Generationally Adaptive LLM-Based Chatbot for Slang and Lifestyle Modeling

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ABSTRACT

Language and cultural expressions of people evolve from generation to generation, which influences the way individuals communicate across time. The current conversational AI models and chatbots lack contextual adaptation to generation specific speech and slangs. This paper presents a novel LLM-based chatbot built using Prompt-Driven Generational Adaptation(PDGA) methodology, which uses prompt engineering with the Ollama Phi-2 LLM model, to make conversations with the users according to their generational background, inferred from historical and contemporary conversational datasets.

This chatbot employs a fine-tuned large language model trained on categorized linguistic data from multiple generations. We implement prompt engineering to determine the user's generational profile and adapt responses accordingly. The system adapts its slang usage, tone, etc., using generation-specific prompt templates from the datasets. Our evaluation metrics assess linguistic accuracy, contextual relevance, and user engagement levels across diverse age groups. The results depict the chatbot's effectiveness in maintaining generation-specific communication, highlighting its potential for applications in education, entertainment, and human-computer interaction. Future work aims to refine slang interpretation and enhance personalization through reinforcement learning .

KEYWORDS

Large Language Model, gen z, chatbot, conversational AI, generation specific.

INTRODUCTION

Conversational AI has evolved significantly with the rise of Large Language Models (LLMs) like GPT-4, BERT, and Claude, etc.[1][2], enabling chatbots to generate texts like humans and respond contextually to user inputs. However, most of the existing chatbot systems adopt a one-size-fits-all approach, overlooking any cultural, generational, and linguistic variations found across generations and localities. Language is not static; it evolves across time, with each generation developing its own set of slang words, idioms, and conversational patterns that reflect their unique cultural differences[3]. Despite these variations, the current AI-driven chatbots fail to adapt to these generational gaps, often leading to impersonal and less engaging interactions [5], [6].

Understanding and incorporating generational slang words, interests, and emotional expression styles is crucial for building AI systems that resonate with users on a personal level. Different generations—such as Baby Boomers (Born 1946–1964), Generation X (Born 1965–1980) , Millennials (Born 1981–1996), and Gen Z(Born 1997–2010)—use distinct language styles and cultural references. For instance, Gen Z often uses slang like "no cap" and "vibe check" [10], while Millennials might reference "adulting" or "Netflix and chill". Traditional chatbots usually lack the ability to identify such slang which marks the differences between generations.This limits their effectiveness in applications that demand personalized user engagement, such as marketing, customer service, and education [9].

This research proposes an LLM-based chatbot specialized in using generation specific slang words and lifestyles references, aiming to bridge the gap between AI and diversity of human conversation. The chatbot will dynamically identify the user's generational background based on linguistic cues and adapt its responses using generation-specific slang, cultural references, and tone [3]. Additionally, it will also incorporate emotion recognition to empathize with users, offering responses that are not only generationally accurate but also emotionally resonate with the user [7]. By creating an AI system that can mimic generational communication styles and empathize with user emotions, this research aims to improve user engagement, enhance conversational quality, and push the boundaries of personalized AI communication [11].

The proposed system will explore the use of fine-tuned LLMs, emotion-aware models, and generational slang datasets to train the chatbot. This approach not only contributes to the field of personalized AI but also opens new avenues for AI-driven applications in social media, customer support, and interactive storytelling [12].

LITERATURE REVIEW

Chatbots and conversational AI systems have been widely explored in Natural Language Processing (NLP) research. Various models have been developed to enhance chatbot interactions, including transformer-based architectures such as GPT-3, BERT, and T5. However, existing chatbots fail to incorporate generational slang, lifestyle cues or emotional connect, leading to impersonal and non-contextualized responses. This review discusses key research contributions in conversational AI, generational language adaptation, sentiment analysis, and personalized NLP models.

The development of transformer-based language models has significantly improved chatbot capabilities. Vaswani [1] introduced the Transformer architecture, which laid the foundation for models like GPT-3 [2], demonstrating the ability to generate human-like text. However, these models primarily rely on broad, general-purpose datasets, lacking mechanisms to tailor responses based on generational language variations. Studies [3] have explored prompt engineering for personalized conversations, but adaptation to generational slang remains underexplored.

Generational slang is a critical aspect of communication, yet it has received limited attention in NLP research. Eckert [4] and Tagliamonte [5] discuss the sociolinguistic evolution of slang, emphasizing how different age groups develop unique lexicons influenced by cultural and technological shifts. While some studies, such as Hovy and Spruit [6], highlight biases in NLP datasets, there is no established dataset dedicated to capturing generation-specific slang and conversational styles. The absence of such datasets limits the ability of current AI models to generate age-adaptive responses.

Sentiment analysis has been widely integrated into chatbot systems to enhance user engagement. Taboada [7] introduced emotion-aware dialogue systems that analyze user sentiment to provide emotionally intelligent responses. However, existing research does not account for how different generations express emotions differently, leading to responses that may not align with the user's cultural and linguistic background. Recent advancements in sentiment analysis models, such as BERT-based emotion classifiers [8], provide opportunities for improving empathy-driven AI responses tailored to generational differences.

Personalized AI-driven conversation systems have been studied extensively, focusing on context-aware dialogue generation. Li [9] proposed persona-based chatbots that adapt responses based on user preferences and historical interactions. Despite advancements in persona-based dialogue models, most research lacks a structured approach for adapting responses to generational speech patterns, slang usage, and interests. The aim of this study is to develop a chatbot which could recognize the generation specific conversational context and be able to provide a response in generation slang used by the user.

MATERIALS AND METHODS

The development of this generationally adaptive chatbot uses the pre-trained model of Ollama Phi-2 for prompt engineering rather than traditional fine tuning. Prompts are carefully crafted to both identify the user's generational and to tailor the chatbot's responses accordingly. The generation-specific instructions are then used to guide the model's behavior and response tone, thus aligning output with the communication style, slang, lifestyle references, and emotional expression specific to each generational (e.g., Gen Z, Millennials, Gen X, etc.). These prompts are created based on generational slang lists, lifestyle patterns, and emoji/emoticon usage trends that are inferred from sources such as Reddit, Urban Dictionary, blogs, and generational surveys [Table 1, Table 2 & Table 3].

Python is used as the primary language, supported by Subprocess for interacting with Ollama during runtime. The frontend interface is created using React for prototype deployment and integrated using Uvicorn and FastAPI for real time communication between the user and bot.

DISCUSSION

This novel LLM-based chatbot gives the linguistic and emotional output with respect to the generational identity of the user. The generational identities are tones, preferences used by different generations. The tone used by Gen Z in conversations could be casual, humorous, using emoji and GIF and they prefer quick replies, tik-tok and instagram style slang in their conversations. These generational identities vary with the user of different generations. Unlike the conventional chatbots which give the same output for all the users regardless of their linguistic background, our proposed chatbot leverages the fine-tuned Large Language Model to give the personalised conversational output to the user. The trust and engagement in human-computer interaction will increase when systems give human-like communications. This integration of generation-based response generation allows the chatbot aligns with the user’s state of mind which is not present in current LLM models. This proposed model enhanced both the contexts and emotional response.

The challenge of this study is identifying the generational cohorts of each generation based on the user input. The slang of each generation evolves continuously which leads to regular updation of the model. Studies show that real time data collection from platforms like Reddit, Twitter, etc,. will help to track the trends.

The proposed LLM-based chatbot demonstrates a novel direction in conversational AI by attempting to adapt linguistic and emotional outputs based on the generational identity of users. Unlike conventional chatbots, which respond uniformly to all users regardless of socio-linguistic background, our approach leverages fine-tuned language models and curated slang corpora to simulate a personalized conversational style. This personalization enhances user engagement and relatability, which aligns with prior studies that highlight the importance of tailoring responses in dialogue systems to user demographics [15], [16].

A key insight from this research is the significant role that sociolects, such as generational slang and lifestyle references, play in shaping user perception of chatbot intelligence and empathy. Prior work has shown that trust and engagement in human-computer interaction increase when systems reflect human-like communication patterns and empathy [17], [18]. Our integration of emotion recognition further advances this principle, allowing the chatbot not only to linguistically adapt but also to emotionally align with the user’s state—a capability that is often absent in current LLM-powered agents [19]. By merging generational cues with emotional understanding, the system enhances both contextual appropriateness and emotional resonance in its responses.

However, challenges remain in reliably identifying generational cohorts based on linguistic input. Although preliminary testing indicates that users tend to exhibit generation-typical language patterns, cross-generational slang usage, cultural blending, and online language evolution may affect classification accuracy [20], [21]. Future iterations may benefit from incorporating multi-modal signals, such as user metadata or behavioral cues, to improve generational inference. Additionally, slang evolves rapidly, especially among younger generations, requiring continuous updates to the slang lexicon. Studies in computational sociolinguistics suggest that real-time data mining from platforms like Twitter, TikTok, and Reddit may help in tracking such dynamic lexical trends [22], [23].

Moreover, the ethical implications of modeling users based on generational stereotypes must be carefully considered. While personalization enhances user experience, it risks reinforcing biases or excluding outliers who do not conform to stereotypical generational behavior [24]. Transparent model behavior, user opt-in mechanisms, and fairness evaluations should be integral to future deployments of such systems. These concerns mirror ongoing debates in responsible AI development and highlight the need for human-centered design in natural language technologies [25].

CONCLUSION

This paper presents a novel implementation of a generationally adaptive chatbot using prompt engineering with the pre-trained Ollama Phi-2 language model. Unlike traditional chatbots that generate responses without considering the user’s age group or cultural background, our system tailors its interactions based on generational slang, emotional tone, and lifestyle relevance. Through carefully crafted prompts, the chatbot not only simulates the conversational style of different generations but also infers the user’s generation based on lexical and stylistic cues in their input. This approach enables dynamic, context-aware interaction without the overhead of fine-tuning large-scale models, making it efficient and adaptable [26], [27].

By leveraging curated slang dictionaries, emoji usage patterns, and generational behavior studies sourced from online forums and research surveys, the chatbot successfully delivers personalized and relatable conversations. The use of prompt engineering for both inference and generation ensures that the system remains flexible, allowing updates and improvements without retraining the model. This makes it particularly suitable for real-time deployments where quick adaptation to language trends is essential.

The future enhancement of this project could be incorporating the sentiment analysis and emotion recognition models which give responses more closely aligned with the user's emotional state. Implementing voice interaction in the model will make the chatbot more interactive. Integrating with the social media APIs will make the model continuously learn and update with the generational slang, trends in the real-time.

Ultimately, this research contributes to the growing interest in humanizing AI systems and adapting them to diverse user needs. The generationally aware chatbot offers practical applications in education, mental health, customer service, and digital companionship, where personalized, culturally attuned communication can significantly enhance user engagement and satisfaction.

TABLES AND DIAGRAMS

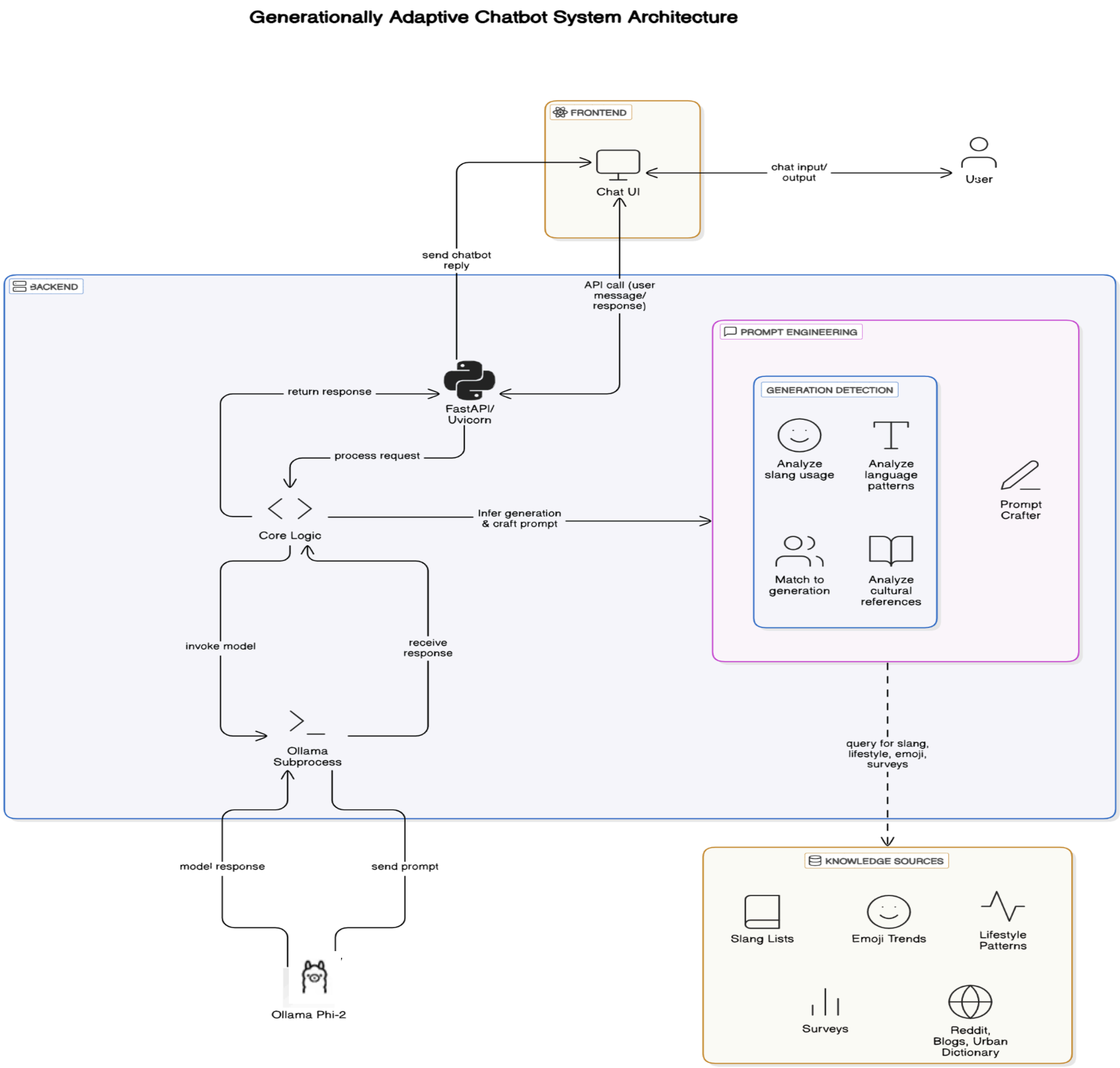

Fig 1

Table 1

Emoji	Meaning	Example	Context
🥹	Teary-eyed, touched	You remembered my birthday 🥹	Expressing deep emotion or being moved
😭	Crying from laughter/sadness	That joke was so funny, I'm literally 😭	Extreme laughter or sorrow
🤡	Foolish, clownish	I feel like a total 🤡 after that mistake.	Self-deprecating humor or silliness
😵‍💫	Dizzy, overwhelmed	After that exam, I'm completely 😵‍💫	Mental exhaustion or shock
🫠	Melting, embarrassed	I waved at the wrong person 🫠	Feeling awkward or deeply embarrassed
😈	Mischievous, playful evil	I'm about to prank my friend 😈	Playful mischief or cheeky behavior
😢	Sadness, sorrow	I miss you so much 😢	Expressing deep sadness or loss
😩	Exhausted, frustrated	I've had the worst day ever 😩	Conveys frustration or extreme fatigue
😔	Melancholy, reflective	Sometimes I just feel so 😔	Feeling reflective or downhearted
😤	Frustrated, determined	I'm fed up but I won't give up 😤	Conveys stubbornness or determination
😡	Angry, furious	That injustice makes me so 😡	Expressing strong anger or outrage
😞	Disappointed	I was really let down by that movie 😞	Mild disappointment or regret
😓	Overwhelmed, stressed	Today was non-stop work, I'm 😓	Indicates stress or being overwhelmed
😣	Struggling, in pain	I'm really going through it 😣	Expresses feelings of struggle or pain

Table 2

<table>
<tr><th>Category</th><th>Emoticon</th><th>Meaning</th><th>Example</th><th>Context</th></tr>
<tr><td>Happiness & Excitement</td><td>(ﾉ◕ヮ◕)ﾉ*:･ﾟ✧</td><td>Excited, happy</td><td>Let’s party! (ﾉ◕ヮ◕)ﾉ*:･ﾟ✧</td><td>Expressing joy and energy</td></tr>
<tr><td>Happiness & Excitement</td><td>٩(◕‿◕｡)۶</td><td>Happy hug</td><td>Come here! ٩(◕‿◕｡)۶</td><td>Offering virtual hugs or affection</td></tr>
<tr><td>Happiness & Excitement</td><td>(＾▽＾)</td><td>Very happy</td><td>Finally Friday! (＾▽＾)</td><td>Expressing joy and enthusiasm</td></tr>
<tr><td>Sadness & Crying</td><td>ಥ_ಥ</td><td>Crying, sad</td><td>That ending got me ಥ_ಥ</td><td>Expressing sadness or being touched emotionally</td></tr>
<tr><td>Sadness & Crying</td><td>(ಥ﹏ಥ)</td><td>Heavy crying</td><td>This movie destroyed me (ಥ﹏ಥ)</td><td>Extreme sadness or emotional distress</td></tr>
<tr><td>Frustration & Anger</td><td>(╯°□°)╯︵ ┻━┻</td><td>Table flip, frustration</td><td>Me after losing a game (╯°□°)╯︵ ┻━┻</td><td>Extreme frustration or rage quit</td></tr>
<tr><td>Confusion & Surprise</td><td>¯_(ツ)_/¯</td><td>Shrug, IDK</td><td>When someone asks me what’s for dinner ¯_(ツ)_/¯</td><td>Used to express uncertainty or indifference</td></tr>
<tr><td>Confusion & Surprise</td><td>(°△°|||)</td><td>Shocked, confused</td><td>Wait… what? (°△°|||)</td><td>Extreme confusion or shock</td></tr>
<tr><td>Sarcasm & Disapproval</td><td>(¬_¬)</td><td>Unimpressed, annoyed</td><td>Oh, sure… (¬_¬)</td><td>Sarcasm or irritation</td></tr>
<tr><td>Sarcasm & Disapproval</td><td>(¬_¬)ﾉ</td><td>Unimpressed wave</td><td>Yeah, sure… (¬_¬)ﾉ</td><td>Casual dismissal or sarcasm</td></tr>
<tr><td>Love & Affection</td><td>(✿◕‿◕)</td><td>Cute, wholesome</td><td>Let’s all be friends (✿◕‿◕)</td><td>Wholesome or friendly vibe</td></tr>
<tr><td>Love &</td><td>ʕ•ᴥ•ʔ</td><td>Bear, cute</td><td>Sending bear hugs ʕ•ᴥ•ʔ</td><td>Cute and affectionate</td></tr>
</table>

Affection				expression
Playfulness & Mischief	(ง°ل°)ง	Let’s fight!	You wanna go?! (ง°ل°)ง	Playful challenge or provocation

Table 3

Slang	Description	Example	Context
Fam	Fam is a shorter word for family, but don't be fooled– it can be used to describe your friends or the way Millennials use "bro".	What’s good, fam? Long time no see!	Used in casual conversation to address close friends or acquaintances.
Ghosting	Common amongst the earlier talking stages of a relationship. Ghosting someone means you start ignoring them or stop texting them back.	We were talking for weeks, and then she just ghosted me.	Used in online dating or friendships where one party disappears with no warning.
Salty	Used when someone feels jealous	He’s just salty because he lost the game	Often used in competitive environments or when someone is overly upset about a minor issue.
Snatched	If someone is looking snatched, they look really good, particularly their outfit	Her makeup was snatched at the event.	Often used in beauty and fashion to indicate someone looks flawless.
Periodt	Used to add emphasis to something	That’s the best movie of all time, periodt.	Often used to add emphasis to a statement, signaling that there’s no further debate.

Basic	Meaning anything mainstream.	Her outfit is so Basic.	Used to criticize someone or something for being overly mainstream or unoriginal.
BURN	Used to reference an insult	That was a sick BURN during the debate!	Refers to a clever or harsh insult, often used humorously.
Sending me	Another term to use if you find something particularly funny.	That meme is sending me!	Used in response to something humorous or amusing, often in digital contexts
Cringe	A response to embarrassment or social awkwardness	That performance was so cringe.	Often used to describe content, behavior, or situations that cause second-hand embarrassment.
Lit	Colloquially: "Enlightened", "Hot", "Fire." The new hotness; something remarkable, interesting, fun or amusing. Generally positive.	That party was lit!	Common in younger generations to describe a positive experience or event.

ALGORITHMS

ALGORITHM 1

1. User Input processing.

   Receive the Input message from the user and tokenize it(converting the words into numerical representation).

2. Context handling

   The context of the conversation is maintained by retrieving the chat history and by using a transformer-based attention mechanism.

3. Embedding generation

   The tokenized input is converted into dense vector representation using word embeddings, then passed to transformer models like GPT-3, etc.,

4. Response generation and delivery

   The attention mechanism determines the relevance of each word to the context and generates response text. The tokenized outputs are converted into human-readable text and send the generated response to the user.

5. Reinforcement Learning

   The system uses reinforcement learning to improve the model responses.

ALGORITHM 2

1. Processing of input.

Gets the input text with emojis, slang, or standard English from the user and preprocesses the text by normalizing emojis.

2. Analysis of the context.

If the user input is heavy on slang, route to fine-tuned Ollama. Or else if it is a general conversation, then use the ChatGPT API. If there is a Meme or GIF request, fetch the response from the tenor API.

3. Response Generation.

The slang is detected, then it asks the fine-tuned Ollama for the response, adds the emojis or memes with respect to the context and also call the ChatGPT API for the structured responses.

4. Meme and GIF analysis.

Detect the keywords like vibe, etc., and fetch the memes and GIFs from Tenor API.

5. Response optimization and delivery of the output.

The tone of the generated response like chill, chaotic, sarcastic., is checked and the necessary word adjustments are made to match Gen Z lingo.

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