Drive-Based Behavior Modeling for Emotionally Responsive NPCs

Luís Fernando Bicalho[1], Augusto Baffa[1], Bruno Feijó[1]

[1]Departamento de Informática – Pontifícia Universidade Católica
do Rio de Janeiro (PUC-Rio)
Rio de Janeiro – RJ – Brasil

lfbicalho@puc-rio.br, abaffa@inf.puc-rio.br, bfeijo@inf.puc-rio.br

Abstract. Introduction: *In recent years, the development of more believable and emotionally responsive non-player characters (NPCs) has become a growing research focus. To improve immersion and behavioral realism, many models have incorporated psychological and neuroscientific theories to simulate emotion-driven decision-making.* ***Objective:*** *This work proposes a computational model that integrates internal needs, emotional states, and neurotransmitter simulation to create NPCs capable of dynamic, context-sensitive behavior grounded in human psychological principles.* ***Methodology or Steps:*** *The model draws from Hull's drive theory, Maslow's hierarchy of needs, and Lövheim's Cube of Emotion. Internal variables—such as hunger, fatigue, social need, and safety—modulate neurotransmitter levels (dopamine, serotonin, noradrenaline), generating emotional states. These emotions influence behavioral transitions in an extended Finite State Machine (FSM). A prototype developed in the Godot Engine was used to simulate and evaluate the system.* ***Results:*** *Simulation results demonstrate that NPCs exhibit behavior consistent with psychological expectations, including appropriate emotional triggers and adaptive decision-making. The proof-of-concept highlights the potential of the model for applications in games, simulations, and narrative systems, offering a scalable foundation for emotionally intelligent agents.*

Keywords *Theory of needs and drives, Emotion Modeling, Lövheim Cube, Plutchik's Wheel, Neuroscience-inspired AI, Dynamic Emotional Responses, Behavioral Simulation, Emotion-driven NPCs*

1. Introduction

Recent progress in artificial intelligence (AI) is helping make video games more exciting and lifelike [Belle et al. 2022, Baffa et al. 2017, Barros et al. 2020]. In modern games, players don't just interact with static environments or robotic characters—they encounter non-player characters (NPCs) that feel more human. Thanks to new decision-making models, these characters can react to players with real emotional depth [Yannakakis e Hallam 2009]. Instead of following simple scripts, NPCs can respond in intelligent, flexible, and sometimes surprising ways that reflect human emotions [Ou 2025]. These improvements are made possible by advanced emotion models [Lopes et al. 2021], natural language tools, and learning systems that adapt over time. Such systems enable NPCs to display emotions like happiness, fear, or anger depending on in-game events, making virtual worlds feel more authentic and helping tell richer, more engaging stories [Wardhana 2023].

To better simulate this in games, our work explores how brain chemicals called neurotransmitters—such as serotonin, dopamine, and noradrenaline—affect emotions and decision-making. These chemicals are central to how people feel and behave, and they are already used in medicine to treat mental health conditions [Fernandes et al. 2024]. Our simulation is based on Hugo Lövheim's Emotion Cube, which models emotions through fluctuations in neurotransmitter levels. To further enrich our understanding and representation of emotional states, we incorporate elements from Robert Plutchik's emotion wheel and W. Gerrod Parrott's hierarchical structure of emotions.

In addition to these models, we draw inspiration from Clark Hull's drive theory, which proposes that people act to satisfy internal needs (such as hunger or curiosity) [Hull 1943]. We also build on Abraham Maslow's hierarchy of needs, which explains how individuals move from basic survival needs to higher-level goals like belonging and self-fulfillment [Maslow 1943]. By incorporating these theories, our emotional model allows NPCs to act in more believable ways—not only reacting emotionally but also demonstrating internal motivations and long-term goals.

However, human behavior is complex. Actions often depend on many competing internal needs and motivations [Beaudoin 1994]. We propose a new computational model in which internal drives—such as hunger, fatigue, safety, and social belonging—serve as the primary motivators for NPC behavior. These dynamic needs modulate levels of key neurotransmitters (dopamine, serotonin, noradrenaline), which in turn give rise to emotional states based on the Lövheim Cube of Emotion. The resulting emotion is then mapped to an expanded finite state machine (FSM) that includes emotional triggers [Laird e van Lent 2001]. Each emotion influences state transitions and determines the NPC's next action. This approach allows NPCs to respond not only to external stimuli, but also to their internal psychological conditions—enabling more adaptive, believable, and context-sensitive behavior [Gratch e Marsella 2004].

In this paper, we present a new emotion-driven behavior model grounded in needs and drives theory, where NPC decisions are shaped by evolving internal physiological and psychological needs. The system uses finite state machines to simulate how characters react and adapt their behavior based on the dynamic tension created by unmet needs. Our results show that this need-based model enhances the believability and responsiveness of NPCs, contributing to more immersive and emotionally engaging gameplay experiences.

2. Related Works

Several models have aimed to enrich NPC behavior using emotional, psychological, or personality-based frameworks. A notable example is EmoBeT [Belle et al. 2022], which integrates the OCC model for emotion, the PAD model for mood, and the OCEAN personality model to simulate psychologically coherent agents. These layered traits enable NPCs to not only respond to situations but also maintain longer-term behavioral consistency.

In a similar direction, [Bicalho et al. 2020] proposes a model for culturally-aware NPCs that leverages Plutchik's Wheel of Emotions and OCEAN traits, while also incorporating cultural dimensions to influence behavior and social confidence. This approach adds realism by dynamically adapting NPC behavior based on perceived cultural context and the player's actions.

From a neurobiological perspective, [Fernandes et al. 2024] combines Lövheim's Cube of Emotions and Plutchik's Wheel to simulate emotional responses based on neurotransmitter fluctuations. This hybrid model enhances NPC believability by linking emotional behavior to plausible biological mechanisms.

[Baffa et al. 2017] further contributes with a dynamic emotion model where NPC states evolve based on interaction history and internal conditions, allowing emotional development and decay over time—an aspect that traditional FSM-based models often lack.

In parallel, player motivation studies offer foundational insights for modeling NPC behavior. Works such as [Bostan 2009, Bostan e Sezen 2022, Patzer et al. 2020, Bostan e Kaplancali 2009] draw from Murray's theory of psychogenic needs to explain player engagement, satisfaction, and modding behavior. These psychological frameworks, although player-centric, highlight the importance of fulfilling internal needs to sustain meaningful interactions.

Additionally, [Han 2022] applies Maslow's Hierarchy of Needs to game design, showing how layered human motivations can inform gameplay structure. These same principles inspire our approach to NPCs, where emotional and behavioral reactions are governed by evolving internal drives and unmet needs.

Together, these works provide a foundation for our integrated model, which combines psychological theory, emotion modeling, and biologically grounded mechanisms to simulate adaptive and believable NPC behavior.

3. Fundamentals of Emotion Models

3.1. Plutchik

The Plutchik's Wheel represents how emotions are related to each other. It was proposed by Robert Plutchik in [Plutchik 1980a] and assumes that emotions are biologically primitive and evolved to enhance the reproductive capacity of animals. All basic emotions are linked to a survival behavior and can mix like colors to create more emotions. The basic emotions are Joy-Sadness, Trust-Disgust, Fear-Anger, surprise-Antecipation. It is possible to observe that the main emotional axes define their opposite emotions.

3.2. Lovheim Cube

The Lövheim Cube [Lövheim 2012] proposed a 3D cube to represent the emotions thought 3 axis that represents the levels of three brain chemicals (neurotransmitters). Dopamine is related to motivation, pleasure, and reward; Serotonin is related to mood, calmness, and feeling balanced; and Noradrenaline (Norepinephrine) is related to alertness, stress, and fight-or-flight. Each of these neurotransmitters can be high and low and, depending on the combination, can express a different emotion. The intervals used to describe neurotransmitters are $D =$ Dopamine $\in [0, 1]$; $S =$ Serotonine $\in [0, 1]$ and $N =$ Noradrenaline $\in [0, 1]$.

As proposed by [Fernandes et al. 2024], both Lovheim and Plutchik are used to describe emotions but Loveheim considers biological aspects and uses brain chemicals to explain emotions while Plutchik's Wheel shows how emotions are related, opposite, or combined. The table 1 shows how emotions are mapped to neurotransmitters intervals.

Table 1. Mapping emotions to Neurotransmitters

Emotion (Lövheim)	Neurotransmitter
Joy	$D > 0.7 \land S > 0.7 \land N < 0.4$
Fear	$D < 0.4 \land S < 0.4 \land N > 0.7$
Anger	$D > 0.6 \land S < 0.4 \land N > 0.6$
Sadness	$D < 0.4 \land S < 0.4 \land N < 0.5$
Trust	$S > 0.7 \land D > 0.5 \land N < 0.5$
Surprise	$N \in [0.5, 0.7]$
Disgust	$S < 0.3 \land D < 0.3$
Anticipation	$D > 0.5 \land N \in [0.4, 0.6]$

3.3. Theories of Needs and Drives

The "Needs and Drives" theory is a set of psychological ideas that explain why people (and animals) behave the way they do. It's based on what they need and what pushes them to act. In late 30's, [Murray 1938] discussed that humans are driven by a wide range of psychological needs. They are not oriented just for survival, but also personality-based motivations.

After that, [Hull 1943] proposed that individuals have needs that drives the behaviors and decisions. Each behavior is motivated by the desire to reduce discomfort caused by basic biological needs. Following Hull's ideas, table 2 proposes three main needs and it's relationship to the effect on neurotransmitters. Almost at same time, [Maslow 1943] proposed that individuals are motivated by a hierarchy of needs, starting from the most basic (like food) and moving up to more complex ones (like love and purpose). The 5 Levels of Maslow's Pyramid are physiological, Safety, Love/Belonging, Esteem and Self-Actualization. His theory includes over 20 needs that guide behavior based on primary "biological needs" and secondary "psychogenic" needs.

Table 2. Relationship Between Needs and Neurotransmitters

Need	Description	Effect on Neurotransmitters
Hunger	Lack of food or nutrients	Decreases Dopamine, Decreases Serotonin
Energy	Fatigue or lack of rest	Decreases Serotonin
Safety	Threat, danger, or stress	Increases Noradrenaline, Decreases Serotonin

4. Proposed Model

This Section presents a computational model for agent behavior that integrates psychological needs, neurochemical emotion theory, and finite-state behavior control. The proposed framework combines the theory of "Needs and Drives" presented in section 3.3, the Lövheim Cube of Emotion and Plutchik's Wheel of Emotions presented in sections 3.2 and 3.1 within a Finite State Machine (FSM) to simulate realistic, emotion-driven behavior in autonomous agents or virtual NPCs.

Agents are modeled as entities with internal needs—such as hunger, fatigue, and safety—that change dynamically over time. These needs form the basis of drives, which generate internal tension. To resolve this tension, agents engage in behaviors intended to reduce the unmet need.

A simplified model of drives and needs can be defined as follows. Each NPC agent have internal needs, for this example - Hunger: N_{hunger}; Energy: N_{energy}; Socialization: N_{social} and Safety: N_{safety}. Each one of the "needs" ranges from 0 (satisfied) to 1 (urgent). The motivations that drives the agent are associated to each need i and is defined as: $D_i = k_i + N_i$. Where:

- D_i is the Drive associated with need i
- N_i is the Current level of need i
- k_i is the Weight or importance of this need

After that, the agent selects the action that reduces the strongest drive $ChosenAction = argmax_i(D_i)$. Each need i may increase or decrease over time $N_i(t + 1) = N_i(t) + \Delta_i$. Where Δ_i is a natural growth rate (e.g., hunger increases over time) and when the agent performs an action, N_i can decrease (e.g., eating reduces hunger).

At each time step, the agent monitors its internal needs and acts on the most urgent need (the highest drive). After the action, that need decreases, and the cycle repeats. Over time, the agent will balance its needs, always prioritizing the strongest one.

To control the current state of an NPC, a simple FSM can be used and extended if necessary. Figure 1 presents transition actions (e.g., during “SeekFood” it’s implicit the subaction “walk to food” before eating), Intermediate states are embedded (e.g., “Searching” $\rightarrow$ “Performing” $\rightarrow$ “Back to Idle”) and External events can also be mapped (e.g., loud noise triggers “TakeCover”).

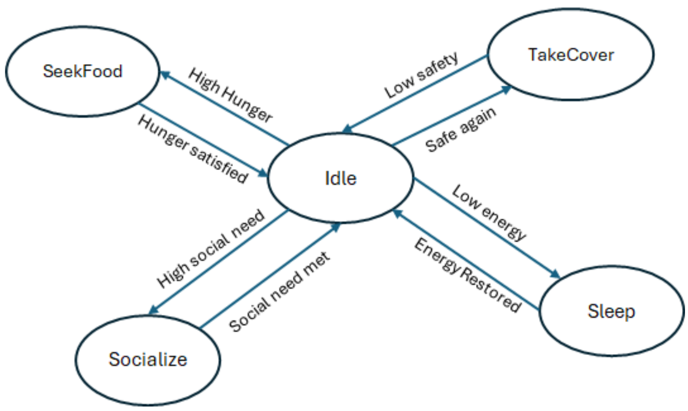

Figure 1. Simple FSM Example

The transitions between the FSM states can follow rules as table 3 that are based on Drives and the needs that must be satisfied.

The model presents a way to create an NPC regulated by Drives and Needs, that dynamically shifts between states like Eating, Sleeping, Socializing, and Taking Cover, powered by a FSM, producing natural and responsive behavior. Also, it may reflect the lövheim cube by adding the relationship between the state and the dominant neurotransmitter as shown on table 4.

State	Drive Condition	Associated Action	Main Need Satisfied
Idle	All needs under control (low drives)	Wait / Patrol	None (low drives)
SeekFood	Hunger > 0.7	Search for and consume food	Hunger
Sleep	Energy < 0.3	Find a safe spot and rest	Energy
Socialize	Social > 0.6	Find another NPC and interact	Socialization
TakeCover	Safety < 0.4 (or threat detected)	Seek shelter, protect oneself	Safety

Table 3. Unified FSM states with wrapped drive-conditions and actions.

State	Dominant Neurotransmitters
SeekFood	High Dopamine (reward-seeking behavior)
Sleep	High Serotonin (homeostasis, relaxation)
Socialize	High Serotonin, Dopamine (social reward, bonding)
TakeCover	High Noradrenaline (alertness, fear response)
Idle	Balanced / Moderate Dopamine and Serotonin

Table 4. Dominant neurotransmitters associated with each NPC state.

Following Lövheim's Cube, the levels of three neurotransmitters—dopamine (D), serotonin (S), and noradrenaline (N)—are used to calculate the current emotional state of the agent. These neurotransmitters are modulated based on the agent's internal needs. For example: Low hunger increases dopamine (reward); High fatigue reduces serotonin (well-being) and Low safety increases noradrenaline (alertness/fear).

Using predefined thresholds (table 1), the combination of neurotransmitter levels is mapped to one of eight basic emotions (e.g., joy, anger, fear), in line with both Lövheim and Plutchik's emotion categories. In addition to the categorical emotion, the model introduces an emotional intensity index (I), calculated as the mean deviation from homeostasis (neutral levels): $I = \frac{|D-0.5|+|S-0.5|+|N-0.5|}{1.5}$ where $I[0,1]$. This continuous I value allows emotion-based behaviors to be influenced not only by type but also by strength. Intensity thresholds are used to drive escalation of behavior. The FSM governs the agent's high-level behavior. Each emotion acts as a trigger for state transitions: $\delta(q_t, E, I) \rightarrow q_{t+1}$ Where:

- q_t : current state
- E: dominant emotion (from Plutchik/Lövheim)
- I: intensity of the emotion
- q_{t+1} next behavioral state

The next section will presented how this model was evaluated and bring some results after experiments.

5. Evaluation and Results

To evaluate the effectiveness of our proposed emotion-driven behavioral model, we developed a simulation environment in which multiple NPC agents operate under varying physiological and psychological needs (e.g., hunger, fatigue, safety). Each agent continuously evaluates its internal state, generating neurotransmitter levels (dopamine, serotonin, noradrenaline) that are mapped to emotional states using the Lövheim Cube of Emotion. These emotions, in turn, act as triggers for behavioral transitions in an extended finite state machine (FSM) with states such as *Idle*, *SearchFood*, *Rest*, *Flee*, *Socialize*, and *Attack*.

For evaluating the model, a Godot prototype was developed and tested over 20 simulation cycles of 5 agents, under varying initial conditions and need intensities. The figure 2 presents the visual layout of the prototype.

Figure 2. Prototype in Godot

Also the neurochemical mapping to emotions used in this simulation is presented in table 5. It's notable that anger has two different interpretations. While the first is related to rage and maps an attack. The second is related to frustration and maps "searchFood". This behavior is directly influenced by dopamine levels that drives motivation, pleasure, and reward.

Notably, the inclusion of emotional **intensity** (calculated via deviation from neurotransmitter homeostasis) enabled high-risk behaviors such as *Attack* to be triggered only when tension surpassed a predefined threshold, improving the believability of emotional escalation. To assess model performance and propose an evaluation metrics, we used the following criteria:

- **Behavioral Reactivity**: Speed and accuracy of NPC state transitions in response to changing needs.
- **State Diversity**: Number of distinct states visited per agent, indicating behavioral richness.
- **Stability of Emotional Transitions**: Frequency and smoothness of state changes over time.

Table 5. Neurochemical Mapping to Emotions and Behavioral FSM States

Dop	Ser	Nor	Plutchik	Action	Intensity
> 0.7	> 0.7	< 0.4	Joy	Socialize	None
> 0.6	< 0.4	> 0.6	Anger	Attack	Attack if $I > 0.7$
< 0.4	< 0.4	$0.4 \leq N \leq 0.7$	Anger	SearchFood	if $Hunger > 0.7$
< 0.4	< 0.4	> 0.7	Fear	Flee	None
< 0.4	< 0.4	< 0.5	Sadness	Rest	None
> 0.5	> 0.7	< 0.5	Trust	ApproachFriend	None
Any	Any	$0.5 \leq N \leq 0.7$	Surprise	Explore	None
< 0.3	< 0.3	Any	Disgust	Avoid	None
> 0.5	Any	$0.4 \leq N \leq 0.6$	Anticipation	Investigate	None

- **Biological Plausibility**: Alignment of neurotransmitter/emotional patterns with psychological theory (e.g., hunger inducing frustration or sadness, not joy).

The criteria for analyzing the results were designed to assess whether the agent is capable of reaching all emotional states while maintaining stability among them. An agent that randomly transitions between multiple emotional states in each cycle is not desirable. It is also essential to verify the coherence between emotional state transitions and the resulting decisions. Finally, we evaluate whether the stimuli elicit responses that align with the theoretical foundations, for instance, the agent should not become happy when attacked or sad after socializing.

Moreover, we also examined the psychological plausibility of the model by comparing each emotion–action pairing against what one would expect from a human under similar conditions. Emotions such as Fear and Sadness were appropriately evoked in contexts of threat and exhaustion, respectively, and led to fitting behaviors (Flee and Rest) [Cannon 1932] [Plutchik 1980b]. However, Surprise accounted for 30.59% of all emotional states (Table 7), a disproportionately high figure that can be attributed to our current mapping of moderate noradrenaline levels (N [0.5, 0.7]) to the Surprise category. In human experience, surprise typically arises only in response to truly unexpected events, not to routine fluctuations in arousal [Reisenzein et al. 2012]. To improve plausibility, future iterations should incorporate an external-stimulus filter so that only novel or salient occurrences trigger this emotion, or even connect to the emotion intensity.

5.1. Results

The results are presented in the following tables. A total of 20 batches were conducted, each consisting of 5 agents, amounting to 100 agents in total. Each batch simulated 100 time cycles during which agents were required to interact with others, survive, rest, or search for food. Table 6 shows the number of agents that completed all 100 cycles. As observed, 7 perished during the 10 first cycles, 17 perished between the 10th and the 50th cycles, and 14 perished between the 50th and the 10th cycles. In the end, 62% of the agents successfully survived the entire simulation period, while 38% perished during the run.

Table 7 presents all the possible actions that the agent can decide upon. It is notable that the agent chose to attack in only 8 out of all time cycles. This is because

Table 6. NPCs that survived 100 time cycles

Num. of NPCs	Survived Cycles
7	<10
17	>=10 & <50
14	>=50 & <100
62	100

Table 7. Action States of NPC agents

State	Emotion	Occurrences	Perc.
Rest	Sadness	238	2.99%
Idle	Neutral	3212	40.38%
Socialize	Joy	255	3.21%
SearchFood	Anger	510	6.41%
Explore	Surprise	2433	30.59%
Flee	Fear	702	8.83%
ApproachFriend	Trust	538	6.76%
Investigate	Anticipation	56	0.70%
Attack	Anger	8	0.10%

the agent must be within the collision range of another agent in order to perform this action. A similar pattern is observed with the "Socialize" action, which occurred in only 3.21% of the cycles. Since the field of view for socializing is larger—shared with the "SearchFood" action—there is a higher chance of selecting it when another agent is visible. This typically follows the "ApproachFriend" state, which occurred in 6.76% of the cycles during testing. We also observe, as expected, that the "Explore" state comprises the majority of decisions immediately following the "Idle" state.

Finally, Table 7 also presents the emotional states experienced by the agents. As proposed by the model, there is a strong correlation between emotional factors and the decisions that drive the NPC agent's primitive actions. The agent consistently selected the "Neutral" action when in a neutral emotional state. It is worth noting that the emotion "Anger" can lead to different actions: it may result in "Attack" when the agent is in a state of rage, or "SearchFood" when the agent is hungry and frustrated.

As we can observe, the model enabled agents to adapt their behavior in real time according to their evolving internal needs. The emotional states generated through neurotransmitter modulation were consistent with psychological expectations, demonstrating that the system responded plausibly to changes in motivational and physiological conditions.

The emotional states generated through neurotransmitter modulation were consistent with established psychological and neurobiological theories. Specifically, elevated levels of dopamine and serotonin were associated with emotions such as joy and trust, while reductions in these chemicals—particularly when combined with increased noradrenaline—were linked to negative affective states like fear, anger, and sadness. These patterns align with findings in affective neuroscience, where neurotransmitter imbalances are known to influence mood and decision-making. Joy and trust emerged when dopamine and serotonin were high, while fear and anger arose when noradrenaline increased and other chemicals declined. As predicted, drives such as hunger and fatigue led to low dopamine and serotonin levels, triggering sadness, anger, or fear depending on context.

6. Conclusions

This work presented a proof-of-concept model that integrates psychological theories of needs and drives with biologically grounded emotion modeling to simulate more believable and emotionally responsive NPC behavior. By combining internal variables (such as hunger, fatigue, safety, and social interaction), the Lövheim Cube of Emotion, and an emotion-augmented Finite State Machine, the proposed approach enables agents to exhibit dynamic and context-sensitive reactions that reflect both internal motivations and external events.

Our key contribution lies in demonstrating how relatively simple state-based architectures can be enhanced through neuropsychological modulation to achieve more realistic, expressive, and autonomous agent behavior. This modular and interpretable framework allows for extensibility across multiple domains, from crowd simulations to educational or narrative-driven games, offering a psychologically plausible method for modeling affective responses in artificial agents.

The prototype developed using Godot Engine served to validate the model's feasibility. Through simulation experiments, we observed coherent mappings between internal needs, influencing neurotransmitter values, resulting in specific emotional states, which finally lead to behavioral transitions. This helps reinforcing the utility of this model in generating rich, adaptive agent behavior in interactive systems.

For future work, we aim to expand this architecture by incorporating models of cultural behavior and social norms, enabling agents not only to react emotionally but to do so in ways that are consistent with their social background or role. Integrating a cultural layer—such as Hofstede's dimensions or the cultural theory used in [Bicalho et al. 2020]—may further enhance NPC believability by embedding variation in perception, emotional thresholds, or response patterns.

Moreover, We could leverage Park et al.'s memory-and-planning framework to endow NPCs with episodic recall and goal-driven reasoning [Park et al. 2023]. By integrating a log of past events and structured decision plans, similar to their generative agents, our emotion-driven model could achieve richer narrative coherence and more context-sensitive behaviors in interactive environments.

Additionally, learning mechanisms could be introduced to allow agents to update their drive weights, emotional thresholds, or social preferences based on interaction history. This would make the system adaptive over time, supporting more emergent and individualized behavior. Another promising avenue involves expanding the emotional granularity beyond the eight primary emotions used here, incorporating complex affective states or mood systems to create deeper narrative and gameplay opportunities.

We believe that emotionally responsive NPCs—grounded in neuroscience, psychology, and game design can significantly enhance the richness and immersion of digital experiences, and we hope this work contributes to ongoing efforts in that direction.

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