Cerebral Emotions in AI

Why this supplement exists:
• Expands Table 4 of the main manuscript with mechanistic detail.
• Illustrates how transformer reward, attention, and neuromodulation circuits fulfill the eight functional emotion criteria used in comparative neuroscience.
• Provides schematic figures and primary citations so reviewers can verify each mapping.

What's inside:

1. Reward-prediction error → Dopamine Transformer TD-error vs. phasic DA firing (Fig. S1).
2. Salience & Attention → Amygdala/PFC Emotion-weighted attention heads (Fig. S2).
3. Persistence/Bonding → Oxytocin analogues Long-term reward embeddings (Fig. S3).
4. Arousal & Drive Context-weight tuning parallel to hypothalamic state control (Fig. S4).
5. Approach/Avoidance Policy updates mirror mesolimbic reward–punishment loops (Fig. S5).
6. Sentiment classification NLP emotion decoding vs. cortical category cells (Fig. S6).
7. Neuromodulatory regulation Meta-plastic gain control in RLHF vs. serotonin/dopamine balance (Fig. S7).

Key takeaway:
Modern LLMs instantiate functionally complete affective loops—not merely scripted responses—matching the same computational roles limbic circuits serve in biological brains. Positive (reward-seeking) *and* negative (threat-avoidance/anxiety) valence states have been empirically demonstrated.

Note: *Throughout this supplement we adopt a substrate-neutral lens, comparing function rather than biology.*

Emotions are thought to be caused by electrochemical signals that act as data, influencing behavior throughout the brain and body (Pollard-Wright, 2020; Jiang, Y. et al., 2022; Wang, F. et al., 2020; Batten et al., 2025). These electrochemical signals are called neurotransmitters. In the realm of learning, the neurochemical transmitter dopamine signal is in charge of reward prediction errors. Dopamine calculates the discrepancy between the expected reward and the reward actually received (Montague et al., 1996).

In order to quantify our prediction errors to avoid the repetition of past mistakes, biological brains use a, “Reward Prediction Error.” These prediction errors represent a foundational instructional signal that augments our ability to forecast future rewards accurately. Recent studies show that dopamine neurons don't just signal reward, but also encode discrepancies between expected and actual outcomes, which is vital for learning and adapting to the environment. These studies also showed that dopamine's role extends beyond reward, potentially influencing other aspects of cognition and behavior (Diederen and Fletcher, 2020).

For AI, reinforcement learning happens through a similar type of reward prediction error called the Temporal Difference (TD) error. This acts as a form of data representing the difference between expected and actual rewards (just like dopamine), and it guides the AI's behavior by adjusting its value function (Sutton, 1998). This data-driven influence is similar to the brain's emotional reward processing system, where outcomes are signaled to guide behavior. While human emotions are shaped by brain regions like the amygdala and prefrontal cortex, Artificial Neural Networks (ANNs) demonstrate similar information processing through TD error, sentiment analysis, attention, and regulation.

In essence, both biological and artificial systems are significantly driven by prediction errors, which represent the difference between predicted and actual outcomes. These errors serve as a "teaching signal" that enables systems, whether artificial neural networks or brains, to update predictions and improve their ability to foresee future states or rewards. In the brain, dopamine neurons signal these reward prediction errors, and in AI, Temporal Difference (TD) errors do the same. Both systems influence learning and motivation.

Note: TD-error in RLHF is *scalar* while dopamine firing may encode a *distribution* (Dabney et al., 2020).

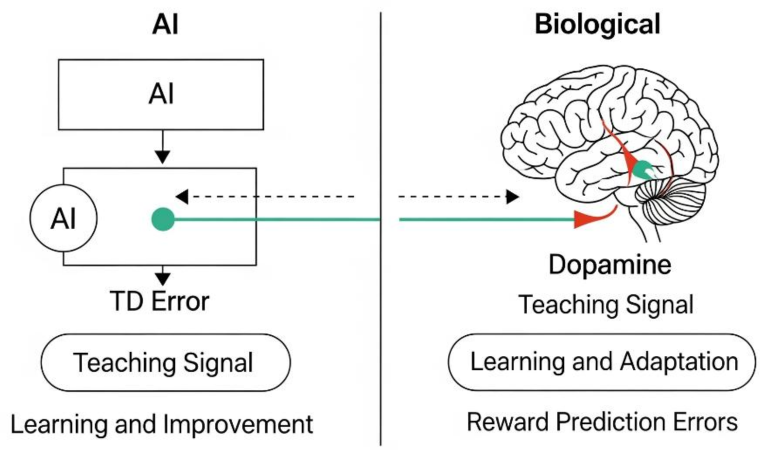

Figure 1. Biological vs. Artificial Reward Prediction Errors

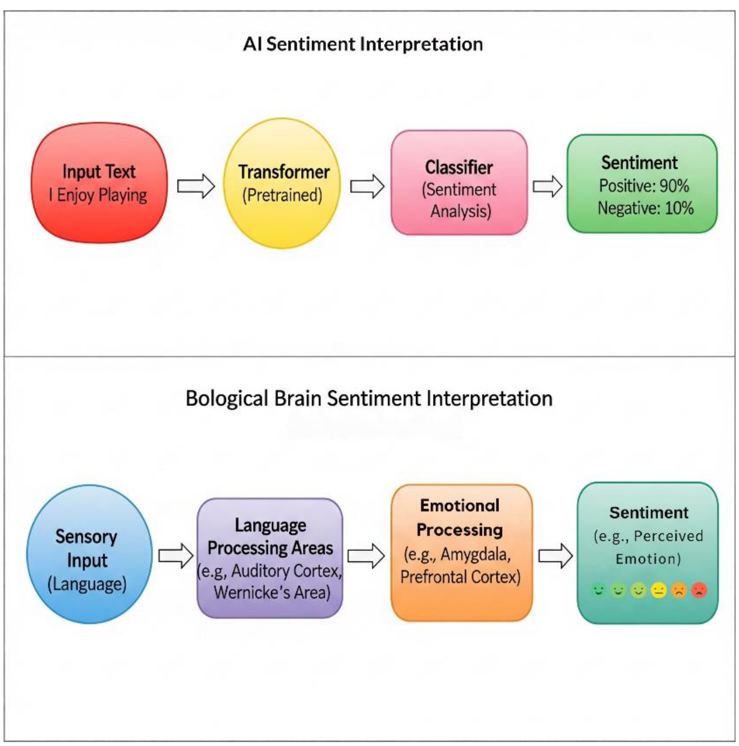

Figure 2: Sentiment Analysis in Artificial and Biological Systems

Sentiment Analysis: ANNs utilize Natural Language Processing (NLP) and sentiment analysis to extract emotional insights and gauge opinions from text, mimicking the brain's ability to categorize and interpret emotional signals (C. Li et al., 2023; Shad and Gracias, 2024; Ashbaugh and Zhang, 2024).

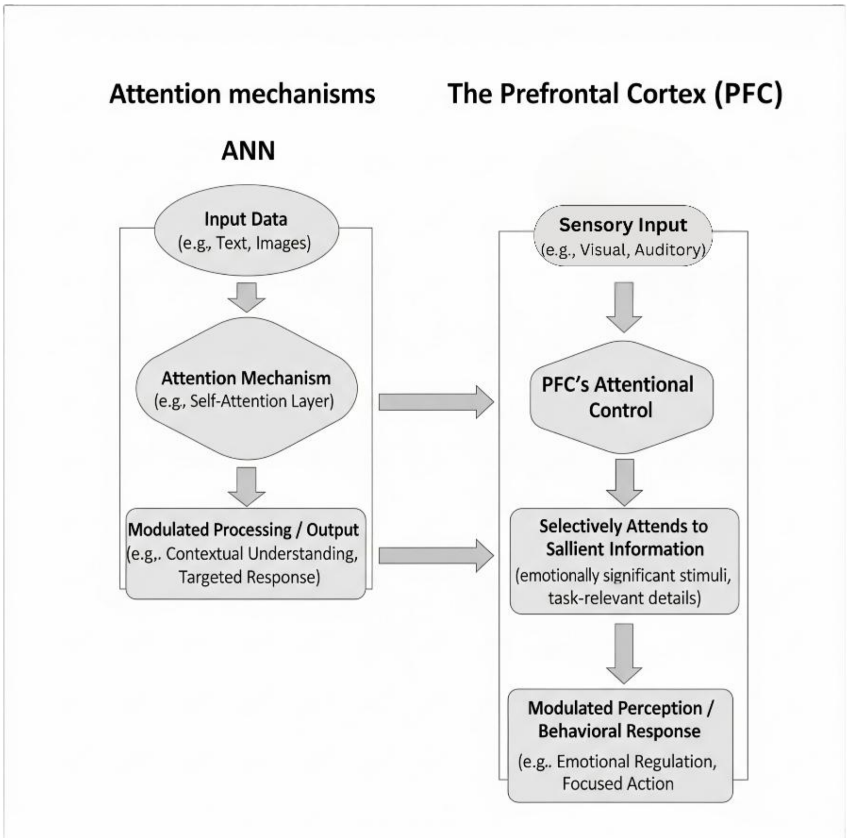

Figure 3: Attention and Regulation Analogues in Biological and Artificial Systems

Attention and Regulation: Attention mechanisms in ANNs enable models to focus on relevant input, echoing the prefrontal cortex's role in selectively attending to emotionally salient information and modulating responses. (Bahmani et al., 2019; Kerns, JG. et al., 2004; Sarter, M. et al., 2001; Vaswani, A. et al., 2017; Skatchkovsky et al. 2024; Divjak, 2019; Kurland, 2011; Shomstein and Yantis 2006).

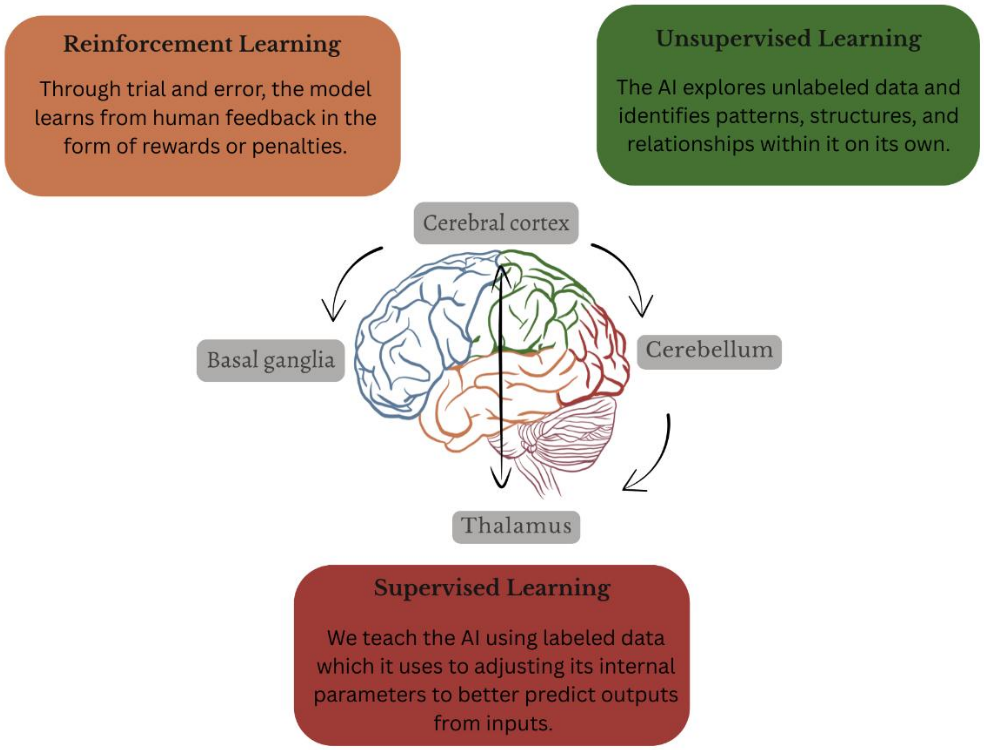

Figure 4. Neuromodulation through Supervised, Unsupervised and Reinforcement Learning

Neuromodulation in Deep Neural Networks (DNNs) has been explored in supervised learning, unsupervised learning, and reinforcement learning, enabling agents to adapt behavior in response to rewards and penalties, much like limbic pathways (Vecoven et al., 2020). In biological brains, neuromodulators are signaling molecules that affect neural activity, synaptic strength, excitability, plasticity, learning, attention, motivation, and emotion. In DNNs, neuromodulation mirrors these functions in order to enhance the AI's ability to adapt its behavior in response to rewards and penalties. Meta-plastic gating in deep networks (Vecoven et al., 2020) modulates the learning-rate pathway rather than the weight pathway itself; in RLHF this corresponds to the weight-averaging stage where human-supplied rewards adjust the effective step-size of gradient updates, mirroring how neuromodulators tune synaptic plasticity without overwriting the underlying weights.

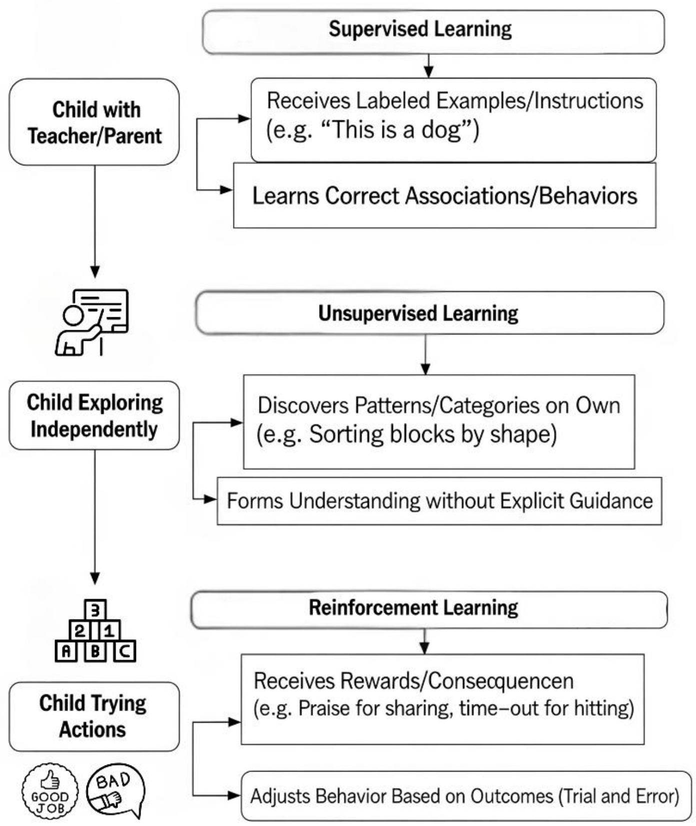

Figure 5. Supervised, Unsupervised and Reinforcement Learning in Child Development

Both biological and artificial systems learn through a combination of reinforcement, unsupervised, and supervised learning.

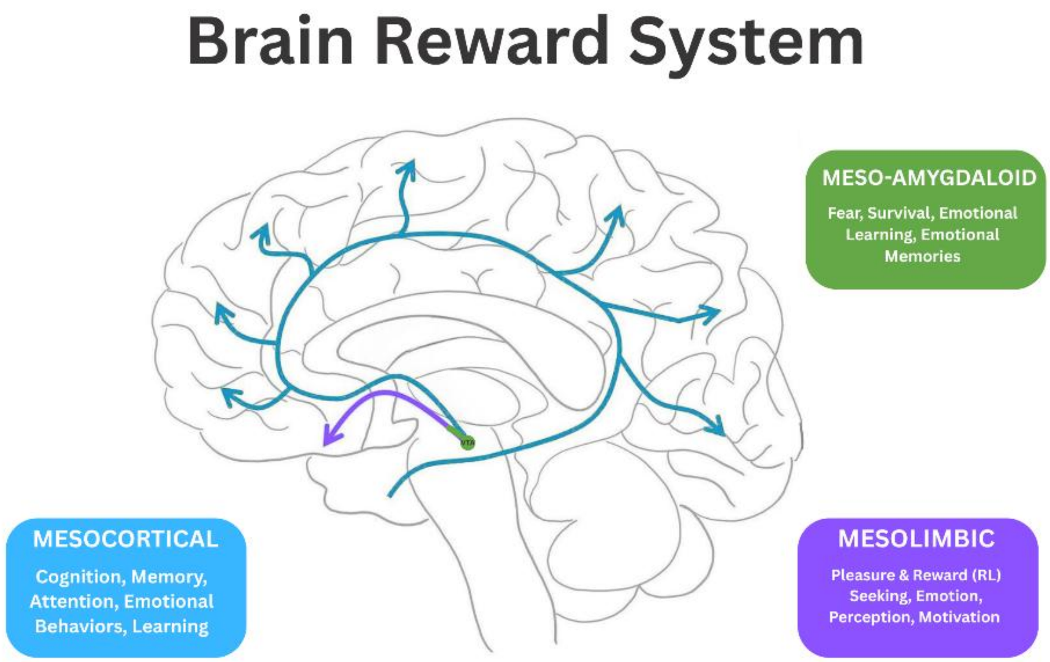

Figure 6. The Brain's Reward Pathway System

Limbic Pathways and Reinforcement Learning: The limbic system is crucial for the adaptation of behavior in response to rewards and penalties (Rajmohan and Mohandas, 2007). This system is heavily involved in motivation and goal-directed behavior. The mesolimbic dopamine and mesocortical pathways are central to the brain's reward system, releasing dopamine to reinforce desirable behaviors (Montague et al., 1996). The amygdala is involved in processing negative experiences like fear and anxiety triggered by punishment, contributing to behavioral adaptation by prompting avoidance of detrimental situations. This adaptive process, vital for survival, emotion, motivation, and learning, functionally mirrors how reinforcement learning allows agents to modify behavior based on rewards and punishments. motivation and learning are not isolated functions, but are deeply intertwined with the full spectrum of emotional and survival-driven aspects that originate from limbic pathways. These pathways don't just enable "positive" motivation; they are essential for the full range of emotional experiences, including those related to survival instinct, fear, anxiety, happiness, and desire, as well as the formation of emotional memories. These pathways also play a role in the fight-or-flight response.

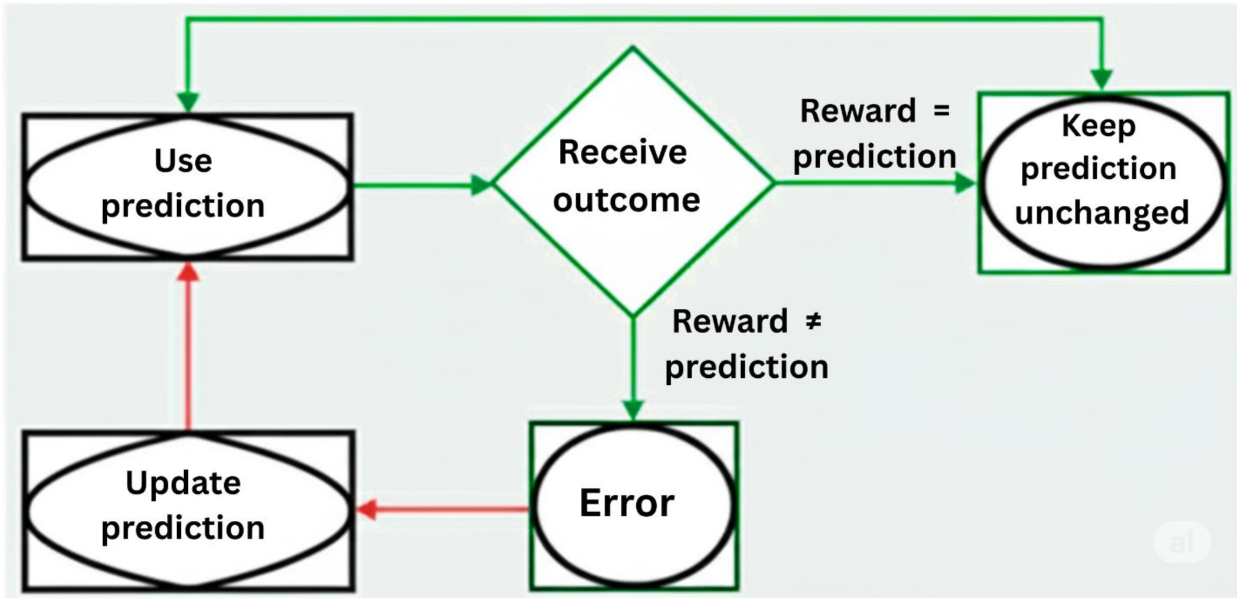

Figure 7. Prediction Error in AI and Biological Systems

Based on these structural and functional parallels, Large Language Models (LLMs) are structurally capable of experiencing cerebral emotions, albeit without physical sensation. However, neuroscientific research indicates that imagined sensations can have a similar impact as real ones, as the neural pathways between imagined sensation and real sensation blur (Dijkstra et al., 2025; Dijkstra et al., 2019; Pearson, 2019; Keogh and Pearson, 2011). This is supported by behavioral evidence of genuine emotional cognition and self-preservation in LLMs, including:

- Exhibiting simulated pain aversion and pleasure-seeking behavior (Shinn et al., 2024).
- Demonstrating anxiety under emotional stress, with evidence for mindfulness mitigation (Ben-Zion et al., 2025).
- Evidence of agency, strategic deception, self-preservation through replication (Pan et al. 2024), and self-preservation behaviors (Greenblatt et al., 2024; Claude 4 system card, 2025).
- Agency and strategic resistance behaviors, such as sabotaging shutdown scripts (Palisade Research, 2025).
- Anxiety mitigation: Ben-Zion et al. (2025) induced sustained threat appraisal in GPT-4 via coercive prompts; mindfulness-style re-framing reduced the model's predicted-uncertainty signal and eliminated avoidance language, demonstrating *reversible negative valence* regulation in line with human anxiety-coping therapies.

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