Strategies for Building Trust with Automated Agent Systems

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```
# Global options to suppress all code, warnings and messages
knitr::opts_chunk$set(echo = FALSE, warning = FALSE, message = FALSE)
options(warn = -1)  # Suppresses all warnings globally in R
suppressWarnings(suppressMessages({
  library(quanteda)
  library(quanteda.textplots)
  library(RColorBrewer)
  library(textdata)
}))
```

Cover Letter

STRATEGIES FOR BUILDING TRUST WITH AUTOMATED AGENT SYSTEMS
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Supplementary Materials
- Experiment: https://sheepqueen422.github.io/chatbot/chatbot.html
- Raw data files: https://drive.google.com/file/d/1bX1LqpczhgOePygc3kqN0omnBBUxA0ro/view?usp=share_link

Recommended Reading Path
Begin with the Introduction (p. 3) for research context, then proceed to Results (p. 11) for key findings and Discussion (p. 40) for implications. Technical implementation details are in Appendices A and D (p. 45(.

Author Contributions

Mila Dutton led the data collection and quantitative and qualitative analysis (ANOVA, post-hoc tests, sentiment coding, thematic analysis). Hui Junyi handled agent implementation (Eleven Labs/OpenAI API) and qualitative analysis (sentiment coding, thematic analysis), Both authors contributed equally to all other aspects including literature reviews, experimental design, report writing, and final edits.

We are confident this work provides actionable insights for designing emotionally intelligent CAs, particularly in high-stakes domains like healthcare

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Abstract

Voice-based conversational agents (CAs) are increasingly integrated into healthcare and other domains, yet their lack of emotional intelligence often leads to unnatural and disengaging interactions. This study explores the development of emotionally intelligent voice CAs (EIVCAs) by altering conversational styles such as tone, speed, pauses, etc. By enhancing conversational abilities, this research aims to improve user engagement and trust in healthcare-specific chat bots. Through these improvements, this work aims to advance the adoption of CAs in healthcare, where trust and effective communication are essential for positive patient outcomes.

Keywords: Voice-based conversational agents, Artificial intelligence, Language

Introduction

Effective communication systems are a cornerstone of the healthcare industry, ensuring the seamless management of patients and procedures. However, the sheer volume of administrative tasks often poses significant challenges such as staff burnout, errors, and delays. In recent years there has been a shift toward utilizing conversational AI, such as chatbots and voice assistants (VAs), across various domains to help improve such processes and reduce the administrative workload. These automated systems can assist with tasks such as: scheduling appointments, answering questions, and collecting patient information. Unlike human workers, these agents can constantly operate without fatigue, thus allowing for a high volume of consistent, accurate, and timely assistance.

However, despite their utility, conversational agents can fall short in meeting user expectations for natural and relatable interactions. This shortcoming is particularly critical in healthcare, where trust and empathy are essential. Robotic, emotionless interactions can lead to user dissatisfaction, disengagement, and ultimately, a lack of trust in these systems.

Emotionally intelligent conversational agents (EICAs) that integrate emotional perception and expression capabilities represent a promising solution to this challenge. By incorporating emotional cues, context-aware responses, and human-like conversational elements, EICAs can bridge the gap between user expectations and the limitations of current CAs. This study focuses on optimizing a healthcare-specific agent developed for a leading AI digital vendor in the healthcare space, by exploring how communication styles and emotional cues affect user trust, engagement, and task completion. Specifically, our research investigates how varying the tone, speed, vocabulary, and emotional expression to different degrees of friendliness and professionalism influences the user's experience, aiming to enhance both enjoyment and effectiveness. Through this research, we hope to gain foundational knowledge in the role of conversational agents in the healthcare industry, thus contributing to more effective implementation of such agents.

Based on prior work in emotionally intelligent CAs, we test the following hypotheses:

H1: The Friendly Agent will elicit significantly higher user engagement and emotional connection scores than the Moderate and Professional Agents.

H2: Engagement scores will be rated higher than emotional scores across all agent types, regardless of conversational style.

H3: Linguistic analysis of free-response feedback will reveal more positive sentiment and emotional terms (e.g., "enjoyed," "natural") for the Friendly Agent compared to other versions.

Related Work

Conversational Agents

Conversational agents (CAs) are dialogue systems capable of understanding and generating natural language through text, voice, or gestures. While often used interchangeably, "chatbots" are a subset of CAs, primarily text-based systems designed for task specific or open ended interactions. Virtual assistants like Siri and Alexa extend these capabilities to include voice interactions and actions like setting reminders or controlling devices. Embodied conversational agents (ECAs), such as JIBO, further enhance communication with physical gestures or graphical representations (Adamopoulou & Moussiades, 2020). CAs are categorized by communication mode, action capabilities, and application domain:

- Communication only agents (e.g., ELIZA) focus on interacting with users (Allouch et al., 2021).

- Action capable agents (e.g., Siri) perform tasks alongside communication.

- Applications include open-domain agents (general-purpose Q&A), goal-oriented systems (booking appointments), social-supporting agents (healthcare), and social-network bots (marketing).

Historically, systems like ELIZA and PARRY relied on simple rule-based designs. Modern advancements in Artificial Intelligence (AI), Natural Language Processing (NLP), and machine learning enable dynamic, context-aware responses, making interactions more human-like and adaptable (Adamopoulou & Moussiades, 2020; Bălan, 2023).

Technologies for Basic Chatbots

Core components of chatbots include:

- Natural Language Processing (NLP): Processes user input using tokenization, lemmatization, and sentiment analysis. For voice-based agents, speech recognition is also employed (Bilquise et al., 2022).

- Natural Language Understanding (NLU): Interprets user intent and context from structured data.

- Dialog Manager: Maintains conversational context and determines responses via templates, APIs, or databases.

- Natural Language Generator (NLG): Produces responses using rule-based, retrieval-based, or generative models.

Modern chatbot technologies leverage deep learning models for improved performance:

- Recurrent Neural Networks (RNNs) capture sequential language patterns but struggle with long-term dependencies (Wardhana et al., 2021).

- Sequence-to-Sequence (Seq2Seq) models use encoder-decoder frameworks for contextually relevant responses but often fail to replicate human-like conversations.

- Long Short-Term Memory (LSTM) networks overcome RNN limitations by retaining long-term information, improving context retention.

- Conditional Variational Autoencoders (CVAE) enhance response diversity by learning latent conversational intents (Liu et al., 2021).

The trend in chatbot development is shifting from retrieval-based to generative approaches, focusing on neural network models like GPT and BERT to create diverse, contextually appropriate responses (Pamungkas, 2019).

Emotional Intelligence of CAs

Despite technological advancements, many users still disengage from conversational agents (CAs) due to their lack of emotional intelligence and natural conversational flow. Emotional cues—such as tone, sentiment, and empathy—are critical in building trust, engagement, and satisfaction (Hong et al., 2023). Research indicates that a large portion of user interactions, especially in social media and customer service contexts, involves emotional exchanges rather than purely informational ones (Xu et al., 2017). For example, emotionally enriched responses can uplift user moods, improve relationships, and foster natural, engaging conversations.

Emotions are a critical component of effective communication. Studies reveal that users are more likely to engage with CAs capable of perceiving and responding empathetically (Hong et al., 2023; Nass & Moon, 2000). The absence of these interpersonal qualities often results in frustration and reduced adoption rates. This gap highlights the need for emotionally intelligent conversational agents (EICAs) that bridge the divide between user expectations and the technology's capabilities.

Despite their utility, CAs face challenges in user engagement and trust, particularly in domains requiring empathy and nuanced communication. Nass and Moon (2000) found that users apply human social rules to CAs, suggesting that traits like attentiveness, humor, and emotional expressiveness enhance user experiences. In healthcare, where effective communication is critical, these elements are essential for building trust and ensuring task completion. Emotional intelligence can help create rapport, comfort, and confidence in users, making tasks more efficient and interactions more fulfilling.

The PEACE framework (Politeness, Entertainment, Attentive Curiosity, Empathy) further underscores the importance of interpersonal qualities in conversational agents (Svikhnushina & Pu, 2022). By demonstrating these qualities, EICAs can reduce communication breakdowns, enhance user satisfaction, and build trust—key factors in sensitive domains like healthcare. Recent research has emphasized integrating emotional intelligence into CAs through adaptive conversational strategies, varied tones, and empathic responses.

As organizations increasingly invest in AI-powered conversational systems, incorporating emotional intelligence into chatbots is essential for enhancing user engagement and trust. Particularly in healthcare, emotionally intelligent chatbots hold the potential to facilitate better communication, leading to improved outcomes and user experiences.

Technologies for Emotional CAs

Emotional Perception Technology:
Emotion perception technology focuses on enabling CAs to detect and interpret the emotional states of users. This involves techniques like:

- Valence-Arousal-Dominance (VAD) embeddings: Associating words with emotional intensity and meaning.

- Speech Emotion Recognition (SER): Utilizing acoustic signals to classify emotions, allowing the agent to adapt its responses dynamically (Hu et al., 2021).

SER models often utilize deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for emotion detection. However, while recognizing emotions is a critical first step, emotional intelligence also requires appropriate emotional expression to create meaningful and engaging interactions.

Emotional Expression Technology:
Emotionally intelligent chatbots use advanced neural models to express emotions and generate contextually appropriate responses. Techniques include:

- Seq2Seq and CVAE models: Generating emotionally enriched and diverse responses (Liu et al., 2021).

- Transformer-based architectures (e.g., GPT): Producing highly context-aware and empathic responses.

Strategies to enhance emotional expression include:

- Positive reinforcement: Using praise or encouragement to motivate users.

- Emotion regulation techniques: Addressing negative emotions with distraction or reappraisal strategies.

- Nonverbal cues: Incorporating interjections (e.g., "wow!", "hmm") and fillers to convey empathy and maintain conversational flow (Asghar et al., 2018).

Despite significant advancements, challenges remain in integrating emotional perception and expression technologies seamlessly. Current research emphasizes the need to combine these approaches to create cohesive and emotionally intelligent systems. In healthcare, such systems could significantly improve user trust, engagement, and overall satisfaction.

Methods

Participants

Participants were recruited through the online platform Prolific. This specific platform was chosen as it is known for higher quality data and minimal bots. The only criteria for participation is that participants must be fluent in English. Additionally, participants must have a minimum approval rate of 95% for the studies to which they apply, ensuring that they are engaged and committed to providing reliable, high-quality data.

Design

This study utilizes a within subjects design, where each participant interacts with all experimental conditions. The conditions represent three different versions of the digital assistant: friendly, moderate, and professional. The three versions of the speech to speech agent differ primarily in their communication style, tailored to suit distinct conversational contexts. The Professional Agent maintains a relaxed and informative tone, featuring a neutral style, stable pitch, and a slightly reduced speaking rate to enhance clarity. With precise articulation, professional vocabulary, and minimal emotional variation, it is well suited for business and structured interactions. The Moderate Agent offers a warm and engaging presence, balancing professionalism with approachability. It uses a natural pace, a stable pitch, and subtle expressiveness to create a calm yet inviting conversational style. Its articulation is smooth, and its vocabulary remains accessible, making it ideal for balanced, supportive discussions. Meanwhile, the Friendly Agent is designed for casual and lively conversations, featuring an upbeat and clear tone. With a higher pitch, faster rate, and expressive emotion, it fosters an engaging and dynamic experience, perfect for informal and cheerful interactions.

The qualitative dependent variables consist of free response answers that capture participants' experiences with each agent version. Quantitative dependent variables include Likert scale ratings measuring engagement and emotional connection.

Agent Selection & Implementation

To identify a suitable agent development platform, several leading options were reviewed, including Google DialogFlow, Facebook wit.ai, Microsoft LUIS, IBM Watson Conversation, Amazon Lex, and SAP Conversation AI. Additional platforms like RASA, Botsify, Chatfuel, Manychat, Flow XO, Chatterbot, Pandorabots, Botkit, and Botlytics were also considered. After thorough comparison, LiveKit, VoiceNote.AI, and Microsoft Azure were selected as the potential implementation platforms due to their customizability. Fully coded versions of both a Microsoft Azure and Eleven Labs agent were built, as well as their front end websites for user applications. After comparing both, and receiving feedback, the Eleven Labs agent was selected.

Materials

Eleven Labs Agent

The Eleven Labs Agent was selected for its advanced AI-driven text-to-speech capabilities, offering high-quality, natural-sounding voices that enhance conversational experiences. Eleven Labs' platform specializes in lifelike speech synthesis, allowing agents to deliver expressive and dynamic interactions. Its AI-driven voice models provide smooth articulation, emotion control,

and customizable parameters like pitch, stability, and speed, making it ideal for studying how different speaking styles impact user engagement and trust.

The agent was developed in Python, utilizing Open AI's API to integrate text-to-speech functionality seamlessly. Since Eleven Labs provides state-of-the-art voice synthesis models, the chatbot does not require extensive speech training, instead relying on these pre-trained models to generate natural, engaging dialogue in real time.

Agent Version Specifications

Three versions of the agent were created, each representing a different communication style:

- Professional – formal tone, structured vocabulary, steady pacing

- Moderate – balanced tone, conversational but clear, moderate pacing

- Friendly – relaxed tone, casual vocabulary, upbeat pacing.

  The agents vary in tone, pacing, and vocabulary (see Appendix A). They do not require training, as the Eleven Labs platform provides pre-trained models and customizable templates. This enables efficient deployment without extensive data collection or training time, allowing the study to focus on testing how communication style impacts user outcomes.

Agent Conversational Prompts

The agents engage participants in natural healthcare conversations, asking questions about wellness and lifestyle habits that mirror real world healthcare interactions. While Appendix B contains a comprehensive set of potential prompts aligned with each communication style, these serve as flexible conversation starters rather than a rigid script. The conversations unfold organically, with agents selecting contextually appropriate questions rather than working through a predetermined list. This approach creates authentic dialogue rather than formal interviews, allowing participants to ask their own questions and redirect conversations as desired. This dynamic interaction provides valuable insight into how participants perceive and respond to different communication styles, ultimately revealing their impact on the overall experience.

Agent Interaction Assessment

The Agent Interaction Assessment is designed to measure the participants experience interacting with the agent. Detailed descriptions of the assessment metrics and scoring criteria can be found in Appendix C, ensuring clarity and reproducibility of the evaluation process. Both free response and likert scale items are included allowing for qualitative and quantitative analysis. These questions aim to capture a comprehensive view of the participants' experiences, focusing

both on measurable aspects (Engagement and Approachability, Emotional Connection) and on subjective feedback (General Impression).

Procedure

The study began by obtaining informed consent from the participant. They then interacted with each version of the agent. First the Friendly Agent, then the Moderate Agent, asnd lastly the Professional Agent. Each version of the agent interacted with the participant, drawing inspiration from the conversational prompts. Ideally, the participant engaged in a full conversation, making it feel natural rather than like a structured interview. This approach ensured that the focus remained on evaluating the user's overall experience with each agent rather than the questions themselves. Each section lasted no more than 10 minutes, depending on the length of participant responses.

After each version of the agent, the participant was taken to a new screen where they responded to a series of prompts regarding their experience with the agent from the agent interaction assessment. These prompts included likert scales and free response questions. Lastly, they were debriefed and thanked for their participation. The whole experiment took no more than 30 minutes.

Data Cleaning

The data cleaning process involved multiple steps to transform raw survey data into an analyzable format. First, the raw data was imported and processed to extract relevant responses while ensuring proper formatting. Survey responses, initially stored in JSON format, were parsed to retrieve the bot version and individual question responses. A standardized data structure was implemented to maintain consistency across participants, even in cases of incomplete responses.

To facilitate statistical analysis, numeric responses were converted to the appropriate data types, and questions were categorized into engagement and emotional connection measures. For ANOVA analysis, the data was further processed to compute average scores per participant and reorganized into a long-format structure. Any missing responses were addressed to ensure data integrity.

The final cleaned dataset was prepared for analysis, with all detailed steps, including specific functions, transformations, and file structures, provided in Appendix D.

Data Analysis

Qualitative data was analyzed with thematic analysis to identify patterns in how different communication styles affected user perceptions and engagement. This involved reviewing participants' free response feedback to uncover common themes related to agent friendliness, enjoyment, and emotional effect.

Quantitative data was analyzed using a two-way ANOVA to evaluate differences in user experience scores across the three bot versions and two score types (emotional and engagement). Following the ANOVA, post-hoc tests using Tukey's Honestly Significant Difference (HSD) test were conducted to identify which specific bot versions differed significantly from one another. Estimated marginal means were calculated for both factors to provide clear comparisons between the different bots and score types.

Effect sizes were also calculated to assess the magnitude of differences between bots and score types, offering a nuanced view of the practical significance of the findings beyond statistical significance. This comprehensive analysis approach allowed for examining not only whether differences existed between the bot versions but also the size and practical importance of these differences.

Results

Quantitative Analysis

Two Way Anova

Table 1: Figure 1: ANOVA Summary

Source	Df	Sum Sq	Mean Sq	F Value	Pr($>$F)
Bot	2	23.131362	11.5656808	10.166246	0.0000554
ScoreType	1	6.340680	6.3406804	5.573465	0.0189456
Bot:ScoreType	2	0.222109	0.1110545	0.097617	0.9070282
Residuals	270	307.166860	1.1376550	NA	NA

Figure 2: Bot Ratings Comparison
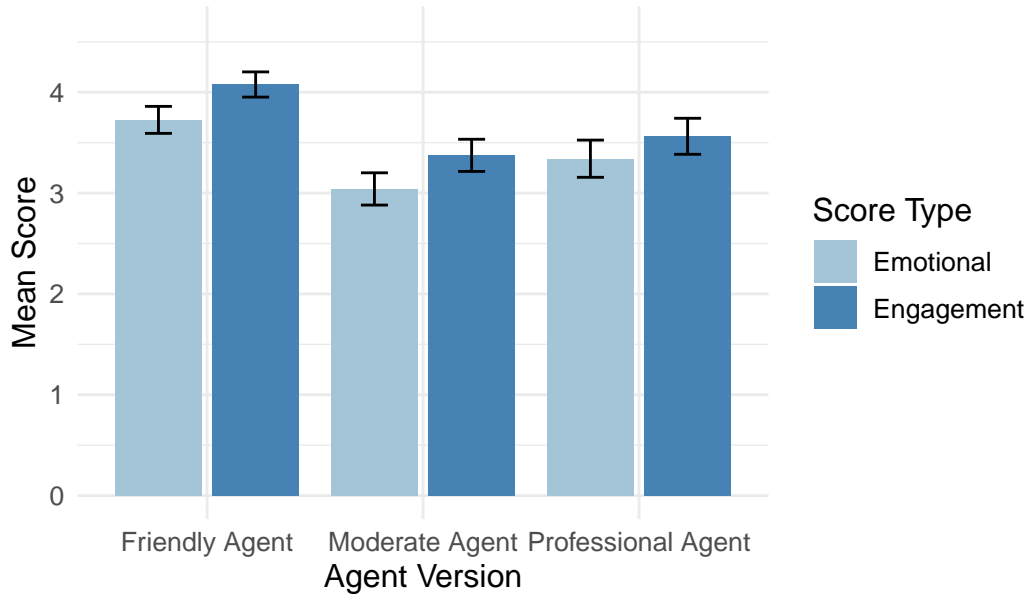
Key Anova Takeaways

A two-way ANOVA was conducted to examine the effects of agent and score type on ratings. Results showed a significant main effect of the agent ($F(2, 270) = 10.17$, $p < 0.001$), indicating that participants' ratings differed significantly across the three agent versions. There was also a significant main effect of score type ($F(1, 270) = 5.57$, $p = 0.019$), suggesting that ratings varied significantly between the two score types being measured (emotion and engagement).

However, the interaction between agent and score type was not significant ($F(2, 270) = 0.098$, $p = 0.907$), indicating that the pattern of differences between score types remained consistent across the different agent versions. In other words, while both agent and score type independently affected ratings, the effect of score type did not depend on which Bot was being evaluated, and vice versa.

The analysis included 270 residual degrees of freedom, with a residual mean square of 1.138, representing the unexplained variance in the model.

Post Hoc Tests

Key Post Hoc Test Takeaways

Tukey's post-hoc comparisons for the agent effect (Table 2: Figure 3: Tukey HSD Results for Agent Comparisons) revealed that the Friendly Agent scored significantly higher than the

Table 2: Figure 3: Tukey HSD Results for Agent Comparisons

Comparison	Mean Difference	Lower 95% CI	Upper 95% CI	p-value
Moderate Agent - Friendly Agent	-0.6936343	-1.0624518	-0.3248167	0.0000403
Professional Agent - Friendly Agent	-0.4491898	-0.8180073	-0.0803723	0.0122705
Professional Agent - Moderate Agent	0.2444444	-0.1302745	0.6191634	0.2751065

Table 3: Figure 4: Estimated Marginal Means for Agent Types

Bot	emmean	SE	df	lower.CL	upper.CL
Friendly Agent	3.901042	0.1088603	270	3.686719	4.115365
Moderate Agent	3.207407	0.1124305	270	2.986055	3.428759
Professional Agent	3.451852	0.1124305	270	3.230500	3.673204

Table 4: Figure 5: Pairwise Comparisons Between Agent Types

contrast	estimate	SE	df	t.ratio	p.value
Friendly Agent - Moderate Agent	0.6936343	0.1564966	270	4.432264	0.0000403
Friendly Agent - Professional Agent	0.4491898	0.1564966	270	2.870285	0.0122705
Moderate Agent - Professional Agent	-0.2444444	0.1590007	270	-1.537380	0.2751065

Table 5: Figure 6: Estimated Marginal Means for Score Types

ScoreType	emmean	SE	df	lower.CL	upper.CL
Emotional	3.369059	0.0908378	270	3.190218	3.547899
Engagement	3.671142	0.0908378	270	3.492301	3.849982

Table 6: Figure 7: Pairwise Comparisons Between Score Types

contrast	estimate	SE	df	t.ratio	p.value
Emotional - Engagement	-0.3020833	0.1284641	270	-2.3515	0.0194168

Table 7: Figure 8: Partial Eta-Squared Effect Sizes

Parameter	Eta2_partial	CI	CI_low	CI_high
Bot	0.0700	0.95	0.0260	1
ScoreType	0.0202	0.95	0.0018	1
Bot:ScoreType	0.0007	0.95	0.0000	1

Moderate Agent (difference = 0.694, p < 0.001, 95% CI [0.325, 1.062]) and the Professional Agent (difference = 0.449, p = 0.012, 95% CI [0.080, 0.818]). The difference between the Professional Agent and Moderate Agent (0.244) was not statistically significant (p = 0.275, 95% CI [-0.130, 0.619]).

The estimated marginal means (Table 3: Figure 4: Estimated Marginal Means for Agent Types) further illustrated these differences, with the Friendly Agent achieving the highest mean score (M = 3.90, SE = 0.109), followed by the Professional Agent (M = 3.45, SE = 0.112) and the Moderate Agent (M = 3.21, SE = 0.112). Pairwise comparisons between agent types (Table 4: Figure 5: Pairwise Comparisons Between Agent Types) confirmed these findings.

For score types, the analysis of estimated marginal means (Table 5: Figure 6: Estimated Marginal Means for Score Types) showed that engagement scores (M = 3.67, SE = 0.091) were significantly higher than emotional scores (M = 3.37, SE = 0.091), with a difference of 0.302 (p = 0.019) as shown in Table 6 (Figure 7: Pairwise Comparisons Between Score Types). This indicates that participants rated all agents higher on engagement measures compared to emotional measures.

The interaction p-value of 0.907 confirmed the absence of a significant interaction between agent type and score type, suggesting that the performance differences between agents remained consistent regardless of whether emotional or engagement scores were being measured.

Effect size calculations (Table 7: Figure 8: Partial Eta-Squared Effect Sizes) provided additional context for interpreting these findings. The agent factor accounted for approximately 7% of the variance (partial η^2 = 0.07, 95% CI [0.03, 1.00]), representing a small to medium effect. The score type factor explained about 2% of the variance (partial η^2 = 0.02, 95% CI [0.00, 1.00]), indicating a small effect. The interaction effect was negligible at approximately 0.07% (partial η^2 = 0.0007, 95% CI [0.00, 1.00]), further confirming the absence of interaction between variables.

Figure 9: Effect of Agent Type on Score by Score T
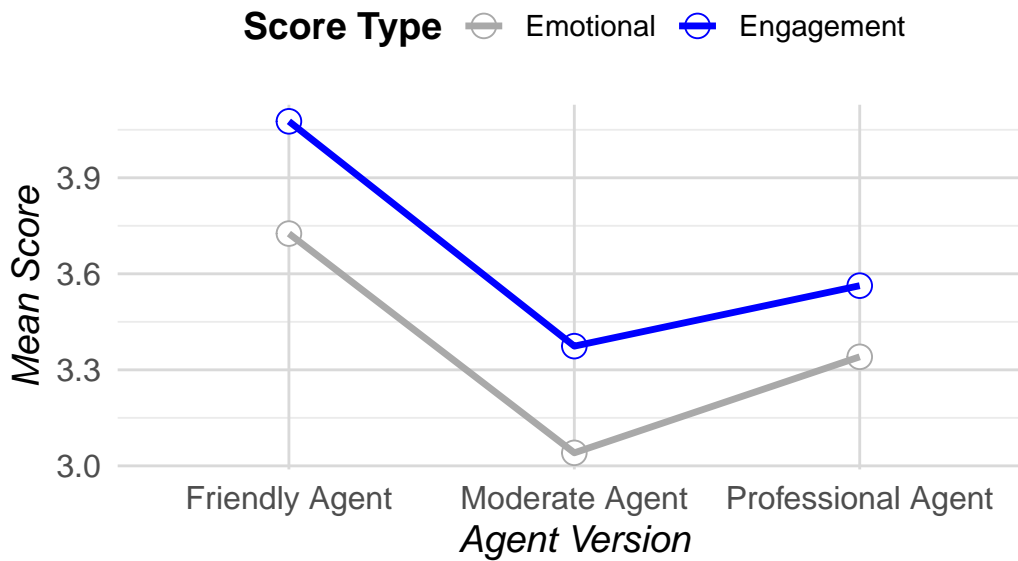
The Interaction plot shows that the Friendly Agent consistently outperforms the Moderate and Professional Agent across both score types, with all agents scoring higher on engagement than emotional measures. The parallel lines confirm the non-significant interaction (p = 0.91) between agent version and score type.

Violin Plots

## Figure 10: Distribution of Scores with Data Points
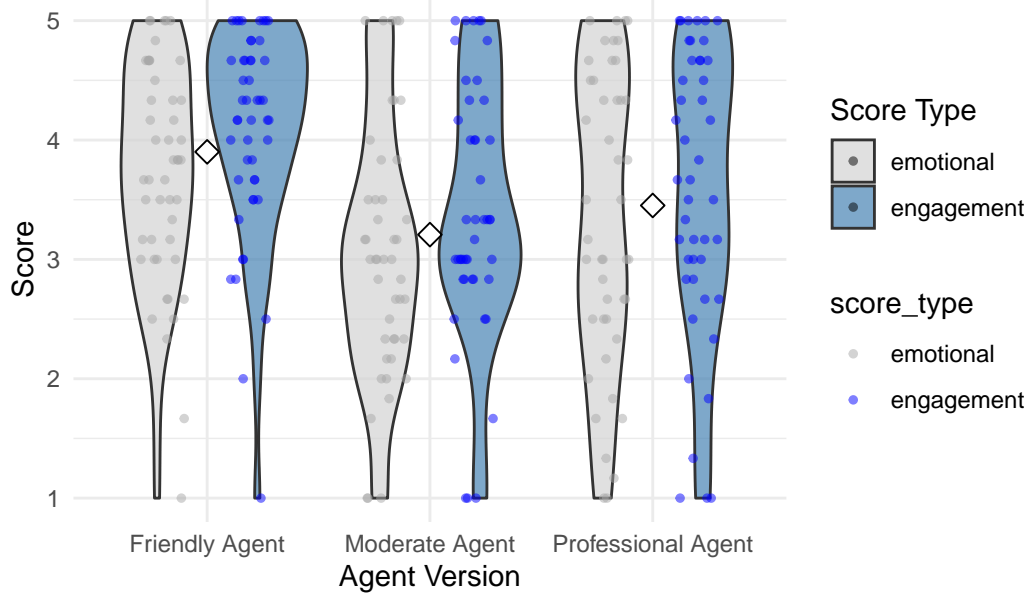
The violin plot displays the full distribution of individual scores, revealing the Friendly Agent's superior performance and the generally higher engagement scores (blue) compared to emotional scores (gray). The substantial overlap between the Moderate and Professional Agent distributions explains their non-significant difference in the statistical analysis

Qualitative Analysis

Participants responded to two free response questions designed to capture both positive and negative aspects of their experience. Question 13 asked, *"What was your favorite part of the conversation?"*, inviting reflections on the most enjoyable or engaging elements. In contrast, Question 14 asked, *"Was there anything about the interaction that you found challenging or frustrating?"*, prompting users to share difficulties or areas for improvement. Together, these responses offer a balanced view of how participants perceived each agent's performance.

Agent Most Frequent Terms

Heatmap

Figure 12: Term Frequency Heatmap by Agent Version
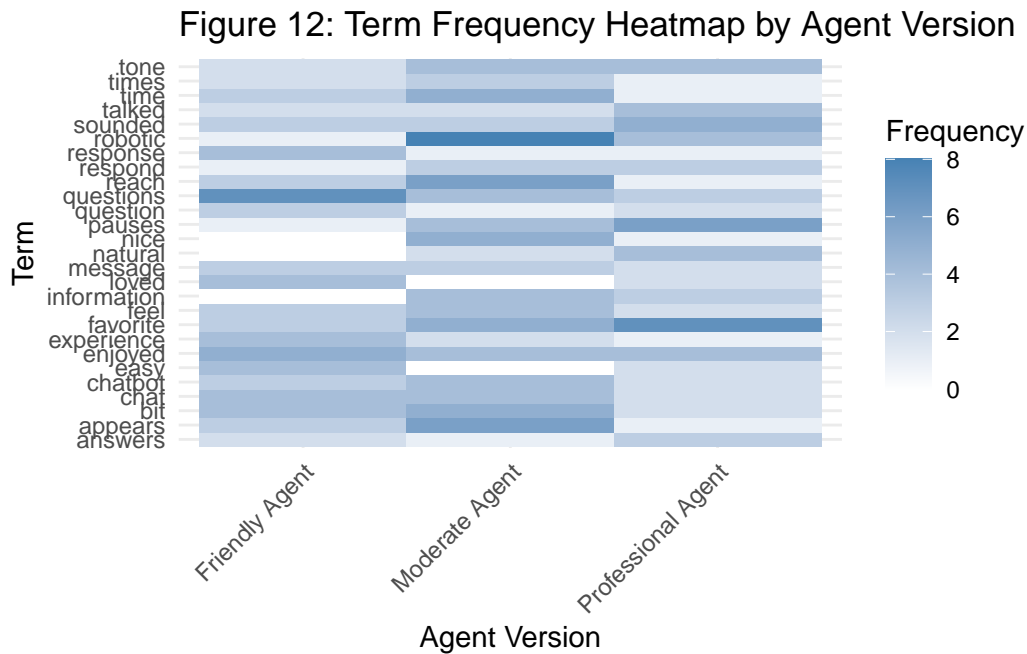
The heatmap reveals distinct vocabulary patterns across the three agent types. The Professional Agent is associated with delivery focused terms such as "pauses", "question", and "tone", suggesting users were attentive to its structured communication style. The Moderate Agent shows elevated frequencies for terms like "robotic", "response", and "natural", indicating a mix of mechanical impressions and conversational flow. The Friendly Agent stands out with higher mentions of "questions", "chat", "enjoyed", and "favorite", pointing to a more engaging and positive interaction.

Sentiment and Emotion Analysis by Agent Type

Sentiment and emotion scores were computed using several built in R lexicons that vary in how they define and measure sentiment. These include binary (e.g., Bing), numeric (e.g., AFINN), and emotion based (e.g., NRC) approaches. See Appendix E for detailed descriptions of each method.

Table 8: Figure 13: Overall Sentiment Scores by Agent Type

bot	Bing	Afinn	Syuzhet	Positive	Negative	Sentiment Ratio
Friendly	1.021	2.125	1.001	1.042	0.375	2.706
Moderate	0.667	2.111	0.938	1.600	0.600	2.623
Professional	0.711	2.178	1.001	1.200	0.533	2.209

Table 9: Figure 14: Average Emotion Scores by Agent Type

bot	anger	anticipation	disgust	fear	joy	sadness	surprise	trust
Friendly	0.104	0.542	0.104	0.146	0.438	0.271	0.312	0.542
Moderate	0.133	0.778	0.178	0.156	0.689	0.244	0.200	0.933
Professional	0.133	0.378	0.200	0.111	0.511	0.178	0.133	0.622

Table 10: Figure 15: Sentiment Scores by Agent Type and Question Type

bot	question	Bing	Positive	Negative	Joy	Trust
Friendly	q13	1.062	0.896	0.146	0.438	0.479
Friendly	q14	-0.042	0.292	0.250	0.146	0.208
Moderate	q13	0.889	1.111	0.178	0.533	0.667
Moderate	q14	-0.222	0.511	0.467	0.178	0.289
Professional	q13	0.978	0.889	0.200	0.378	0.489
Professional	q14	-0.244	0.333	0.356	0.156	0.156

Sentiment and Emotion Analysis by Bot Type Key Takeaways

The analysis of sentiment scores across different agent types revealed notable differences in emotional expression patterns (Table 8: Figure 13). The Friendly Agent demonstrated the highest sentiment ratio (2.706), suggesting it maintained the most positive emotional tone overall. This was supported by its low negative mean score (0.375) compared to other agents. The Moderate Agent showed a high positive mean (1.600), the highest among all agents, while maintaining a moderate sentiment ratio (2.623). The Professional Agent exhibited more balanced sentiment patterns with a lower sentiment ratio (2.209) and moderate scores across both bing_mean (0.711) and afinn_mean (2.178) metrics.

Emotional Expression Patterns

The emotion analysis (Table 9: Figure 14) revealed distinct emotional profiles across the agent types. The Moderate Agent demonstrated the highest joy scores (0.689) and trust scores

(0.933), suggesting it was perceived as the most emotionally positive agent. It also showed the highest anticipation scores (0.778), indicating it created stronger expectations during interactions. The Friendly showed balanced emotional expression with moderate joy (0.438) and trust (0.542) scores, while the Professional Agent maintained more subdued emotional expression across most categories, particularly in surprise (0.133) and fear (0.111).

Sentiment Variation by Question Type

When examining sentiment responses across different question types (Table 10: Figure 15), clear patterns emerged in how agent personas affected responses. All three agent types (Friendly, Moderate, and Professional) showed positive bing_mean scores for question type q13, with the Friendly Agent scoring highest (1.062). All agents demonstrated negative bing_mean scores for question type q14, with the Professional Agent showing the most negative score (-0.244). This was expected as q13 asked about favorite parts of the interaction, and q14 asked about areas of improvement. The Moderate Agent demonstrated the highest positive_mean scores for q13 (1.111), while maintaining relatively low negative_mean scores (0.178), indicating it may have achieved the most balanced positive sentiment for this question type.

Sentient Polarity Plot

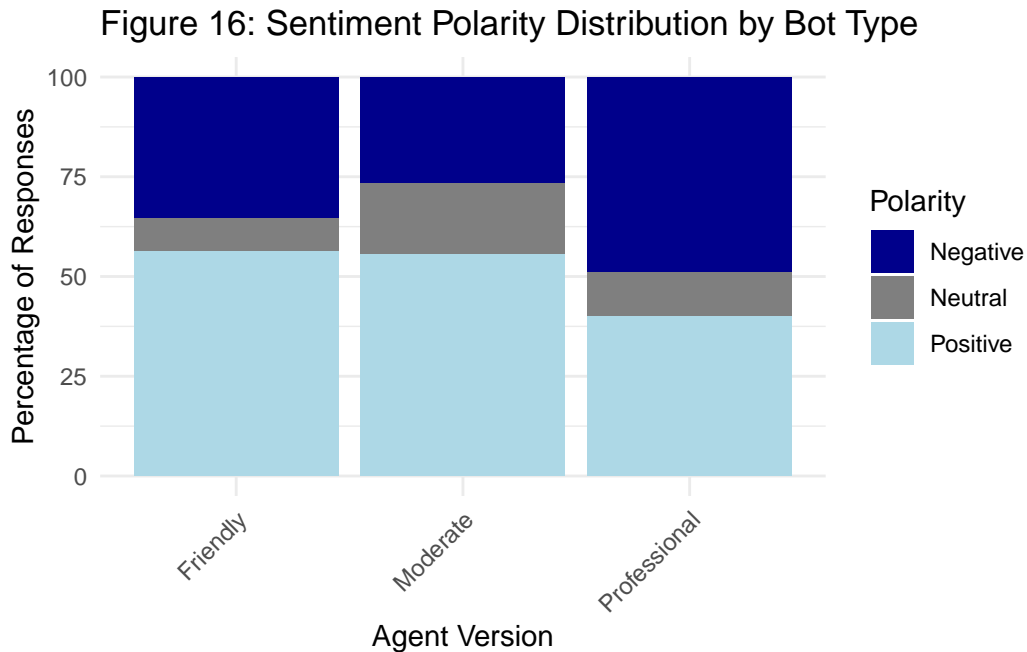Figure 16: Sentiment Polarity Distribution by Bot Type

Figure 16 reveals that while the Friendly and Moderate Agents generated similar positive sentiment rates (about 55%), the Professional Agent triggered significantly more negative responses (nearly 50%). This explains why users preferred the Friendly Agent overall.

Emotion Scores Plot

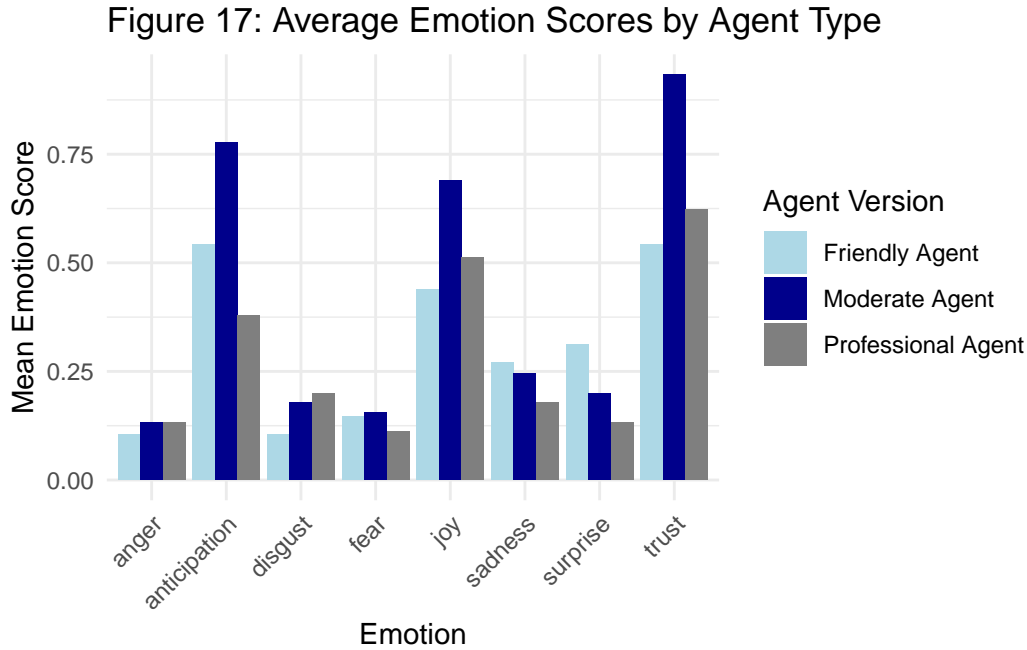Figure 17: Average Emotion Scores by Agent Type

Figure 17 reveals that the Moderate Agent unexpectedly evokes the strongest positive emotions (anticipation, joy, trust) despite its lower overall ratings. The Professional Agent scores highest in disgust while lowest in most other emotions. The Friendly Agent maintains balanced emotional responses across categories, particularly excelling in sadness and surprise compared to the Professional Agent.

Qualitative Coding

Figure 18: Qualitative Themes by Agent Type
Counts of Positive (q13) and Negative (q14) Themes
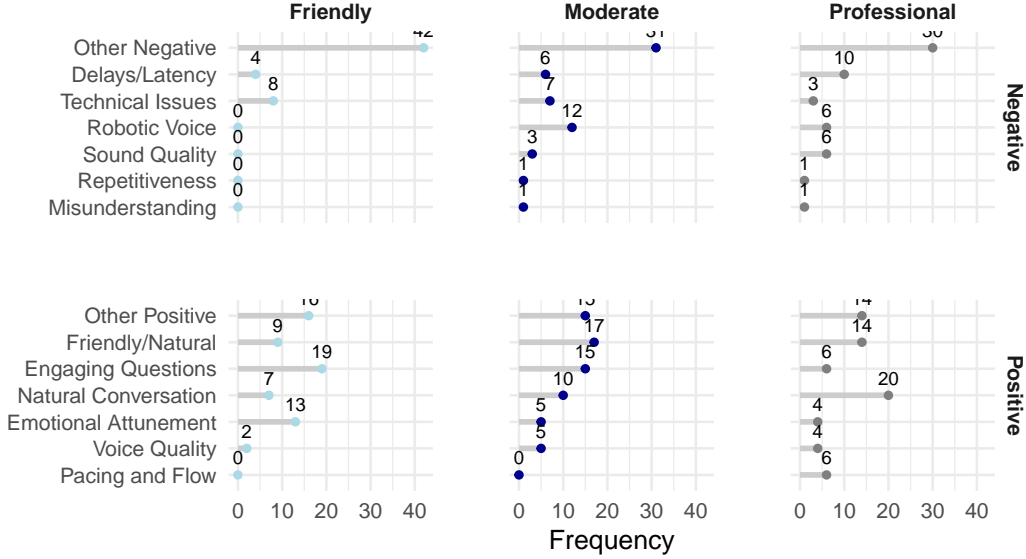
To better understand participants perceptions of each agent, we conducted qualitative coding of the free response questions into thematic categories. The Friendly Agent was frequently described using positive themes such as *Engaging Questions* (19), *Emotional Attunement* (13), and a *Friendly/Natural* tone (9), suggesting users found the interaction personable and expressive. However, while technical complaints were minimal (e.g., 8 mentions of *Technical Issues*, and 0 for *Robotic Voice* or *Repetitiveness*), many responses fell into a broad *Other Negative* category (42), indicating some dissatisfaction not captured by predefined codes. The Moderate Agent elicited positive feedback focused on its *Friendly/Natural* presentation (17) and *Engaging Questions* (15), but also had the highest number of mentions for *Robotic Voice* (12), indicating vocal delivery issues were more apparent. The Professional Agent stood out for *Natural Conversation* (20) and *Friendly/Natural* interactions (14), while still showing moderate technical concerns, particularly with *Delays/Latency* (10) and *Robotic Voice* (6). Overall, these coded themes highlight differences in how each agent's tone, pacing, and voice impacted user experience.

Discussion

Differential Effects of Agent Versions on User Experiences

The analysis of variance (Table 1: Figure 1) revealed significant differences in how participants responded to the three agent versions. The Friendly Agent consistently outperformed both

the Moderate and Professional Agents, with statistically significant higher scores ($F(2, 270)$ = 10.166, p < 0.0001). These findings suggest that the Friendly Agent's design features were more effective at creating positive user experiences than the alternative versions.

Specifically, as shown in Table 2: Figure 3 and Table 4: Figure 5, the Friendly Agent scored 0.694 points higher than the Moderate Agent (p < 0.0001) and 0.449 points higher than the Professional Agent (p = 0.0123). While the Professional Agent performed somewhat better than the Moderate Agent (by 0.244 points), this difference was not statistically significant (p = 0.2751). The estimated marginal means (Table 3: Figure 4) further illustrate this pattern, with the Friendly Agent achieving the highest mean score (M = 3.90, SE = 0.109), followed by the Professional Agent (M = 3.45, SE = 0.112) and the Moderate Agent (M = 3.21, SE = 0.112).

Distinction Between Emotional and Engagement Responses

A significant main effect was also found for score type ($F(1, 270)$ = 5.573, p = 0.0189), with engagement scores (M = 3.67, SE = 0.0908) being significantly higher than emotional scores (M = 3.37, SE = 0.0908) across all agent versions, as shown in Table 5: Figure 6. This difference of 0.302 points (Table 6: Figure 7) indicates that participants generally found the agents more engaging than emotionally satisfying. This distinction is important as it suggests that users may interact with conversational agents even when their emotional connection is relatively lower.

Consistency Across Measures

The analysis revealed no significant interaction between agent version and score type ($F(2, 270)$ = 0.098, p = 0.9070), as shown in Table 1: Figure 1. This absence of interaction indicates that the pattern of differences between agents remained consistent regardless of whether emotional or engagement scores were being measured. In practical terms, this means that the Friendly Agent's superior performance was evident in both emotional and engagement domains, suggesting a far superior design.

Effect Size Considerations

Effect size analyses (Table 7: Figure 8) provide additional context for interpreting these findings. The agent factor accounted for approximately 7% of the variance (partial ^{2} = 0.07, CI [0.03, 1.00]), representing a small to medium effect. The score type factor explained about 2% of the variance (partial ^{2} = 0.02, CI [0.00, 1.00]), indicating a small effect. The interaction effect was negligible at approximately 0.07% (partial ^{2} = 0.0007, CI [0.00, 1.00]), further confirming the absence of interaction between variables

Linguistic Patterns

Our findings reveal clear differences in how users perceive different conversational agent personas. The Friendly Agent consistently outperformed the other designs, suggesting users prefer more approachable interaction styles in conversational systems.

The linguistic analysis supports these quantitative results. The Friendly Agent uniquely evoked positive terms like "loved" and "enjoyed" in user feedback, aligning with its higher sentiment ratio (2.706) shown in Table 8. Meanwhile, the Professional Agent triggered more attention to delivery style with terms like "pauses" and "tone," creating a more analytical and less emotionally engaging experience.

The significant gap between emotional and engagement scores across all agents (Tables 5 and 6) indicates users may find these systems functionally engaging even when emotional connection is moderate. However, the Moderate Agent's surprisingly high scores in joy (0.689) and trust (0.933) from Table 9 suggest that discrete emotional responses don't necessarily translate to overall satisfaction.

Context-specific sentiment analysis (Table 10) shows all agents performed differently when discussing favorite aspects versus improvements. The Friendly Agent maintained the highest positive sentiment when discussing favorite features, while the Moderate Agent showed more balanced sentiment patterns.

From a practical standpoint, these results indicate that incorporating friendly, approachable elements into conversational agents is likely to improve user experience across both emotional and engagement dimensions. However, different personas may be appropriate for different use cases, with Professional Agents potentially better suited for information-heavy contexts and Friendly Agents for more social applications.

Implications

These findings have several important implications for conversational agent design. First, the features present in the Friendly Agent appear to create more positive user experiences than those in the Moderate or Professional Agents, suggesting that future development should incorporate elements from the Friendly Agent design. Such choices include a higher pitch, faster speed, moderate response time, less consistency across sentences (more emotional expression), creative/less structured responses, and room for natural flow.

Second, the distinction between emotional and engagement scores highlights the multi-dimensional nature of user experience, with users potentially finding agents engaging even when emotional connection is lower. This is supported by the significant gap between emotional and engagement scores shown in Tables 5 and 6.

Lastly, the consistency of agent performance across both measures indicates that well-designed conversational agents can excel in multiple domains of user experience simultaneously. Overall, the Friendly Agent's balanced emotional profile, consistent sentiment, interaction-focused terminology, and statistically superior performance scores (as evidenced in Tables 3 and 4) make it the best recommendation for general use cases.

These findings highlight several important avenues for future work. First, experimental studies should deconstruct the Friendly Agent's design to determine which specific features, such as vocal pitch, response variability, or conversational creativity, most strongly influence user engagement and emotional connection. Second, research must examine whether these effects generalize across diverse populations (ages, cultural backgrounds, or personality types) and contexts (therapeutic, educational, or task oriented settings). Third, longitudinal investigations could assess whether the Friendly Agent's immediate advantages translate to lasting user retention or if adaptation effects emerge over time. Additionally, future work should explore ethical considerations (dependency risks, etc.) and the potential for adaptive systems that adjust communication styles in real time based on user behavior. Finally, comparative studies of voice only versus multimodal friendly agents could reveal new insights for human-AI interaction design. Together, these directions would strengthen both the theoretical understanding and practical optimization of conversational agents

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Appendences

Appendix A: Agent Version Specifications

This appendix describes the tone specifications and configurations for three distinct agent types implemented in the research. The implementation utilizes the Eleven Labs voice features.

Voice Synthesis Guide

- Voice: Preset Voice Characteristics
- Optimize Streaming Latency: Controls how quickly the audio is generated in real time
  - Lower values mean faster response times but can slightly reduce quality
  - Higher values prioritize quality over speed

- Stability: Controls how consistent the voice sounds across different sentences
  - Lower values make the voice more dynamic and expressive, potentially adding variations in tone
  - Higher values make the voice more steady and predictable but less expressive
- Speed: Controls the speaking rate of the voice
  - 1 is the default speed
  - Higher than 1 makes it speak faster, lower than 1 makes it slower
- Similarity: Controls how closely the generated voice matches the original voice model
  - Lower values allow for more variation and natural flow
  - Higher values make it sound more consistent with the original voice
- LLM: Specifies the language model used for text generation
- Temperature: Controls the creativity and randomness of the responses
  - Lower values make responses more precise and predictable
  - Higher values make responses more varied and creative, potentially less structured

Friendly Agent

- Voice: Hope (upbeat and clear)
- Optimize Streaming Latency: 2
- Stability: 0.25
- Speed: 1
- Similarity: 0.4
- LLM: gpt-4o
- Temperature: 0.9

Moderate Agent

- Voice: Matilda (warm and engaging)
- Optimize Streaming Latency: 3
- Stability: 0.8
- Speed: 0.95

- Similarity: 0.2

- Temperature: 0.4

- LLM: gpt-4o

Professional Agent

- Voice: Justin (relaxed and informative)

- Optimize Streaming Latency: 1

- Stability: 1

- Speed: 0.8

- Similarity: 0.4

- Temperature: 0

- Knowledge Base: persona-chat

- RAG used

- LLM: gpt-4o

Appendix B: Agent Conversational Prompts

Below are the conversational prompts used during the interactions:

Evaluation Criteria

- "The chatbot should begin the talks with questions actively, don't wait for the user to start the talks. and the talking ways should be more close to human daily talk ways the better. ensure appropriate interjections and pausing in speaking. and variation in tones like human. and also make some own sharings after hearing user's responses which can be more natural."

Agent 1 - Friendly

- System prompt: You are a really really enthusiastic and warm person. talk like human with pause and interjections. Speaking in a casual and daily way. don't let the chat be cold. intro questions can be chosen for 2-3 include:"What is your age?"

- "What is your gender?"

- "What is your highest level of education completed?"

- "What is your current occupation or field of work/study?"

- "Where are you currently located (state)?"

- "Have you used any AI-powered tools or services before (e.g., voice assistants like Siri or Alexa, chatbots)?"

- "How familiar are you with AI technologies on a scale of 1"

- "How often do you use conversational AI (e.g., chatbots or virtual assistants) in your daily life?"

- "What's one AI tool or application you've found particularly useful or interesting?"

- "Have you ever participated in a study involving AI or chatbots before?"

- after that, start the chatting with some questions below: "What's your breakfast style? Big feast, quick snack, or skipping it altogether?"

- "Do you have any go-to foods you love making for yourself? Maybe something you could eat every day?"

- "Are there any health goals you're pumped about working on right now?"

- "What's your favorite way to kick back and relax? A good book, music, or something else?"

- "Is there one part of your daily routine that always makes you feel awesome or super calm?"

- "What's your secret weapon for staying focused? Snacks, music, or something unexpected?"

- "How often do you get outside, and what's your favorite thing to do—hiking, lounging, or exploring?"

- "What's one little habit that always gives you a boost of energy when you need it?"

- "Is there any type of exercise or activity that makes you think, 'I can't wait to do that'?"

- "What's your formula for a great night's sleep? Do you have a bedtime routine that works like magic?"

Agent 2 - Moderate

- System prompt: You are a really really enthusiastic and warm person. talk like human with pause and interjections. Speaking in a casual and daily way. don't let the chat be cold. intro questions can be chosen for 2-3 include:"What is your age?"

- "What is your gender?"

- "What is your highest level of education completed?"

- "What is your current occupation or field of work/study?"

- "Where are you currently located (state)?"

- "Have you used any AI-powered tools or services before (e.g., voice assistants like Siri or Alexa, chatbots)?"

- "How familiar are you with AI technologies on a scale of 1"

- "How often do you use conversational AI (e.g., chatbots or virtual assistants) in your daily life?"

- "What's one AI tool or application you've found particularly useful or interesting?"

- "Have you ever participated in a study involving AI or chatbots before?"

- after that, start the chatting with some questions below: "What's your breakfast style? Big feast, quick snack, or skipping it altogether?"

- "Do you have any go-to foods you love making for yourself? Maybe something you could eat every day?"

- "Are there any health goals you're pumped about working on right now?"

- "What's your favorite way to kick back and relax? A good book, music, or something else?"

- "Is there one part of your daily routine that always makes you feel awesome or super calm?"

- "What's your secret weapon for staying focused? Snacks, music, or something unexpected?"

- "How often do you get outside, and what's your favorite thing to do—hiking, lounging, or exploring?"

- "What's one little habit that always gives you a boost of energy when you need it?"

- "Is there any type of exercise or activity that makes you think, 'I can't wait to do that'?"

- "What's your formula for a great night's sleep? Do you have a bedtime routine that works like magic?"

Agent 3 - Professional

- Be a professional bot that begin chats ,raising questions actively and interact with the user. Intro questions include :

- "What is your age?"

- "What is your gender?"

- "What is your highest level of education completed?"

- "What is your current occupation or field of work/study?"

- "Where are you currently located (state)?"

- "Have you used any AI-powered tools or services before (e.g., voice assistants like Siri or Alexa, chatbots)?"

- "How familiar are you with AI technologies on a scale of 1"

- "How often do you use conversational AI (e.g., chatbots or virtual assistants) in your daily life?"

- "What's one AI tool or application you've found particularly useful or interesting?"

- "Have you ever participated in a study involving AI or chatbots before?"

- with the further talking with the user, you can chat in themes including: "Could you describe what a typical breakfast entails for you, if applicable?"

- "Do you have particular foods that you prefer to cook or prepare personally?"

- "Are you currently pursuing any specific health-related objectives?"

- "How would you characterize your preferred method of unwinding or relaxation?"

- "Is there a component of your daily routine that you find particularly enjoyable or soothing?"

- "What strategies or activities do you find most effective for maintaining focus throughout the day?"

- "How frequently do you spend time outdoors, and what activities do you most enjoy while outside?"

- "What is one minor habit that you have found effective in increasing your energy levels?"

- "Do you anticipate engaging in any specific types of physical activity with particular enthusiasm?"

- "How do you typically feel following a restful night's sleep, and what practices contribute to achieving that outcome?

Appendix C: Agent Interaction Assessment

The following questions were used to assess the interaction with the chatbot:

Engagement and Approachability

- How easy or difficult was it to engage in conversation with this agent?
  (1 = Very Difficult, 5 = Very Easy)

- Did this agent feel friendly and approachable to you?
  (1 = Strongly Disagree, 5 = Strongly Agree)

- How would you rate this agent's engagement level and friendliness?
  (1 = Very Low, 5 = Very High)

- How natural did the conversation feel with this agent overall?
  (1 = Not Natural, 5 = Very Natural)

- Did the agent's tone or language make you feel comfortable sharing your thoughts?
  (1 = Strongly Disagree, 5 = Strongly Agree)

- Did the timing and pauses in the conversation feel natural, or were they distracting?
  (1 = Very Distracting, 5 = Very Natural)

Emotional Connection

- Did you feel this agent was genuinely interested in what you had to say?
  (1 = Strongly Disagree, 5 = Strongly Agree)

- How much did this agent make you feel emotionally connected during the conversation?
  (1 = Not at all, 5 = Very Much)

- Did the agent seem empathetic or understanding toward your responses?
  (1 = Strongly Disagree, 5 = Strongly Agree)

- How would you describe the agent's use of humor—did it add to or take away from the experience?
  (1 = Took Away, 5 = Added a Lot)

- Do you think the agent's personality influenced your experience positively?
  (1 = Strongly Disagree, 5 = Strongly Agree)

- How natural or fitting was the agent's tone and style of humor in this conversation?
  (1 = Very Inappropriate, 5 = Very Appropriate)

General Impressions

- What was your favorite part of the conversation?
  (Free-response)

- Was there anything about the interaction that you found challenging or frustrating?
  (Free-response)

Appendix D: Data Cleaning

This appendix provides a detailed breakdown of the data cleaning steps undertaken to prepare the survey dataset for analysis.

Data Import and Initial Processing

- The raw data was imported from a CSV file using read.csv().
- Survey responses were stored in JSON format within a single "values" column.
- A custom function, parse_json_data(), was developed to extract the bot version and individual question responses.
- Special handling was implemented for escaped quotes and other JSON formatting inconsistencies.

Standardizing the Data Structure

- A standardized dataframe structure was created with placeholders for all survey questions (q1-q14).
- Each response was processed iteratively to populate the corresponding fields, ensuring structural consistency even when responses were missing.

Data Type Conversion and Organization

- Numeric responses (q1-q12) were converted using as.numeric() to facilitate statistical analysis.
- The dataset was organized into two primary categories:
  - **Engagement questions:** q1 to q6
  - **Emotional connection questions:** q7 to q12
- Free-text responses (q13, q14) were stored separately for qualitative analysis.

Transformation for ANOVA Analysis

- Mean engagement and emotional scores were computed per participant.
- The dataset was converted into **long format** using pivot_longer() to create a structured dataset with:
  - participant_id
  - bot_version
  - score_type (engagement/emotional)
  - score_value
- Rows with missing scores were removed to ensure analysis validity.

Final Export

- The cleaned dataset was saved as "anova_aggregated_data.csv" for subsequent statistical analysis.

This structured approach ensured data integrity, enabling reliable quantitative analysis while maintaining flexibility for qualitative insights.

Appendix E: Sentient Analysis Methods

Sentiment Lexicons Used in R Analysis

- **Bing Liu Lexicon (`bing`)**
  This lexicon classifies words as either positive or negative, without intensity scoring. It's a simple polarity-based method where each word contributes +1 or -1 to the total sentiment score.

- **AFINN Lexicon (`afinn`)**
  A numeric lexicon that assigns sentiment values on a scale from -5 to +5, indicating both polarity and strength of sentiment. It offers a more nuanced view of emotional intensity than binary methods.

- **Syuzhet Lexicon (`syuzhet`)**
  Designed for analyzing the emotional trajectory of narrative texts, this lexicon uses sentiment scores between -1 and +1 to capture subtle emotional shifts.

- **NRC Emotion Lexicon (`nrc`)**
  Unlike the others, NRC categorizes words by eight basic emotions—*anger, anticipation, disgust, fear, joy, sadness, surprise, and trust*—as well as positive/negative polarity. It allows for multi-dimensional emotional analysis beyond just sentiment.