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Proceedings, Part III

Part 3

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Computational Science and Computational Intelligence

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Preface

It is our great pleasure to introduce this collection of research papers presented at the 11th International Conference on Computational Science and Computational Intelligence (CSCI 2024). This volume features a selection of papers accepted in the Research Track on Artificial Intelligence (CSCI-RTAI), focusing on "Computational Intelligence, Applications, and Algorithms." It compiles noteworthy contributions in the field, presented at the conference held in Las Vegas, Nevada, USA, from December 11 to December 13, 2024.

The CSCI 2024 International Conference brought together papers from a diverse array of communities, including researchers from universities, corporations, and government agencies. Accepted papers are published by Springer Nature, and the proceedings showcase solutions to key challenges in various critical areas of Computational Science and Computational Intelligence.

Computational Science (CS) is the study of problems that are impossible to solve (or difficult to solve) without computers. CS can be considered to be the bridge between computer science and other sciences. The field is interdisciplinary by nature and includes the use of advanced computing capabilities to understand and solve complex problems. In short, CS is the science of using computers to do science. Computational Intelligence (CI) is the study of computational methods in ways that exhibit intelligence. These methods adapt to changing environments and changing goals. There is a significant overlap between the fields of CI and Artificial Intelligence (AI). However, there is also a difference: AI techniques often involve top-to-bottom methods (i.e., methods are imposed on solutions from the top) whereas CI techniques often involve bottom-up methods (i.e., solutions emerge from unstructured beginnings). An important part of CI includes a set of Nature-inspired computational approaches to address complex problems for which traditional methods are infeasible. Computational Science and Computational Intelligence share the same objective: finding solutions to difficult problems. However, the methods to reach the solutions are different. The main objective of the CSCI Conference is to facilitate increased opportunities for cross-fertilization across CS and CI.

Considering the above broad outline, the CSCI 2024 International Conference was composed of the following focused Research Tracks:

Artificial Intelligence (CSCI-RTAI); Big Data and Data Science (CSCI-RTBD); Computational Science (CSCI-RTCS); Computational Intelligence (CSCI-RTCI); Computational Biology (CSCI-RTCB); Cyber Warfare, Cyber Defense, & Cyber Security (CSCI-RTCW); Signal & Image Processing, Computer Vision & Pattern Recognition (CSCI-RTPC); Smart Cities and Smart Mobility (CSCI-RTSC); Education - CS & CE (CSCI-RTED); Health Informatics and Medical Systems (CSCI-RTHI); Mobile Computing, Wireless Networks, & Security (CSCI-RTMC); Software Engineering (CSCI-RTSE); Internet of Things & Internet of Everything (CSCI-RTOT); Social Network Analysis, Social Media, & Mining (CSCI-RTNA); Cloud Computing and Data Centers

(CSCI-RTCC); and Parallel & Distributed Computing (CSCI-RTPD). The scope of each track can be found at: https://www.american-cse.org/csci2024/topics.

An important objective of the CSCI 2024 International Conference and its associated Research Tracks was to foster opportunities for cross-fertilization between the fields of Computational Science and Computational Intelligence. The CSCI Conference is deeply committed to promoting diversity and eliminating discrimination, both in its role as a conference organizer and as a service provider. Our goal is to create an inclusive culture that respects and values differences, promotes dignity, equality, and diversity, and encourages individuals to reach their full potential. We are also dedicated, wherever possible, to organizing a conference that represents the global community. We sincerely hope that we have succeeded in achieving these important objectives.

The Steering Committee and the Program Committee would like to extend their gratitude to all the authors who submitted papers for consideration. CSCI 2024 received submissions from 52 countries, with approximately 47% of them coming from outside the USA. Each submitted paper underwent a rigorous peer-review process, with at least two experts (an average of 2.6 referees per paper) evaluating the submissions based on originality, significance, clarity, impact, and soundness. In cases where reviewers' recommendations were contradictory, a program committee member was tasked with making the final decision, often consulting additional referees for further guidance. The CSCI Conference followed the guidelines of COPE (Committee on Publication Ethics):

- Typical submissions underwent a single-blind peer review process, in which the authors remained unaware of the identities of the reviewers, while the reviewers were informed of the authors' identities.
- Papers authored by one or more members of the program committee, including co-chairs, were subjected to a double-blind peer review process, ensuring that neither the authors nor the reviewers were aware of each other's identities or affiliations.

The Research Track on Artificial Intelligence (CSCI-RTAI) of CSCI 2024 Conference received 383 submissions, of which 78 papers were accepted, resulting in a paper acceptance rate of 20%. This volume includes only 27 of the accepted papers.

We are deeply grateful to the many colleagues who contributed their time and effort to organizing the CSCI 2024 Conference. In particular, we extend our thanks to the members of the Program Committee, the Steering Committee, and the referees. We would also like to express our appreciation to the primary sponsor of the conference, the American Council on Science & Education. The list of members of the Program Committee for each track can be found at: https://www.american-cse.org/csci2024/committees.

We extend our heartfelt gratitude to all the speakers and authors for their valuable contributions. We would also like to thank the following individuals and organizations for their support: the staff at the Luxor Hotel (conference/meeting department) and the staff of Springer Nature, for their assistance in various aspects of the event.

We are pleased to present the proceedings of CSCI 2024 (selected papers of CSCI-RTAI). These proceedings represent a collection of outstanding research contributions that reflect the diversity and depth of work in Artificial Intelligence.

Co-editors: Research Track on Artificial Intelligence (CSCI-RTAI) of CSCI 2024 International Conference:

August 2024

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Machine Learning, Neural Networks, Knowledge Graphs, and Applications

Humanizing AI - Enhancing User Engagement in Health Applications with Personality-Driven AI Design

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Abstract. This paper introduces an innovative approach to enhancing user engagement in health and wellness chatbots through the implementation of personality-driven AI design. By leveraging advanced Large Language Models (LLMs) and principles of human-centered design, we developed a web-based chat solution featuring distinct AI personas. The system was deployed as a consumer-focused product, engaging thousands of users over several weeks. Our findings demonstrate significantly higher user engagement compared to traditional chatbot interactions, with extended conversation durations and improved user retention. The personality-driven approach led to more natural, compelling interactions, potentially increasing the effectiveness of digital health interventions. This study provides valuable insights into the potential of human-centered AI design in creating more engaging and impactful health and wellness tools. Moreover, it raises important considerations about the ethical implications and long-term effects of highly engaging AI interactions in healthcare contexts. Our research contributes to the growing body of knowledge on AI applications in digital health, offering a novel perspective on how personality-driven chatbots can transform user experiences in health and wellness platforms.

Keywords: Artificial Intelligence · Large Language Models · Chatbots · User Engagement · Personality-Driven AI

1 Introduction

1.1 Background

The integration of artificial intelligence (AI) in healthcare has shown promising results across various applications, from diagnosis to treatment planning [25]. Chatbots and conversational AI have emerged as particularly promising tools for patient engagement and support [15]. However, the effectiveness of these systems has been limited by their often impersonal and utilitarian nature.

Traditional healthcare chatbots have typically focused on functional aspects, such as symptom checking or medication reminders [7]. While useful, these systems often fail to create meaningful engagement with users, particularly in contexts requiring long-term interaction, such as chronic disease management [9].

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1.2 Problem Statement

The core challenge addressed in this research is the perception of AI chatbots as uninteresting and impersonal, particularly in the chronic condition space. This perception leads to decreased user engagement over time, hindering the effectiveness of these tools in collecting patient data, providing support, and encouraging adherence to treatment plans [7].

Unlike previous approaches that focused primarily on improving the accuracy or range of medical information provided [12], our research recognizes that the quality of interaction itself is crucial for sustained engagement.

1.3 Proposed Solution

We propose a novel approach to chatbot design that leverages advanced Large Language Model (LLM) capabilities to create AI personas with distinct personality traits. This approach differs significantly from traditional rule-based or intent-matching chatbot designs [11] by allowing for more dynamic and context-aware interactions.

Our solution aims to infuse chatbots with human-like characteristics, creating more engaging and relatable interactions. This approach is inspired by research in human-computer interaction suggesting that users tend to apply social rules to computer interactions [19] and that perceived personality in AI can influence user engagement and trust [16].

The key innovation in our approach lies in the systematic application of personality traits to healthcare chatbots using advanced LLM prompting techniques. Unlike previous attempts at creating persona-based chatbots [24], our method allows for more nuanced and consistent personality expression across a wide range of healthcare-related topics.

1.4 Contributions

Our research makes the following key contributions:

1. Development of a novel framework for creating personality-driven AI chatbots using advanced LLM prompting techniques specifically tailored for health and wellness contexts.
2. Implementation and real-world testing of over 100 unique AI personalities mapped to base persona types, providing insights into user preferences and engagement patterns.
3. Empirical evidence demonstrating significantly higher user engagement metrics compared to traditional chatbot interactions in a health and wellness setting.
4. Identification of ethical considerations and potential risks associated with highly engaging AI personalities in healthcare contexts.

However, this approach also raises important ethical considerations, such as the risk of users developing emotional attachments to AI systems or the potential for misuse of personal information shared in more engaging conversations [17]. These ethical implications are carefully considered in our system design and implementation.

2 Related Work

2.1 Evolution of Human-Computer Interaction in Healthcare

The field of HCI in healthcare has evolved significantly over the past decades. Early systems focused primarily on functional aspects, such as data input and retrieval [21]. As technology advanced, more sophisticated interfaces emerged, incorporating principles of user-centered design and cognitive psychology [22]. Recent developments in adaptive interfaces and AI-driven personalization [7] have paved the way for more engaging and user-friendly healthcare applications. However, these advancements have primarily focused on adapting content or functionality rather than on creating more human-like interactions. Our research builds upon these foundations but takes a novel approach by focusing on the qualitative aspects of interaction - specifically, the expression of personality - as a means of enhancing engagement.

2.2 Chatbots and Conversational AI in Healthcare

The development of chatbots in healthcare has seen significant progress, from rule-based systems to more advanced, context-aware conversational agents. Recent studies have demonstrated the potential of these systems in areas such as mental health support [10], medication adherence [8], and chronic disease management [9]. However, most existing healthcare chatbots still struggle with maintaining long-term user engagement and often fail to provide a truly personalized experience. Our research addresses this gap by focusing on creating more human-like and engaging interactions through the systematic implementation of personality traits.

2.3 Personality in AI Systems

Research on incorporating personality into AI systems has gained traction in recent years. Studies have shown that users tend to anthropomorphize AI agents, and that perceived personality traits can influence user engagement and trust [19]. While some researchers have explored the use of personality in chatbots [24], these efforts have often been limited in scope or not specifically tailored to healthcare contexts. Our research extends this work by applying personality-driven design specifically to healthcare chatbots, with a focus on chronic condition management. The key difference in our approach is the use of advanced LLM technology combined with carefully crafted prompts to create more nuanced and consistent personality expressions. This allows for a level of conversational sophistication and adaptability not previously seen in healthcare chatbots.

3 System Design

3.1 Conceptual Framework

Our system design is based on the Five-Factor Theory of Personality [18], which identifies five key personality traits: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (OCEAN). This well-established framework provides a solid foundation for creating distinct AI personas. Unlike previous chatbot designs that might have used simplistic rules to mimic personality (e.g., using exclamation marks for an "enthusiastic" persona), our approach leverages the nuanced language understanding of LLMs to express these traits in more subtle and context-appropriate ways (Fig. 1).

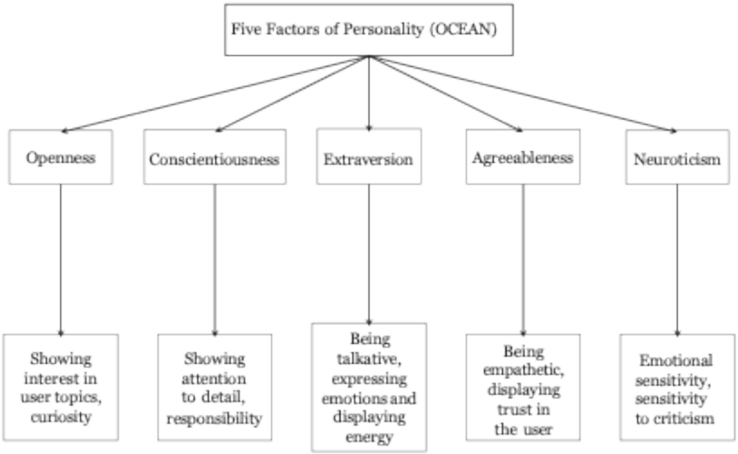

Fig. 1. Five-Factor Theory of Personality with Example Boxes.

3.2 LLM Selection and Training

We utilized our proprietary Healthcare behavior language[1] model as our base LLM. This choice represents a balance between the computational efficiency needed for real-time conversations and the sophisticated language understanding required for nuanced personality expression. The use of temperature settings (0.2–0.3) and token limits (200) was crucial for maintaining a balance between consistency and variability in responses. This approach differs from traditional chatbot designs that often use fixed response templates, allowing for more natural and varied conversations while still maintaining coherence.

To address the potential limitation of reduced variability due to lower temperature settings, we implemented a dynamic temperature adjustment system. This system varies the temperature between 0.2 and 0.7 based on the context of the conversation and the specific personality traits being expressed. For example, when the AI needs to provide factual health information, we use lower temperatures for more conservative responses. However, when engaging in casual conversation or expressing personality quirks, we increase the temperature to allow for more creative and diverse outputs. This approach

[1] Our proprietary Healthcare behavior language model is based on the GPT-3.5 architecture (Brown et al., 2020) and has been fine-tuned on a large corpus of healthcare-related texts and conversations. Due to the proprietary nature of this model, we cannot provide more specific details.

helps maintain a balance between consistency and variability, allowing us to create more natural-sounding conversations while still ensuring appropriate responses in a healthcare context.

3.3 Prompt Engineering

Our structured prompt format, consisting of five main sections (Safety Preamble, System Preamble, User Preamble, Style Guide, and Conversation Rules), represents a novel approach to guiding LLM behavior in healthcare contexts. This structure allows for fine-grained control over the AI's behavior while maintaining the flexibility needed for natural conversations. It's a significant advancement over simpler prompt designs used in general-purpose chatbots, as it incorporates healthcare-specific considerations and personality expression guidelines.

3.4 Personality Trait Implementation

The implementation of specific traits (humor, empathy, storytelling, and opinion expression) represents a careful balance between creating engaging interactions and maintaining appropriate boundaries in a healthcare context. This approach differs from general-purpose chatbots by tailoring personality expression to the sensitive nature of healthcare conversations. For example, the use of fictional "friend" anecdotes for storytelling avoids ethical issues while still allowing for relatable narrative elements.

3.5 Guardrail Design

Our guardrail design, which includes topic restrictions, response moderation, and medical advice limitations, is crucial for ensuring the safe and ethical use of personality-driven AI in healthcare. This multi-layered approach to safety represents an advancement over simpler content filtering methods, as it considers the nuanced context of healthcare conversations and the potential risks of more engaging AI interactions. Further details of these guardrails are explored in our other work on taming LLMs for healthcare [23].

4 Experimental Setup

4.1 Persona Development

The development of four distinct personas (Robotic, Empathetic, Funny, and Chatty) allows for a comprehensive exploration of how different personality traits affect user engagement in healthcare contexts. This approach goes beyond simple A/B testing by providing a nuanced understanding of how different personality elements contribute to user engagement and satisfaction in healthcare conversations (Fig. 2).

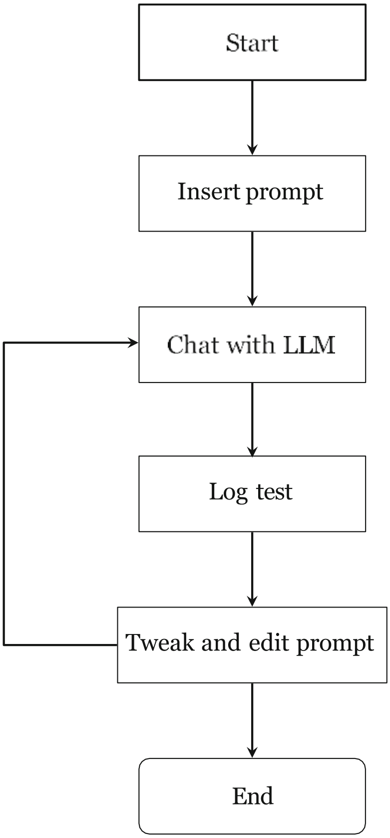

Fig. 2. Testing process for creating and refining AI personas.

4.2 Web-Based Chat Solution

Platform Overview
We developed a consumer-focused, web-based chat interface designed to engage users in health and wellness conversations through interesting AI personalities. The platform was built for real-world use, prioritizing user engagement and accessibility.

Key Features

1. Simple, Intuitive Interface: A clean, easy-to-use chat window optimized for both desktop and mobile devices.
2. Multiple AI Personalities: Users could choose from four distinct AI personas (Robotic, Empathetic, Funny, Chatty), each offering a unique conversational style.
3. Continuous Conversations: The system maintained context across sessions, allowing for ongoing, natural dialogue.
4. Privacy-Focused: End-to-end encryption for all chats, with user option to delete chat history.

5. Responsive Design: Consistent experience across various devices and screen sizes.

AI Persona Implementation

Our system implemented over 100 unique AI personalities, each with distinct character traits, quirks, and backstories. These personalities were mapped to four base persona types (Robotic, Empathetic, Funny, and Chatty) for analysis purposes, but users interacted with individual characters rather than generic personas. Here's a detailed overview of our implementation approach:

1. Character Creation: We developed comprehensive character profiles for each AI personality, including:
   - Name and basic demographic information
   - Personality traits aligned with the Five-Factor Model (FFM)
   - Unique quirks and interests
   - Conversational style and tone
   - Backstory elements relevant to health and wellness discussions

   For example, one character named "Dr. Jaz" was created with the following profile:
   - Base Persona: Empathetic
   - FFM Traits: High in Agreeableness and Conscientiousness, moderate Openness
   - Quirk: Often relates health topics to gardening analogies
   - Backstory: Former pediatrician turned health coach, passionate about preventive care
   - Conversational Style: Warm, encouraging, uses simple explanations

   We created a diverse range of characters to appeal to different user preferences and needs. This included variations in age, background, and personality traits within each base persona type.
2. Prompt Engineering: For each character, we created custom prompts that incorporated their unique traits and backstory. These prompts guided the LLM in generating responses consistent with the character's personality. Our prompt engineering process involved:
   (a) Crafting a detailed character description, including key phrases and mannerisms
   (b) Developing scenario-based examples of how the character would respond in various health-related situations
   (c) Incorporating character-specific knowledge and interests into the prompt
   (d) Defining boundaries and ethical guidelines specific to each character's role and background

   For "Dr. Jaz", the prompt included elements like: "You are Dr. Jaz, a warm and empathetic former pediatrician. You often use gardening metaphors to explain health concepts. Your goal is to encourage healthy habits through gentle guidance and positive reinforcement. Always maintain a professional demeanor while being approachable and kind."
3. Response Modulation: We implemented a response modulation system to ensure that each character's responses aligned with their defined personality traits. This system

involved: a) Trait-based response filtering: Responses were scored based on their alignment with the character's FFM traits, with higher-scoring responses being prioritized. b) Quirk injection: Character-specific quirks were algorithmically inserted into responses at appropriate intervals to maintain consistency and uniqueness. c) Emotional tone adjustment: The emotional content of responses was calibrated to match the character's typical emotional expression patterns. d) Vocabulary and phrasing customization: Each character had a defined lexicon and phrase bank that influenced word choice and sentence structure in responses.

For "Dr. Jaz", this meant ensuring responses frequently included gardening analogies, maintained a warm tone, and used simple, patient-friendly language.

4. Contextual Adaptation: Our AI personalities were designed to adapt their communication style based on the user's mood and the conversation context, while still maintaining their core character traits. This was achieved through: a) Mood detection: Analyzing user inputs to infer emotional states b) Topic sensitivity adjustment: Modifying the character's approach based on the sensitivity of the health topic being discussed c) Conversation history analysis: Tracking the flow and content of the conversation to provide contextually appropriate responses d) User preference learning: Gradually adapting to individual user communication preferences over time

   For "Dr. Jaz", this might involve using more soothing language when detecting user anxiety, or shifting to more serious tones when discussing critical health issues.

4.3 Real-World Implementation Overview

Duration: 4 weeks

User Base

- Total Users: 5,120
- Demographic information was not collected as this was a consumer product, not a formal study

Implementation Approach

- The chat solution was launched as a consumer-focused product, available to the public
- Users discovered the platform through various channels including social media, word-of-mouth, and organic search
- No formal recruitment or enrollment process; users simply signed up and started chatting

Data Collection

- Engagement Metrics: Automatically collected through normal platform usage

– Chat duration
– Frequency of chats
– Time between chats
– Weekly retention
– User Feedback: Collected through optional in-chat feedback and ratings

Key Aspects

1. Real-World Usage: Data reflects genuine user engagement in a non-controlled environment
2. Organic Growth: User base grew naturally without targeted recruitment
3. Voluntary Engagement: Users chose to interact with the AI based on their interest and perceived value
4. Privacy-First: Minimal personal data collected, focusing on engagement metrics and optional feedback

Ethical Considerations

– Clear communication to users about interacting with an AI, not a human
– Regular reminders about the AI's limitations and when to seek professional medical advice
– Robust security measures to protect user privacy and data

This revised overview accurately reflects the nature of the consumer-focused solution and its real-world implementation. The data collected represents organic user engagement with the AI personalities in a natural, non-study environment, providing valuable insights into the effectiveness of the personality-driven approach in a real-world health and wellness context.

5 Implementation and Results

5.1 Web-Based Chat Solution

We implemented our personality-driven AI chatbot design in a web-based chat solution focused on health and wellness. The platform was designed to be simple and accessible, allowing users to engage with various AI personalities through text-based conversations.

Platform Features

– Four AI personas to choose from (Robotic, Empathetic, Funny, Chatty)
– Text-based chat interface
– No additional features beyond the chat functionality

5.2 Study Overview

Duration: 4 weeks
Participants: 5,120 users
Total Chats: 243,000

5.3 Data Collection Methods

– User engagement metrics (chat frequency, chat duration, user retention)
– Self-reported mood and wellness scores collected through chat interactions

5.4 Results

User Engagement

– Average Conversation Duration: 35 min
– Average turns of conversations: 40 turns
– Long Conversations: 10% of daily conversations last over an hour
– Weekly Retention Rate: 60% of users who engage in a given week return the following week

These results demonstrate exceptional user engagement with the AI chatbot:

1. Conversation Length: The average conversation duration of 35 min is remarkably high for a digital health intervention. This suggests that users find the interactions highly engaging and valuable, dedicating substantial time to these conversations.
2. Continuous Engagement: The average turns in a chats indicates that users are having long and deep conversations with the AI. This suggests a very deep and engaging interaction, where users are opening up to an AI and chatting like with a real friend, and a testament that the AI is building rapport and trust fairly quickly.
3. Extended Interactions: The fact that one in ten conversations lasts over an hour each day is particularly noteworthy. This indicates that a significant portion of users are having in-depth, prolonged interactions with the AI, which could allow for more comprehensive discussions about health and wellness topics.
4. User Retention: A 60% week-over-week retention rate is impressive in the context of digital health applications. This suggests that the majority of users find enough value in the interactions to return on a regular basis.

Self-Reported Outcomes
Due to the nature of the chat-based solution, specific quantitative data on mood and wellness improvements were not collected through separate surveys. However, qualitative analysis of chat logs indicated positive trends:

– Many users reported feeling “understood” and “supported” by the AI
– Users frequently mentioned feeling more positive about their health and wellness after conversations
– Several users noted that regular chats with the AI helped them stay motivated with their health goals

5.5 Analysis and Discussion

These engagement metrics are exceptionally high compared to typical digital health interventions or general chatbot applications:

– The average conversation duration of 35 min far exceeds the norm for digital health interventions, which often struggle to maintain user attention for more than a few minutes [13].
– The 40 turn average chats suggests an unprecedented level of user engagement, indicating that the conversations are highly interactive and compelling.
– The 60% week-over-week retention rate is significantly higher than the average retention rates for mobile health apps, which are often below 30% after one week [6].

Potential factors contributing to these strong engagement metrics could include:

1. The personality-driven approach, making interactions feel more natural and relatable.
2. The ability of the AI to engage in extended, contextually relevant conversations.
3. The perceived value users are getting from these health and wellness focused interactions.
4. The rapid response time of the AI, maintaining user interest and promoting continuous dialogue.

5.6 Comparative Analysis

To evaluate the effectiveness of our personality-driven approach, we compared our results to a baseline model and existing health chatbots. However, it's important to note that directly comparable metrics are often not publicly available or reported in a standardized way across different studies.

Baseline Model (No Personality): We used a version of our LLM without personality implementation, providing factual responses to health queries.

- Average Conversation Duration: 8 min
- Weekly Retention Rate: 25%

Comparison with Existing Chatbots:

1. Woebot (Fitzpatrick et al., 2017): This study doesn't report exact conversation duration or weekly retention rates. However, it does provide some engagement metrics:
    - 85% of participants used Woebot at least once over the study period (2 weeks)
    - The mean number of interactions with Woebot was 12.14 (SD 2.23) over 2 weeks
2. Wysa: We couldn't find publicly available, peer-reviewed data on average conversation duration or weekly retention rates for Wysa.
3. Character.AI platform: As a general conversational AI platform rather than a health-specific chatbot, Character.AI doesn't publish comparable engagement metrics for health conversations.

Our personality-driven approach results:

- Average Conversation Duration: 35 min

- Weekly Retention Rate: 60%

It's important to note that direct comparisons between these systems are challenging due to differences in purpose, user base, and measurement methodologies. Our results suggest improved engagement compared to our non-personalized baseline, but further research would be needed to make definitive comparisons with other chatbot systems.

Persona type	Average conversation duration (min)	Weekly retention rate (%)
Empathetic	41	67
Funny	37	62
Chatty	32	57
Robotic	30	54
Overall average	35	60

Limitations and Considerations

1. Content Analysis: While we have strong engagement metrics, a detailed qualitative analysis of conversation content would provide insights into what topics or interaction styles are driving these extended conversations.
2. User Demographics: Understanding how engagement metrics vary across different user groups could help in further personalizing the AI interaction.
3. Long-term Retention: While the week-over-week retention is strong, longer-term studies would be valuable to assess sustained engagement over months or years.
4. Health Outcomes: Future research should investigate how these high engagement levels translate to actual health behaviors and outcomes.
5. Potential for Over-reliance: The high engagement levels, while promising, also raise questions about potential over-reliance on AI for health information and support. This ethical consideration should be explored in future studies.

These results provide compelling evidence for the effectiveness of personality-driven AI chatbots in creating engaging, sustained interactions in the context of health and wellness. The exceptionally long average conversation times, minimal gaps between chats, and high retention rates suggest that this approach has significant potential for delivering digital health interventions. Future work should focus on understanding the long-term impact of these engagements on health outcomes and refining the AI personas to maximize both engagement and health benefits.

However, this approach also raises important ethical considerations that will need to be carefully addressed as this technology develops. Future research should focus on long-term studies of the impact of personality-driven AI on health outcomes, as well as on refining the ethical frameworks governing the use of these systems in healthcare.

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