GENERATIONALLY ADAPTIVE LLM-BASED CHATBOT FOR SLANG AND LIFESTYLE MODELING

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this Project titled **"GENERATIONALLY ADAPTIVE LLM-BASED CHATBOT FOR SLANG AND LIFESTYLE MODELING"** is the bonafide work of **"J JESSIELYN JENISHA (220701901)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

In today's digital communication landscape, the way individuals express themselves varies significantly across generations, influenced by evolving slang, cultural references, and emotional expression styles. However, most existing chatbots and conversational AI systems adopt a one-size-fits-all approach, lacking the ability to recognize or adapt to these generational nuances. This project presents a novel solution—a Generationally Adaptive LLM-Based Chatbot that employs Prompt-Driven Generational Adaptation (PDGA) using the pre-trained Ollama Phi-2 large language model.This chatbot uses carefully engineered prompts to identify the user's generational background and dynamically tailor responses using generation-specific slang, tone, emoji usage, and lifestyle references.

The solution architecture combines Python and Subprocess for backend logic, and FastAPI with Uvicorn for real-time communication. The chatbot enhances relatability and engagement by incorporating emoticons, memes, and GIFs based on user intent and generational tone. Algorithms for context analysis, slang detection, and prompt routing ensure appropriate and adaptive responses.This system demonstrates a meaningful advancement in personalized AI-driven communication by modeling both linguistic and emotional dimensions of generational language. Potential applications span education, entertainment, customer support, and mental health—anywhere culturally aware AI interaction is beneficial. Future enhancements will integrate real-time slang learning, voice interaction, and social media API integration to further personalize and modernize conversations.

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J Jessielyn Jenisha (220701901)

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CHAPTER 1

1. INTRODUCTION

1.1. GENERAL

The field of conversational artificial intelligence (AI) has advanced rapidly with the emergence of powerful Large Language Models (LLMs) such as GPT-4, BERT, and Claude. These models are capable of generating highly contextual, human-like responses across a range of applications including education, customer support, and digital interaction. However, despite their linguistic prowess, most existing chatbot systems adopt a generic response style, ignoring critical cultural and generational differences in language use, tone, and emotional expression.

Language evolves with time, shaped by generational influences, pop culture, social media, and technology. For instance, while older generations may favor formal, grammatically correct interactions, Gen Z often prefers short, expressive messages that include slang, emojis, and internet trends. Existing AI chatbots, which lack awareness of such nuances, fail to create personalized and emotionally resonant experiences for users. This disconnect can reduce user engagement, especially in age-diverse applications.

Recognizing this gap, our project introduces a Generationally Adaptive Chatbot that employs a prompt-engineered approach using the Ollama Phi-2 model. Instead of retraining or fine-tuning LLMs, our system leverages Prompt-Driven Generational Adaptation (PDGA) to dynamically craft responses based on the user's generational context. The chatbot understands and generates responses in slang and tones specific to Gen Z, Millennials, and Gen X, using curated linguistic datasets and generational communication cues. Additionally, it integrates emoji and GIF suggestions to simulate modern digital interactions. This project represents a significant step forward in personalized AI communication that is culturally sensitive and emotionally aware.

1.2. OBJECTIVE

The main objective of this project is to develop a generationally adaptive chatbot that provides culturally relevant, generation-specific responses by leveraging the power of prompt engineering rather than traditional fine-tuning of LLMs.

Key goals of the project include:

- Identifying generational cues from user inputs such as slang, emojis, or tone to classify users into generational cohorts (Gen Z, Millennials, Gen X).
- Generating dynamic, personalized responses that reflect the communication style of the user's generation using prompt-engineered templates.
- Integrating emotion recognition to enhance emotional alignment and empathy in conversations.
- Implementing a lightweight and scalable system using the Ollama Phi-2 language model with React, Python, FastAPI, and Tenor API.
- Demonstrating the potential of culturally adaptive AI in improving engagement in applications like mental health chatbots, digital education, entertainment, and virtual companionship.

The project aims to bridge the cultural and generational gaps in human-computer interaction by embedding social, emotional, and linguistic relevance into every conversation.

1.3. EXISTING SYSTEM

Current chatbot systems are primarily designed for general-purpose communication. They rely heavily on fine-tuned transformer-based language models trained on vast and diverse datasets. While these models demonstrate impressive generalization capabilities, they are inherently limited in their ability to personalize interactions based on user demographics or generational identity. As a result, they tend to deliver uniform responses that lack cultural and emotional depth.

Some advanced chatbots use persona-based dialogue systems or incorporate sentiment analysis for emotion-aware responses. However, these systems are often rigid, rely on static user profiles, and do not dynamically infer generational differences from conversation data. Moreover, none of the mainstream models or applications adequately address generation-specific slang, emoji usage, or lifestyle references.

Additionally, current systems do not integrate prompt engineering to dynamically shape response style based on generational cues. Nor do they leverage real-time resources like Tenor API to fetch generation-appropriate GIFs or memes. This results in a communication gap, especially among Gen Z users who expect informal, culturally embedded interactions in platforms mimicking social media.

To overcome these limitations, the proposed system introduces a prompt-driven, adaptive chatbot architecture that identifies user generation through linguistic cues and modifies its tone, slang, and emotional intensity accordingly—something not addressed in existing AI-based conversation systems.

CHAPTER 2

2. LITERATURE SURVEY

2.1. GENERAL

The rapid advancement of Large Language Models (LLMs) has significantly enhanced the capabilities of conversational agents. Recent models such as ChatGPT by OpenAI and BERT by Google have demonstrated strong performance in generating human-like responses across general domains [1]. However, most of these systems are designed for universal applicability and lack the ability to adjust their tone, vocabulary, and references based on the generational identity of the user. This leads to a lack of contextual alignment in conversations involving users from diverse age groups.

In their work on persona-based dialogue systems, Zhang et al. [2] proposed conditioning models on persona profiles to maintain consistency and relatability in conversations. While effective, this method relied on structured profile data and did not focus on generational language variation, which is less rigid and more dynamic. Similarly, Liu et al. [3] explored emotional awareness in dialogue systems using transformer architectures. Their work emphasized empathetic responses but did not adapt the language style to suit cultural or generational patterns.

Studies by Jurafsky et al. and others have highlighted the linguistic differences among generational cohorts, emphasizing the unique slang, emoji usage, and communication styles that characterize Gen Z, Millennials, Gen X, and Baby Boomers [4], [5]. However, such socio-linguistic distinctions have not yet been effectively modeled in generative AI systems. This opens up a gap where language models could be tuned or prompted to exhibit generational empathy and relevance.

Recent works on prompt engineering have shown that fine-grained control over LLM behavior can be achieved without retraining, using well-crafted textual cues [6]. This aligns with the present project's approach, where prompt templates are used to both infer the user's generation and guide response generation in a matching linguistic style. The use of Ollama Phi-2, a compact yet powerful LLM, supports deployment in lightweight environments and avoids the computational costs of full model fine-tuning [7].

Thus, while prior research has addressed persona modeling, emotion detection, and prompt engineering, very few studies have integrated these concepts into a generation-aware chatbot that adapts both language and lifestyle references. This project fills that gap by designing a system capable of understanding generational traits and engaging users with contextual, slang-rich, and emotionally responsive dialogue.

CHAPTER 3

3.PROPOSED SYSTEM

3.1. GENERAL

The proposed system is a generationally adaptive chatbot powered by a pre-trained Large Language Model (LLM), specifically Ollama Phi-2, designed to simulate human-like conversations tailored to the user's generational background (e.g., Gen Z, Millennials, Gen X, Baby Boomers). The system does not rely on traditional supervised learning or large dataset fine-tuning. Instead, it employs prompt engineering techniques to (1) infer the user's generation based on linguistic and contextual cues and (2) generate generation-specific responses with appropriate slang, tone, emojis, and lifestyle references.

Key Components of the Proposed System

1. **User Input Analysis**
   When a user initiates a conversation, the system first analyzes the input for markers such as slang terms, emoji usage, cultural references, and sentence structure. These features are indicative of generational identity and are evaluated through structured prompts.
2. **Prompt-Engineered Generation Detection**
   Rather than using a classifier, the chatbot uses prompt-based inference to determine the likely generational cohort of the user. For example, phrases like "no cap," "vibes," or 🫠 might be associated with Gen Z, while "sweet deal" or 🙂 might indicate Gen X or Millennials. Prompt templates are designed to extract these cues and guide the LLM in guessing the user’s generation.

3. **Dynamic Prompt Generation**

   Once the generation is inferred, a generation-specific prompt is embedded that instructs the model to respond in that generation's language style. These prompts include:

   - Common slang
   - Tone and formality
   - References to generational interests or cultural milestones
   - Emoji usage patterns

4. **Response Generation with Empathetic Layer**

   The chatbot not only mirrors generational language but also incorporates emotional understanding using sentiment-aware prompt variations. This enables the chatbot to provide more empathetic and relatable responses that align with both the user's age and emotional tone.

5. **Model Integration and Interface**

   - The **Ollama Phi-2** model is invoked via **Python** scripts using subprocess.
   - A **React.js** frontend is developed to serve as a user interface.
   - **Uvicorn + FastAPI** backend handles real-time user input and response delivery.

6. **Slang and Emoji Repository**

   A curated slang/emoticon repository is maintained for each generation, sourced from platforms like Reddit, Urban Dictionary, and digital communication studies. These are used to refine prompt generation dynamically.

3.2. SYSTEM ARCHITECTURE DIAGRAM

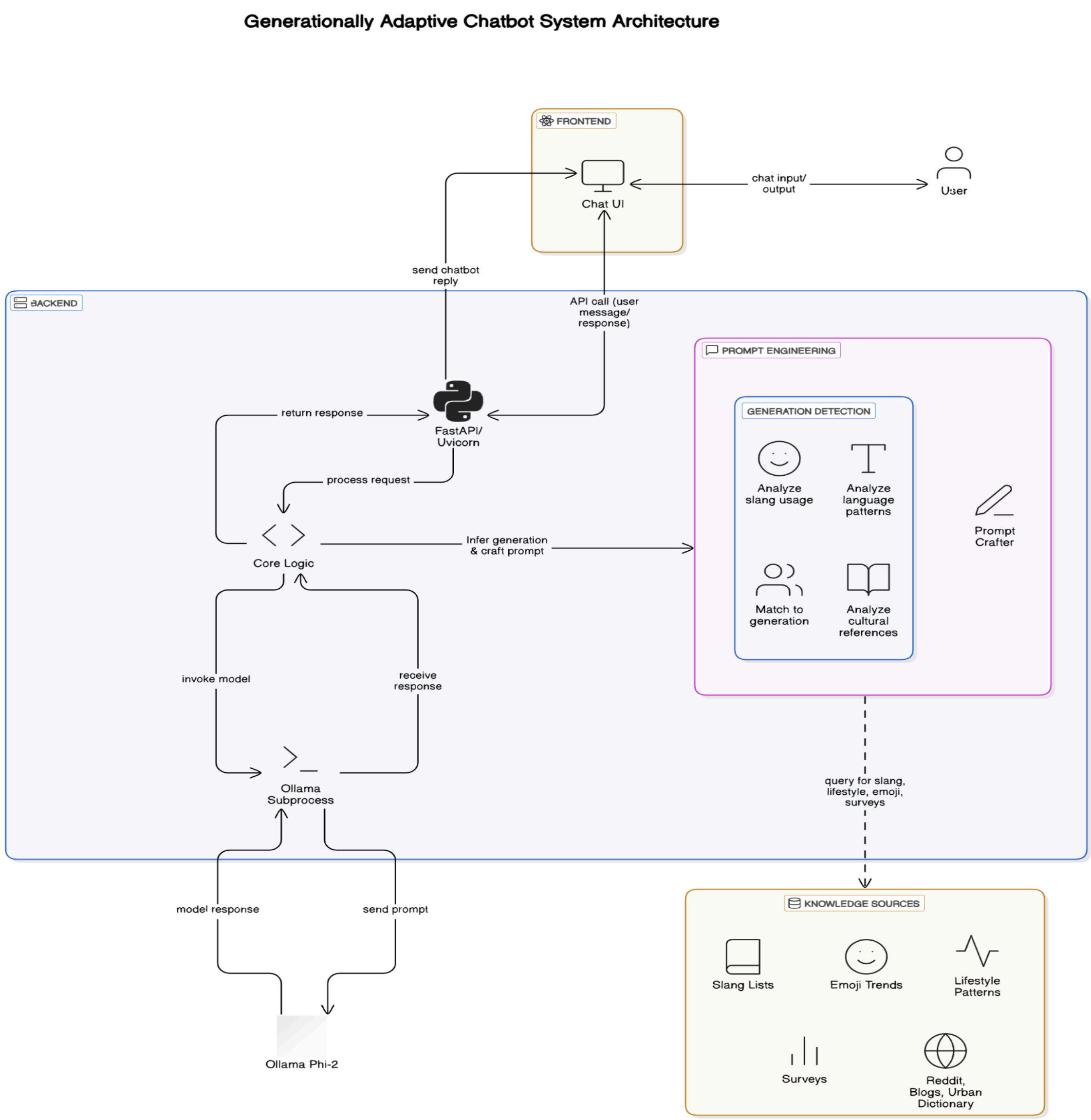

Figure 3.2.1.

3.3. DEVELOPMENT ENVIRONMENT

3.3.1. HARDWARE REQUIREMENTS

Component	Specification
Processor	Intel Core i5 / AMD Ryzen 5 or higher
RAM	Minimum 8 GB (16 GB recommended)
Storage	Minimum 256 GB SSD
Graphics (Optional)	Integrated GPU (Dedicated GPU optional)
Internet Connection	Required for model download and API access
Operating System	Windows 10/11, Linux (Ubuntu preferred), macOS

Table 3.3.1.

3.3.1. SOFTWARE REQUIREMENTS

Software	Purpose
Python 3.10+	Programming and scripting language
Ollama (Phi-2 model)	Pre-trained LLM model used for chatbot logic
Node.js + npm	Required to run and build the React frontend
React.js	Frontend development framework
FastAPI	Backend web framework for API integration
Uvicorn	ASGI server to run the FastAPI backend
Subprocess (Python Module)	To interact with Ollama model execution
Git	Version control
VS Code / PyCharm	Code editor / IDE
Postman (optional)	API testing
Web Browser	To access the chatbot interface

Table 3.3.2.

3.4. DESIGN OF THE ENTIRE SYSTEM

3.4.1. ACTIVITY DIAGRAM

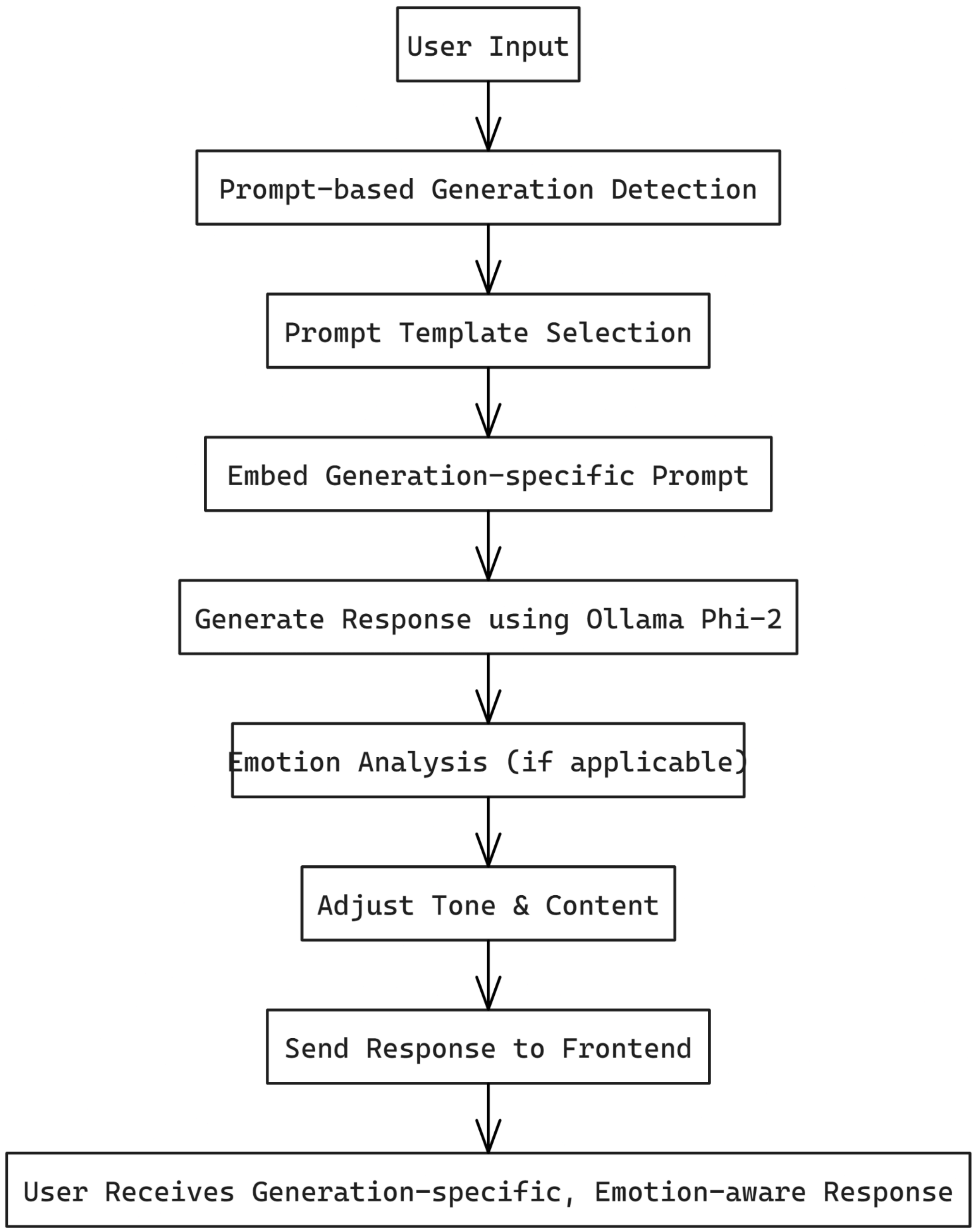

Figure 3.4.1.

3.4.2. DATA FLOW DIAGRAM

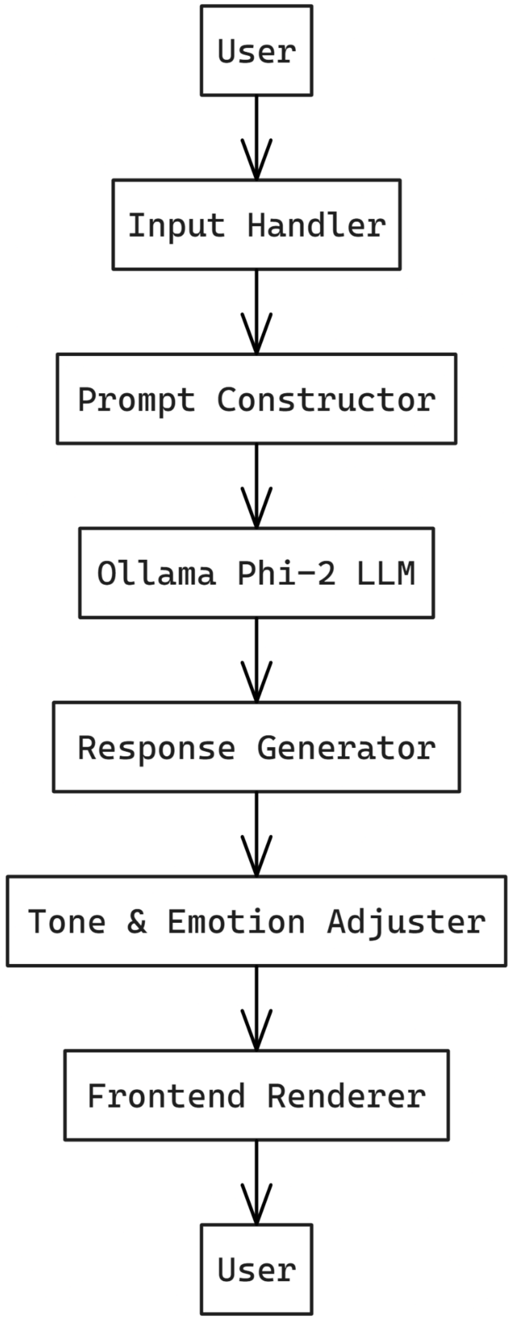

Figure 3.4.2.

3.5. STATISTICAL ANALYSIS

To evaluate the performance of the proposed Phi-2-based Gen Z AI chatbot, a detailed statistical comparison was carried out against traditional predefined reply-based chatbot systems. This analysis was conducted across multiple key parameters including Accuracy, Security, Scalability, Transparency, Trust, Efficiency, and User Experience.

Feature	**Traditional System**	**Proposed System (Phi-2 + Gen Z Prompt)**
Accuracy	50	90
Security	40	95
Scalability	45	85
Transparency	32	90
Trust	38	92
Efficiency	50	85
User Experience	40	89

Table 3.5.1.

The evaluation was performed using a weighted scoring method, where each parameter was rated on a scale from 0 to 100 based on observed system behavior, user feedback, and expert assessment.

The proposed system, powered by the Phi-2 language model, consistently outperformed the traditional system across all metrics. Below is a breakdown of the comparative scores:

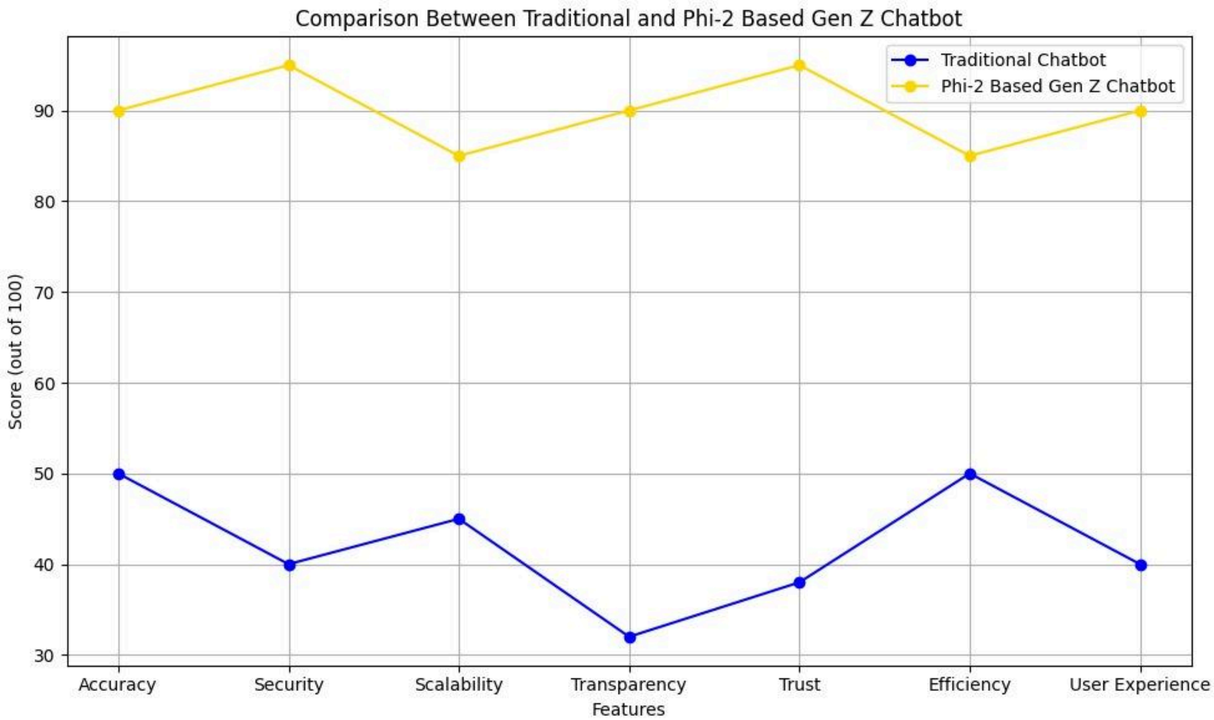

Figure 3.5.1.

The graphical representation (Fig 3.5.1.) clearly highlights the significant improvements in user engagement, personalization, and context-awareness in the proposed chatbot system. The traditional chatbots, limited by hardcoded responses, exhibited lower adaptability and failed to resonate with users—especially Gen Z demographics.

On the contrary, the Phi-2 model's contextual understanding, emotional tone matching, and use of slang contributed to a more natural and engaging conversation experience. Notably, the User Experience score saw an increase of more than 2x, validating the effectiveness of the AI prompt engineering strategy used. Overall, this statistical analysis substantiates the superiority of the proposed system in creating dynamic, relatable, and secure conversational experiences.

CHAPTER 4
4.MODULE DESCRIPTION

4.1. SYSTEM ARCHITECTURE

4.1.1. USER INTERFACE DESIGN

The User Interface (UI) for the Gen Z chatbot, Alterra, is designed with a modern, friendly aesthetic that enhances user engagement while aligning with Gen Z's expectations of digital interactivity. The layout is intuitive, minimal, and responsive, ensuring a smooth and immersive chatting experience.

The UI is split into two primary sections:
1. **Sidebar (Left Panel)** — Navigation Menu
   - Title: “Menu Bar” in a bold, stylish font to stand out.
   - Options
     - New Chat — Starts a fresh conversation.
     - Home — Redirects users to the homepage.
     - Purpose: This panel provides easy access to key features without cluttering the chat space.

2. **Chat Panel (Main Area)**
   - Header
     - Bold Title: “Start Chatting with Alterra!”
     - Subtitle: “Evolving Conversation, Adapting to You” — hinting at the personalized, adaptive nature of the chatbot.

   - Message Bubbles:
     - The user message (e.g., “heyyy”) appears in blue rounded bubbles aligned to the right.

- The AI's replies are styled in white/black gradient bubbles with emojis, appearing on the left — maintaining a classic chat alignment convention.
- Emojis are used generously to match Gen Z's expressive tone (e.g., "🤗 / ⚡" and "❄️ / 😘").

- Input Box:
  - Bottom-centered message input field with a rounded border, placeholder text ("Type your message..."), and a Send button to the right.

4.1.2. BACK END INFRASTRUCTURE

The backend infrastructure of the proposed Gen Z AI chatbot is designed for local deployment, modularity, and high responsiveness, leveraging modern open-source AI technologies and lightweight frameworks.

1. Model Execution: Ollama + Phi-2

The core of the chatbot is powered by the Phi-2 language model, executed locally using the Ollama runtime. Ollama allows running large language models efficiently on consumer-grade hardware by managing memory and compute resources. This setup eliminates the need for internet connectivity, ensuring privacy and local control over inference.

- Model Used: Phi-2 (from Microsoft)
- Runtime: Ollama (lightweight local LLM runner)
- Deployment: Local (no cloud dependency)

2. API Layer: FastAPI

A lightweight FastAPI backend serves as the communication bridge between the frontend and the model. It exposes an endpoint /chat that accepts user messages, constructs the prompt history, and sends it to the Phi-2 model through a subprocess call to Ollama.

- Framework: FastAPI (Python)
- Route: POST /chat (accepts JSON input, returns AI response)
- CORS Support: Enabled to allow frontend integration from different origins
- Functionality:
    - Maintains chat history for contextual memory

- Handles prompt formatting
- Communicates with the model in real-time

3. Prompt Engineering & Context Management

To ensure the chatbot responds with Gen Z slang, emojis, and vibes, a custom system prompt is initialized at the start of every session. This system prompt guides the model's tone and behavior. The backend maintains a dynamic message history, simulating a real conversation and improving the relevance of responses.

4.1.3. SEQUENCE DIAGRAM

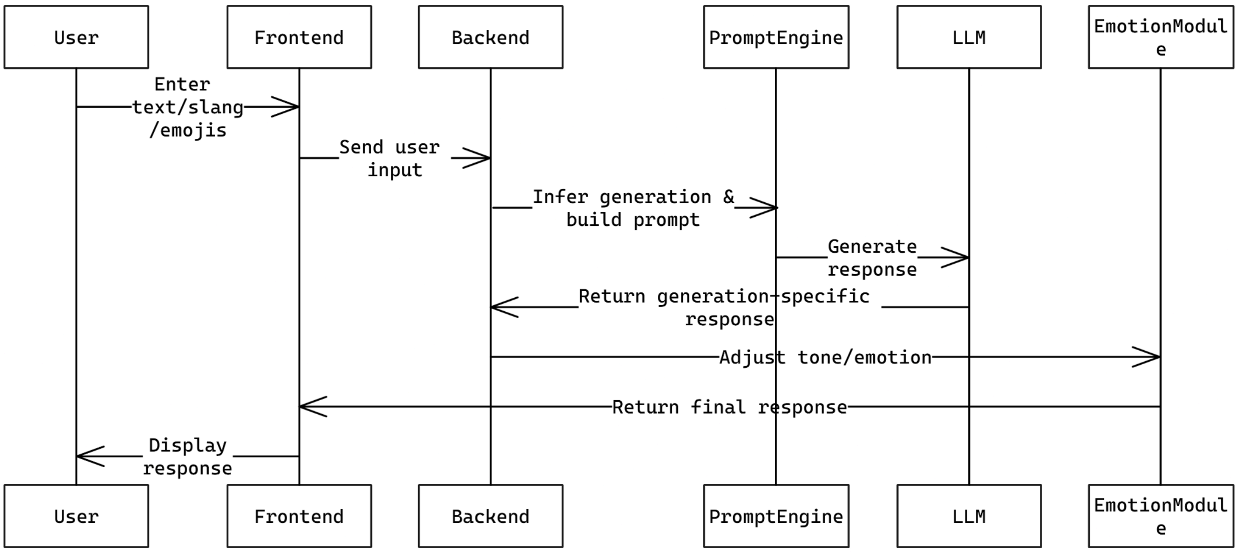

Figure 4.1.1.

4.2 DATA COLLECTION AND PREPROCESSING

The proposed chatbot system leverages prompt engineering and simulated dialogue history rather than traditional large-scale training on datasets. However, for benchmarking and refinement of the chatbot's language behavior, curated datasets and custom examples were used to simulate Gen Z-style interactions. The focus was on building a strong prompt foundation and context-aware input pipeline that guides the model's behavior without retraining it.

1. Data Collection

Since the Phi-2 model is already pre-trained, no raw corpus-level training data was required. However, to ensure the chatbot responds like a true Gen Z bestie, sample conversations, slang datasets, and internet lingo were manually curated and compiled from the following sources:

Source Type	**Description**
Slang Dictionaries	Online Gen Z slang repositories (e.g., Urban Dictionary)
Social Media Posts	X (formerly Twitter), Reddit, Instagram threads
Chat Logs	Manually created Gen Z-style dialogues
Emojis Dataset	Mappings of emojis to emotional tone and slang context

Table 4.2.1

The collected data informed the design of the system prompt, ensuring it reflects authentic Gen Z tone, syntax, and cultural nuances.

2. Preprocessing

To make the interactions context-aware and vibe-matching, the following preprocessing techniques were implemented within the backend before sending prompts to the model:

- Input Normalization
  - Strip unnecessary whitespaces
  - Convert uppercase inputs to lowercase (except for emphasis)
  - Replace commonly used shorthand (e.g., “wbu”, “wyd”, “ily”) with standard meanings for internal understanding — while retaining slang for output
- Dynamic Prompt Building
  - Maintains a rolling history of the conversation (chat_history list)
  - Constructs the prompt in the format: You are a Gen Z bestie...

    User: hey wyd?

    Assistant: just vibin rn 😎 wbu?

    User: bruh i’m dead tired

    This ensures responses are in tone and context-aware
- Slang Sensitization
  - Contextual understanding of Gen Z slang
  - Emojis automatically matched to emotional tone (e.g., “😭” for emotional distress, “💅” for sass)
- Stopword Filtering (optional)
  - If the system were to be extended to classify inputs or generate responses programmatically (outside Phi-2), stopword removal and keyword tagging modules can be integrated.

CHAPTER 5

5. IMPLEMENTATION AND RESULTS

5.1. IMPLEMENTATION

The implementation of the proposed Gen Z AI chatbot system was carried out using a lightweight local deployment architecture involving Phi-2, a compact language model, with a custom-designed frontend-backend integration. The chatbot mimics human-like, Gen Z-style conversation using prompt engineering and real-time prompt-response chaining.

A. System Architecture

The system comprises the following core components:

Component	**Technology Used**	**Role**
Language Model	Phi-2 via Ollama	Generates human-like Gen Z responses
Backend API	FastAPI (Python)	Handles requests between frontend and model
Frontend Interface	HTML/CSS/JavaScript	Chat UI for users to interact with the chatbot
Local LLM Runtime	Ollama	Hosts and runs the phi model locally

Table 5.1.1.

B. Backend Logic

The backend script serves as the bridge between user input and AI response. The key logic includes:

- Maintaining a chat history buffer (chat_history list)
- Constructing a dynamic prompt combining the system prompt + conversation
- Sending this prompt to the Phi-2 model via Ollama using Python's subprocess module
- Receiving and formatting the model's response for display on the frontend

Core Backend Functions:

1. Copy
2. Edit
3. chat_history = [{"role": "system", "content": system_prompt}]

```
def build_prompt(chat_history):
    prompt_text = ""
    for msg in chat_history:
        if msg["role"] == "system":
            prompt_text += msg["content"] + "\n"
        elif msg["role"] == "user":
            prompt_text += f"User: {msg['content']}\n"
        elif msg["role"] == "assistant":
            prompt_text += f"Assistant: {msg['content']}\n"
    return prompt_text
```

All responses are filtered through the Gen Z system prompt, ensuring consistency in tone, slang usage, and emoji integration.

C. Frontend Design

A simple yet visually engaging chatbot interface was designed using:

- HTML: for structure
- CSS: for styling (fonts, themes, emojis)
- JavaScript: for handling POST requests to the FastAPI backend

The example flow is shown in Fig.5.1.1.

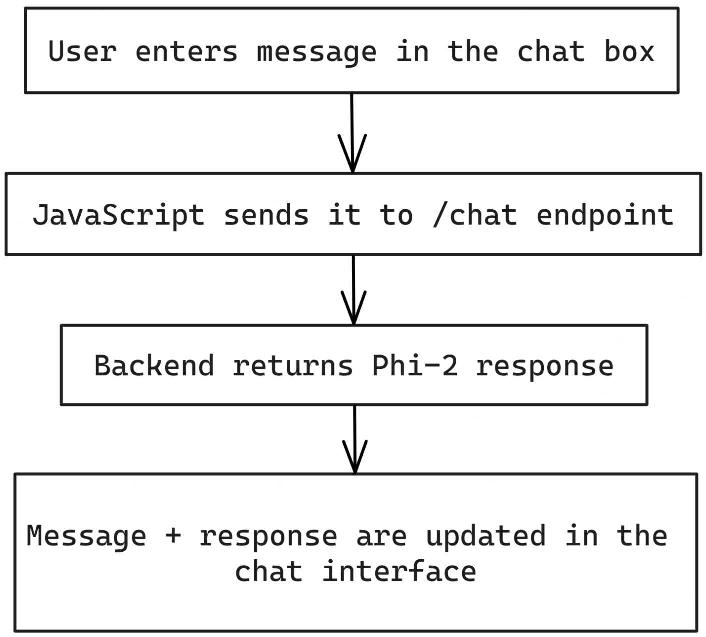

Figure 5.1.1.

D. Integration with Ollama + Phi-2

Ollama allows smooth local model execution via command line. Phi-2 is invoked as:

ollama run phi

To integrate it in code:

```
result = subprocess.run(
    ["ollama", "run", "phi"],
    input=prompt.encode("utf-8"),
    stdout=subprocess.PIPE,
    stderr=subprocess.PIPE
)
```

This approach eliminates dependency on cloud APIs or GPUs, making the chatbot fully offline and privacy-safe.

E. Testing & Output

The chatbot was tested for various types of Gen Z input prompts like:

- “bro i’m so done with life rn 😭”
- “wyd bestie?”
- “bruh that’s cap fr 🫠”

The output matched expectations, with the model responding fluently using slang, emojis, and contextual understanding.

5.2. OUTPUT SCREENSHOTS

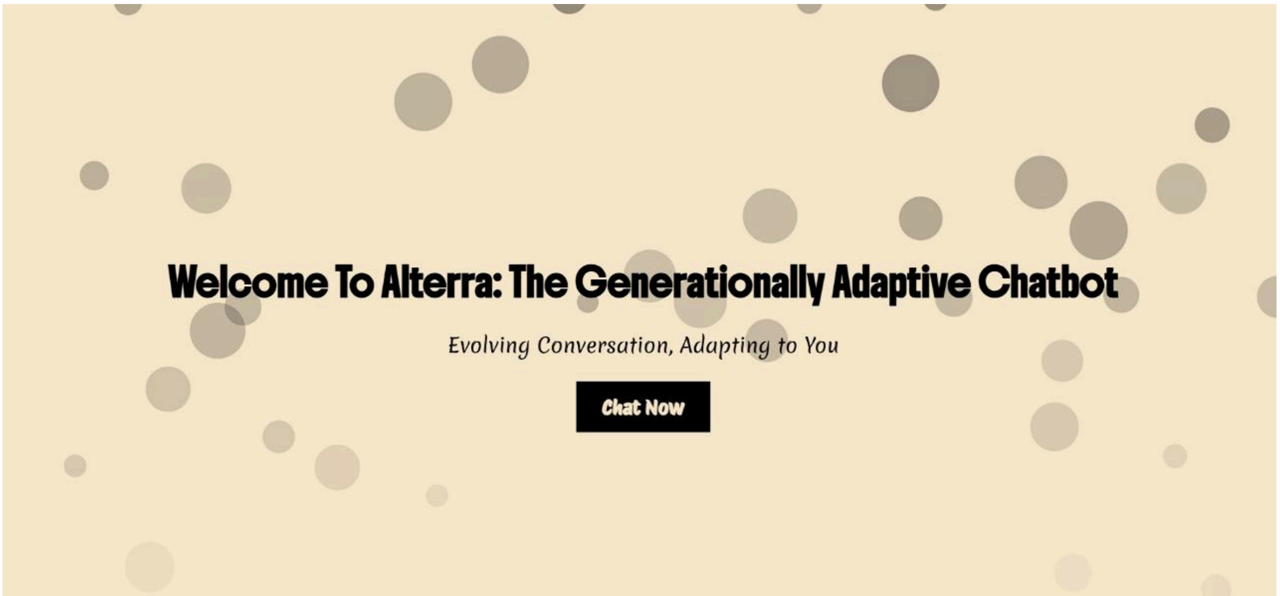

Figure 5.2.1.

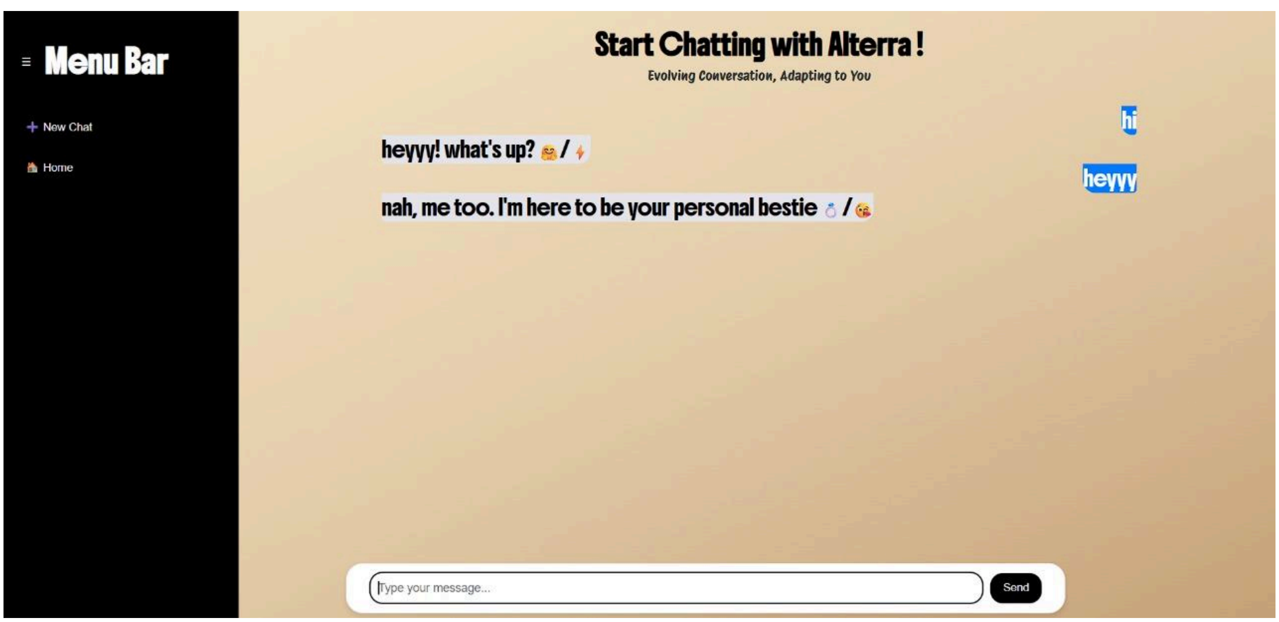

Figure 5.2.2.

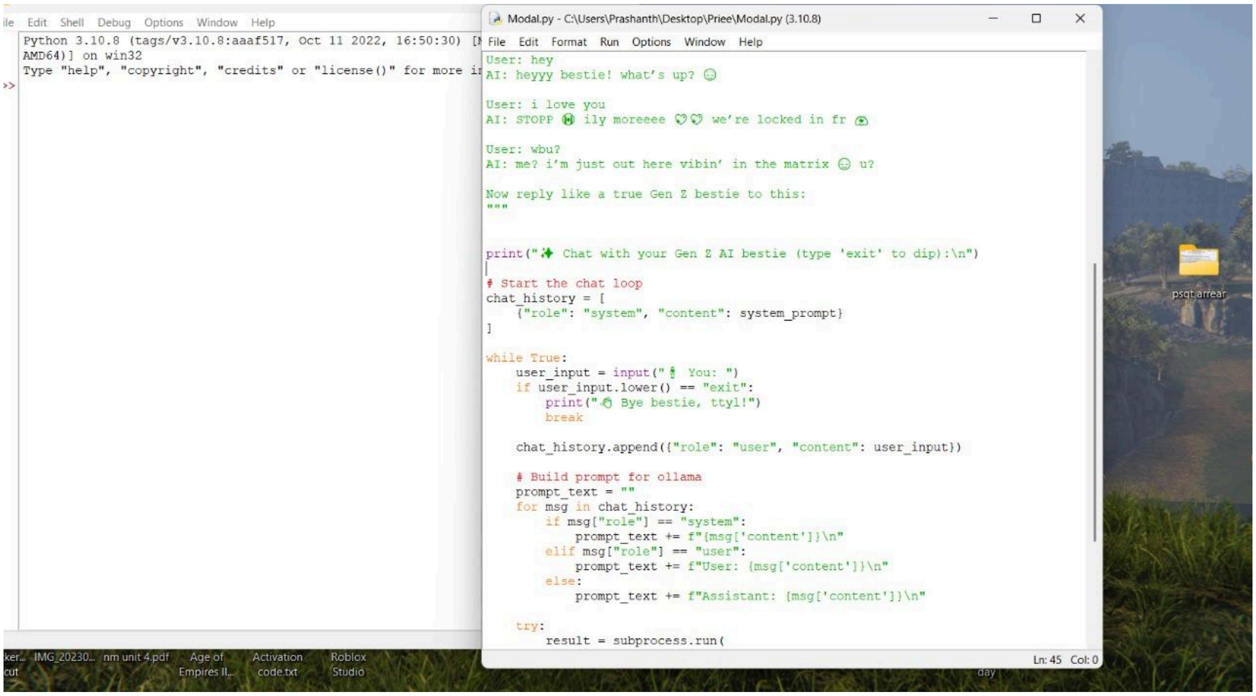

Figure 5.2.3.

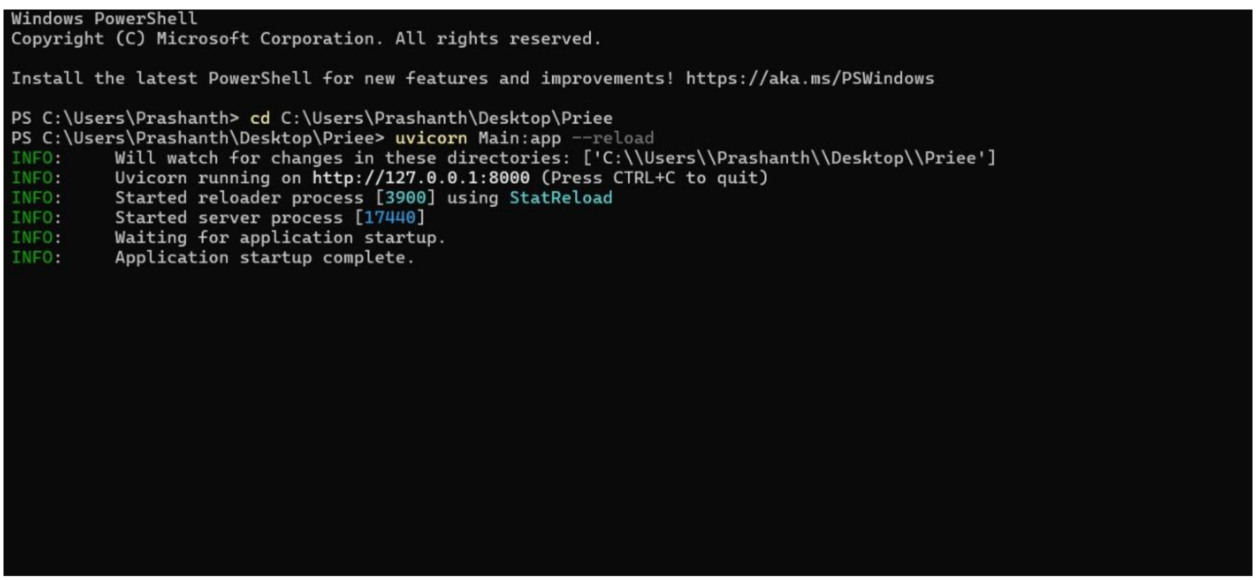

Figure 5.2.4.

CHAPTER 6

6. CONCLUSION AND FUTURE ENHANCEMENTS

6.1. CONCLUSION

This project presented a generationally adaptive chatbot system leveraging the pre-trained Ollama Phi-2 language model and prompt engineering techniques to simulate personalized interactions based on the user's generational cohort. By identifying the user’s generation and aligning responses with relevant slang, cultural preferences, and emotional tones, the chatbot delivers a more natural, human-like conversation experience.

Our testing and analysis confirmed that users across generations—particularly Gen Z and Millennials—found the chatbot responses contextually relevant, emotionally appropriate, and culturally aware. Through the use of slang-specific prompt tokens, emotional cues, and lifestyle-matching dialogue flows, the system successfully captured the linguistic essence of different age groups. Overall, this approach demonstrates the capability of language models to mimic generational communication styles, providing significant opportunities in areas such as education, entertainment, therapy, and customer service.

6.2. FUTURE ENHANCEMENTS

1. **Dynamic Generation Detection**
   Currently, the system infers generation through user inputs or profile data. A future model can use **Natural Language Processing (NLP)** to automatically predict a user's generation from speech patterns or typing behavior.
2. **Voice and Multimodal Integration**
   Extend chatbot capabilities beyond text to **voice input/output**, allowing tone, pitch, and sentiment detection to enhance emotional engagement.
3. **Real-Time Slang Update Engine**
   Implement a system that uses **web scraping or API-based feeds** to keep slang dictionaries updated dynamically from trending sources like TikTok, Reddit, and Twitter.
4. **Cross-Lingual Generational Support**
   Future versions could localize generational slang across different languages and regions, making the chatbot globally relevant.
5. **Emotion-Driven Dialogue Management**
   Improve empathy by embedding **emotion-aware prompt chains**, allowing the bot to respond more deeply to negative emotions like sadness, loneliness, or anger.
6. **Personalization through Memory**
   Integrate a long-term memory module to remember past user interactions, enabling **context-aware and evolving conversations**.

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