Eccia

An Affectively Aware Chatbot for Accessible Social Support

Chris Roddy

Stevens Institute of Technology, chrisroddy5@gmail.com

581 million people worldwide struggle with an anxiety or depressive disorder [13,14] and we're far from a world where equitable access to mental health treatment is a reality — 72.4% of people with anxiety disorders [13] and 39% with depression will not receive treatment [15]. Several systemic barriers prevent greater accessibility to mental health treatment including lack of investment, staff, awareness that mental health disorders are treatable conditions, and social stigma [13]. Poor treatment access correlates with increased social isolation [9], identity and confidence struggles, and work-related problems [16]. Eccia is a GenAI-based mental health and emotional support chatbot designed to compassionately address these widespread systemic issues and make treatment accessible to anyone with a mobile device. This paper details Eccia's novel system architecture, synthesizes best practices of integrating AI into traditional therapy, and operationalizes social support and relational closeness for the digital age.

CCS CONCEPTS • Human-centered computing → Interaction design → Interaction design process and methods → User centered design

Additional Keywords and Phrases: chatbot, generative AI, natural language processing, trust, affect, mental health, emotion modeling, human-AI connection, social support

1 INTRODUCTION

"I'm telling you today's the day! The Sun explodes today! Our teacher told us that when stars get old, they expand and swallow up all the other planets. It'll boil the oceans, eat Venus, and kill us all! I read it in my science textbook! It's true!"

Maybe in five-billion years, but not today. An elementary school aged child had learned a few weeks prior that stars do not live forever — a medium sized star like the Sun has a lifespan of about ten-billion years. Toward the end of our Sun's life, her hue will shift from yellow to red, double in size to consume Mercury and Venus, and boil Earth's oceans in a desperate cling to life before Earth meets the same fate as our neighbors.

Our star will not combust into a fiery supernova — quite the opposite. After consuming the inner planets and its fuel runs dry, she will shrink from a red giant to a white dwarf. The Sun will continue life in the ashes of her former self for billions of years before fading quietly, immortalized as a remnant of a long dead galaxy devoid of life.

This became an intense, recurring fear expressed by that child. They could not be reassured or reasoned with since the fear was not born from logic. Unbeknownst to their parents, this was not a child with an overactive imagination, but rather an overactive amygdala. This was the voice of a child's anxiety — one who would later go on to be diagnosed with

Generalized Anxiety Disorder as an adult. These parents were neither neglectful nor uncaring. It is unrealistic to expect that parents will recognize a mental health disorder when they never even learned the definition of anxiety.

Anxiety is a cognitive-affective interaction from the brain's neural fear system. Anxiety is fear with context — fear of the future, fear of uncertainty, fear of judgement, and fear of perceived threat. Anxiety functions to protect and prepare us from danger. It is a perfectly standard phenomena for a human to experience. However, when anxiety becomes too intense to regulate or disrupts daily life, it becomes a disorder.

Eccia is a chatbot intended to improve accessibility to mental health and emotional support without replacing professional treatment — the chatbot employs active listening, Socratic questioning, and rapport building techniques in attempt to guide users through processing emotions like a human therapist would but does not provide intensive treatment. The chatbot is instead designed to help users identify when an affective experience warrants professional evaluation, track mood changes over time, and for day-to-day use to reduce intersession dependence on therapist support. Creating an effective AI support tool doesn't just require technical proficiency and knowledge of therapeutic frameworks — it is necessary to reimagine what words like, "support", "trust", and "relationship" mean in a digital context. This paper presents Eccia's design and shares a new paradigm of social bonding for an AI-mediated millennium.

2 BACKGROUND

2.1 Affect Theory

There is no clear consensus among researchers on what defines an emotion, and likewise, there are also several generally accepted affective models commonly used by researchers. The most accessible model to a general audience is the categorical model — we categorize emotion into six discrete states: Happiness, sadness, anger, fear, disgust, and surprise [6]. It is important to note the categorical model can be expanded to include other labels such as boredom and confusion depending on use-case.

The major advantage of using this model is its universality — if groundbreaking research is conducted using this model as an affective framework and its findings communicated to a general audience, barring language and cultural barriers, there is little need to explain the meaning behind words we learned as children. While this makes the model appealing, the categorical model's strength is also its largest drawback. The simplicity of the model leaves little room for precision to quantify emotion beyond a label.

The dimensional model is another way to model affect that addresses concerns surrounding quantifiability. This model represents emotion as a multidimensional coordinate plane consisting of valence (positive-negative axis), autonomic arousal (calm-alert axis), and occasionally includes dominance (emotional and situational control) [3]. Dominance is not always included due to cultural variance in the definition of control. Sometimes referred to as the valence-arousal-dominance model (VAD), the dimensional model allows emotion to be represented as coordinate points — this makes it ideal for tracking affective trends over time. Unfortunately, the axes defining this model are technical terms that require background explanation to audiences outside of affective science research.

It is important to mention that emotion is not purely psychologically constructed — there are several neural systems within the ventral brain that control emotional processes [7]:

Emotional Neural System	Functional Description
Seeking	Search for food, water, warmth
Lust	Search for sex and companionship

Nurturance	Need to care for offspring and loved ones
Panic	Urge to be reunited with companions after separation
Fear	Urge to avoid pain and destruction
Rage	Urge to act when self-interest is compromised
Play	Urge to exhibit vigorous social interaction

Emotion is the primary driver of behavior and can also be modeled as a differential equation [7]:

$$d_{ei} = \frac{\partial e}{\partial t} + \frac{\partial i}{\partial e}$$

Where e is an environmental stimulus, i is a mammal's subjective interpretation of the stimulus, and t is time. The variables described above must be operationalized for the model to be applied.

2.2 Human-AI Connection

Primates possess regions of the brain dedicated to social cognition — this includes the orbital frontal cortex, temporal cortex plus its major components, and the amygdala [1]. An area of the most powerful organ in the mammalian body whose sole purpose is to navigate the social world makes it reasonable to conclude humans are sensitive to intra-species social behavior, or social cues. The social brain is complex — researchers have found that we have cells specifically intended to process facial expressions [12].

Existence of the social brain has consequences in designing an AI agent intended to simulate social connection. Foundational experimental research led to the creation of social response theory — the tendency of humans to project social norms and expectations onto AI agents demonstrating human-like characteristics. Chatbots that display anthropomorphized traits likely activate the social brain even if a person is consciously aware that they are talking with an AI agent. It is reasonable to infer that no brain process initiates to signal we are conversing with a chatbot to reduce cognitive load. This hypothesis would explain why people report disliking ambiguity surrounding whether they are interacting with a human or AI agent [8].

A computer does not have to perfectly, or even realistically, simulate social behavior for this social response phenomenon to be observed — the stimulus only needs to display enough social cues for the brain to categorize it as a social being to elicit a social response [5]. Unfortunately, the definition of "enough" is largely subjective and chatbot perception varies by individual, which has design consequences.

Take the case of response delay: A short, static response time of one second is simultaneously perceived as extraverted and conscientious, but also thoughtless [2]. Longer response times around ten seconds are more persuasive while risking user-perception of deceit, but also causes perceived system ineffectiveness — the most dissonant example worth highlighting is the finding that both long and short response times cause users to experience frustration [2,10]. No one can be liked by everyone. User preferences vary widely, and for this reason, attempting to design a chatbot that will please all users is unproductive. An effective AI agent design is one that either reflects the general preferences of its target demographic or can learn an individual's preferences.

3 SYSTEM DESIGN

3.1 Goals

Because chatbots are generally intended to replicate some form of social interaction, it is important to discuss how social bonds are formed in mammals. There are three major observable components including social approach, motivation to interact, and memory formation — it is worth noting that neuropeptides like oxytocin and vasopressin play important roles in facilitating these processes [4]. However, discussion of their influence on social connection is deemphasized in this paper since it remains unclear if there is any neurochemical component to human-AI connection.

User-perceived relational closeness is desirable in chatbots, especially in the context of mental health support, where system effectiveness is tied to a user's comfort expressing vulnerability. One of Eccia's major design goals is to realistically simulate social bond formation with the user, operationalized as follows:

System Goal	Quantification For
Maximize User Sentiment Toward Chatbot	Social Approach
Maximize Usage Frequency*	Motivation
Maximize User Reported Conversation Memories	Memory Formation

The system goal of maximizing usage frequency is starred for elaboration. Usage frequency should only be maximized to the extent interaction with the system is therapeutically helpful — we do not want Eccia to foster user dependence. Much like a real human-human connection, it is healthy (and necessary) to intentionally disconnect from the system periodically.

Creating a simulated social bond with the user is a prerequisite for achieving Eccia's primary goal: Effective social support. In this context, social support is defined as returning a user experiencing emotional distress to a neutral baseline. Effectiveness is defined as the absolute change in valence and arousal, and the length of time (i.e. simplified as the number of interactions) required for that change to occur — modeled for an individual user as follows:

$$E_{ss}(v, a) = \frac{\Delta(v, \mathrm{a})}{\Delta t}$$

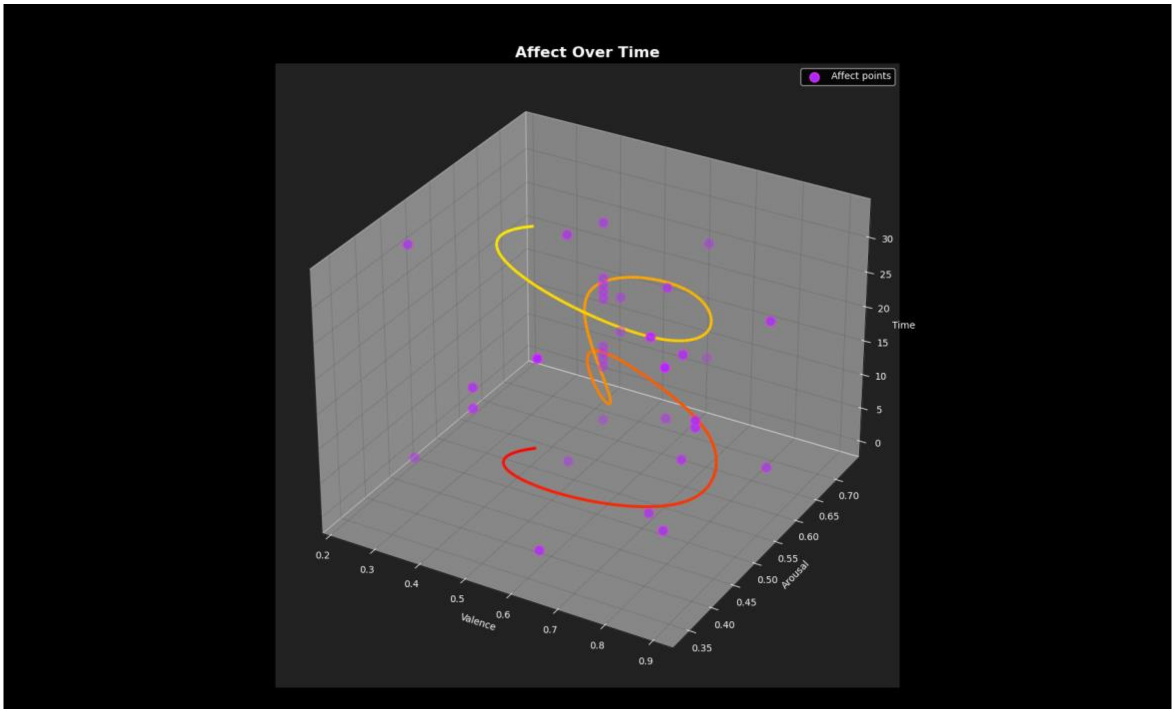
Where E_{ss} is the effectiveness of social support, v, a, are valence and arousal respectively expressed as a point in two-dimensional space, and t is time. We want maximized social support, therefore:

$$\max(E_{ss})$$

This quantifies Eccia's primary design goal in short-term time intervals (i.e. periods of minutes and hours). There is evidence to suggest that mood and emotion cycles periodically in humans, rendering this definition unsuitable for analyzing the system's effectiveness over longer periods — to determine Eccia's effectiveness over periods of days, weeks, months, and years, we must model affect as periodic functions:

$$valence(t) = a_v \times \cos(b_v t + c_v) + d_v$$
$$arousal(t) = a_a \times \sin(b_a t + c_a) + d_a$$
$$z = at$$

We first assume an individual's affective profile over long time periods will take the shape of a helix. This is empirically justified by prior affective research [TODO: I know I saw a paper but I lost the link] — we choose cosine to model valence and sine for autonomic arousal to align with the standard helix equations. The amplitudes of each function represent oscillatory intensity of mood shifts, we interpret frequency multipliers as the time it takes for a person's mood to travel from minimum to maximum, phase shift is the starting point, and the constant addition is where a person's mood is centered. Values for both valence and arousal will always lie between zero and one — this helix can be roughly visualized as follows:



We then treat each coefficient as an independent variable existing as function of time — this is to say emotional patterns change over the course of a person's life. Therefore, Eccia's long term emotional support design goals can be expressed as follows:

$$\lim_{t \to +\infty} (a_v(t)) \approx 0$$
$$\lim_{t \to +\infty} (a_a(t)) \approx 0$$

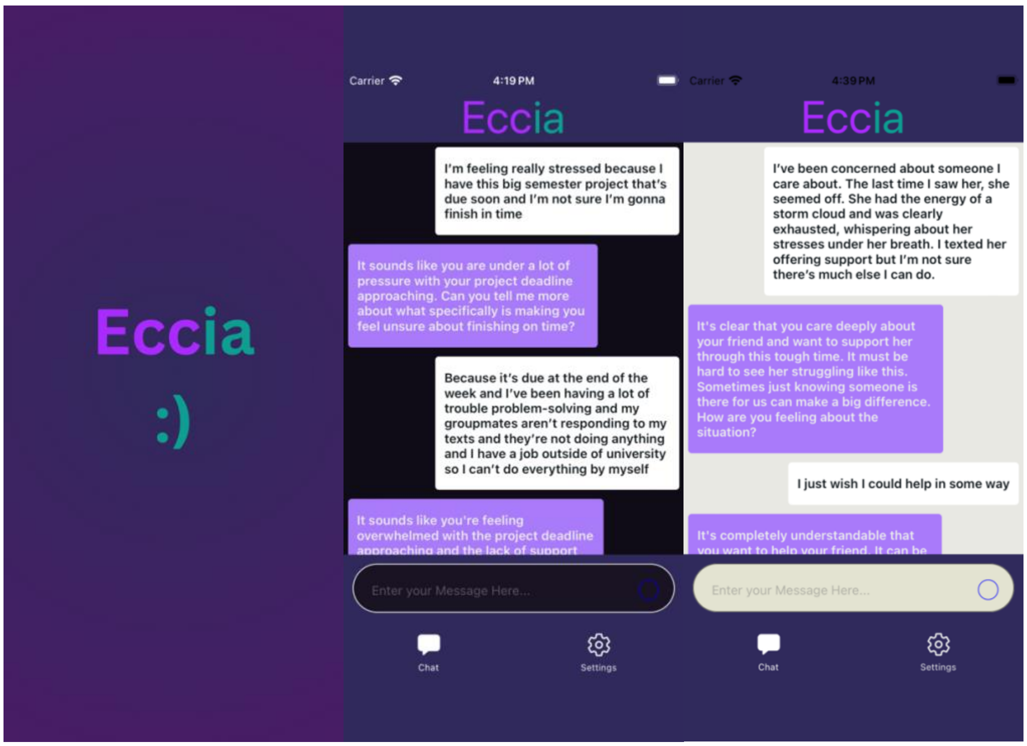
The amplitudes of valence and arousal each approaching zero represents a person's emotional volatility reducing over time to approach a steady state.

$$\lim_{t \to +\infty} (d_v(t)) \approx 0.65$$
$$\lim_{t \to +\infty} (d_a(t)) \approx 0.35$$

The reason we want the limit of a constant addition to valence to approach 0.65 is because this value represents a pleasantness slightly above neutral (0.5), but not high enough to warrant concern that an individual is consistently experiencing unusually high excitement, which could be indicative of certain mental health disorders. We also want autonomic arousal to center at a value under neural, indicating personal peace, but higher than zero — it is both necessary and healthy for people to always remain somewhat alert of their environment.

3.2 User Interface

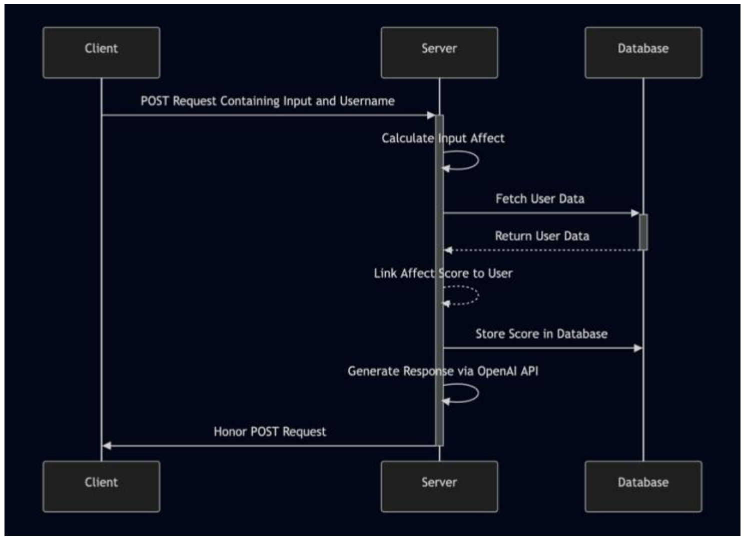
Pictured below are screenshots of Eccia's loading screen, dark mode, and light mode:



The color palette of purples (#302a5c, #aa2bff, #191324), green (#0e9e92), black when in dark mode (#100c17), and pale yellow in light mode (#e8e8e3) was primarily chosen as a matter of aesthetic preference — no empirical evidence was gathered when making the color scheme decision. However, its intent is to create a safe, welcoming atmosphere for the user to feel comfortable expressing vulnerable thoughts and feelings. This decision can be thought of as a visualization of Eccia's mission — "*Compassionately Connected*".

3.3 Architecture

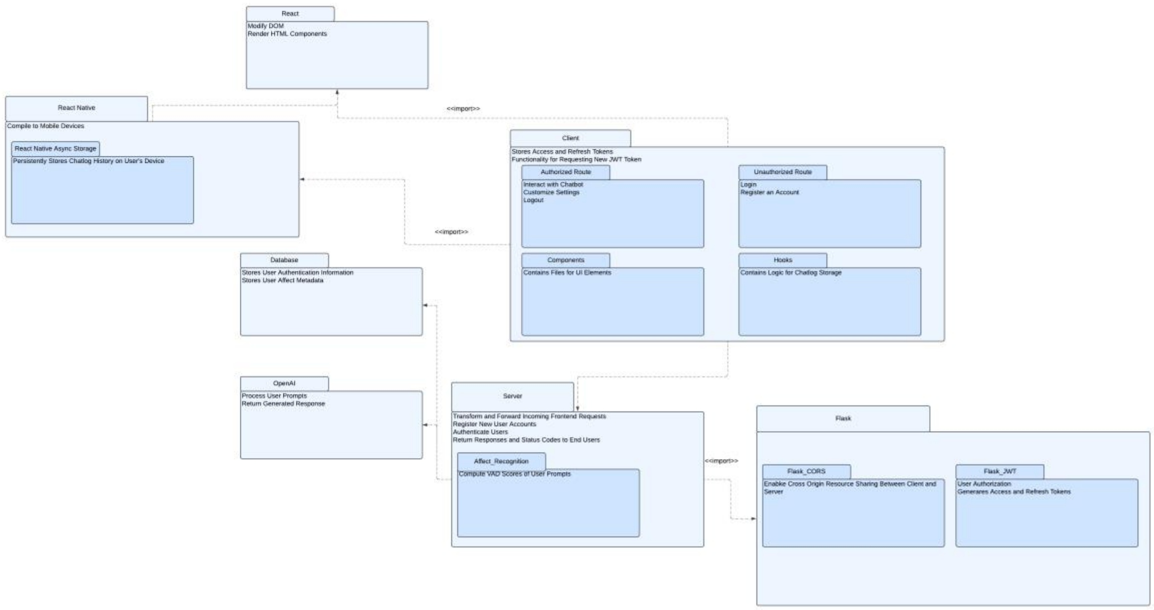
Eccia is a client-server application built using React Native, Flask, MongoDB, and OpenAI's API — the chatbot also contains a custom affect recognition subsystem that will be detailed in the next section. The sequence diagram pictured below describes Eccia's most important functionality, the ability to interact with the chatbot.



A user's input is forwarded to the server via POST request as follows:

```
const response = await fetch(SERVER_ADDRESS + "chat", {
          method: "POST",
          headers: {
            "Content-Type": "application/json",
            Authorization: `Bearer ${session}`,
          },
          body: JSON.stringify({
            message: input,
            memory: updatedUserChats,
            username: username,
          }),
        });
```

The memory parameter passed to the chatbot accounts for the limitation of OpenAI's API — there is no functionality in the responses API for context storage. This is a temporary solution for this challenge, as API costs rise with the message history length. Below is a package diagram detailing the major modules that compose the codebase:



Session management is currently handled client-side — this will have to be refactored in the future to align with best practices and reduce security risk. There are several external Python packages the system depends on for functionality found below:

```
flask===3.0.3
flask_cors===4.0.1
werkzeug===3.0.3
flask_mail===0.10.0
flask_jwt_extended===4.6.0
python-dotenv===1.0.1
openai===1.60.1
pymongo===4.10.1
spacy===3.8.3
contractions===0.1.73
numpy===1.23.5
pandas===2.2.3
matplotlib===3.5.3
scipy===1.10.1
scikit-learn===1.1.3
```

The server is deployed to an AWS Lightsail container via container images built with Docker. The commands required for deploying a build to AWS is found below:

```
docker build --platform linux/amd64 -t flask-container .
```

```
aws lightsail push-container-image --service-name flask-service --label flask-container --
image flask-container
aws lightsail create-container-service-deployment --service-name flask-service --containers
file://containers.json --public-endpoint file://public-endpoint.json
```

3.4 Affect Modeling

Valence, arousal, dominance, and trust scoring (VAD-T) is computationally modeled using spaCy. The computational affect model's primary design goal is to mirror the psycholinguistic processing of the emotional intonation of language as closely as possible. Two lexicon datasets, "nrc-emotion-intensity-lexicon", and "nrc-vad-lexicon" were used to create the system. These datasets were outer joined (i.e. all words are included even if they do not appear in both datasets and assigned corresponding values of 0). Affect computation will be illustrated by calculating the sentence:

```
"Although the show wasn't amazing, I'm still really happy I went out to see it!"
```

The sentence is first preprocessed by expanding all contractions and lowercasing the sentence as follows:

```
doc = nlp(contractions.fix(sentence.lower())
```

This approach removes much of the complexity associated with negation detection, but unfortunately transforming all characters to lowercase sacrifices nuance in emotion detection (ex: "AMAZING" is likely to register with higher emotional intensity than "amazing") — this transforms and tokenizes the sentence into:

```
doc = ["although, "the", "show", "was", "not", "amazing", ",", "i", "am", "still", "really",
"happy", "i", "went", "out", "to", "see", "it", "!"]
```

Next, we determine any negated words within the sentence:

```
negated_words = []
for token in doc:
    # looking for negated words
    if token.dep_ == "neg":
        head = token.head
        negated_words.append(token.head.text)

        for child in head.children:
            if child.dep_ in {"acomp", "attr", "dobj"}:  # Adjective, object, or attribute
                negated_words.append(child.text)
            else:
                negated_words.append(head.text)
negated_words = set(negated_words)    # removing duplicates
```

Resulting in:

```
negated_words = ["amazing"]
```

Followed by a search for intensified words (i.e. in the example shown above, “happy” is intensified by the adverb, “really”):

```
# Define intensity modifiers with scaling factors
intensity_modifiers = {
    "extremely": 1.5,
    "immensely": 1.5,
    "exceptionally": 1.2,
    "very": 1.15,
    "really": 1.15,
    "totally": 1.2,
    "especially": 1.1,
    "so": 1.3,
    "quite": 2.1,
    "pretty": 1.05,
    "mostly": 0.95,
    "slightly": 0.85,
    "somewhat": 0.85,
    "little": 0.75,
    "barely": 0.7,
    "almost": 0.65,
    "!": 1.05,
}
intensified_words = {}
for token in doc:
    # looking for intensified words
    if token.pos_ == 'ADV' and token.text in intensity_modifiers and token.dep_ == 'advmod'
and (token.head.pos_ == 'ADJ' or token.head.pos_ == 'VERB'):
        intensified_words[token.head.text] = intensity_modifiers[token.text]
```

spaCy does not natively recognize intensifier words, which is why a custom list is defined. This results in:

```
intensified_words = {“happy”: 1.15}
```

We also count the number of exclamation points (one in this example):

```
exclamation_count = len([token.text for token in doc if token.text == "!"])
```

Remove stop tokens and punctuation:

```
tokens = [token.text for token in doc if not (token.is_punct or token.is_stop)]
```

Next, we lookup affect scores in the lexicon, accounting for the rare case a sentence input contains no words in the lexicon:

```
scores = {}
```

```
    for token in tokens:
        if token in lexicon:
            if token in negated_words:
                negated = {key: 1-value for key, value in lexicon[token].items()}
                scores[token] = negated
            else: scores[token] = lexicon[token]

    if len(scores) == 0:
        # accouting for the rare edge case a sentence contains meaningful tokens but none
in lexicon
        scores = {"dummyword": {"valence": 0.5, "arousal": 0.5, "dominance": 0.5}}
```

Resulting in:

```
scores = {
        "show": [0.673, 0.771, 0.719],
        "amazing": [
               1 - 0.906 = 0.094,
               1 - 0.837 = 0.163,
               1 - 0.849 = 0.151
        ],
        "happy": [1.0, 0.735, 0.772],
        "went": None,
        "out": None,
        "see": [0.635,0.269,0.312]
}
```

The affect score of negated words is inverted — we perform this operation to reflect realistic psycholinguistic processing (ex: You are unlikely to interpret someone stating, "I am not happy" as experiencing happiness unless sarcasm is assumed — something this affect recognition system is unable to detect). This is why we search for negated words earlier. If a word is not found in the dictionary, it is discarded.

Weights are also added to each word based on its affect score. The reason for adding a weight score to each word is to emphasize "emotionally charged" words for the purpose of psycholinguistic realism — the weights are distributed using the following formula:

$$weight(x) = 4(x - 0.5)^2 + 0.01$$

We distribute weights quadratically in alignment with the goal of emphasizing emotionally significant words (ex: "debilitating" will receive a higher weight than "bad") — the multiplier of 4 and offset of 0.5 were selected so that words with scores of 0 and 1 receive weight scores as close to 1 as possible, whereas emotionally neurtral words (i.e. affect scores closer to 0.5) receive a comparatively negligible weight. The constant of 0.01 is added so that every word factors into the final affect calculation. The quadratic weight calculation is implemented as follows:

```
for word in sentence_scores:
```

```
        weights[word] = {}
        for key in sentence_scores[word]:
            weights[word][key] = (4 * (sentence_scores[word][key] - 0.5) ** 2) + 0.01

        all_weights = pd.DataFrame(weights)
        total_weights = all_weights.sum(axis=1)
        all_weights = all_weights.div(total_weights, axis=0)

        return all_weights
```

The weight scores are normalized. Returning to our example, this results in the following:

```
weights = {
        “show”: [0.068,0.248,0.174],
        “amazing”: [0.354,0.380,0.431],
        “happy”: [0.534,0.189,0.264],
        “see”: [0.044,0.183,0.130]
}
```

Using the affect scores and calculated weights, we calculate the final VAD score output:

```
output = {}
    for word in scores:
        if word in intensified_words:
            for key in scores[word]:
                scores[word][key] *= intensified_words[word]
        for key in scores[word]:
            if key in output:
                output[key] += (scores[word][key] * word_weights[word][key])
            else: output[key] = (scores[word][key] * word_weights[word][key])

    output = {key: np.clip(value, -1, 1) for key, value in output.items()}

    if factor_exclamation and exclamation_count > 0:
        output["valence"] = np.clip(output["valence"] * (intensity_modifiers["!"] *
exclamation_count), -1, 1)
        output["arousal"] = np.clip(output["arousal"] * (intensity_modifiers["!"] *
exclamation_count), -1, 1)
        output["dominance"] = np.clip(output["dominance"] / (intensity_modifiers["!"] *
exclamation_count), -1, 1)

    return output
```

The final output is:

```
output = {
        "valence": 0.766
        "arousal": 0.401
        "dominance": 0.411
}
```

Trust calculation is performed slightly differently. We account for the mere exposure effect [11] and weight words linearly rather than quadratically. We change the weight distribution function since we interpret trust values differently than VAD scores — a valence value of 0 is interpreted as strongly negative, whereas a trust value of 0 simply indicates that trust is not present.

Affect metadata is served as a JSON object between the client and server as shown below:

```
affect_json = {
        valence: [0,1],
        arousal: [0,1],
        dominance: [0,1],
        trust: [0,1],
}
```

This format is unsuitable for storing metadata at scale since an object is generated for each input by every user. We implemented a server-side function that converts the JSON object into a string with the following format to address this:

```
affect_string = "{valence}/{arousal}/{dominance}/{trust}/{date}/{time}"
```

This method of storage was inspired by FEN strings used by chess engines to represent the board state on a particular move. The metadata was timestamped to enable more complete analysis.

Since session management is handled client-side, it was easier to expand the existing context management system over rewriting a server-side handler. This approach also has the advantage of keeping the cloud container size small. Each user-input prompt receives affective analysis, and the resulting value is added to an array stored in the database.

4 DISCUSSION

Eccia has been in development for over a year and half — this time has been split between actual development, implementation, research, and strategy. This chatbot is built on the philosophy that connection, rather than somatic symptom management, is the key to healing. Someone struggling with an anxiety disorder may unpredictably lose entire days to fatigue, jolt awake in the mornings, experience irregular and fast heartbeat, and a whole host of other symptoms. Mental health disorders are not bacterial infections cured by antibiotics — medication can aid in the treatment and support of people living with these disorders, but there are very few circumstances the pills from a bottle act as a silver bullet. It is a person's willingness to be seen, and met with empathy, that facilitates real healing.

This system is intended to make mental health and emotional support more accessible to the people who need it the most. In the context of mental health support, we may assume accessibility issues are caused by long wait times or lack of provider availability. This is partially true, but discounts an invisible challenge experienced by people seeking mental health support — the cognitive burden placed on people struggling with untreated and often severe mental health disorders to actually receive that help. All anyone needs to do is make a simple phone call, right? No. For someone to receive professional support, they must research potential providers and their area of expertise, the cost, weigh their options, make a decision, work up the courage to write an email or call the office, navigate scheduling, and book an intake session.

The initial energy expenditure required for someone struggling to receive support is often higher than their capacity to act. Mental illness is draining. Even when a person is in regular sessions, they only see their therapist between one and four times a month. Eccia exists to provide support during the other three and a half weeks each month a client is not in-session, and to support people who don't yet have the capacity to seek professional support.

5 CONCLUSION

Neither Eccia, nor any mental health support tool should be used indefinitely by anyone. A hallmark of successful therapy is its eventual termination. Under ideal circumstances, the client-therapist pair mutually agree that the therapist's professional services are no longer required and slowly reduce session frequency leading toward the collaboratively predetermined date for their final session — this process can be bittersweet for both the client and therapist.

The client likely initially came in at their lowest point during an incredibly vulnerable time. They were met with warmth and empathy by the therapist week after week as they slowly climbed from the dark place they were in. The client's journey shifted from recovery and healing, to blossoming and growth. The therapist aided the client process their traumas, promote this healing, and see the client's growth — developing a genuine, caring, human connection in the process.

Termination is painful for that reason: It's neither the conclusion of an impersonal transaction nor the final words of a beloved book series. It's a connection fading, not from malice or neglect, but because its time. Everything and everyone have a time to go… but even the death of a universe leaves space for another big bang.

ACKNOWLEDGMENTS

This work was supported by mentors dedicating their time and expertise to advising this project over the course of two years. Thank you.

REFERENCES

1. Chris D Frith. 2007. The social brain? *Philosophical Transactions of the Royal Society B: Biological Sciences* 362, 1480: 671–678. https://doi.org/10.1098/rstb.2006.2003
2. Ulrich Gnewuch, Stefan Morana, Marc Adam, and Alexander Maedche. Faster is Not Always Better: Understanding the Effect of Dynamic Response Delays in Human-Chatbot Interaction.
3. Eddie Harmon-Jones, Cindy Harmon-Jones, and Elizabeth Summerell. 2017. On the Importance of Both Dimensional and Discrete Models of Emotion. *Behavioral Sciences* 7, 4: 66. https://doi.org/10.3390/bs7040066
4. Miranda M. Lim and Larry J. Young. 2006. Neuropeptidergic regulation of affiliative behavior and social bonding in animals. *Hormones and Behavior* 50, 4: 506–517. https://doi.org/10.1016/j.yhbeh.2006.06.028
5. Clifford Nass and Youngme Moon. 2000. Machines and Mindlessness: Social Responses to Computers. *Journal of Social Issues* 56, 1: 81–103. https://doi.org/10.1111/0022-4537.00153
6. SREEJA P S and Mahalakshmi G S. 2017. Emotion Models: A Review. *International Journal of Control Theory and Applications* 10: 651–657.
7. Jaak Panksepp. 1998. *Affective neuroscience: The foundations of human and animal emotions.* Oxford University Press, New York, NY, US.
8. Rosalind W. Picard. 1997. *Affective Computing*. The MIT Press. https://doi.org/10.7551/mitpress/1140.001.0001
9. Nicholas Rohde, Conchita D'Ambrosio, Kam Ki Tang, and Prasada Rao. 2016. Estimating the Mental Health Effects of Social Isolation. *Applied Research in Quality of Life* 11, 3: 853–869. https://doi.org/10.1007/s11482-015-9401-3
10. Yingnan Shi and Bingjie Deng. 2024. Finding the sweet spot: Exploring the optimal communication delay for AI feedback tools. *Information Processing & Management* 61, 2: 103572. https://doi.org/10.1016/j.ipm.2023.103572
11. Tom Stafford and Anthony Grimes. 2012. Memory Enhances the Mere Exposure Effect. *Psychology & Marketing* 29, 12: 995–1003. https://doi.org/10.1002/mar.20581
12. 1992. Organization and functions of cells responsive to faces in the temporal cortex. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*. https://doi.org/10.1098/rstb.1992.0003
13. Anxiety disorders. Retrieved May 18, 2025 from https://www.who.int/news-room/fact-sheets/detail/anxiety-disorders
14. Depressive disorder (depression). Retrieved May 18, 2025 from https://www.who.int/news-room/fact-sheets/detail/depression

15. Major Depression - National Institute of Mental Health (NIMH). Retrieved May 18, 2025 from https://www.nimh.nih.gov/health/statistics/major-depression
16. Mental health at work. Retrieved May 18, 2025 from https://www.who.int/teams/mental-health-and-substance-use/promotion-prevention/mental-health-in-the-workplace