Journal on Interactive Systems, 2025, 16:1, doi: 10.5753/jis.2025.5642

Exploring extensions of neurotransmitter-based emotion models

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Received: 04 March 2025 • **Accepted:** 28 May 2025 • **Published:** 14 June 2025

Abstract: Advancements in artificial intelligence have significantly enhanced the gaming experience, enabling more engaging and adaptive interactions between players and digital characters. A key aspect of this progress is the ability of non-player characters (NPCs) to display more lifelike realistic emotional responses that simulate the fluid and unpredictable nature of human emotions. This work presents a novel emotion model integrating Lövheim's Cube of Emotions with Plutchik's Wheel of Emotions, combining the dynamic aspects of the former with the detailed structure of the latter. The model was expanded from a 22-emotion, 21-point mapping to a more detailed version with 24 emotions across 52 points, allowing for better emotional differentiation. Two algorithms were upgraded and tested: an extended cube of emotions using the Euclidean distance, and the same cube incorporating fuzzy logic. Both methods showed significantly better results than their previous versions, with the Euclidean being the best overall. That indicates a more precise mapping of emotions. However, it can only return one emotion at a time. While the Fuzzy Logic method allows for more than one emotional response at the same time, associating neurotransmitters and emotions within fuzzy rules was quite complex.

Keywords: Emotion Modeling, Lövheim Cube, Plutchik's Wheel, Fuzzy Logic, Neuroscience-inspired AI, Dynamic Emotional Responses, Behavioral Simulation, Emotion-driven NPCs

1 Introduction

Recent advancements in artificial intelligence aims to improve the gaming experience by introducing more dynamic, immersive, and responsive interactions between players and digital entities. One of the most significant aspects of this progress is the enhanced intelligence and emotional depth of non-player characters (NPCs). Modern AI-driven NPCs are no longer limited to rigid, scripted behaviors. Instead, they can exhibit nuanced, context-aware reactions that closely mimic human emotions. Using advanced emotion models, natural language processing, and adaptive learning, these characters react to players in a more natural and unpredictable way. The search for a more realistic virtual world enhances player engagement and enriches the storytelling, more authentic and immersive experiences. As AI improves, interactions in gaming will become even more lifelike, further bridging the gap between virtual and real experiences.

Naturally, real life decision-making is not so simple. An individual's actions and their outcomes may depend on various factors, some of which can be replicated within a game. The most prominent example in this paper is the simulation of neurotransmitters. They are molecules from the central nervous system (CNS) and their function is to regulate behaviors. This approach has become a well-established strategy for treating psychiatric disorders, as many medicinal drugs directly influence neurotransmitter systems (Cuevas [2007]). Neurotransmitters are molecules synthesized from precursor compounds within their respective cells. Produced in neurons, they function as chemical messengers, transmitting electrical signals to affect other cells Cuevas [2007]. Notably, serotonin, noradrenaline, and dopamine belong to the monoamine class, as they are derived from a single amino acid. A key characteristic they share is their production in small brain regions by a relatively limited number of neurons.

An emotion model represents emotional states based on theoretical frameworks, aiding in the visualization of the emotional spectrum and the relationships between different emotions Plutchik [1980]. This study adopts Hugo Lövheim's cube of emotions Lövheim [2012] as its baseline model while also incorporating key aspects of Robert Plutchik's wheel of emotions Plutchik [1980] and W. Gerrod Parrott's emotion framework Parrott [2001] to enhance the interpretation of inferred emotions and their interconnections.

This study aims to explore a simulation of emotions inspired by monoamine systems and integrate them into decision-making processes using state machines, where transitions are influenced by the emotional state of the NPCs.

This document is structured into 9 sections. After the introduction, Section 2 contains the related works, where we go through each main reference, including previously developed emotion engines for NPCs, and their influences, such as the ”Loewenstein and Lerner model of emotions” Johansson and Dell'Acqua [2012], the brain's reward system Berridge and Kringelbach [2015] and surely both Plutchik's wheel of emotions Plutchik [1980] and Lövheim's cube of emotions

Lövheim [2012]. Some possible representations for emotional transitions are also mentioned, namely the use of colors and the AI technique fuzzy logic. Given the importance of so many of these research topics for this study, Section 3 explains the fundamentals behind the wheel of emotions, while Section 4 explores the cube of emotions, Parrott's emotion framework Parrott [2001], the color of emotions and fuzzy logic. Section 5 features the proposed approach. In it, we present an updated version from Fernandes *et al*. [2024]'s Extended Lövheim Cube emotion model. Section 6 shows how algorithms for this model were implemented, comparing the use of coordinates as representations of emotional states with Euclidean distances and fuzzy logic. Sequentially, the conducted tests and their outcomes are present in Section 7. Both upgraded Euclidean and Fuzzy Logic methods presented improvements when compared to their previous versions, with the Euclidean having better results overall. Our conclusions and suggestions for future works are the remaining Sections 8 and 9, respectively.

2 Related Works

Research on emotion models for NPCs is still limited in the literature. One of the earliest collections of related research can be found in the proceedings of the "Emotion in Games Workshop" Yannakakis *et al*. [2011]. Some previous studies, such as the model presented in Bicalho *et al*. [2020], which integrates emotion and culture, serves as our source of inspiration. Li and Campbell [2010] introduce a model based on psychological and sociological research, emphasizing ease of use. Meanwhile, Popescu *et al*. [2014] propose an emotion engine called GAMYGDALA. However, none of these works account for complex combinations of emotional states.

In the initial stages of the investigation, it was crucial to determine which notation models would be used to describe emotions, particularly those employed in psychology and neuroscience. We focused on adopting logical notations that could be implemented to enhance game AI within a gaming environment. For simulating emotions in digital characters, both Russell's Arousal-Valence model of affect Russell [1980] and Plutchik's wheel of emotions Plutchik [1980] had been used in prior research, such as Bicalho *et al*. [2020] and Baffa *et al*. [2017], with positive results reported by the authors. However, the emotion model proposed by Lövheim [2012], known as the cube of emotions, appeared to lack significant references in the context of this implementation. Unlike the other models, which were developed by psychologists, this model is inspired by neuroscience. It proved to be an essential part of the research, particularly as we explored the connections it defines between emotions and neurotransmitters. Studies like Terenzi *et al*. [2021] explore the roles of these neuromodulators and investigate their correlation with social behaviors, drawing on current literature to provide valuable insights into the hormone oxytocin. This understanding played a key role in shaping the decisions for the proposal of a new, extended cube of emotions.

The study by Baffa *et al*. [2017] proposes the development of an emotional model for non-player characters (NPCs). This model is built upon the OCEAN personality framework, widely used in psychology to assess individual traits, and Robert Plutchik's emotion model, which, grounded in psychoevolutionary theory, categorizes and contrasts emotions.

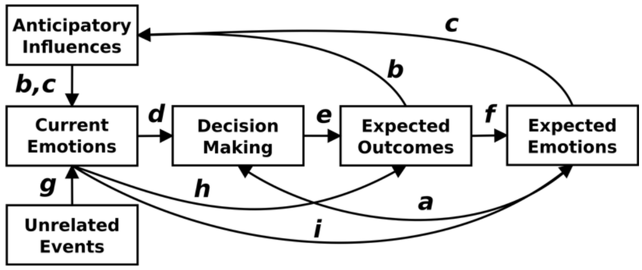


Figure 1. Loewenstein and Lerner model of emotions.

The paper Johansson and Dell'Acqua [2012], which is about the AI technique known as EmoBT, explained the "Loewenstein and Lerner model of emotions". According to it, current emotions have an influence in people's decisions (fig 1). As seen in link g, those emotions can be unrelated to the event some person is experiencing at the moment or what they are doing. However, the decision-making process can be affected. For example, emotions have a role in the way a person perceives risks and anticipates possible outcomes (link d). They can also change how a person feels about the expected outcomes or emotions, as represented in links h and i, respectively. Logically, certain emotions can be presumed from the predictable consequences of actions (links e and f) and they also have a role when people try to choose their preferred consequences (link a). There is also a cycle between the consequences and emotions caused by the decisions made, which become anticipatory influences (links b and c) that result in the current emotions. This cycle sparked interest in further exploring potential connections between different emotions.

These concepts lead us toward a mechanism for the automatic learning and reinforcement of cause-and-effect relationships between action and emotion. The brain's reward system consists of three regions: the ventral tegmental area (VTA), the nucleus accumbens (NAc), and the prefrontal cortex (PFC). These areas are responsible for processing rewards, which trigger the release of the neurotransmitter dopamine, thereby activating the NAc (Berridge and Kringelbach [2015]). This results in a pleasurable sensation that encourages repeated actions to achieve the same outcome. Such reinforcement can increase the frequency of a behavior, which may be either healthy or unhealthy. This idea brought to mind the concept of NPCs having "a life" of their own (Mateas [2003]). A simulation of the reward system could be a way of creating such life illusion. Furthermore, if some behaviours are motivated by the association with pleasure, there can be more kinds of relationships between actions and other emotions. In this sense, the "Loewenstein and Lerner model" seems to be accurate as it also states the expected feeling of a decision has as an influence on taking a new one. Learning about the reward system in particular led to a bigger focus in the role of neurotransmitters in emotions. Besides the emotion models themselves, their social relevance to current day society was also an important consideration. In addition to the evacuation simulation mentioned in the Introduction, the application of emotions in games has also resulted in a framework which seeks to provide emotional support to people suffering hardships (Galvão *et al.* [2025]).

In another aspect, emotions are often expressed through the use of color palettes. The concept of using various color palettes to influence emotional perception is widely employed in visual storytelling across movies, theater, and animation. The studies by Hanada [2018] and Suk and Irtel [2010] explores the relationship between emotions and colors. Color perception is essential for the human visual experience, such as object recognition, and is the most powerful channel of information among the five human senses, capable of making observers feel emotions and feelings.

Just as we use color gradients to represent smooth transitions between different colors, we can apply a similar approach to emotions, using emotional gradients to demonstrate continuous shifts between emotional states. This concept can be modeled through fuzzy logic, a system that allows for the representation of uncertainty and gradual transitions.

3 Plutchik's Wheel of Emotions

Robert Plutchik was an American psychologist who, in 1980, developed a model based on evolutionary psychology theories of emotions Plutchik [1980]. Plutchik's model assumes that emotions are biologically primitive and evolved to enhance the reproductive capacity of animals. Each basic emotion is linked to a strong survival behavior, such as fear, which inspires the fight-or-flight response. In Plutchik's approach, these basic emotions are represented by a three-dimensional circumplex framework, where emotional words are arranged based on their similarity Baffa *et al.* [2017]. The "wheel of emotions" (Figure 2) suggests eight primary emotions (anger, fear, sadness, disgust, surprise, anticipation, trust, and joy) grouped into three sectors, and each sector represents a level of intensity through the saturation of colors. That is, emotions intensify as they move toward the center of the wheel Cabral [2020]. At each level, emotions are further defined according to their intensity; for instance, serenity at a low intensity is similar to joy, while ecstasy represents a higher intensity of the emotion. Plutchik's model includes four axes, each pairing two basic emotions that are considered opposites: joy vs. sadness, anticipation vs. surprise, anger vs. fear, and trust vs. disgust. The model incorporates intensities, which enable more gradual transitions between emotions. Also, the basic emotions in the model can be combined in pairs to form complex emotions. These combinations fall into four categories: Primary Dyads (frequently experienced), Secondary Dyads (sometimes perceived), Tertiary Dyads (rare), and Opposite Dyads (cannot be combined) Baffa *et al.* [2017]. Primary Dyads are obtained by combining adjacent emotions, for example, Joy + Trust = Love. Secondary Dyads are obtained by combining emotions that are two axes apart, for example, Joy + Fear = Excitement. Tertiary Dyads are obtained by combining emotions that are three axes apart, for example, Joy + Surprise = Amazement. Opposite Dyads are on the same axes but on opposite sides, for example, Joy and Sadness cannot be combined, or cannot occur simultaneously Plutchik [2001]. This model establishes key associations between emotions and it is well-established that emotions govern our actions, making it crucial to understand their impact on decision-making Bicalho *et al.* [2020].

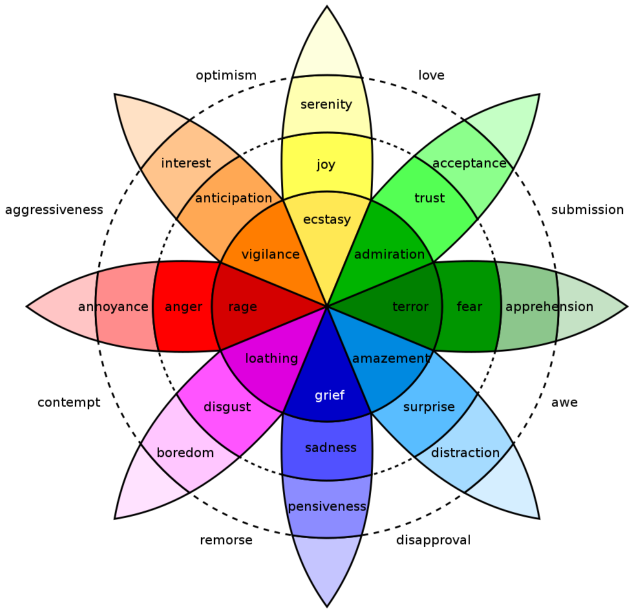


Figure 2. Plutchik's wheel of emotions Bicalho *et al.* [2020].

4 Lövheim's Cube of Emotions

Lövheim's model (Figure 3) maps eight emotions spread across vertices: enjoyment/joy, interest/excitement, contempt/disgust, shame/humiliation, fear/terror, surprise, anger/rage, distress/anguish. These emotions are distributed according to the levels of three neurotransmitters: serotonin (represented on the on X-axis), noradrenaline (also known as norepinephrine, represented on the Y-axis) and dopamine (represented on the Z-axis). For instance, emotions like shame/humiliation, distress/anguish, contempt/disgust and surprise are associated with low levels of dopamine, while fear/terror, anger/rage, enjoyment/joy and interest/excitement are positioned higher on the dopamine spectrum. Fear/terror is characterized by low levels of serotonin and noradrenaline, whereas anger/rage and enjoyment/joy are liked to maximum levels of noradrenaline and serotonin, respectively. Interest/excitement, on the other hand, is a combination of three neurotransmitters. The eight corners of the cube correspond to the eight possible combinations of low or high levels of the three monoamines (Table 1). The model thus proposes a direct relationship between specific combinations of the signaling substances' levels and certain basic emotions Lövheim [2012].

Based on Silvan Tomkins's theory of basic emotions Tomkins and McCarter [1964], it is possible to group two emotions together, with the exception of surprise. According to his theory, there area only eight basic emotions, and each emotion has two names: the left one represents its weaker manifestation, while the right name refers to its strongest form Kolmogorova *et al.* [2021]. Initially, Tomkins paired

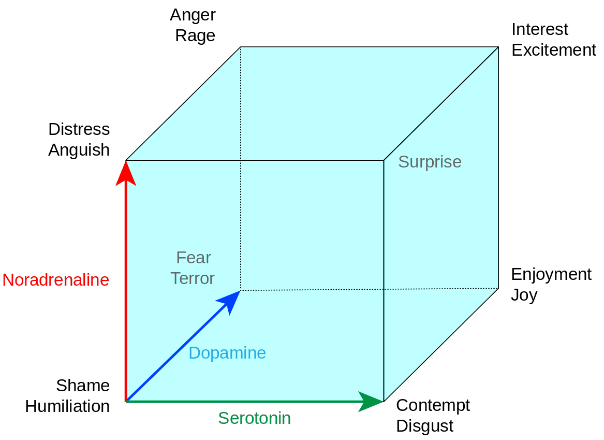


Figure 3. Lövheim's cube of emotions .

the emotion "startle" with surprise, but later research showed that the two are not direclty related Ekman *et al*. [1985].

At first, the direct connection of dopamine to the emotion of fear/terror might be considered inconsistent, although it is typically associated with stimulation in the reward system Berridge and Kringelbach [2015]. However, in Lövheim [2012], Lövheim justifies this by explaining that both fear/terror and other emotions can reinforce habits, particularly in the context of avoiding dangerous or frightening situations. Also, his work suggests that there is a rewarding effect associated with them. It is important to note that representing neurotransmitters as axes does not imply they operate independently in real life. In fact, the author acknowledges that these neurotransmitters likely interact with each other in more complex ways.

The paper Heudin [2016] adopts Hugo Lövheim's Cube of Emotions (Figure 3) as the emotional model for intelligent agents. Introduced in 2012, Lövheim's Cube of Emotions is a theoretical framework that illustrates the relationship between the monoamine neurotransmitters serotonin, dopamine, and noradrenaline and their associated emotions. This model helps to map how these neurotransmitters influence emotional states and provides a basis for understanding emotional dynamics in artificial intelligence systems. By integrating the Cube of Emotions, intelligent agents can simulate more realistic emotional responses, reflecting the biochemical underpinnings of human emotions.

Basic Emotion	Serotonin	Dopamine	Noradrenaline
Shame/Humiliation	Low	Low	Low
Distress/Anguish	Low	Low	High
Fear/Terror	Low	High	Low
Anger/Rage	Low	High	High
Contempt/Disgust	High	Low	Low
Surprise	High	Low	High
Enjoyment/Joy	High	High	Low
Interest/Excitement	High	High	High

Table 1. Relationships between monoamines and emotions

4.1 Parrott's Emotion Framework

One other model that influenced this project was Parrott's emotion framework Parrott [2001]. It is a classification of emotions organized in a tree structure. Figure 4 illustrates its three levels: primary, secondary, and tertiary emotions.

Primary emotions	Secondary emotions	Tertiary emotions
love	Affection	Compassion, Sentimentality, Liking, Caring, ...
	Lust/Sexual desire	Desire, Passion, Infatuation
	Longing	
Joy	Cheerfulness	Amusement, Enjoyment, Happiness, Satisfaction, ...
	Zest	Enthusiasm, Zeal, Excitement, Thrill,Exhilaration
	Contentment	Pleasure
	Optimism	Eagerness, Hope
	Pride	Triumph
	Enthrallment	Enthrallment, Rapture
Surprise	Surprise	Amazement, Astonishment
Anger	Irritability	Aggravation, Agitation, Annoyance, Grumpy, ...
	Exasperation	Frustration
	Rage	Outrage, Fury, Hostility, Bitter, Hatred, Dislike, ...
	Disgust	Revulsion, Contempt, Loathing
	Envy	Jealousy
	Torment	Torment
Sadness	Suffering	Agony, Anguish, Hurt
	Sadness	Depression, Despair, Unhappy, Grief, Melancholy, ...
	Disappointment	Dismay, Displeasure
	Shame	Guilt, Regret, Remorse
	Neglect	Embarrassment, Humiliation, Insecurity, Insult, ...
	Sympathy	Pity, Sympathy
Fear	Horror	Alarm, Shock, Fright, Horror, Panic, Hysteria, ...
	Nervousness	Suspense, Uneasiness, Worry, Distress, Dread, ...

Figure 4. Table representing Parrott's emotion framework. Picture obtained from Murgia *et al*. [2014].

Each level breaks down the previous one into more specific and less abstract feelings. This approach led to the identification of unique connections between emotions that were not present in other models.

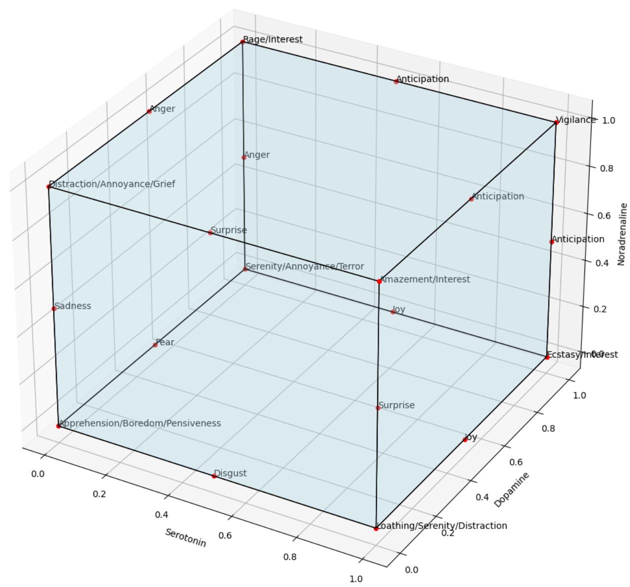
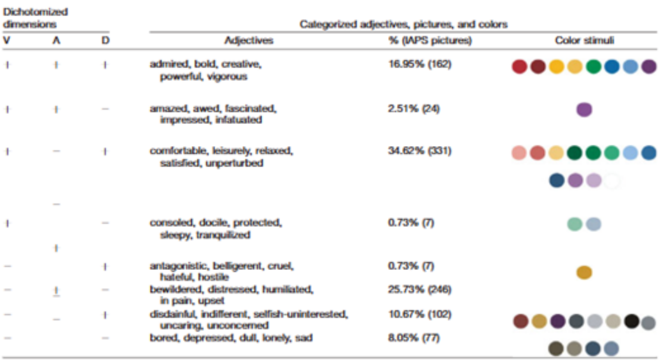


Figure 5. Extended cube of emotions proposed by Fernandes *et al*. [2024].

With the fundamentals from Plutchik, Lövheim and Parrott's emotion models, Fernandes *et al*. [2024] proposed a new extension of the cube of emotions, with 22 emotions distributed in 21 points. Figure 5 represents that extended cube.

4.2 Color of emotions

During the literature review on how to represent the complex concept of emotions, several articles emerged linking emotional responses to colors. Color perception plays a crucial role in the human visual experience and is considered the most powerful channel of information among the human senses Adams and Osgood [1973]. The author from the book Goldstein [2010] differentiated color visualization from other visual experiences, asserting that the connection between the physical properties of color and the experience of color itself is arbitrary, unlike other visual qualities such as shape, depth, location, and movement. This makes color an effective tool for persuasive communication purposes (Hine [1997] and Miller and Kahn [2011]). In Figure 6, various colors are associated with different adjectives, which can be linked to emotions, demonstrating that emotional responses are more strongly influenced by the chroma and lightness of colors than by their hue. After that, considerable attention has been focused on research regarding the affectivity of colors, leading to the investigation of emotional responses to color across various disciplines Suk and Irtel [2010]. We emphasize that the use of color to represent emotions was applied solely as a criterion for information visualization. It serves as a visual aid to facilitate data interpretation within the current scope of our study.



Dichotomized dimensions			Categorized adjectives, pictures, and colors		
V	A	D	Adjectives	% (IAPS pictures)	Color stimuli
+	+	+	admired, bold, creative, powerful, vigorous	16.95% (162)	
+	+	−	amazed, awed, fascinated, impressed, infatuated	2.51% (24)	
+	−	+	comfortable, leisurely, relaxed, satisfied, unperturbed	34.62% (331)	
+	−	−	consoled, docile, protected, sleepy, tranquilized	0.73% (7)	
−	+	+	antagonistic, belligerent, cruel, hateful, hostile	0.73% (7)	
−	+	−	bewildered, distressed, humiliated, in pain, upset	25.73% (246)	
−	−	+	disdainful, indifferent, selfish-uninterested, uncaring, unconcerned	10.67% (102)	
−		−	bored, depressed, dull, lonely, sad	8.05% (77)	

Figure 6. Relationship between color and emotion Suk and Irtel [2010].

Building on this idea, the initial approach was to use the RGB cube in model development to illustrate the transition from one emotion to another. In this model, each emotion would be represented by a color, and as the color changed, the corresponding emotion would also shift.

However, this approach proved impractical, as the computer took too long to calculate the color of each pixel in the cube for the creation of an RGB cube. As a result, the decision was made to color only the emotion points of the model by adapting RGB. Yet, as shown in Figure 7, the emotion points were not displaying the expected colors associated with each emotion. For example, the points for Anger and Rage were blue, and those for Disgust and Loathing were red, among others. The list of emotions and colors is presented in table 2. Attempts to adjust the RGB coloring formula for the points did not produce satisfactory results, as one set of emotions was consistently colored incorrectly.

Upon recognizing that the RGB color cube formula could not be effectively adapted, a simpler approach was devised. Based on Plutchik's wheel of emotions model, an array with RGB values was created for each emotion, where the intensity of the color corresponded to the strength of the emotion, where lighter colors represented weaker emotions, while more saturated colors represented stronger emotions:

- Red: Rage, Anger, Annoyance.
- Dark Green: Terror, Fear, Apprehension.
- Purple: Loathing, Disgust, Boredom.

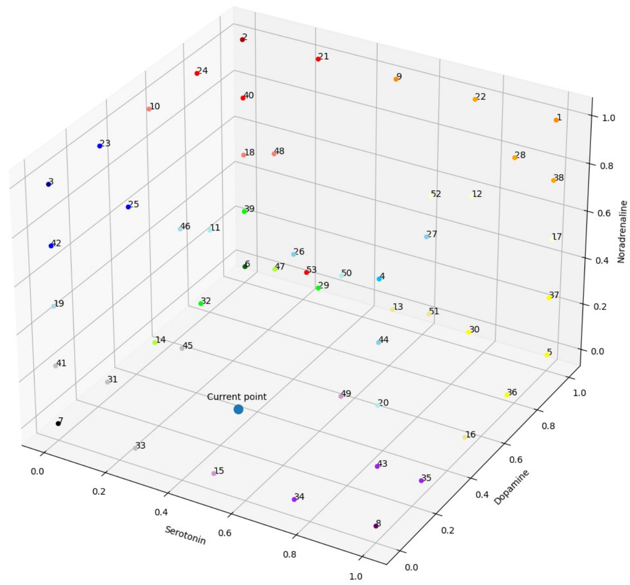


Figure 7. Emotional Model with colors. The emotions and colors are listed in table 2.

- Yellow: Ecstasy, Joy, Serenity.
- Dark Blue: Anguish, Sadness, Pensive.
- Light Blue: Astonishment, Surprise, Distraction.
- Orange: Vigilance, Anticipation, Interest.

This array of RGB values was used to color, in order, each point of the cube with the color corresponding to the associated emotion, making it easier to visualize the emotions and understand the model.

Future research should conduct empirical evaluation with users to assess the effectiveness, interpretatibility, and potential impact of this visualization approach.

4.3 Fuzzy Logic and Games

Fuzzy Logic works by assigning values to emotions that lie between extremes, capturing the complexity and fluidity of emotional states. For example, instead of strictly categorizing emotions as either happy or sad, Fuzzy Logic can account for nuanced states, such as feeling ”somewhat happy” or ”slightly sad.” This gradual transition helps to better reflect how emotions are experienced in real life, where they often blend and evolve over time.

In previous works, Fuzzy Logic has been successfully used to model emotional responses in AI systems, such as in emotion-based character interactions in virtual environments (Kaneko and Okada [2024]) or video games, where characters' emotional states transition smoothly depending on context (Yin and Xiao [2024]). By using fuzzy logic, we can create more realistic and dynamic emotional responses, enhancing the believability of characters and their emotional evolution over time. The technique can also be adopted to adjust and balance the difficulty levels imposed on players according to their skills (Chrysafiadi *et al*. [2023]).

Eventually, the research focused on fuzzy logic. Waltham and Moodley [2016] claimed that fuzzy state machines, particularly, had great potential and their only disadvantage was the expertise required to properly develop fuzzy rules. The capability of dealing with ambiguity, as better explained in chapter 6, was a feature that could help in the code implementation of emotion models. Some of the studies that facilitated the comprehension of fuzzy concepts include Zadeh [1988] and Mohmed *et al*. [2020]. Alvim and de Oliveira Cruz [2008] inspired ideas for code implementation. It details a fuzzy state machine for emotions on electronic game characters.

5 Proposed Approach

This work proposes a revision to the new emotion model "extended cube of emotions" proposed by Fernandes *et al*. [2024], as seen in Figure 5. It mixed concepts from both the aforementioned Plutchik (Plutchik [1980]) and Lövheim (Lövheim [2012]) models, since both have similarities such as many of the same emotions represented, but also interesting differences that could be combined, like the wheel of emotions' growing intensity of feelings. That intensity could fill up spaces left between the vertices in Lövheim's cube. That is why the cube remained the basis for the model, but all emotions that were identical to Plutchik's model were replaced with the latter's labels.

The bullet points below, which are the same from Fernandes *et al*. [2024], demonstrate the translation between the emotions featured in Lövheim's model to their equivalents in Plutchik's wheel of emotions.

- Contempt/Disgust → Boredom, Disgust and Loathing
- Fear/Terror → Apprehension, Fear and Terror
- Enjoyment/Joy → Serenity, Joy and Ecstasy
- Anger/Rage → Annoyance, Anger and Rage
- Surprise → Distraction, Surprise and Amazement
- Interest/Excitement → Interest, Anticipation and Vigilance

The origin point from Lövheim's model, when all the monoamine concentration levels are low, is shame/humiliation. In Fernandes *et al*. [2024], that point became apprehension/boredom/pensiveness. Many other points had more than one emotion because they are placed in a way that makes sure there is a progression in all of three edges and that it remains consistent with Plutchik's model while expanding Lövheim's. One good example is loathing/serenity/distraction, because reducing serotonin levels results in disgust, which is the less intense version of loathing, increasing dopamine leads to joy, which is a more intense emotion from the same Plutchik axis as serenity, and finally, the same is true for distraction becoming surprise with higher noradrenaline levels.

It is important to understand these translations made in the previous version to understand clearly the fundamentals of the upgraded extended cube of emotions. Despite those explanations being already provided in the original paper, we consider important to reaffirm them as they also pertain to the extensions made.

A neutral state was also incorporated, positioned precisely at the cube's center. This aspect is mentioned in the original paper Lövheim [2012]. The choice stemmed from the necessity of defining an emotion at this location for coding experiments, irrespective of ongoing debates about whether such a state truly exists Gasper *et al*. [2019].

Some emotions challenged the established models, particularly shame, humiliation, and sadness. Plutchik does not classify shame or humiliation as basic emotions, and Lövheim similarly excludes sadness. According to the tertiary dyad framework, shame emerges from a blend of fear and disgust Kołakowska *et al*. [2015], but this conflicts with the cube model, as shame is linked to low dopamine and serotonin, while fear and disgust manifest at extreme levels. Parrott's emotion hierarchy (Figure 4) was used to address this gap by categorizing shame as a secondary offshoot of sadness and humiliation as a tertiary one. It remains a limitation since the conceptual basis of each model differs and their nominal definitions of emotions do not necessarily align. Emotions are positioned within the cube based on which monoamine regulates them or whether they arise from its deficiency. Research linking sadness and humiliation suggests that experiences of humiliation can trigger severe depression McCarley [2009]. Lövheim himself noted that depression correlates with reduced serotonin levels, which is why many antidepressants function by boosting serotonin Coleman *et al*. [2016]. While serotonin is the most widely targeted neurotransmitter in depression treatment Moret and Briley [2011], dopamine and noradrenaline are also involved. Ketamine therapy enhances dopamine release Jiang *et al*. [2022], whereas desipramine and nortriptyline increase noradrenaline. Additionally, studies show that depleting noradrenaline can cause depressive symptoms to reappear post-recovery Moret and Briley [2011]. These findings suggest that diminished activity across all three monoamine systems plays a role in both depression and emotions like shame and humiliation.

Another one of the perceived limitations of this model was the pairing of multiple emotions at certain points, such as Rage and Interest, emotions that do not belong to the same emotional axis (according to Plutchik's model). Rage is a strong emotion, while Interest is a weaker one, yet both are present at the same point (when the Serotonin level is 0, and the levels of Dopamine and Noradrenaline are 1). To address this limitation, the proposed model added 31 points: 2 points on each edge of the cube and 4 points inside it. This approach allowed the model to preserve the most intense emotions (Rage, Grief, Amazement, Vigilance, Loathing, Ecstasy, and Terror) at the vertices of the cube, while using the edge points to represent varying intensities of emotions, in line with Plutchik's intensity model. The further from a given vertex (indicating lower levels of specific monoamines), the less intense the emotion becomes. However, the new model still lacked emotions at the points where the levels of all three monoamines were low or close to zero (ranging from 0 to 0.25). To address this, Humiliation and Shame were added to the model, drawing from Hugo Lövheim's Emotion Cube, which associates these two emotions with low levels of Serotonin, Dopamine, and Noradrenaline. Following Plutchik's emotion intensity model, Humiliation (considered more intense) was placed at the cube's vertex (where all three neurotransmitters are zero), while Shame (considered less intense than Humiliation) was placed at the points near Humiliation.

This was necessary because, after distributing emotions to the along the new points of the upgraded model, without the emotions of "Admiration, Trust and Approval", that were incompatible with Lövheim's Emotion Cube, there were five points in the model without emotions. According to Lövheim's model of Emotion Cube "Humiliation and Shame" were the emotions present around the blank points of the upgraded model, therefore they were utilized to circumvent this problem and additionally solved one of the limitations of Fernandes's model.

The table 2 presents the new distribution of emotions of the upgraded model. It has five different levels for the monoamine systems low, mid-low, medium, mid-high and high, that correspond to the values 0, 0.25, 0.5, 0.75 and 1.0. In the upgraded model the strongest, most intense emotions, appear only in one point of the model (the vertices of the cube), while less intense emotions like Anger, Joy, Sadness, Disgust, Fear, Surprise and Anticipation appear in the three closest points to the more intense emotions. The only exception is Shame, which appears in four points. Anger is close to Rage, Joy is close to Ecstasy, Sadness is close to Grief, Disgust is close to Loathing, Fear is close to Terror, Surprise is close to Amazement, Anticipation is close to Vigilance and Shame is close to Humiliation. Lastly, the weakest emotions, like Annoyance, Serenity, Pensiveness, Boredom, Distraction, Interest and Apprehension appear one or two times in the middle point of the edges of the upgraded cube model respectively.

While some of the observed limitations from the previous model were corrected in this extension, there a few limitations that remained. For example, neither the emotions distress nor anguish are included in Plutchik's wheel of emotions, but they are part of Lövheim's model. Distress is often more closely associated with stress than sadness, while anguish can imply a sense of suffering. Although sadness is among the most fundamental and easily recognizable emotions, it encompasses a broad range of terms, as explained in Arias *et al*. [2020]. Both distress and anguish can be used to convey particularly intense forms of sadness. Within the wheel of emotions, grief is positioned as the most profound level of sadness, with distress frequently cited as a reaction to it Pop-Jordanova [2021]. Because distress and anguish are strongly linked to both sadness and grief, the model substituted them for grief. However, it is important to clarify that these terms are not interchangeable, so it is still an issue that could be improved.

The biggest omission from Fernandes *et al*. [2024] that was also kept in the mentioned upgrades was the trust emotion, which simply does not exist in Lövheim and has no similar feeling because it would not be possible. Its exclusion is justified by the role of oxytocin, a hormone that influences trust but does not belong to the same class as serotonin, noradrenaline, and dopamine. Monoamines originate from a single amino acid, whereas oxytocin is derived from peptides. Research has linked oxytocin to various social bonding behaviors, including cooperation, generosity, and trust itself Terenzi *et al*. [2021]. Multiple attempts were made to integrate oxytocin into Fernandes *et al*. [2024]'s model, but the authors claimed it went beyond the model's intended scope because it is not related to the fundamentals of Lövheim's model. The relationship between oxytocin and monoamines remains unclear, since studies on its connection to trust have yielded mixed results, and dopamine's involvement may be more related to the reward system than to trust specifically Terenzi *et al*. [2021].

Serotonin	Noradrenaline	Dopamine	Result	Color
High	High	High	1. Vigilance	Deeporange
Low	High	High	2. Rage	Deepred
Low	High	Low	3. Grief	Deepblue
High	High	Low	4. Amazement	Deepskyblue
High	Low	High	5. Ecstasy	Deepyellow
Low	Low	High	6. Terror	Deepgreen
Low	Low	Low	7. Humiliation	Black
High	Low	Low	8. Loathing	Deeppurple
Medium	High	High	9. Interest	Paleorange
Low	High	Medium	10. Annoyance	Palered
Medium	High	Low	11. Distraction	Paleturquoise
High	High	Medium	12. Interest	Paleyellow
Medium	Low	High	13. Serenity	Khaki
Low	Low	Medium	14. Apprehension	Greenyellow
Medium	Low	Low	15. Boredom	Palepurple
High	Low	Medium	16. Serenity	Khaki
High	Medium	High	17. Interest	Paleyellow
Low	Medium	High	18. Annoyance	Palered
Low	Medium	Low	19. Pensiveness	Paleblue
High	Medium	Low	20. Distraction	Paleturquoise
Mid-Low	High	High	21. Anger	Red
Mid-High	High	High	22. Anticipation	Orange
Low	High	Mid-Low	23. Sadness	Blue
Low	High	Mid-High	24. Anger	Red
Mid-Low	High	Low	25. Sadness	Blue
Mid-High	High	Low	26. Surprise	Skyblue
High	High	Mid-Low	27. Surprise	Skyblue
High	High	Mid-High	28. Anticipation	Orange
Mid-Low	Low	High	29. Fear	Green
Mid-High	Low	High	30. Joy	Yellow
Low	Low	Mid-Low	31. Shame	Silver
Low	Low	Mid-High	32. Fear	Green
Mid-Low	Low	Low	33. Shame	Silver
Mid-High	Low	Low	34. Disgust	Purple
High	Low	Mid-Low	35. Disgust	Purple
High	Low	Mid-High	36. Joy	Yellow
High	Mid-Low	High	37. Joy	Yellow
High	Mid-High	High	38. Anticipation	Orange
Low	Mid-Low	High	39. Fear	Green
Low	Mid-High	High	40. Anger	Red
Low	Mid-Low	Low	41. Shame	Silver
Low	Mid-High	Low	42. Sadness	Blue
High	Mid-Low	Low	43. Disgust	Purple
High	Mid-High	Low	44. Surprise	Skyblue
Mid-Low	Mid-Low	Mid-Low	45. Shame	Silver
Mid-Low	Mid-High	Mid-Low	46. Pensiveness	Paleblue
Mid-Low	Mid-Low	Mid-High	47. Apprehension	Greenyellow
Mid-Low	Mid-High	Mid-High	48. Annoyance	Palered
Mid-High	Mid-Low	Mid-Low	49. Boredom	Palepurple
Mid-High	Mid-High	Mid-Low	50. Distraction	Paleturquoise
Mid-High	Mid-Low	Mid-High	51. Serenity	Khaki
Mid-High	Mid-High	Mid-High	52. Interest	Paleyellow
Medium	Medium	Medium	53. Neutral	Red

Table 2. Proposed model Lövheim vs Emotions. This cube of emotions is presented in figure 8.

Lastly, Fernandes *et al*. [2024] highlighted potential inconsistencies across the sentiment models that remain valid, particularly regarding the concept of opposing axes. In the wheel of emotions, certain feelings, such as fear and anger, are considered mutually exclusive. Lövheim himself acknowledged this issue, stating that Plutchik's model, which organizes emotions by similarity and incorporates an intensity dimension, may have been influenced by its two-dimensional origins, leading to the possibly incorrect assumption that emotions exist in opposing pairs Lövheim [2012]. However, Lövheim's own interpretation of sadness as "the inability to experience the core emotions of enjoyment or joy" closely resembles the notion of emotional opposites. Another minor inconsistency arises in terminology: one model classifies excitement as an intensified form of interest, while another uses vigilance. Though vigilance is not explicitly represented in the cube, it is associated with the noradrenaline axis. The upgraded model retains those possible inconsistencies from Fernandes *et al*. [2024]'s model and Lövheim's original.

6 Implementation

Considering the changes that were made from Fernandes *et al*. [2024]'s proposed emotional model, naturally, they would be reflected in the algorithms we developed. In the original paper, three models were implemented: the first one was a full representation of Lövheim's model Lövheim [2012] considering the same associations between the neurotransmitters and emotions, using the Euclidean distance method in the same manner as explained in the next section, the second one used the same mathematical approach with the 21 emotional points from the original Extended Lövheim Cube and the third one used Fuzzy Logic with those same emotional points.

6.1 Euclidean distance Method

In this method, emotions are represented as points within a 3D cube, allowing us to calculate the distance between points using the Euclidean distance method. This approach helps determine the emotion an agent is experiencing based on the values of serotonin, dopamine, and noradrenaline. Each edge is connected to two strong emotions, such as Anger and Terror or Vigilance and Joy, which are present at the extreme of each edge. As the values of the axes move away from these extremes, the emotions become less intense. Unlike the model developed in Fernandes *et al*. [2024], the edges have a total of 5 points, 2 at their extremes for the more intense emotions and 3 points along the edge for less intense emotions. For example, if Terror is at point zero and Rage is at point one of an edge, point 0.25 will have the emotion Fear and point 0.75 will have the emotion Anger, which are less intense than Range and Terror (according to Plutchik). Following this idea, 8 points were defined within the cube with the weaker emotions (according to the wheel of emotions) of each emotion present at the vertices of the model. Following the formula presented in the article Fernandes *et al*. [2024], given three input values in the range from zero to one for the levels of neurotransmitters, we calculate their distance to one of the vertices of the cube. Next, the result is transformed into a score using the formula provided below. Dividing by the square root of three ensures that the maximum possible distance occurs between the coordinate system's origin, $(0, 0, 0)$, and the farthest vertex in the cube, $(1, 1, 1)$. By subtracting this division from one, we reverse the scale, meaning that larger distances correspond to lower scores. Finally, the result is multiplied by one hundred to convert it into a percentage, as shown in Equation 1, where ser represents serotonin, nor stands for noradrenaline, and dop refers to dopamine.

$$score = \left(1 - \frac{\sqrt{(ser-x)^2+(nor-y)^2+(dop-z)^2}}{\sqrt{3}}\right) \times 100 \quad (1)$$

The formula 1 is performed on all eight vertices and on the internal points of the model. After that, the values need to be scaled so that they sum up to one hundred. However, a point that is significantly closer to the input than the others should not go through this process. To preserve the relative difference between the points, if there is a maximum value, it remains the same, and the factor applied to the others takes this into account (see Algorithm 1) .

Algorithm 1
Selecting the emotion closest to the indicated point

for i in range(len(score)) **do**
  if score.count(max_score) > 1 **then**
    final_score[i] = score[i] $\times \frac{100}{\sum score}$
  else
    if score[i] $\neq$ max_score **then**
      final_score[i] = score[i] $\times \left(\frac{100-\text{max\_score}}{\sum score-\text{max\_score}}\right)$
    end if
  end if
end for

Consequently, the final maximum score, which corresponds to the closest point, determines the resulting emotion. It is the emotion represented by the closest vertex (Figure 8).

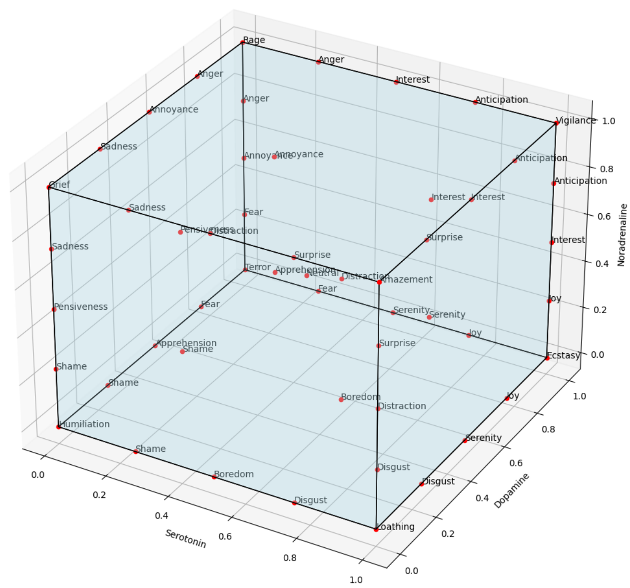


Figure 8. The cube implemented with the new emotional points.

6.2 Fuzzy Method

Adapting the method presented in the paper Fernandes *et al*. [2024], for the creation of an extended emotion cube with fuzzy logic, it was first necessary to determine the inputs, outputs, fuzzy sets, and fuzzy rules. The levels of monoamines (serotonin, dopamine and noradrenaline) remained as the antecedents (inputs of the function, as presented in figure 9), receiving an exact value between 0 and 1, but now they are fuzzified into sets of low, mid-low, medium, mid-high and high, with the following values: $0, 0.25, 0.5, 0.75$ and 1.0. The addition of 31 points to the model caused each edge of the cube to have 5 points. These 5 levels were used to create fuzzy rules, using the tools provided by the SciKit-Fuzzy library, following the method proposed in the article Fernandes *et al*. [2024].

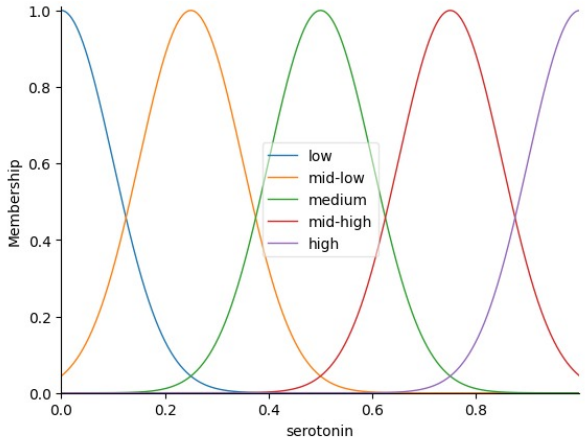


Figure 9. The levels of monoamines (serotonin, dopamine and noradrenaline) remained as the antecedents (inputs of the function)

The consequents (outputs, as presented in figure 10) of the Fuzzy Logic are the axes of the emotions in Plutchik's wheel of emotions, which can return up to 4 resulting emotions. The method has 4 consequents:

- "joy_axis" (the joy axis, which can return 'Anguish', 'Sadness', 'Pensive', 'Serenity', 'Joy', 'Ecstasy' or 'Neutral'),
- "disgust_axis" (the disgust axis, which can return 'Disgust', 'Revulsion', 'Boredom', 'Humiliation', 'Shame', 'Neutral1' or 'Neutral'),
- "fear_axis" (the fear axis, which can return 'Anger', 'Rage', 'Annoyance', 'Apprehension', 'Fear', 'Terror' or 'Neutral') and
- "surprise_axis" (the surprise axis, which can return 'Vigilance', 'Anticipation', 'Interest', 'Distraction', 'Surprise', 'Astonishment' or 'Neutral')

For example, in the "fear_axis", a rule is created so that the result is "Anger" when the levels of dopamine and noradrenaline are defined as high, and the level of serotonin is defined as low. The Fuzzy Logic uses the rules defined for each consequent and its knowledge base to determine the emotion output.

The presence of only one emotion at each point made it easier to create the fuzzy rules, but despite these established rules, some inputs were reaching inconsistent degrees of association, such as low percentages of expected emotions and incorrect associations. Unlike the deterministic Euclidean distance score, Fuzzy Logic should offer the opportunity for NPCs to simulate the human complexity of "feeling" more than one emotion at the same time.

7 Tests and Results

Just as the simpler algorithms from Fernandes *et al*. [2024] were tested, the same procedures were applied to the extensions mentioned in Section 6. They considered seven possible player actions and their respective consequences on the

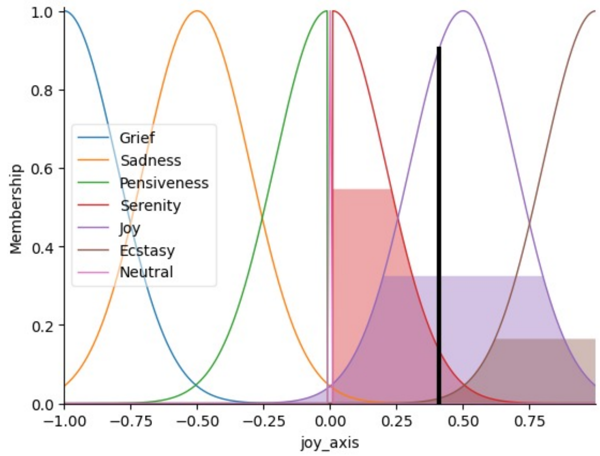


Figure 10. The consequents (outputs for Joy vs Sadness) are the axes of the emotions in Plutchik's wheel of emotions

neurotransmitter levels of NPCs (table 5). The expected emotional reactions to these actions are then compared to their actual resulting outputs on random initial states (table 6). Firstly, we analyzed the results from the upgraded Euclidean (table 3) and Fuzzy (table 4) methods' emotional points to see if they made sense.

After coding the Extended Cube of Emotions emotional models, several tests were conducted to observe if the emotions returned by the method were valid. The results obtained by inputting a set of 32 values of serotonin, dopamine, and noradrenaline, along with the responses of the developed method, are analyzed and compared with responses of the same value from the Euclidean and Fuzzy methods developed in the article Fernandes *et al*. [2024].

The Euclidean method from Fernandes *et al*. [2024] had limitations, such as the use of a single point to represent more than one emotion (mainly at the cube's vertices) and the fact that the intensity of emotions seems to be divided into different edges rather than being on the same edge. For example, if we insert values $(0, 1.0, 0.5)$ and $(0, 1.0, 0.65)$, the resulting emotion is Annoyance (the midpoint of an edge), but using $(0, 0.30, 1.0)$ results in Anger (a more intense emotion than Annoyance), which appears on a different edge from Annoyance (and is also represented at a midpoint).

Table 3, on the other hand, shows the result table obtained by the developed method using the Euclidean distance method. The first relevant difference is that the result no longer returns more than one emotion at the same point; however, several points still maintain valid values when compared to the inconsistencies pointed out from Fernandes *et al*. [2024]. Following the same example, we can already observe the changes. $(0, 1.0, 0.5)$ results in the emotion Annoyance, a point which remains the same, but $(0, 1.0, 0.65)$ returns the emotion Anger. This shows that the intensities of emotions can be represented by the movement of the point in the cube, as demonstrated above in tests 2 and 30 (as the point moves closer to the Anger point $(0, 1.0, 1.0)$, the emotion transitions from Annoyance to Anger and from Anger to Fury). However, this method is still limited to "feeling" only one emotion at a time.

Finally, table 4 shows the result table obtained by the developed Fuzzy Logic method at the same points as 3. The method offers a broader range of emotional responses, al-

#	Ser	Dop	Nor	Result
1	0	0	0	Humiliation
2	0	0	1.0	Grief
3	0	1.0	0	Terror
4	0	1.0	1.0	Rage
5	1.0	0	0	Loathing
6	1.0	0.5	0	Serenity
7	1.0	0.30	0	Disgust
8	0.5	0	0	Boredom
9	0.5	1.0	0	Serenity
10	0	0.5	0	Apprehension
11	0	0.7	0.8	Anger
12	1.0	0.5	1.0	Interest
13	0	1.0	0.5	Annoyance
14	1.0	0	0.62	Distraction
15	0.5	1.0	1.0	Interest
16	1.0	0	1.0	Amazement
17	1.0	1.0	1.0	Vigilance
18	0	0	0.5	Pensiveness
19	1.0	1.0	0.5	Interest
20	1.0	1.0	0	Ecstasy
21	0.5	0.5	0.5	Neutral
22	1.0	0.65	0	Joy
23	0.30	0	0	Shame
24	0.63	0	0	Disgust
25	0.63	1.0	0.12	Joy
26	0	0.63	0.2	Fear
27	0	1.0	0.65	Anger
28	0	0.30	1.0	Sadness
29	1.0	0	0.5	Distraction
30	0	1.0	0.5	Annoyance
31	0.5	1	0	Distraction

Table 3. Result of the developed method (euclidean distance).

#	Ser	Dop	Nor	Result
1	0	0	0	Humiliation, Fear
2	0	0	1	Grief, Shame, Anger, Surprise
3	0	1	0	Joy, Terror
4	0	1	1	Rage, Anticipation
5	1	0	0	Joy, Loathing, Surprise
6	1	0.5	0	Serenity, Disgust
7	1	0.3	0	Joy, Disgust, Surprise
8	0.5	0	0	Boredom, Fear, Surprise
9	0.5	1	0	Serenity, Fear, Anticipation
10	0	0.5	0	Shame, Apprehension
11	0	0.7	0.8	Sadness, Shame, Anger, Anticipation
12	1	0.5	1	Interest
13	0	1	0.5	Joy, Shame, Annoyance, Anticipation
14	1	0	0.62	Serenity, Disgust, Surprise
15	0.5	1	1	Shame, Anger, Interest
16	1	0	1	Amazement
17	1	1	1	Vigilance
18	0	0	0.5	Pensiveness
19	1	1	0.5	Joy, Interest
20	1	1	0	Ecstasy, Anticipation
21	0.5	0.5	0.5	Humiliation
22	1	0.65	0	Joy, Disgust, Surprise
23	0.3	0	0	Shame, Fear, Distraction
24	0.63	0	0	Joy, Disgust, Apprehension, Surprise
25	0.63	1	0.12	Joy, Fear, Anticipation
26	0	0.63	0.2	Joy, Shame, Fear
27	0	1	0.65	Shame, Anger, Anticipation
28	0	0.3	1	Sadness, Shame, Anger, Surprise
29	1	0	0.5	Joy, Disgust, Distraction
30	0	1.0	0.5	Sadness, Humiliation, Annoyance, Neutral
31	0.5	1	0	Sadness, Humiliation, Anger, Distraction

Table 4. Result of the developed method (fuzzy logic).

lowing multiple emotions to be expressed simultaneously. However, some results may be inconsistent, with unexpected emotions or weaker associations. While the ability to represent multiple emotions is a strength, these inconsistencies introduce unpredictability and reduce the method's reliability when used alone. To address this, the developed method will combine two approaches: Euclidean distance to ensure the most relevant emotion is identified, and Fuzzy Logic to allow for a diverse emotional range, ensuring more consistent and reliable outcomes while maintaining emotional complexity.

By consolidating the data from experiments presented in tables 3 and 4, we obtain the results presented in table 8. The simulation expected the impact of each player action on the NPC's neurotransmitters and its consequent emotion. It was planned as follows: For every initial emotion, it was analyzed the resulting emotions after a player's action. The accuracy criterion was whether the actions led to the expected emotions presented in table 6.

Action	Ser. Lev. Change	Nor. Lev. Change	Dop. Lev. Change
is_attacking	Decrease by 0.3	Increase by 0.3	None
is_giving_item	Increase by 0.1	None	Increase by 0.3
is_stealing_item	None	None	Decrease by 0.3
is_giving_money	None	Increase by 0.3	None
is_stealing_money	Increase by 0.1	Decrease by 0.3	Increase by 0.1
is_talking_politely	Increase by 0.3	None	Increase by 0.1
is_not_talking_politely	Decrease by 0.3	None	None

Table 5. Player actions and their impact on the levels of monoamine concentrations. Table obtained from Fernandes *et al*. [2024].

Action	Expected Emotions
is_attacking	Anger, Rage, Annoyance, Terror, Distraction, Grief, Fear
is_giving_item	Joy, Ecstasy, Interest, Amazement
is_stealing_item	Sadness, Apprehension, Pensiveness, Disgust, Annoyance, Loathing, Distraction
is_talking_politely	Boredom, Serenity, Surprise, Distraction
is_not_talking_politely	Pensiveness, Anticipation, Vigilance, Apprehension
is_giving_money	Amazement, Interest, Joy, Ecstasy
is_stealing_money	Distraction, Annoyance, Grief, Loathing, Rage, Disgust, Surprise, Fear, Anger

Table 6. Expected emotions from the updated methods based on player actions.

Analyzing the results presented in Fernandes *et al*. [2024] (table 7), we observe that the Extended method form Lövheim's cube had the worst overall performance. Although, the Euclidean method for Lövheim's cube produced notably different values, despite using the same approach as the extended cube in the next column. Its lower precision is due to considering fewer emotions. When comparing the fuzzy algorithm (which also uses the extended cube) with the others, there is an improvement in three actions, but a decline in the rest. However, the fuzzy results remain similar to those in the preceding column.

Action	Lövheim	Extented	Fuzzy
is_attacking	96.9%	78.31%	67.15%
is_giving_item	44.9%	82.48%	70.29%
is_stealing_item	53.1%	96.97%	100.00%
is_talking_politely	51.7%	72.28%	64.08%
is_not_talking_politely	30.0%	96.14%	100.00%
is_giving_money	22.9%	95.87%	100.00%
is_stealing_money	36.2%	71.00%	62.34%

Table 7. Result from Fernandes *et al*. [2024]

In contrast, the proposed model for the Euclidean method demonstrated better results compared to the extended method from Fernandes *et al*. [2024], indicating a more precise mapping of emotions (table 8). Additionally, the fuzzy method presented in the current work showed overall improved results for the tested actions. However, it performed slightly worse in the "is_attacking" action, suggesting that further refinements may be needed to enhance its accuracy in specific scenarios.

Action	Euclidean	Fuzzy
is_attacking	83.57%	61.08%
is_giving_item	87.58%	79.60%
is_stealing_item	97.25%	100.00%
is_talking_politely	78.94%	83.59%
is_not_talking_politely	96.14%	100.00%
is_giving_money	97.25%	100.00%
is_stealing_money	65.73%	70.43%

Table 8. Results based on expected emotions presented in Table 3 and Table 4

8 Conclusion

The work presented in Fernandes *et al*. [2024] introduces a novel emotion model that integrates Lövheim's Cube of Emotions with Plutchik's Wheel of Emotions, combining the dynamic aspects of the former with the rich detail of the latter. The first method applied Lövheim's framework and the Euclidean distance formula, while the second extended the cube and used the same formula to map emotions in greater detail. The final method incorporated Fuzzy Logic within the extended cube to account for the ambiguity of emotional states, while also allowing more than one emotion to be felt at the same time. The extended cube is crucial for applying fuzzy logic, as it defines an ordered distribution of emotions, which is not present in the basic cube. The goal of the present work was to upgrade the previous developed algorithms and the proposed extended cube. That base model was expanded from a 22-emotion mapping with 21 points to a more detailed version mapping 24 emotions across 52 points. The addition of 31 points allowed for improved emotional differentiation, with stronger emotions placed at the cube's vertices and less intense emotions distributed along its edges. This expansion also ensured that no two emotions are mapped to the same point.

The results presented in Table 8 indicated that the Euclidean method upgrade, when compared to Fernandes *et al*. [2024]'s algorithms, was more accurate. That indicates a more precise mapping of emotions. The Fuzzy Logic method, on the other hand, presented a slightly worse result in the "is_attacking" action. Considering all the other actions, however, we can observe a clear improvement on their performances. Compared to the previous fuzzy method, the actions "is_stealing_item", "is_not_talking_politely" and "is_giving_money" had results that remained the same, but "is_giving_item", "is_talking_politely" and "is_stealing_money" all had a substantial increase in the amount of times that the expected emotions were selected. The Euclidean method upgrade performed better, compared to the fuzzy method, in 2 of the 7 actions. Nevertheless, it presented more consistent results overall.

The Euclidean method is not an ideal approach for real-world decision-making, as it identifies only one emotion at a time, turning the behavior of the NPCs predictable and limiting their ability to respond to unexpected events. In contrast, the Fuzzy Logic method, allows for a more diverse range of emotional responses, which in turn makes it less predictable.

This work contributes to the simulation of emotions for non-player characters by extending the emotion model proposed in Fernandes *et al*. [2024]. It also updated the Euclidean and Fuzzy Logic implementations, improving their previous results. However, it remains clear that Fuzzy Logic can be quite confusing when used to create rules between neurotransmitters and emotions.

9 Future Works

In addition to the real-time simulation environment and other suggestions made in the original article (Fernandes *et al*. [2024]), the relationship between colors and emotions could be further explored, to have a more significant impact on NPC behavior or to visually represent the emotions that intelligent agents are experiencing during a simulation.

The psychological or cognitive effects of using colors to represent emotions must be validated. Tests with users should be conducted in future research to evaluate the effectiveness, interpretability, and potential impact of this visualization approach. These studies should help to determine whether the chosen colors enhance understanding or introduce biases in perception. Besides that, further statistical analyses will be performed with other formal methods such as significance testing.

Since Fuzzy Logic was used to calculate emotions in the proposed extended cube, it might be possible to develop a similar algorithm for Lövheim's original model, where the consequents are the eight vertices of the cube, to test and compare results. Another idea for future work would be to transform the Fuzzy Logic code into a fuzzy state machine, where characters would have emotional states and the transitions between these states could be modeled by their associations with neurotransmitter levels. This approach would also allow for partial and multiple emotions to be experienced, potentially reducing some of the inconsistencies observed in the inference system.

Declarations

Funding

This work was partially supported by CNPq (National Council for Scientific and Technological Development, linked to the Ministry of Science, Technology, and Innovation), CAPES (Coordination for the Improvement of Higher Education Personnel, linked to the Ministry of Education), FINEP (Brazilian Innovation Agency), and ICAD/VisionLab (PUCRio).

Authors' Contributions

PF conducted the investigation of the Lövheim cube and performed the experiments of the Extended and original Fuzzy methods. JP continued the exploration by improving the original model, mapping new emotional points and performing the experiments of the

Euclidean method and refinements of the fuzzy method. AB and BF guided JP and PF during the project execution process, collaborated with writing the article. BF also presented the article on SBGames.

Competing interests

The authors have no conflicts of interest to declare that are relevant to the content of this paper.

Availability of data and materials

All the algorithms that were developed and tested in this study are publicly available in the following Google Colab link: `https://colab.research.google.com/drive/1uraHLtoUwfVbVB-0vjZlZZWFlGJhCOU_?usp=sharing`

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