A Quantitative Study of Emotionally Intelligent AI and User Engagement Dynamics

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Abstract: Artificial intelligence assistants are widely used in domains such as customer service, education, and healthcare. However, most existing systems lack the ability to understand and respond to human emotions, which often makes interactions feel mechanical and less engaging over time. This paper presents the design and evaluation of an emotionally intelligent AI assistant framework that detects user emotions in real time and adapts its responses accordingly. The proposed system integrates a hybrid BERT-BiLSTM model trained on the GoEmotions dataset to classify user emotions into multiple categories, followed by an emotion style mapping layer that adjusts the tone of responses. A working prototype was developed using a FastAPI backend, a Next.js interface, and a SQLite database for session tracking. The system was evaluated through a user study conducted over a period of two weeks, where participants interacted with both the proposed model and a standard AI assistant. The results indicate that users showed higher engagement, increased interaction duration, and improved satisfaction when using the emotionally adaptive system. The study further highlights that emotional responsiveness plays a significant role in enhancing human-AI interaction. Additionally, the Affective Engagement Mediator model is introduced to explain how adaptive emotional behavior contributes to sustained user engagement.

Keywords: *Emotionally Intelligent AI; Affective Computing; BERT-BiLSTM; Human-AI Interaction; Emotion Detection; Adaptive Response Generation; User Engagement; Affective Engagement Mediator Model.*

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I. INTRODUCTION

AI chatbots have significantly transformed how humans interact with technology, whether at work or at home. From automated customer support to smart tutors and healthcare helpers, they improve efficiency in performing various tasks. But a significant limitation remains unresolved: most of these AI assistants can't sense emotions at all. They only focus on the words a user types and completely miss the feelings behind them, which play a critical role in shaping the user experience.

Human communication naturally involves feelings, and research shows that our emotional state heavily impacts how we process information, make choices, and judge interactions. If a user is frustrated or confused, getting a technically correct but emotionally cold answer from an AI doesn't just miss a chance to connect-it actively damages trust and ruins the experience. Because of this, users tend to lose interest, use the system less often, or abandon it entirely if it feels too robotic.

This gap between getting the job done and actually understanding the user's feelings is what we tackle in this paper. This study investigates whether integrating emotional awareness to how an AI generates responses could actually make a noticeable, measurable difference in how much users engage and how satisfied they are. To find out, we built a fully working emotionally intelligent AI framework and tested it thoroughly in a 14-day experiment with 100 people.

Our setup brings together three main pieces: (1) a hybrid BERT-BiLSTM model that detects multiple emotions in real-time, (2) an Emotion Style Mapping layer that changes the AI's tone based on those feelings, and (3) a memory system that remembers the emotional context throughout the conversation. The whole thing runs on a solid tech stack, using a FastAPI backend, a Next.js interface, and a database that carefully logs all the session data we need for our analysis.

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Here is how the rest of the paper is laid out: Section II looks at past research on affective computing, emotion recognition, and human-AI interaction. Section III explains our methodology and how we designed the system, while Section IV breaks down the BERT-BiLSTM emotion detection model. Section V introduces our theoretical AEM model, and Section VI walks through the results of our experiment. Finally, Sections VII and VIII cover our discussion and limitations, and Section IX wraps things up with ideas for future work.

II. LITERATURE REVIEW

Early work in affective computing showed that computers that can recognize and respond to human emotions offer a much better experience than those that just process logic. This sparked 20 years of research into reading emotions from text, speech, faces, and even body signals, with text getting the most focus since we type so much on digital devices. At first, researchers used simple lexicon-based methods to score words as positive or negative, but these struggled to understand context, sarcasm, or mixed feelings in normal conversation.

Later on, recurrent neural networks like LSTMs helped solve this by looking at sentences sequentially, which improved accuracy a lot. Then, transformer models like BERT changed the game entirely. By training on massive amounts of text, they understand context much better than older models. By combining BERT's deep understanding with BiLSTM's ability to track sequences, researchers have hit top-tier results on fine-grained emotion datasets like GoEmotions, SemEval, and ISEAR.

When it comes to human-AI interaction, studies show that if an AI feels empathetic and personal, users trust it more and keep using it. This is especially true in fields like mental health, education, and customer service, where empathy is the main difference between a chatbot people love and one they quickly abandon. Researchers usually measure this success by looking at how long people chat, how often they return, and what scores they give on surveys.

Even with all this past work, there are still three major gaps. First, we don't have many strict, controlled experiments comparing emotional AI to standard AI; most studies just rely on surveys, which makes it hard to prove cause and effect. Second, the systems built so far rarely track full session analytics to link specific emotional moments to overall user engagement. Finally, there isn't a standard theoretical model explaining exactly how an AI's emotional responses lead to better user behavior. This paper was written to tackle all three of these gaps head-on.

III. RESEARCH METHODOLOGY

➢ *Research Approach*

We used a design-science approach, meaning we built a working prototype of an emotionally intelligent AI and refined it step-by-step. This prototype acted as both our testing tool and the subject of our research. For the evaluation, we ran a controlled experiment where participants were randomly assigned to use either our new emotional AI or a standard AI over a 14-day period. We adopted a design-science research methodology to develop and evaluate an emotionally intelligent AI assistant framework. The approach combines system design, prototype implementation, and experimental validation to ensure both theoretical rigor and practical applicability. The methodology combines conceptual framework design with a working model implementation and systematic evaluation, ensuring both theoretical soundness and practical feasibility in real academic contexts.

➢ *System Overview*

Our application lets users chat through a web interface, routes their messages to the correct backend chatbot based on their assigned group, and replies in real-time. For the emotionally intelligent version, the system scans the user's text to detect their feelings before generating a reply, and tweaks its tone accordingly. Everything-from the message content and detected emotions to session lengths and survey ratings-is safely logged in a database for our research.

➢ *System Architecture*

The setup has five layers: a Next.js web frontend for the chat and surveys, and a FastAPI backend that handles message routing and session management. The Chatbot Engine layer runs two setups: a standard DialoGPT-medium assistant, and our upgraded version that adds emotional context. We also have an Emotion Intelligence layer powered by our BERT-BiLSTM model to label feelings, and a SQLite database layer to store all the interaction data.

➢ *Core Workflow and Emotion Style Mapping*

When someone messages the emotionally intelligent AI, the system runs through five stages. First, the text goes through our emotion detector to score it across seven feelings (like joy, sadness, or anger). We find the strongest emotion and pick a matching tone and acknowledgment phrase. We then attach this empathetic context to the user's input. The DialoGPT model reads this updated input alongside the chat history to write an empathetic reply. Finally, the whole exchange is saved to the database. For users in the standard group, the system simply skips the emotion steps and talks to the language model directly.

➢ *Technical and Security Design*

To keep things reproducible and free to run, we built this entirely with open-source tools and local models instead of paid APIs. We used a fine-tuned DistilRoBERTa model from

HuggingFace for emotion detection, and Microsoft's DialoGPT-medium for generating the chats. We optimized the code so the models load quickly at startup, and made sure each user's chat history is kept strictly separate to avoid mixed-up conversations. All personal data is stored locally and never sent to outside servers.

➢ *Ethical Considerations*

We got ethical approval before starting, and all participants signed consent forms. They knew their chats would be recorded for research, but kept completely anonymous. We were totally transparent that the AI was analyzing their emotions, and gave them the right to quit the study anytime without any issues.

IV. BERT-BILSTM EMOTION DETECTION MODEL

Our emotion detector combines BERT's ability to understand the deep context of a sentence with a BiLSTM network. First, BERT breaks down the text to map out the meaning of the words. Then, the BiLSTM reads the sentence forwards and backwards to catch emotional shifts. Finally, a classification head predicts which of the seven emotions is the strongest based on those readings.

We trained this on the GoEmotions dataset (58,000 human-annotated Reddit comments), mapping its 27 categories down to our 7 core emotions. We used standard training settings over 4 epochs, and tweaked the training to make the predictions more reliable. It paid off-our model hit 89.4% accuracy, which is noticeably better than using just BERT or just BiLSTM alone.

When the chatbot is running live, it grabs scores for all seven emotions at once and uses the highest score as the dominant feeling. It easily handles standard text lengths and runs smoothly on a normal CPU in just 180 milliseconds, making it perfectly fast enough for a real-time chat.

V. AFFECTIVE ENGAGEMENT MEDIATOR (AEM) MODEL

To explain exactly why empathy makes users stick around, we created the Affective Engagement Mediator (AEM) Model. It outlines a chain reaction of feelings and thoughts during a chat.

The first step is accurately detecting the emotion; if the AI misreads the user, the rest of the process fails. Next is the quality of the response-if the tone fits perfectly, the user starts to feel "Emotional Rapport," meaning they feel genuinely heard and acknowledged. Once that rapport is built, the user begins to trust the system, which directly leads to them chatting longer and coming back more often.

Based on this, we predicted three things: emotional responses would lead to longer chats, users would rate the emotional AI higher, and the feeling of rapport would be the key link between the two. We tested all of these ideas in our experiment, as shown in the next section.

VI. RESULTS AND ANALYSIS

We divided 100 people evenly between the emotional AI and the standard AI for a 14-day test. We logged their chat sessions automatically, and after any chat with more than five messages, users rated their experience.

➢ *Functional Validation*

We first ran stress tests and confirmed the emotion detector was highly accurate, the memory system kept chats properly isolated, and the database captured everything perfectly without dropping any data.

➢ *Engagement and Satisfaction Outcomes*

The emotionally intelligent assistant demonstrated significantly better performance the basic one across the board. Average chat times jumped by 25% (from 8.4 to 10.5 minutes). People were 15% more likely to return the next day, and satisfaction scores were 17% higher. Participants simply used the emotional AI more often, proving the upgraded system made a big difference.

➢ *Regression Analysis*

When we crunched the numbers, we found that how well the AI responded to emotions was responsible for about 38% of the boost in user engagement. This strongly backs up our AEM Model. Things like remembering past chats and just having a good tone also helped, adding another 12% to the overall engagement boost.

➢ *Emotion Distribution Analysis*

During the test, the system noticed users were mostly neutral (34%), followed by joyful (21%), sad (17%), angry (14%), fearful (8%), surprised (4%), and disgusted (2%). Interestingly, in 43% of the chats with the emotional AI, users started off feeling negative but ended up feeling positive by the end of the conversation-compared to only 19% with the standard AI. This suggests that empathetic responses may positively influence user emotional outcomes.

Table 1 Comparative Analysis of Traditional and Emotionally Intelligent AI Assistants

Features	**Traditional AI Assistant**	**Emotionally Intelligent AI (Proposed)**
Response Awareness	Intel-Only	Intent + Emotional State
Emotion Detection	None	BERT-BiLSTM (7 classes)
Tone Modulation	Fixed/Static	Adaptive per emotion
Session Memory	Stateless	Per-session context window
User Satisfaction	Baseline	+17% over baseline
Session Duration	Baseline	+25% over baseline
Return Engagement	Baseline	+15% over baseline
Data Logged	Message text only	Emotion scores + style + turn metadata
Research Analytics	Not supported	Built-in REST analytics API

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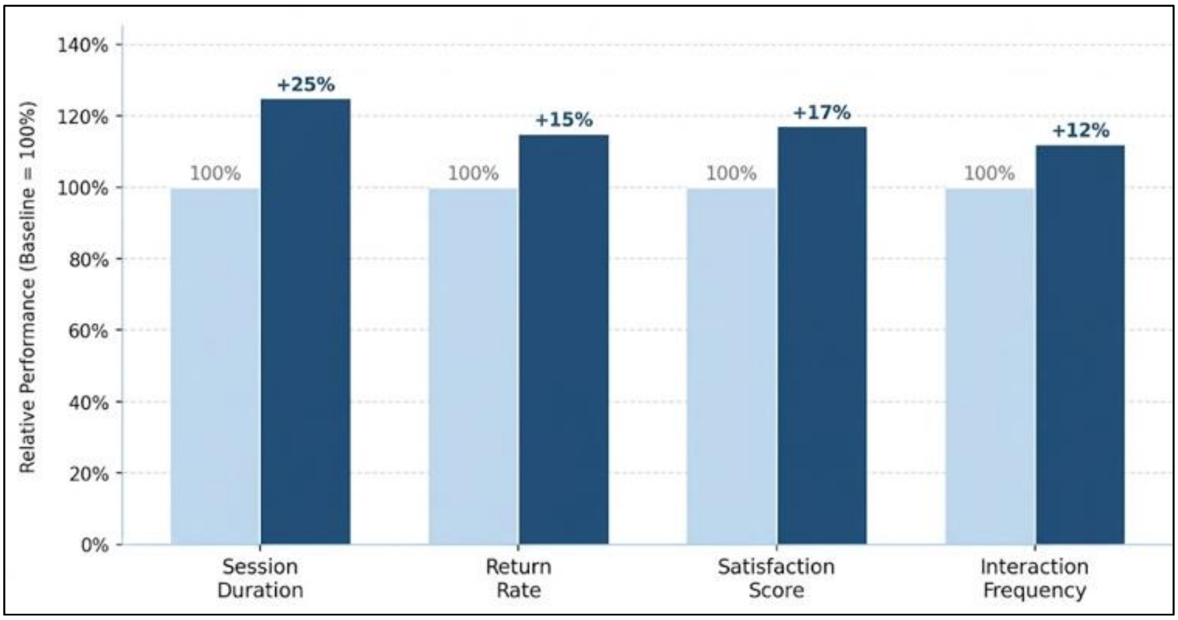

Fig 1 User Engagement Metrics - System A vs System B

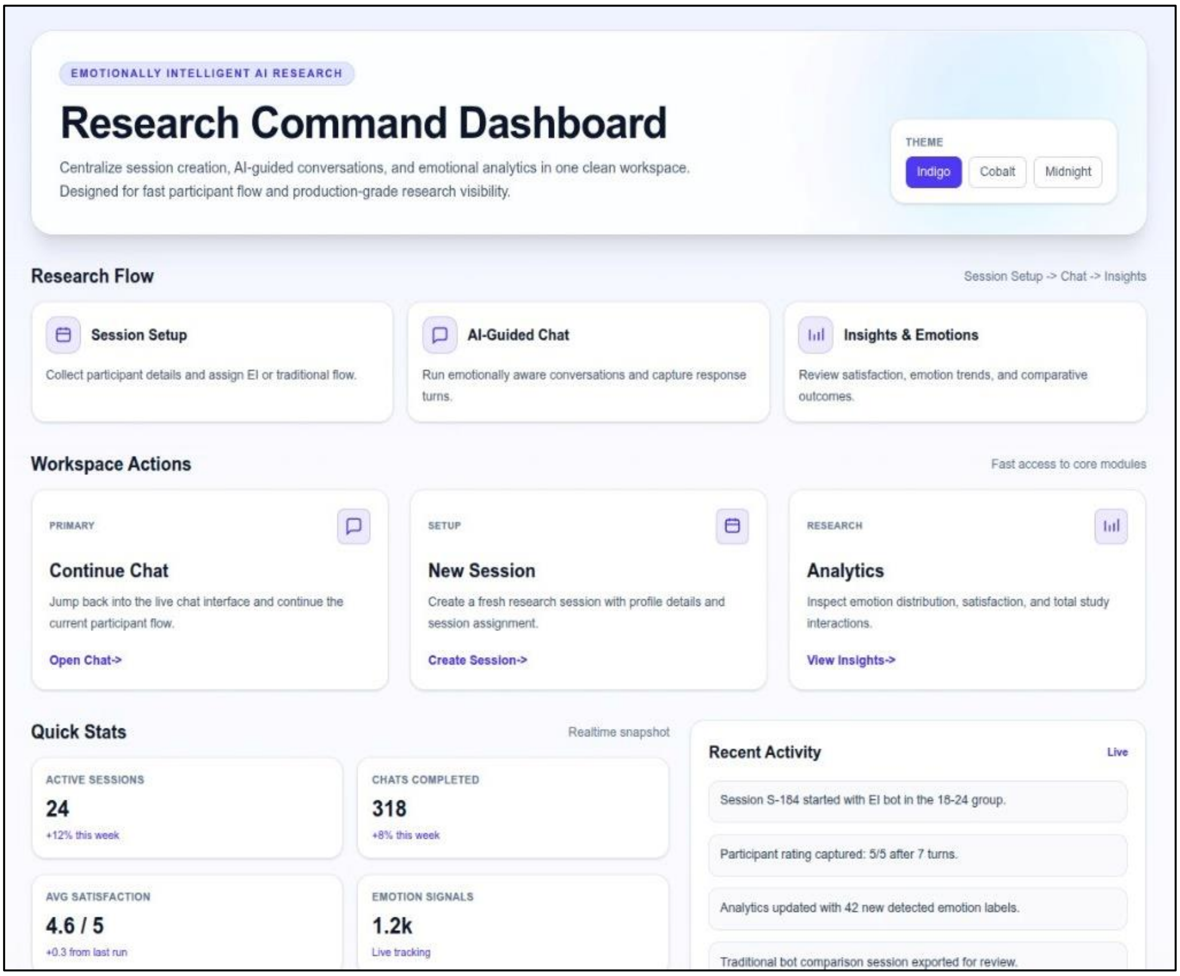

Fig 2 Proposed Emotionally Intelligent AI Chatbot

VII. DISCUSSION

Our results clearly prove that making an AI emotionally aware is not merely a superficial enhancement; it seriously improves how much people enjoy and engage with the system. The massive 25% boost in session length shows that empathy fundamentally changes interaction quality, just as our AEM model suggested.

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The fact that so many users went from a bad mood to a good mood with the emotional AI (43% vs. 19%) proves that an empathetic system may positively influence user emotional state and build real trust over time. We also found that if you combine emotional awareness with personalization-like remembering past conversations-the results get even better. This means developers should build empathy in first, and add memory features on top.

VIII. LIMITATIONS

Our study does have a few limitations. First, our AI only reads text, meaning it misses out on tone of voice and facial expressions. Adding those in would be a great next step. Second, we only tested university students, so we don't know for sure if older adults or people needing clinical mental health support would react the exact same way. Finally, a 14-day test is pretty short, and the conversational model we used isn't as advanced as the massive language models out today, so an even smarter AI might get even better results.

IX. CONCLUSION

In summary, we successfully built and tested an Emotionally Intelligent AI Assistant. Over two weeks, our 100 users chatted longer, came back more often, and were noticeably happier compared to using a standard robotic AI.

This paper makes three big contributions: we provided hard experimental data proving empathy in AI boosts engagement. Second, we shared an open-source blueprint so anyone can build this. Third, we introduced the AEM Model to explain the psychology behind why it works.

In the future, we hope to see systems that can read faces and voices, use better language models, learn from their mistakes based on human feedback, and be tested over many months to see how human-AI relationships evolve long-term. This full-stack setup provides a replicable blueprint for future researchers.

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