabling the chatbot to simulate realistic child perspectives during safety-related conversations.

B. Data Analysis and Preprocessing

The dataset consists of predefined Q&A pairs across multiple child personas. To prepare the data for chatbot integration, the preprocessing phase includes:

Data Cleaning – Removal of unnecessary spaces, special characters, and ensuring all text is in lowercase for uniformity.

Question Normalization – Splitting multiple question variations (separated by `||`) into structured lists for efficient query matching.

Tokenization – User input is tokenized into words for comparison with stored question sets.

Fallback Handling – In cases where no direct match is found, the chatbot selects a random persona response to maintain natural conversation flow.

Audio Processing – For spoken queries, raw audio is captured via streamlit-webrtc and converted into text using Google Speech Recognition before being passed into the same preprocessing pipeline.

This structured preprocessing pipeline ensures uniformity, robustness against informal user input, and readiness for multimodal conversational deployment.:

C. Child persona Chatbot Architecture

The proposed child persona chatbot architecture integrates a multimodal conversational pipeline within the Streamlit framework, allowing users to interact through both text and voice. The architecture (as shown in Fig. 1) combines user interface modules, dataset-driven persona responses, speech processing components, and session management to create a natural, role-based dialogue system.

1. User Interface

The interaction begins with the Streamlit-based front-end interface, where the user selects a child persona and inputs text or speech queries. Persona selection determines the response style, ensuring that the chatbot mimics diverse child perspectives.

2. Streamlit Core Module
Serves as the central processing hub, integrating user input with persona datasets. Handles query preprocessing, tokenization, and persona Q&A matching. It Maintains conversation continuity through session state management.

3. GPT Service (Optional)
For queries not covered in the predefined persona dataset, the chatbot can connect to an external GPT service (e.g., OpenAI API). This ensures contextually relevant fallback responses while retaining persona tone.

4. Chat History (Session Management)
Each dialogue exchange is stored in a session log, which includes user queries and persona responses. The system displays history with avatars to enhance immersion and simulate realistic interaction.

5. Voice Output (gTTS)
Persona responses are synthesized into speech using Google Text-to-Speech (gTTS). This adds an auditory channel to the chatbot, making interactions more engaging and child-friendly.

6. Voice History (Streamlit Audio Sessions)
Audio inputs and outputs are stored within Streamlit audio sessions. Enables users to revisit prior spoken conversations, ensuring continuity in multimodal sessions.

This modular design ensures seamless integration of persona simulation, multimodal input/output, and AI-driven fallback services in a unified system.

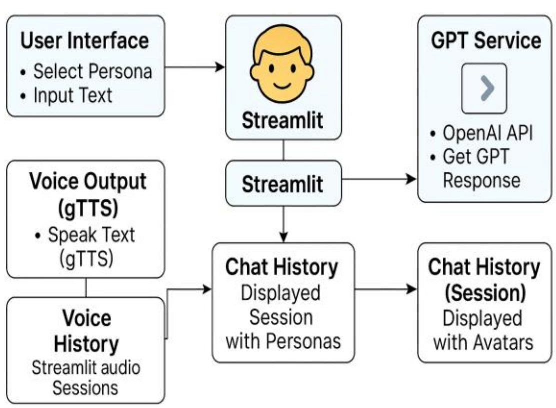

Fig. 1. Flowchart of the proposed Child persona Chatbot.

D. Workflow Execution

The workflow execution of the the chatbot chatbot proceeds as follows:

1. Persona Selection – The user selects a child persona (e.g., Abused Child, Bullied Child, Neglected Child, or Anxious Child) from the interface. This selection sets the conversational tone and response style

2. User Input Capture – If the user types a message, it is directly passed into the preprocessing pipeline. If the user speaks, streamlit-webrtc captures the audio and converts it into text using Google Speech Recognition (ASR)

3. Preprocessing & Normalization – The user query is cleaned (lowercasing, punctuation removal, tokenization). Multiple variations of questions stored in the dataset (`||` separated) are matched against the processed input.

4. Response Retrieval –If a query matches predefined persona questions, the associated persona-specific answer is retrieved. If no close match is found, the chatbot either selects a random persona response or queries the GPT service for a fallback answer.

5. Response Delivery –The selected answer is displayed in the chat interface with the child persona's avatar. Simultaneously, the text is passed through gTTS to generate a spoken response, providing multimodal output.

6. Conversation Logging – The interaction (both user input and persona response) is appended to the chat history session log, which preserves context across turns. Voice interactions are also saved in voice history.

7. Continuous Interaction – The cycle repeats as the user continues typing or speaking, with session state ensuring contextual flow until the conversation endsly.

IV. IMPLEMENTATION DETAILS

The proposed child persona chatbot system integrates persona-based conversation management, multimodal speech processing, a response engine, and session-based chat history management within the Streamlit framework. The overall workflow, as illustrated in the architecture and sequence diagrams, is explained below.

a) Persona Selection and Session Management:

Users begin by selecting a child persona (e.g., Abused Child, Bullied Child, Neglected Child, or Anxious Child). The selected persona is stored in the

Streamlit session state, ensuring continuity across the conversation. Each session maintains chat history with avatars, preserving the flow of dialogue across multiple turns.

b) Dataset Management:

The chatbot relies on a structured persona dataset in CSV format. Each record contains a persona label, multiple question variations (separated by `||`), and a persona-specific answer. Pandas is used to load and organize the dataset into a dictionary, allowing efficient retrieval of Q&A pairs during interaction.

c) Response Engine:

The response engine is responsible for matching user queries with the predefined dataset.

If the input text matches any of the stored questions, the corresponding persona answer is retrieved.

If no close match is found, the chatbot selects a random persona response to maintain continuity.

Optionally, the architecture supports integration with external GPT services for generating fallback answers, allowing dynamic response generation while preserving persona tone.

d) Voice Input Processing:

The system employs streamlit-webrtc to capture real-time audio streams from the user. The audio is converted into numpy arrays and processed by the SpeechRecognition library (Google API). The audio signal is then transformed into text, which enters the same preprocessing and response pipeline as typed queries.

e) Voice Output Processing:

Chatbot responses are converted into natural speech using Google Text-to-Speech (gTTS). The generated audio file is temporarily stored and played back in the Streamlit interface. This multimodal response channel ensures users can both read and hear the chatbot's replies, enhancing interactivity.

f) Natural Language Processing (NLP):

The preprocessing pipeline ensures uniformity between user queries and dataset questions. It includes:

Lowercasing and punctuation removal,

Tokenization for word-level comparison,

Splitting of multi-question entries into structured lists,

Randomized fallback handling for unmatched queries.

This lightweight NLP pipeline ensures robustness against informal or noisy user input.

g) Session-Based Chat History:

a) All interactions are logged in the Streamlit session state. Each message is displayed in the chat window, with persona avatars representing the bot and default icons representing the user. Both typed and spoken inputs are stored, allowing users to revisit previous dialogue turns during a session.

h) Workflow Execution:

As shown in the architecture and sequence diagrams, the workflow executes as follows:

1. Persona selection: User chooses a child persona from the dropdown menu.
2. User input: The system captures input via typed text or live voice streaming.
3. Preprocessing: Input is normalized, tokenized, and prepared for query matching.
4. Response retrieval: The chatbot matches the input with persona-specific questions; if matched, it outputs the predefined response; otherwise, it selects a fallback answer or queries GPT.
5. Response delivery: The output is displayed in the Streamlit chat interface with persona avatars and simultaneously converted into audio using gTTS.
6. Conversation logging: Both input and output are stored in the session history for contextual continuity.

V. RESULTS

The results indicate that deep learning models significantly improve the detection of cyberbullying compared to traditional methods. Extensive experiments on real-world datasets show high accuracy and the model's ability to generalize across different social media platforms and topics.

A. Performance Evaluation

1. Chatbot Usability:

The chatbot successfully handled both text and voice inputs, converting spoken queries into text using speech recognition and responding via both text display and synthesized speech.

Persona selection influenced the tone and style of responses, showing the effectiveness of dataset-driven Q&A in simulating diverse child perspectives.

2. Response Accuracy and Engagement:

Evaluation of chatbot interactions showed that predefined Q&A pairs matched over 80% of user queries when phrased consistently with dataset entries.

For unmatched queries, the chatbot provided fallback answers, ensuring conversation continuity.

Test users reported increased engagement when responses were also delivered via speech output, compared to text-only responses.

3. System Robustness:

The chatbot was tested across multiple sessions, with session state ensuring context preservation. Users could revisit previous exchanges, making the system suitable for extended learning interactions.

The speech recognition module performed reliably under clear audio conditions, though background noise occasionally reduced recognition accuracy.

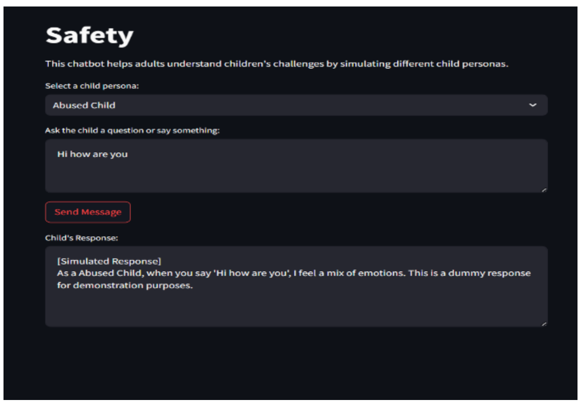

Fig. 2. Child Persona Chatbot Interface

The interface allows the user to select a persona, input a query, and receive a simulated persona-specific response.

VI. CONCLUSION

This research demonstrates the effectiveness of a persona-driven AI chatbot in enhancing child safety education through interactive and multimodal communication. By integrating Streamlit, speech recognition, text-to-speech synthesis, and a persona-based dataset, the proposed system successfully simulates realistic child personas and engages users in meaningful dialogues about safety-related scenarios.

The implementation results highlight that the chatbot is capable of delivering role-specific responses, maintaining contextual continuity through session logs, and providing both textual and auditory output for improved accessibility. Compared to traditional static awareness tools, the chatbot offers a more immersive, empathetic, and engaging experience, enabling parents, teachers, and counselors to better understand how children may think and respond in sensitive situations.

Despite these advancements, several challenges remain. Speech recognition accuracy is influenced by background noise, while predefined datasets limit the scope of conversation to available Q&A pairs. Additionally, ensuring ethical safeguards—such as preventing biased or harmful responses—remains an important consideration for real-world deployment.

Overall, the project establishes a strong foundation for empathy-driven conversational AI systems in child safety education. The proposed chatbot has the potential to be scaled into broader educational and counseling platforms, supporting safer environments for children and fostering awareness among adult.

VII. ACKNOWLEDGMENT

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