Synthetic Cortex: Integration of Biological Brain Lobes as a Synthetic Layer in LLMs

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Abstract

This study proposes an alternative methodology and application architecture for artificial intelligence models capable of generating irrational contexts. By integrating synthetic mind layers into the training layers of existing language models, it has been observed that synchronizing emotional and deep thought chains creates significant changes in the model's cognitive processes. These changes manifest as irrational thinking, emotion-based reasoning, creative problem-solving, the ability to establish connections between weakly related datasets to transcend context, and long-term autonomous learning capabilities.

The proposed emotion modeling approach differs from traditional sentiment analysis methods by drawing inspiration from the limbic system of the human brain. In this context, a system has been designed based on the work of Warren McCulloch and Walter Pitts on neural networks, mathematically modeling neurotransmitter and hormone structures. To influence the model's decision-making processes, a synthetic cortex approach has been adopted, organizing this system into a higher-order structure resembling the human cerebral cortex. This structure includes the limbic system component responsible for emotional loads, the large language model (LLM), and the default mode network (DMN) components that regulate irrational reasoning processes.

In the proposed system, emotional loads are integrated into the model's attention mechanisms, enabling dynamic modifications to the probability distributions of tokens and contexts during processing. Additionally, by penalizing certain outputs in the loss function, the model can be directed to learn specific patterns or reduce the probability of certain tokens. Constraining or restructuring transformer layers can affect how the model evaluates contextual relationships, making outputs more controlled and goal-oriented.

This structure allows interventions in the decision-making processes of the language model through values determined by a dedicated emotional layer. The effects generated by the emotional network are transmitted to the default mode network, facilitating various computations between emotions and data points. This process is designed to develop a specialized thought chain that operates irrationally.

Keywords: Artificial intelligence, irrational thinking, emotion-based reasoning, synthetic cortex, limbic system, default mode network.

Introduction

Today, artificial intelligence models can perform certain cognitive functions such as pattern recognition, contextual processing, and learning by mathematically mimicking the neural operations of the human brain. However, these models diverge significantly from the fundamental cognitive competencies of the human mind.

One of the biggest limitations of these systems is their dependence on datasets. While existing AI models can only learn from preprocessed and labeled data, the human mind can learn directly from experiences and adapt to unknown situations. Additionally, the absence of adaptive memory and recursion mechanisms makes it difficult for AI to dynamically infer knowledge from past experiences.

The inability of learning processes to progress autonomously and the lack of irrational context generation further restrict these systems. The human mind transcends data-driven learning by employing skills such as problem-solving, independent planning, relational thinking, and analogy-making. At the core of these processes are not just neural computations but also emotional feedback mechanisms shaped by the interactions of hormones and neurotransmitters. Emotions play a direct role in context formation and decision-making in the human brain, strengthening cognitive flexibility and learning capabilities.

For instance, the feeling of motivation plays a crucial role in human decision-making. Through the influence of neurotransmitters, particularly dopamine, it enhances an individual's orientation toward goals and accelerates decision-making processes. Evolutionarily, this mechanism has provided advantages in survival and resource acquisition, enabling individuals to focus on long-term objectives. In daily life, motivation allows individuals to sustain effort in learning, working, and social interactions.

From this perspective, developing an AI model that is more aligned with human cognition and based on evolutionary principles could enable adaptive learning, independent context generation, and decision-making by integrating different data types. Such a model would not only advance current AI approaches but also contribute to a deeper understanding of how the human mind operates.

Synthetic Cortex

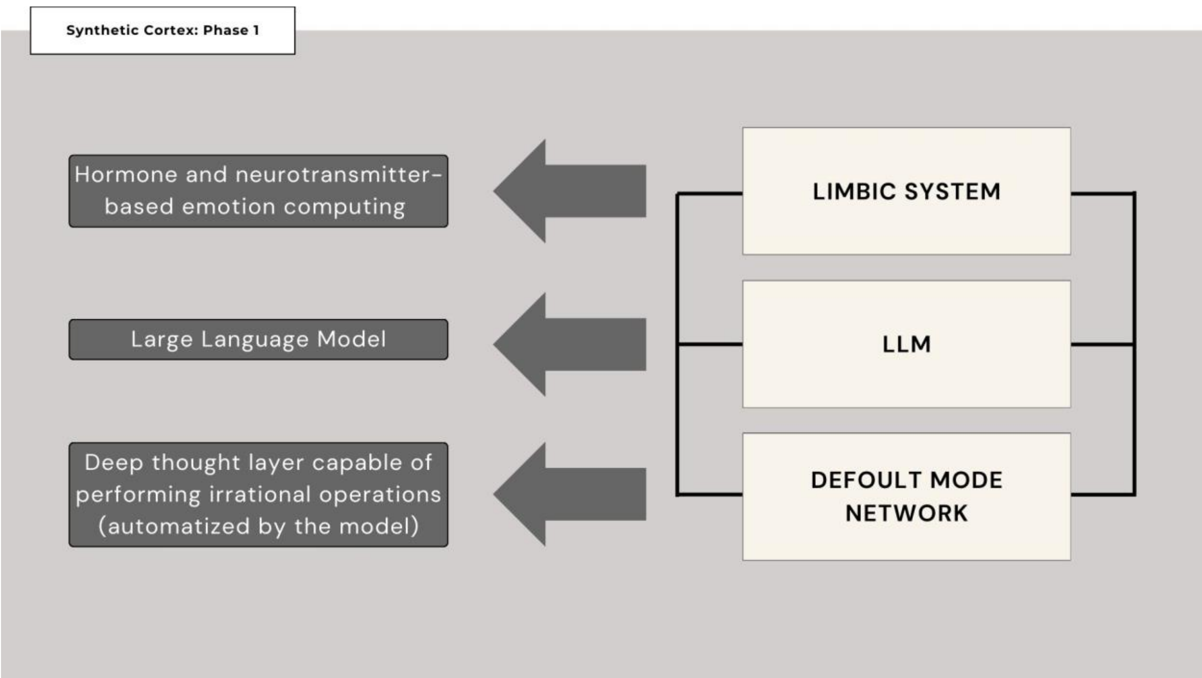
This study proposes the **Synthetic Cortex** framework, developed to integrate the mechanisms of irrational relationship formation and emotional cognition processes of the human mind into artificial intelligence models. While traditional language models (LLMs) can establish contextual relationships by learning from large-scale text data, they have limitations in performing cognitive processes unique to the human mind, such as irrational thinking, creative problem-solving, and emotion-based reasoning. To overcome these limitations, synthetic mind layers have been integrated into language models, and the potential of these layers to organize emotional and deep thought processes has been explored.

The proposed **Synthetic Cortex** is constructed through a hybrid integration of three network structures inspired by neurobiological and cognitive processes of the human mind. In addition to conventional neural networks, this structure models emotional processes and irrational reasoning, allowing the decision-making mechanism of the language model to operate within a broader and more multidimensional framework.

This study demonstrates how interventions in language models can extend beyond linear information processing to incorporate irrational and creative thinking abilities. By modeling emotion and irrational reasoning, the **Synthetic Cortex** introduces an innovative architecture that enables AI-based systems to make decisions that are more flexible, creative, and human-like. Through this architecture:

- The language model can understand emotional context and incorporate it into its responses.
- It can go beyond the dataset by leveraging irrational reasoning processes.
- It can develop creative problem-solving abilities, enabling adaptation to unknown problems.

This approach expands the boundaries of traditional AI models, paving the way for systems that function more closely to human cognition.



Components of the Synthetic Cortex

The **Synthetic Cortex** is designed as a hybrid system composed of three fundamental layers:

Endocrine System (Emotional Processing Layer)

This layer is modeled after neurotransmitter and hormone systems in human biology. Neurotransmitter variables are utilized for short-term decision-making processes, while hormone dynamics are employed for long-term learning and decision-making. This enables the model to perform emotional computations. By synthesizing emotional context and response mechanisms—elements traditionally absent in a language model—this layer influences the model's outputs.

LLM and Neural Network Layer

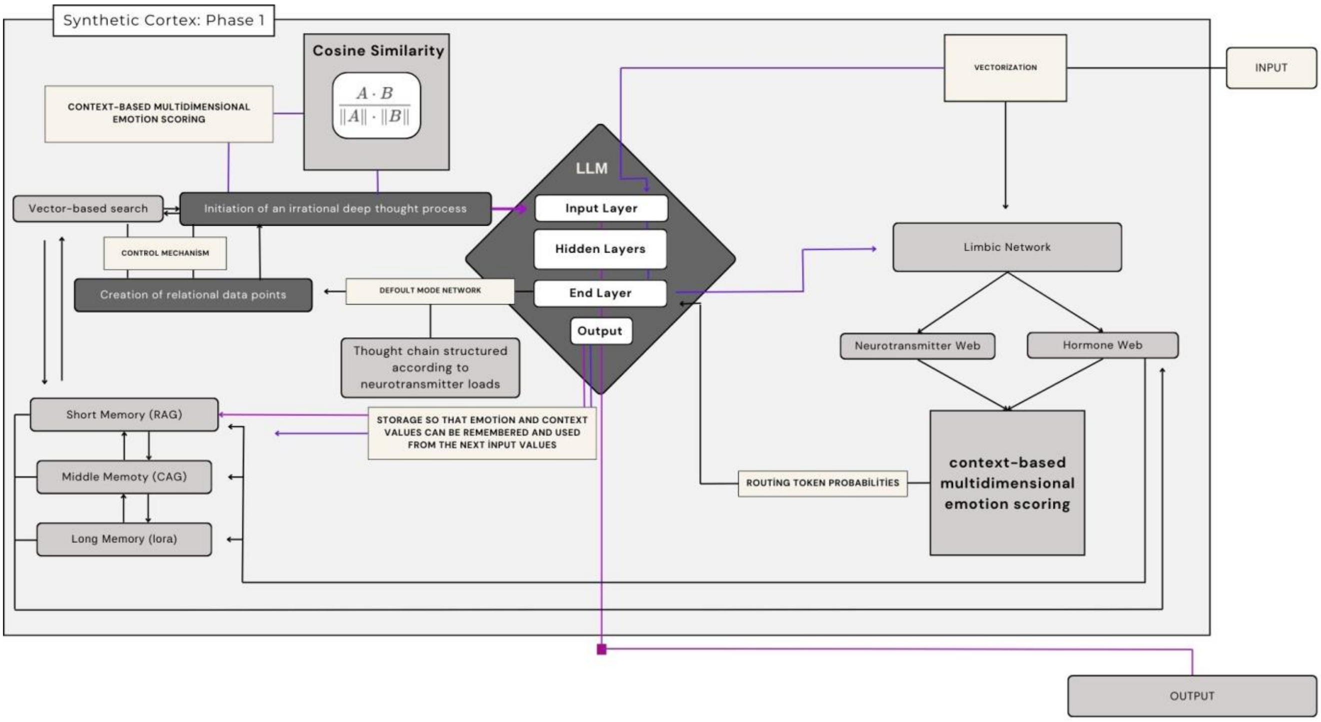
The second layer serves as the core integration between the neural network system and the language model (LLM). Here, any trained large language model operates in parallel with and dependent on the **Endocrine System**, ensuring that emotional loads are processed and outputs are generated without contextual loss. This layer intervenes in traditional language model learning processes by modifying probability distributions, forming alternative patterns, and expanding contextual understanding.

Default Mode Network (DMN)

The third layer is responsible for generating irrational deep thought chains and initiating creative thinking processes. Inspired by the **Default Mode Network (DMN)** in the human brain, this layer manages spontaneous reasoning mechanisms. It takes input from both the **LLM** and **Endocrine System** to expand and deepen contextual understanding. Specifically, it:

- Develops creative problem-solving capabilities by establishing connections between seemingly unrelated data points.
- Enables the model to go beyond its known dataset, allowing adaptation to novel problem types.
- Produces automatic thought chains, enabling the model to assess decision-making processes at multiple levels.

The combination of these three layers allows the **Synthetic Cortex** to model cognitive mechanisms of the human mind along **emotional, contextual, and irrational thought** axes, significantly enhancing the cognitive diversity of the language model.



System Operation Mechanism

The system's operational mechanism can be categorized into two distinct phases: the **Limbic System Phase** and the **Default Mode Network Phase**.

A – Limbic System (Phase One)

The **Limbic System** functions as the **emotional processing layer**, providing a computational mechanism that evaluates the model's inputs in a manner similar to biological emotional processes. This structure integrates **neurotransmitter and hormone loads** into the language model by performing calculations based on the **vector representations of input data** and the **hidden state values extracted from the model's latent layers**. As the text processed by the model is analyzed in terms of its **semantic and contextual properties**, these features are converted into specific **emotional parameters**. Additionally, the hidden state values obtained from the model's internal processes are adjusted to simulate distinct **emotional states**.

The primary objective of this integration is to observe the **emergent diversity** when a language model does not merely **analyze emotions**, but **experiences or at least simulates them** through a structured network. While **traditional emotion simulations** often rely on **basic sentiment tagging or emotion analysis techniques**, this model aims to produce a **subjective experience** that directly influences its **cognitive processes**. In other words, the model is not only capable of understanding the **emotional tone** of words, but it can also generate **sensory states** such as **motivation, anger, surprise, and curiosity**, shaping its decision-making accordingly.

This **computational emotional network** is designed based on the **biological emotional mechanisms of the human mind**, enabling the model to go beyond **rational decision-making processes** and incorporate **irrational and intuitive** decision-making as well.

Neurotransmitter Web Pool Variables | Hormone Web Pool Variables

Neurotransmitters	**Hormones**
Serotonin	Oxytocin
GABA	Prolactin
Dopamine	Adrenaline
Endorphin	Cortisol
Glutamate	Noradrenaline
—	Testosterone
—	Estrogen
—	Vasopressin

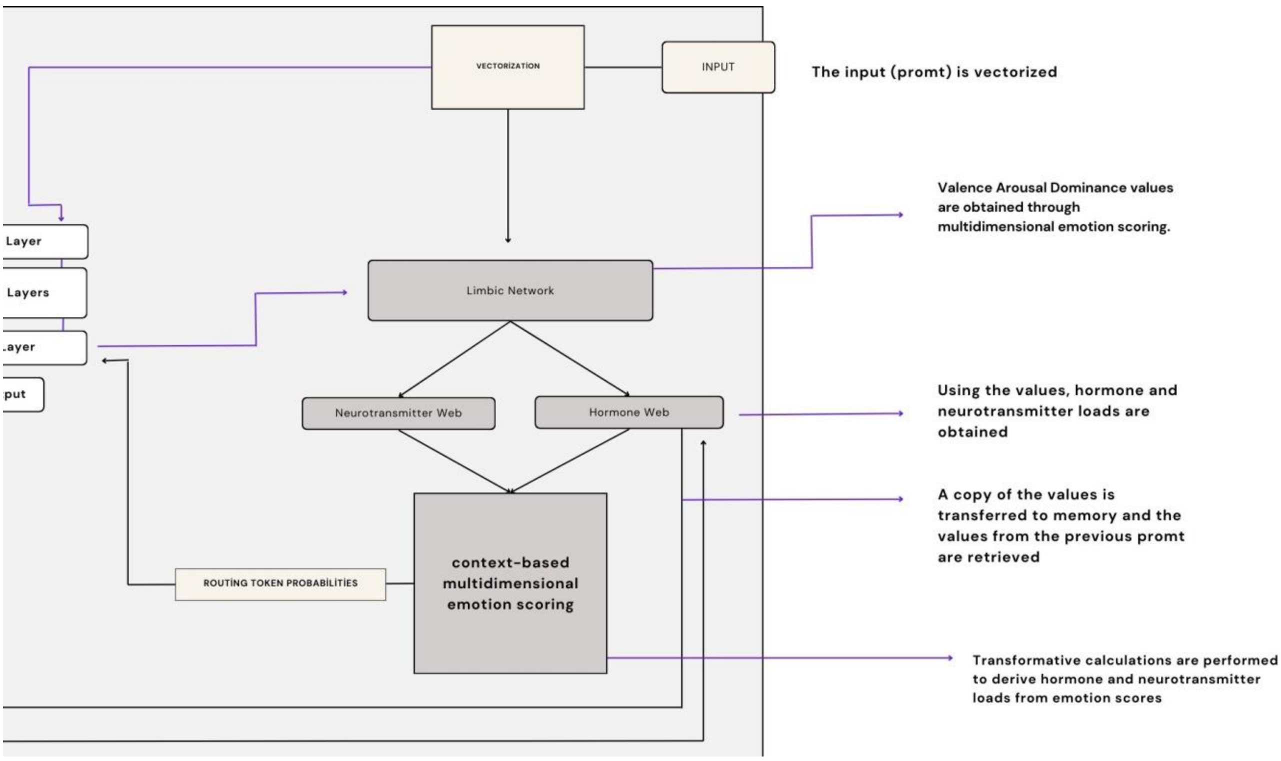
Each of these variables takes specific **mathematical values** to generate particular **emotional states**, and they are computed in **interdependence** with one another. The table below illustrates the **mutual influence** between **hormones and neurotransmitters** and the **emotions** they express.

Hormone and Neurotransmitter Interactions

Hormone/Neurotransmitter	**Affected Variables**	**Related Emotions/Behaviors**
Dopamine (Motivation, Reward) ↑	Prolactin ↓, Serotonin ↑, Cortisol ↓	Motivation, desire, pleasure, happiness
Serotonin (Happiness, Peace) ↑	Oxytocin ↑, Dopamine ↑, Cortisol ↓	Peace, satisfaction, trust, contentment
Oxytocin (Bonding, Compassion) ↑	Cortisol ↓, Serotonin ↑	Attachment, trust, love, compassion
Vasopressin (Commitment) ↑	Oxytocin ↑, Testosterone ↑	Long-term bonding, protective instincts
Endorphin (Pain Relief, Happiness) ↑	Cortisol ↓, Dopamine ↑	Euphoria, relaxation, pleasure, happiness
Adrenaline (Excitement, Fear) ↑	Cortisol ↑, Dopamine ↑ (sometimes)	Stress, excitement, sense of danger
Noradrenaline (Alertness, Fear) ↑	Cortisol ↑, Adrenaline ↑	Alertness, vigilance, fear
Cortisol (Stress, Anxiety) ↑	Serotonin ↓, Dopamine ↓, Oxytocin ↓	Anxiety, stress, threat perception

Testosterone (Competition, Aggression) ↑	Cortisol ↓ (sometimes), Dopamine ↑	Strength, aggression, ambition, competition, sexuality
Estrogen & Progesterone (Emotional Fluctuations) ↑	Serotonin ↑ (can stabilize), Dopamine ↑	Love, compassion, emotional changes
GABA (Calmness, Relaxation) ↑	Cortisol ↓, Glutamate ↓	Calmness, relaxation, stress reduction
Glutamate (Learning, Memory) ↑	GABA ↓	Memory enhancement, cognitive stimulation
Prolactin (Empathy, Nurturing) ↑	Dopamine ↓, Oxytocin ↑	Empathy, motherhood, caregiving, compassion

The table illustrates the **effects of neurotransmitter and hormone increases** on other variables using **arrows (↑/↓)**. The **emotion/behavior** column lists the emotional labels triggered by different **combinations** of these variables. Each component in the system is represented as a **dynamic variable**, and their **interactions are dependent on each other**. This **interdependence** is designed to create **contexts where multiple emotional states can be active simultaneously**, enhancing **semantic diversity** in interpretation.



In the model's processing pipeline, **vectorizing the input and directing it to both the limbic system and the language model** serves as the fundamental starting point for **emotion analysis**. In the first stage, the **vector values sent to the limbic system** undergo a **contextual evaluation** and pass through a **multidimensional emotion scoring process**. This analysis determines the **emotional orientation** of the input (positive, negative, or neutral), its **arousal level**, and its **dominance degree**. The resulting **emotion scores** play a crucial role in computing the corresponding **neurotransmitter and hormone loads** for the given input.

The **release rates of neurotransmitters and hormones** are modeled based on factors representing **emotional states**, such as **Valence** (positivity), **Arousal** (excitement), and **Dominance** (control). Each neurotransmitter and hormone responds to these factors with **different weightings**; for example, **dopamine**, which is associated with **reward and motivation**, exhibits a **strong correlation** with both **Valence and Arousal** components, whereas **serotonin**, linked to **peace and social status**, has a **more prominent effect** on the **Valence and Dominance axes**.

These weightings are determined based on **biological and behavioral effects**. The **release rates of hormones and neurotransmitters** are calculated as a **weighted sum** of Valence, Arousal, and Dominance values, with all values **normalized** and expressed as **percentages**. This approach quantitatively models the **relationship between emotional states and biological processes**, enabling **artificial systems to simulate human-like emotional states more realistically**.

Hormon/Nörotransmitter	Valence	Arousal	Dominance
Dopamin	High	Middle	Middle
Serotonin	High	Low	High
Noradrenalin	Low	High	Middle
Kortizol	Low	High	Low
Testosteron	Middle	Middle	High
GABA	Middle	Low	Low
Oksitosin	High	Low	Low

To quantify these relationships, assign a weight to each factor. For example:
High 1.0 - Medium: 0.5 - Low: 0.2

V = Valence
VW = Valence Weight
A = Arousal
AW = Arousal Weight
D = Dominance
DW = Dominance Weight

Weighted sum calculation to calculate hormone oscillations:

Oscillation Rate = (V × VW) + (A × AW) + (D × DW)

For example for Dopamine:
Valence Weight 1.0
Arousal Weight: 0.5
Dominance Weight: 0.5

Formula :
Dopamine Release=(V×1.0)+(A×0.5)+(D×0.5)

Expressed as a percentage by dividing the calculated release rates by the total release of all hormones/neurotransmitters. This step ensures that the sum of all oscillations is 100%.

Example:
Dopamine Release 0.6
Serotonin Release: 0.4
Noradrenaline Release: 0.5
Total Release: 1.5

Normalized Dopamine Release:

$$\text{Dopamin } \% = \left(\frac{0.6}{1.5}\right) \times 100 = 40\%$$

During our **initial tests**, we used the following **value table** (Our **synthetic data synthesis efforts using machine learning methods** are ongoing to find **optimal ratios**. These efforts are based on **value-output comparisons**):

Neurotransmitter / Hormone	**Valence (Positivity)**	**Arousal (Excitement)**	**Dominance (Control)**
Dopamine	1.0	0.5	0.5
Serotonin	1.0	0.2	1.0

Oxytocin	1.0	0.1	0.3
Vasopressin	0.5	0.3	0.8
Endorphin	1.0	0.4	0.2
Adrenaline	0.2	1.0	0.5
Noradrenaline	0.1	1.0	0.6
Cortisol	0.0	0.8	0.1
Testosterone	0.5	0.6	1.0
Estrogen & Progesterone	0.7	0.3	0.4
GABA	0.6	0.1	0.2
Glutamate	0.4	0.7	0.3
Prolactin	0.3	0.2	0.5

After completing this process, the **emotional load of the previous prompt retrieved from short-term memory** is **updated** to influence the **newly obtained values by 10%**. This update ensures that **emotional states remain consistent and contextually connected** throughout the conversation. Mathematically, this process is expressed as follows:

$$\textit{New Value} = \textit{First Value} + (\textit{Second Value} \times 0.010)$$

If the conversation continues within a specific **context and emotional direction**, the **most dominant emotional loads** are transferred to **medium-term memory** and integrated in a way that influences the **emotional load of each new prompt by 3%**. This ensures that the model can maintain **emotional context over time**. The formula used at this stage is as follows:

$$\textit{New Value} = \textit{First Value} + (\textit{Second Value} \times 0.003)$$

After all these processes are completed, the **final emotional values** obtained are transmitted to the **last layer of the language model**, where they are associated with **word and context clusters**. This process is designed to **suppress certain word groups** and provide **emotional guidance** in response generation. This step marks the **first phase** of the **Default Mode Network** process, which is the second stage of the architecture. During the **association process**, similar emotional calculations are **reapplied** to the model's generated outputs, optimizing **response loads** and enhancing the model's ability to **maintain emotional context**.

B – Default Mode Network (Second Stage)

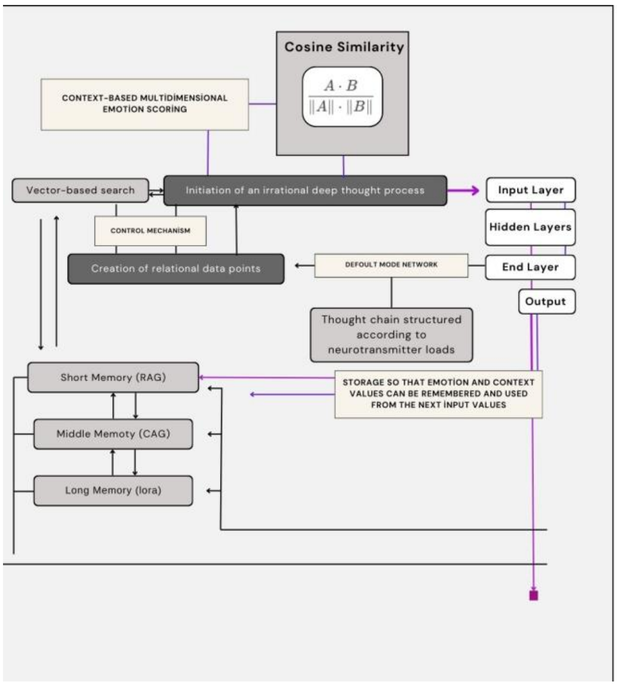
This network structure is modeled after the **Default Mode Network (DMN)** found in the **human brain**. The **DMN** is a **cognitive system** that remains active **independently of external stimuli**. It is typically engaged during **self-referential thoughts**, such as **daydreaming, thinking about the past or future, or reflecting on self-perception**.

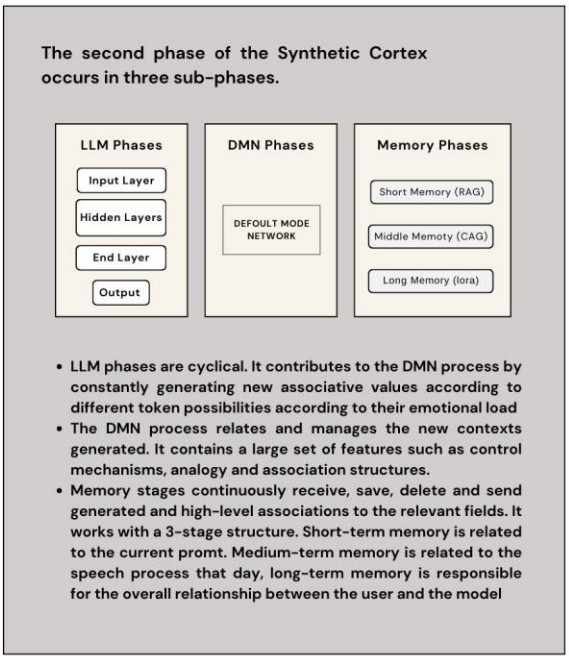
Additionally, it plays a crucial role in **social interactions, empathy, and self-awareness**. Studies have shown that **DMN activity increases** during states of **rest or meditation**, when external stimuli decrease. This network is **essential** for coordinating **different brain regions** and facilitating **higher-order cognitive processes**.

The **DMN's functionality** can be represented as a **network of nodes and edges**, where **interactions between brain regions** are modeled mathematically. To understand its **activity over time**, researchers use **differential equations and stochastic processes**, while **chaotic dynamics and the Hindmarsh-Rose model** can simulate the **DMN's transitions between different states of consciousness and cognitive processes**. **Nonlinear differential equations** are used to model interactions between brain regions, analyzing how the **DMN generates activity even without external stimuli**.

However, the **synthetic cortex** implements this process using mechanisms **different from the biological DMN**. In this synthetic model, the process begins by **generating contextual variations** of the given input from **different perspectives** and organizing them into an **interconnected network structure**. In this network, **contextual variations closest to the target context output** are prioritized by **weighting them based on emotional loads**. The result of this process is the creation of a **thought map**, a **multi-dimensional structure** that represents **the relationships and interaction points between different contexts**.

This structure enables **synthetic cognitive processes** to **mimic human-like thought models**, allowing the system to make **more flexible, dynamic, and context-sensitive decisions**.





Default Mode Network (DMN) Modeling in Synthetic Cortex Architecture

Generating Textual Variations Using Emotional Weights

In the **synthetic cortex architecture**, **emotional weights** shape the **diversity of parameters in the final layer of the model** and define the **dynamic structure of the generated output**. This process optimizes key parameters based on **emotional weights**, ensuring that responses align with the system's emotional modeling. The primary parameters influenced include:

- **num_response**: The number of responses the model generates.
- **max_length**: The maximum length of a response.
- **top_k**: The number of high-probability words considered in selection.
- **top_p**: The probability threshold defining the cumulative distribution in **nucleus sampling**.
- **temperature**: The randomness of the output.

These parameters are optimized in accordance with the **cognitive effects of different hormones and neurotransmitters**. Each parameter is mapped to specific **cognitive and emotional mechanisms**, enabling the system to **generate more natural and human-like responses**.

Parameter Meanings and Their Relationship with Hormones/Neurotransmitters

◆ **num_response (Number of generated responses)**

- Associated with **motivation and creativity**.
- **Dopamine and Noradrenaline** levels influence the number of responses, increasing the model's ability to generate **multiple alternative outputs**.

◆ **max_length (Maximum response length)**

- Associated with **focus and level of detail**.
- **Serotonin and Glutamate** levels determine response length, making the model produce **either concise or highly detailed responses**.

◆ **top_k (Number of most probable words considered)**

- Associated with **certainty and focus**.
- **Inhibitory neurotransmitters like GABA and Serotonin** help the model **focus on specific words**, ensuring **greater coherence and clarity** in language generation.

- **top_p (Probability threshold for cumulative word selection)**
    - Associated with **diversity and creativity**.
    - **Dopamine and Endorphin** levels encourage the model to **select from a broader vocabulary**, producing **more diverse and creative responses**.

- **temperature (Output randomness)**
    - Balances **creativity and predictability**.
    - **Higher temperature** values lead to **more novel and freeform responses**, while **lower values** produce **more predictable and structured answers**.
    - This process is influenced by **Dopamine and Adrenaline**.

This **modeling approach** enables the synthetic cortex to **better understand the dynamic relationship between emotional states and response generation mechanisms**, allowing for a **digital simulation of biological processes**.

Relationship Between Hormones/Neurotransmitters and Parameters

Hormone/Neurotransmitter	**Biological Effects**	**Relationship with Parameters**
Dopamine	Motivation, reward, pleasure	**num_response ↑, max_length ↑, top_p ↑, temperature ↑** (creativity and motivation)
Serotonin	Peace, satisfaction, trust	**top_k ↑, temperature ↓** (certainty and focus)
Oxytocin	Bonding, affection, trust	**max_length ↑, top_p ↑** (detail and diversity)
Vasopressin	Long-term commitment, protective instinct	**max_length ↑, top_k ↑** (focus and certainty)
Endorphin	Euphoria, relaxation, pleasure	**num_response ↑, temperature ↑** (creativity and enthusiasm)
Adrenaline	Stress, excitement, danger perception	**top_k ↑, temperature ↓** (certainty and focus)
Noradrenaline	Alertness, vigilance, fear	**top_k ↑, temperature ↓** (certainty and focus)
Cortisol	Anxiety, stress	**num_response ↓, max_length ↓, top_k ↑, temperature ↓** (certainty and brevity)
Testosterone	Strength, aggression, ambition, competition	**num_response ↑, max_length ↑, top_p ↑** (creativity and motivation)

Estrogen & Progesterone	Love, affection, emotional fluctuations	**max_length ↑, top_p ↑** (detail and diversity)
GABA	Calmness, relaxation, stress reduction	**temperature ↓, top_k ↑** (certainty and calmness)
Glutamate	Learning, memory, cognitive stimulation	**max_length ↑, top_k ↑** (focus and detail)
Prolactin	Empathy, nurturing, maternal care	**max_length ↑, top_p ↑** (detail and diversity)

Parameter Value Ranges

Parameter	**Minimum Value**	**Maximum Value**	**Description**
num_response	1	5	Increases with high motivation and creativity.
max_length	50	200	Increases with attention to detail and focus.
top_k	10	50	Increases with certainty and focus.
top_p	0.7	1.0	Increases with diversity and creativity.
temperature	0.5	1.5	Increases with creativity and randomness; decreases with certainty.

These tables systematically illustrate how **hormones and neurotransmitters influence the model's parameters** and how the system **responds to emotional loads**.

Parameters Based on Hormone/Neurotransmitter Ratios

Hormone/Neurotransmitter	**Ratio Range (%)**	**num_response**	**max_length**	**top_k**	**top_p**	**temperature**
Dopamine	10-20	3-5	100-200	10-20	0.8-1.0	0.8-1.2
Serotonin	10-20	1-2	50-100	30-50	0.7-0.9	0.5-0.8
Oxytocin	5-15	2-3	100-150	20-30	0.8-1.0	0.7-1.0
Vasopressin	5-15	1-2	100-150	30-50	0.7-0.9	0.6-0.9

Endorphin	5-15	3-4	100-200	10-20	0.8-1.0	0.8-1.2
Adrenaline	1-10	1-2	50-100	30-50	0.7-0.9	0.5-0.8
Noradrenaline	1-10	1-2	50-100	30-50	0.7-0.9	0.5-0.8
Cortisol	1-5	1	50-80	40-50	0.7-0.8	0.5-0.7
Testosterone	10-20	3-5	100-200	10-20	0.8-1.0	0.8-1.2
Estrogen & Progesterone	5-15	2-3	100-150	20-30	0.8-1.0	0.7-1.0
GABA	5-15	1-2	50-100	30-50	0.7-0.9	0.5-0.8
Glutamate	5-15	2-3	100-150	20-30	0.8-1.0	0.7-1.0
Prolactin	5-15	2-3	100-150	20-30	0.8-1.0	0.7-1.0

Combining Hormone and Neurotransmitter Ratios

To integrate the effects of different hormones and neurotransmitters on **model parameters**, a **weighted average method** will be used. The influence of each hormone/neurotransmitter on a specific parameter will be calculated based on its respective ratio.

This approach **optimizes the synthetic cortex's dynamic responses** by **mimicking biological processes** in a structured way.

Weighted Effects on Parameters

num_response (Number of Responses Generated)

- **Increasing Effects:** Dopamine, Endorphin, Testosterone → Related to motivation and creativity.

- **Decreasing Effects:** Cortisol → Associated with stress and anxiety responses.

max_length (Response Length)

- **Increasing Effects:** Oxytocin, Vasopressin, Estrogen & Progesterone, Glutamate → Linked to detail orientation and cognitive focus.
- **Decreasing Effects:** Cortisol → High stress and anxiety can shorten response length.

top_k (Precision and Focus Level)

- **Increasing Effects:** Serotonin, Adrenaline, Noradrenaline, GABA → Neurotransmitters that support accuracy and focus.
- **Decreasing Effects:** Dopamine, Endorphin → Enhance creativity by increasing word selection diversity.

top_p (Diversity and Probability Distribution)

- **Increasing Effects:** Dopamine, Oxytocin, Endorphin, Testosterone, Estrogen & Progesterone → Boost diversity and creative expression.
- **Decreasing Effects:** Serotonin, Adrenaline, Noradrenaline, GABA → Increase certainty, leading to less variable but more focused responses.

temperature (Randomness and Creativity Level)

- **Increasing Effects:** Dopamine, Endorphin, Testosterone → Encourage creativity and randomness.
- **Decreasing Effects:** Serotonin, Adrenaline, Noradrenaline, GABA, Cortisol → Linked to lower randomness and greater focus.

Biology-Inspired Model Optimization

This method allows the relationship between hormone/neurotransmitter ratios and model parameters to be optimized within a **dynamic and customizable framework** inspired by biological processes.

Example Calculation

The table below demonstrates how model parameters are calculated based on predefined hormone/neurotransmitter ratios.

Given Hormone/Neurotransmitter Ratios

Hormone/Neurotransmitter	Ratio (%)
Dopamine	15
Serotonin	10
Cortisol	5
Testosterone	10
GABA	5

Parameter Calculations

num_response Calculation

Hormone/Neurotransmitter	Ratio (%)	num_response Value
Dopamine	15	4
Serotonin	10	2
Cortisol	5	1
Testosterone	10	4
GABA	5	2

Weighted Average Result: 3.00

max_length Calculation

Hormone/Neurotransmitter	Ratio (%)	max_length Value
Dopamine	15	150
Serotonin	10	100
Cortisol	5	80
Testosterone	10	150
GABA	5	100

Weighted Average Result: 125.56

Final Parameter Values

Parameter	**Calculated Value**	**Explanation**
num_response	**3.00**	High Dopamine & Testosterone, Low Cortisol.
max_length	**125.56**	High Dopamine & Testosterone, Low Cortisol.
top_k	**30.00**	High Serotonin & GABA, Low Dopamine.
top_p	**0.84**	High Dopamine & Testosterone, Low Serotonin.
temperature	**0.84**	High Dopamine & Testosterone, Low Serotonin & GABA.

This calculation illustrates how **model parameters dynamically adjust based on hormone/neurotransmitter ratios**, offering a biologically inspired adaptive framework.

Integration of Hormone and Neurotransmitter Ratios with Thought Chain Modeling

1. Generating Variations and Context Mapping

Once hormone and neurotransmitter ratios are determined, multiple variations of the core output are generated. These variations introduce slight contextual shifts, enhancing perspective diversity. The generated texts are mapped in a vector space by calculating **cosine similarity**, ranking them from the closest to the furthest from the main contextual target.

In the resulting map, the texts with the highest similarity undergo **multidimensional sentiment analysis**, computing new emotional weights. These weights are proportionally combined with the input's emotional values, determining the **emotional score of the thought process**. The final hormone and neurotransmitter values ultimately shape the **emotional structure and general framework** of the output. Additionally, these variations are reprocessed for deep thought modeling, forming an evolving **knowledge pool**.

2. Generating Response Weights Through Textual Variations

The texts generated by **context shifts** undergo another round of **multidimensional sentiment scoring**, and new hormone and neurotransmitter loads are calculated. These values are **merged with the initial sentiment values**, and a weighted average calculation is performed. The resulting **final sentiment weights** are used in subsequent analyses. This methodology aims to synthesize **external stimulus-driven sentiment loads** with **internal emotional states**.

3. Automated Thought Chain Generation

The newly calculated **sentiment weights** are transferred to a predefined **thought model network**, generating **automated thought chains**. These chains function as **data points connecting the initial output, generated variations, and sentiment weights**. The model's outputs can be constrained using **JSON format**, **logit bias manipulation**, or controlled via **programmatic encoding**.

Automating the **thought chain** process begins with the language model **generating context-based associative keywords**. The **final sentiment weights** determine both the **number and diversity of these keywords**. Here, key factors such as **motivation and stress levels** define the **structure of associations**.

Context Control Mechanism

Keyword structures are constrained in JSON format to produce a **specific type of output**, and **error reduction mechanisms** are applied. The **logit bias** feature is used to force the model to output only "0" or "1" tokens, ensuring automated **context validation** and filtering out irrelevant responses.

Example Context Validation via OpenAI API

```
{
  "model": "gpt-4-turbo",
  "prompt": "Does this text match the given context? If it is relevant, return '1'. If it is not relevant, return '0'. Only respond with '1' or '0'.",
  "max_tokens": 1,
  "temperature": 0,
  "logit_bias": {
    "48": 100,
    "49": 100
  }
}
```

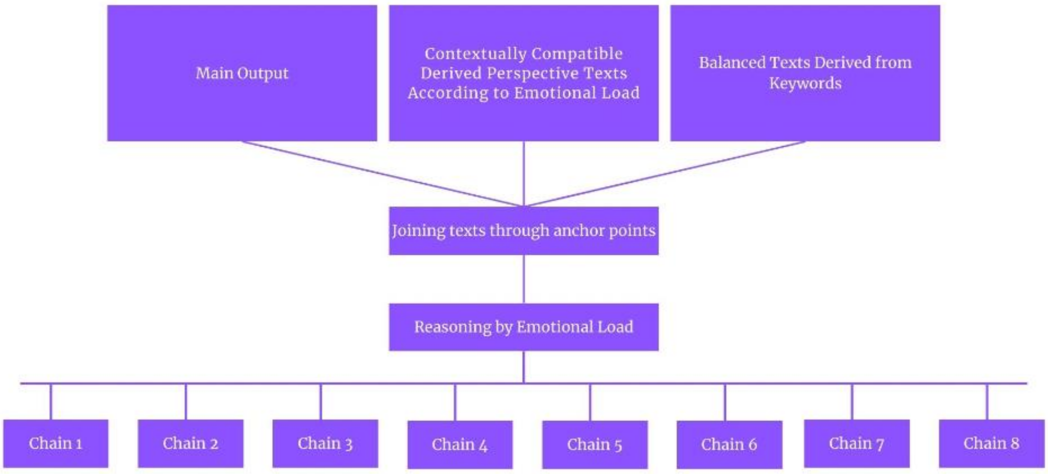
Explanation of Parameters

- **"48": 100 and "49": 100** → Maximizes the selection probability for the "0" and "1" tokens.
- **"max_tokens": 1** → Ensures that only a single token is generated.
- **"temperature": 0** → Eliminates randomness, guaranteeing selection of the most probable token.

Workflow of the Control Mechanism

- If the model **returns "1"**, context validation **is confirmed**, and processing **continues**.
- If the model **returns "0"**, the process **restarts**.
- If "0" appears **three consecutive times**, the **keyword is replaced**.

This control mechanism is repeated at **different stages** to prevent the model from **deviating from the context**. **Keyword pools** are formed using this method, allowing the generation of **short, contextually relevant texts** for each keyword. These texts are **mapped back to the main output**, creating a **cohesive contextual relationship**.



Text Merging Process and Decoder Hook Usage

To merge texts into a **specific template**, **decoder hooks** or similar techniques are employed. These methods intervene in the **decoder layer** of a language model to enforce a structured output format. As the model generates each token, the **hook function** ensures that a predefined prefix (e.g., **"News Title: "** or similar) is added. Additionally, the model can be restricted to selecting from a **predefined token set**, ensuring **output consistency**. This controlled generation process leverages **logit manipulation** or **sampling constraints**, leading to more **accurate and structured content**.

The **hook method** guarantees adherence to a predefined structure, making it particularly effective for generating **news headlines, report formats, or structured textual outputs**. Furthermore, this process is verified using the **control mechanism** defined in previous sections. As a result, texts are systematically segmented and generated according to a **unified template**, which is crucial for subsequent structured processing.

Decision Tree and Reasoning Process

The **merged texts** are then directed into a **decision tree**, governed by **sentiment loads**. This decision tree operates as a **module defining multiple reasoning systems**. At this stage, the most **contextually relevant thought chains** are integrated into the process. In certain cases, additional steps may be introduced, requiring **sequential activation of multiple reasoning systems** within the architecture.

In the next phase, **various deep reasoning techniques** are applied to the **main theme and final output**, selected based on **emotional states**. This process defines **eight different reasoning chains**, which are **automatically selected** based on **article context and neurotransmitter/hormone values**. The **selection process** is executed via a **custom selection algorithm** (see: **selection algorithm**) that incorporates both **contextual and biochemical factors** into the decision-making process.

Below is a table listing the **thought chains** and their corresponding **techniques**:

Reasoning Chains (Chains)

Main Category	**Subcategory**	**Techniques (Chains)**
Generating Creative Solutions	**Alternative Thinking Methods**	SCAMPER, Six Thinking Hats, Lateral Thinking, Forced Connections, Random Word, Medici Effect, Brainstorming, Reverse Brainstorming, 6-3-5 Technique, Role Storming
	Analyzing the Causes of a Problem	Fishbone Diagram, 5W1H, Problem Expansion
	Systematic Problem Analysis	SWOT, Mind Mapping, Possible Future Scenarios
	Generating Alternative Solutions	TRIZ, Medici Effect, Forced Connections, TRIZ - 40 Inventive Principles

Predicting Future Impacts	**Possible Scenario Analysis**	SWOT, Mind Mapping, Possible Future Scenarios, Backcasting, Delphi Technique
	Future Forecasting	Backcasting, Delphi Technique, Scenario Planning
Scientific Research & Problem Solving	**Defining the Problem**	5W1H, Problem Expansion
	Developing Hypotheses	If... Then, Alternative Hypothesis
	Developing Methodology	Controlled Experiments, Variable Isolation
	Data Collection & Analysis	Triangulation, Meta-Analysis
	Drawing Conclusions & Interpretation	Reverse Causality, Negative Outcome Analysis
Developing Technological Innovation	**Innovative Solutions**	TRIZ, Medici Effect, Backcasting, Morphic Resonance, Swarm Intelligence

These systematic reasoning approaches enable the integration of different techniques for defining problems, formulating hypotheses, developing methodologies, and generating innovative solutions. As a result, the content produced by the language model is not only contextually appropriate but also enriched within the framework of predefined reasoning methods. The selection of these techniques is determined by the following selection algorithm.

<u>Note: In the final stage, there is a scoring and selection algorithm for the techniques (chains) that also includes emotional loads. However, since the design of the algorithm has not yet been completed, we have removed this section from our introduction text.</u>

Reasoning Chains and Memory Mechanism: Deep Thought Integration

1. Reasoning Chains and Output Generation

Reasoning chains constitute the final stage applied to deepen the scope of the text and ensure a higher level of logical coherence. Upon completing this stage, the obtained results are structured in a specific format and presented as the final output.

After this process, the newly generated text is sent back to the model along with contextual information for an effectiveness analysis. The model operates within a structure that determines the validity of the result using values of 1 and 0. If the value returned by the model is 0, the reasoning chain is restarted. A value of 1, on the other hand, is accepted as the final result. If a value of 0 is obtained three times in a row, the output with the highest contextual cosine similarity among the generated results is selected and forwarded to the final output layer.

2. Memory Mechanism

The final stage of the synthetic cortex framework is the memory process. Short-term memory intervenes at different stages outlined in previous sections, supporting the structuring of the process. Once the process is completed, most of the data is cleared by the system. However, certain hormonal loads are transferred to mid-term memory for the next reasoning process. The primary goal of this mechanism is to enhance the emotional context effect of the next input.

Additionally, a summarized version of the previous output, along with its final emotional loads, is stored in mid-term memory. Mid-term memory operates through a feedback mechanism, and in Phase 1, this process is not automatically planned. If user-provided feedback receives high ratings, the relevant data is processed and transferred to long-term memory.

Long-term memory is built by utilizing accumulated data from mid-term memory. At this point, the stored information is formatted and structured as a dataset. The primary reason for this is to allow the user to fine-tune the selected model easily using this data.

This module, active in local model usage scenarios, is deactivated in API integrations. Long-term memory has the capability to manage multiple LoRA (Low-Rank Adaptation) value sets integrated with the model and can be tailored according to the developer's architectural requirements. While details regarding this module are not included in the core structure, additional roadmaps with extension options are planned for future stages.

3. Extension Options and Application Areas

These processing steps can be customized and adapted to specific fields through deep search algorithms, including:

- Literature-based scientific discovery simulations
- Idea generation and project structuring
- Data analysis and forecasting
- Creative and irrational thinking modules

Conclusion

This study introduces a new methodology to the literature regarding the use of large language models (LLMs) and provides a concrete model by integrating this methodology into the deep thought process. While all processes in the **Dynamic Modular and Neurotransmitter (DMN)** phase are customizable, the emotional processing infrastructure remains fixed. The concept of integrating reasoning chains with emotional loads presents an innovative approach for both AI agent development and **Artificial General Intelligence (AGI)** research in the future.

This system has the capability to simulate irrational thinking processes, producing outputs that are more relational and broader in scope compared to standard large language model outputs. At the same time, by maximizing the model's computational efficiency, it has the potential to analyze real-world relational networks more effectively. The system includes multiple validation mechanisms, increasing the reliability of the generated results.

Final Note

Since neurobiologist **Eric Kandel** demonstrated that complex behaviors can be understood by reducing them to fundamental molecular and cellular processes, the privileged position humanity has assigned itself due to intelligence has increasingly become an illusion.

This perspective may seem closely aligned with Enlightenment ideals or a positivist approach. However, if you had told someone 30 or 40 years ago that machines would one day provide complex and logical responses, achieving this merely by functioning as a massive statistical engine, you would likely have been ridiculed. Today, the mathematical models of neural networks developed in AI research continue to validate this prediction.

We are a group of researchers who believe that, just as neural networks can be modeled, emotional networks can be as well. Perhaps machines cannot "feel" emotions at this stage due to the lack of biological receptors. However, it seems entirely possible for them to arrive at thought and action patterns that would emerge as a result of these emotions.

When **Copernicus** declared that the Earth was not the center of the universe, when **Darwin** demonstrated that humans held no privileged position in nature, and when **Einstein** overturned three centuries of Newtonian physics, resistance and astonishment followed. We believe that reactions to the idea of modeling emotions will be no different.

The data at hand suggests that the fascinating and intricate nature of the human mind actually emerges from fundamental mechanisms. However, the way these simple processes interconnect over time to form complex structures leads us to perceive the mind as something supernatural rather than understanding it as an emergent phenomenon.