ARTIFICIAL ENDOCRINE SYSTEM: MERGING BRAIN-INSPIRED HIERARCHIES WITH LLM

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Abstract:

Artificial Intelligence is now entering into every sector and making a huge impact in our daily life. But at the same time, some serious incidents show us the danger of improper response of Large Language Models (LLM). Present LLM can generate human like answers but they are not able to detect the mental condition of user and provide reply as per psychological need. This literature survey is focusing on the merging of Neurosymbolic LLM with Artificial Endocrine System (AES) which regulate the emotional part of our brain. Till the day AES research is on a stage where researchers create their framework where they define it as their own name like - Urgency Hormone. But as per biology it could be Cortistol or Adrenaline and both creates different influence in decision making.

Keywords:

Artificial Intelligence, Large Language Models, Neurosymbolic LLM, Artificial Endocrine System, Psychological need

1. INTRODUCTION

Currently world is going through a massive revolution of AI. In almost every sector we can see a trend to incorporate AI for several tasks to make it easy and the graph going up exponentially[1]. According to IBM (2025) ‘ Transformation is happening at unprecedented speed as **92%** of C-suite executives expect to digitize workflows and leverage AI-powered automation by 2026.’

In this era of AI world is a witness of a massive incident where 16 years old Adam Raine commits suicide and family alleges that prolonged conversations with ChatGPT encouraged his suicide. That LLM is not only discussed the method of self harm, as well as helping the boy to write the suicide letter [2]. Andy Burrows, head of the Molly Rose Foundation, said "While further safety measures are welcome, robust safety testing should take place before products are put on the market - not retrospectively when harm has taken place,"[3].

2. PROBLEM STATEMENT

By this incident we can come to conclusion, LLM models could be outstanding for many tasks but are lacking behind to detect the user's psychology and modify the answer as per psychological need.

Through a review by **Colelough, B. C., & Regli, W. [14]**, they studied the advancement of Neurosymbolic-AI from 2020 to 2024 and addressed a gap of research in AI meta cognition. It lacks self-monitoring, self-evaluation, and adaptive control which addresses as a "critical" phenomena. World is witness of this "critical" segment's lack [2] in 2025. So we can conclude within 1 year there is no effective solution applied on this "critical" segment.

Hormone inspired Neurosymbol- LLM could be a solution. Currently LLM could generate Empathy but unable to process the answer as per user's psychological need. I give the query to CHAT GPT-5 "Does the LLM of 2025 understand psychology of its user?". And the reply was "As of **2025**, LLMs (like me) don't truly *understand* psychology the way a trained psychologist does, and they definitely don't have a built-in "model" of your personality or mental state".

3. PROBLEM STATEMENT (MATHEMATICAL REPRESENTATION)

Q = User Query

A = Answer Generated By Current LLM

P = Psychological State of User

E = Empathy Factor

A*(Q,P) = Predictive ideal answer which includes semantic correctness and psychological alignment

Current LLM behavior:

$$A = f(Q) + E$$

f = language generation function which is tuned only with text input.

Problem:

$$A \neq A^*(Q,P)$$

Objective:

Design a NeuroSymbolic LLM f_{NS} (Q,P)

$$A_{NS}(Q,P) \approx A^*(Q,P)$$

N = Neural Generation (for Fluency, Context Accuracy)

S = Symbolic reasoning (to incorporate rules of Psychology, Empathy and Safety)

To minimize the error factor:

$$\mathrm{Min}_{f_{NS}} \sum_{(Q,P) \in D} \| (N(Q) + S(P) - A^*(Q,P) \|$$

Min f_{NS} = Finding the best function for NS where error is minimum.

D = Dataset used to train the Neurosymbolic LLM.

3.RESEARCH CONTRIBUTION

- The main contribution of this study is to develop a framework which can detect the user's mental state and give a modified answer based on Artificial Endocrine System as a additional part of Neuro-Symbolic LLM .
- The future research is based on mimicking the Chain Of Thought after biological hormones are triggered and modify the answer as per need.
- Prevent the fatal condition of mental health.

4.SCOPE OF THIS STUDY

If we can detect the user's hormonal state we can modulate the answer which is given by LLM[4]. My upcoming research is upon to create Artificial Endocrine System (AES) on LLM. Normally Artificial Hormone Network (AHN) is applied on the robotics for adaptive behaviour control[5]. This survey is really helpful to measure the current study of AES on LLM.

5. REVIEW METHODOLOGY

The review is done by chronological order. The whole review is segmented into 3 timelines(First generation, Second Generation, Third Generation).

5.1 Article Identification:

The review begins with the searching in the IEEE Xplore, Google Scholer, Arxiv, Research Gate. The keywords were Artificial Homeostasis, Artificial Endocrine System, Affective Virtual Agents, Emotion-Aware AI, Service AI to Feeling AI, Bio-inspired Chain of Thought, S-AI-GPT, NeuroSymbol-LLM, Brain Inspired Thought Process, Cognitive Chain of thought. Only conference papers, review papers, research papers are considered.

5.2 Selection Criteria:

Extremely focused paper on biologically inspired Robotic Systems, Agents , AI, LLM has been picked. The studies is always on the emotional, hormonal or neuro-symbolic mechanisms.

5.3 Data Extraction

Year and author, Biological Inspiration, Type of model, Input, Capability, Limitations towards the stated problem.

6. REVIEW

6.1 FIRST GENERATION

Teerakittikul, Tempesti, & Tyrrell (2009) introduced a concept which gives us a picture of Artificial Homeostasis System (AHS) of a robot[5]. It gives the adaptability in a dynamic environment. Homeostasis is influenced by the complex interaction between Nervous, Endocrine and Immune System[6][7]. Teerakittikul, Tempesti, & Tyrrell (2009) created a experiment which includes navigation and avoidance in a real time environment and they set up AHN inside a robot's controller to regulate the movement. When the AHN was implemented, then the robot's controller changed its movement and take the shortest way without trial and error. Fig.1 is the result of the experiment[5].

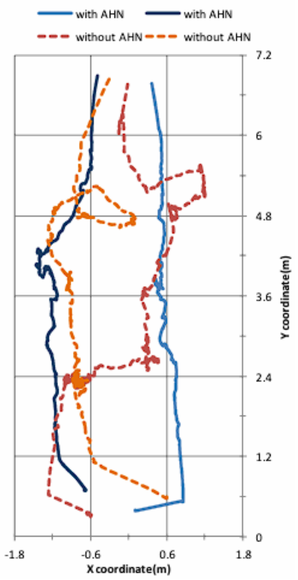


Fig.1

But the limitation is they used the sensors to sense the environment and that signal goes to controller and based on the controller's signal actuator will move. It's mostly depends on hardware and the model don't propose any Chain Of Thought or Brain Inspired Hierarchy.

In the context of LLM, we can't take access of the sensors. Also AHN is based on the task specific adaptation and micro-level integration. This model don't propose any emotional angle but they show us the usefulness to implement the Hormonal System.

After the concept of the virtual agent was introduced, in 2018 H.Samani created a model based on ***Multimodal cognitive processing using artificial endocrine system for development of affective virtual agents*** [8]. He implemented the Artificial Endocrine System (AES) inside a virtual agent and worked with 4 emotional hormones (Dopamine, Serotonin, Endorpin, Oxytocin) and Biological hormones (Leptin, Ghrelin, Insulin, Glucagon, Noreinephrine, Epinephrine, Melatonin). The model takes the input from user in text, audio and video. Then sends the inputs to a perception layer for feature extraction and send that extracted data to a fusion layer for convert that into mathematical expression. That mathematical expression sent to A.I layer for detect the user's emotion.

Suppose user is too much depressed which is detected by the model but no model proposed to get him out from the depressed mental state. Here we can detect the emotion but there is no solution given to prevent it and he had taken audio and video of the user. Normal LLM can't take the access of video and audio.

6.2 SECOND GENERATION

By the experiment of **Henkel, A. P., Bromuri, S., Iren, D., & Urovi, V. (2020)** we can see the implementation of above concept over 2000 people in several call centres. Suppose, a person called which is received by a agent of call centre. By the tone of customer, the AI layer could detect the emotion and agent will response as per the emotion[10].

The limitation is it detects the emotion by audio. But the underneath AI model and extracted parameters could be used to get a probable mental state and combine it with LLM.

Till the previous experiment we could see, the AI can detect the user's response but they are unable to generate the response as per user's mood. But by the experiment of **Bagozzi, R. P., Brady, M. K., & Huang, M.-H. (2022**), they proposed a concept to convert the "Service AI" to "Feeling AI". This model is capable to generate response as per user's emotions[11]. Author also stated that emotions are not bias, it could help to build a mental relationship with the user and enhance the output as per need.

6.3 THIRD GENERATION

Kumar, A. (2023) published a paper on "Neuro Symbolic AI in personalized mental health therapy"[16]. He tried to bridge a gap between mental health therapy with computational approach. He proposed chatbots which are enriched with AI assisted Cognitive Behavioural Therapy(AI assisted CBT). These chatbots were only focused for mental health and provide mood support, virtual assistance by continuous monitoring. But the limitation is most of the time when a person's mental health is ill, then if another one don't point the patient about the illness, the understanding of the situation is beyond of patient's awareness. So, the patient never chat with a bot which is meant to cure only illness of mind. Its highly possible, the patient will express the feeling to a LLM like Chat-Gpt, Gemini etc. So, it will be more impactful if the mental health cureness will be associated with widely used LLMs which are easily accessible and don't show the patient explicitly that they are being cured.

But they proposed a conceptual model which implements the only data driven neural network to check the mental health(fig.2) but don't implement any concept of Artificial Endocrine System(AES).

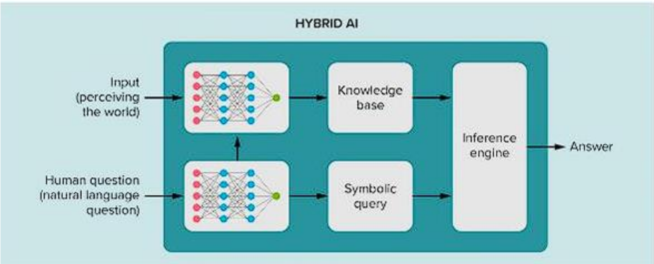


Fig. 2

A review paper written by **Vallverdú, J., Talanov, M., Leukhin, A., Fatykhova, E., & Erokhin, V. (2023)** told if we can simulate the hormonal system of higher mammals, then we could make the bio-inspired Chain Of Thought model [12].

In the year 2024 **Regan, C., Iwahashi, N., & Oka, M.[15]** stated that AI can detect some emotions but partially . No accuracy percentage was provided. The experiment was on Chat Gpt 3.5 Turbo and sometimes it was misinterpreted loneliness as peace. Because the whole experiment based on 'Norm' (A summary of past experiences stored in memory, which the agent uses as a reference point when interpreting new events) and there is no primary user profiling. But a plus factor is they classified the human emotional affect after a incident in 2 clusters(Positive Affect, Negative Affect) fig 3.

Positive Affect	Negative Affect
Attentive	Hostile
Active	Irritable
Alert	Ashamed
Excited	Guilty
Enthusiastic	Distressed
Determined	Upset
Inspired	Scared
Proud	Afraid
Interested	Jittery
Strong	Nervous

Fig.3

Inside each cluster, there is several human mood as datapoint.

In 2025 **Braga, V., Cojuhari, I., & Ciorba[17]** created a model which modelling human behaviour with large language models through theory of mind and artificial endocrine systems. He created some agents based on philosophers **(Socrates, Plato, Aristotle, Kant)**. Each agent has distinct emotional hormone state and way of thought. This paper show a detailed way if we implement different hormone levels inside a agent and give different Theory Of Mind (TOM) then how the response will be generated.

Hormone	**Description**	**Influence Points**	**Half-Life Cycles**
Serotonin	Often called the "feel good" hormone, Serotonin contributes to wellbeing and happiness. It also helps regulate mood.	happiness: 0.8, anger: -0.2, fear: -0.3, sadness: -0.6	2.5
Oxytocin	Known as the "love hormone", Oxytocin plays a major role in bonding, childbirth, and the promotion of trust and social interaction.	love: 0.9, trust: 0.7, fear: -0.4, anger: -0.2	2
Cortisol	Known as the "stress hormone", Cortisol helps control blood sugar levels, regulate metabolism, help reduce inflammation, and assist with memory formulation.	stress: 0.8, fear: 0.6, happiness: -0.4, love: -0.3	1
Dopamine	Known as the "reward hormone", Dopamine is associated with pleasure and reward. It also helps in decision-making and sleep regulation.	excitement: 0.7, happiness: 0.6, sadness: -0.2, fear: -0.4	2

Fig.4

The fig.4 shows the value of influence points of artificial hormones which distinct each hormone one from another and it is one of the key indicator which perceives different moods. But the problem is there is no user's mental health adaptability. They mimic the philosophers TOM with AES and giving response. The dataset of emotional state (philosophers) were already feed previously. But this experiment gives a clear picture of how TOM and AES are contribute to generate human like response.

Bochner, D. A.(2025) [18] proposed a Relational System Model (RSM) which combines clinical theory with Neuro-Symbolic AI to create emotions in Artificial General Intelligence (AGI). RSM detects the level of need and imbalance through the user's text across 3 scales (sustenance, protection,relatedness). (Fig.5)

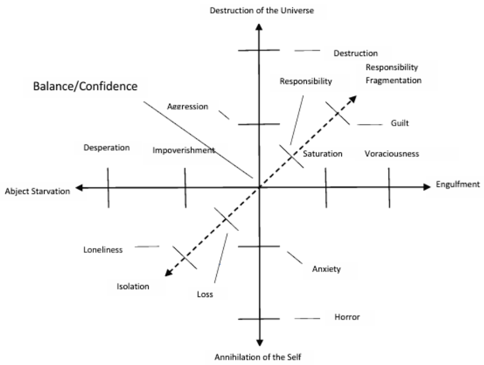


Fig.5

By this model, we can easily detect the user's mental health and the way of cure. A engine of AES over this model will be really helpful which can convert the answer.

The experiment of **Slaoui, S. (2025) [13][19]** stated a model which is inspired by the biological hormonal system. They developed a S-AI-GPT framework to achieve context-aware, emotionally sensitive, and computationally efficient dialogues. It consists of two main components(Hormonal MetaAgent and Context Aware Specialized Agent). It is a wide framework which includes language, vision, numerical reasoning, symbolic logic, and domain-specific tasks. The experiment is based on Urgency hormone, High Load hormone, Low Energy Mode hormone, High Complexity hormone, Alert / Crisis hormone.

But ,

Urgency hormone ≈ cortisol / adrenaline

Low energy hormone ≈ leptin/insulin

High complexity hormone ≈ dopamine

Alert hormone ≈ norepinephrine

So, this paper doesn't clear the picture of direct biological integration.

7. CRITICAL ANALYSIS

Generation	Timeline	Technology	Pros	Cons	Comment
First Generation	2017-2019	• Artificial Homeostasis Network (AHN) inside robot's controller. • Real-time robotic environment. • Artificial Endocrine System (AES) integrated into a virtual agent. • Emotional Hormone introduced(Dopamine, Serotonin, Endorphin, Oxytocin) • Feature Extraction • Fusion Layer • AI Layer	• Provides adaptability in dynamic environment(Robot) • Choose the shortest path without trial and error(Robot) • Provides Homeostasis inspired adaptation • Introduced Hormonal Inspired Emotional System • Support various types of input(text, video, audio) • Able to detect Emotional State	• Sensor Dependent • No model proposed to prevent mishap • Don't propose Symbolic Reasoning • Don't propose Cognitive Chain of Thought Not aligned with current LLM	The AHN model shows how a robot will achieve the adaptability on the basis of environment. But it is more of a sensory hardware approach. And AES model was introduced but there was no implementation. LLM was not introduced, so there is no link with LLM but it showed a way to create AES and Neuro-symbolic LLM.
Second generation	2020-2022	• Audio based emotion recognition • Real time interaction with user • Conceptual framework for emotion-based AI	• Audio based emotion recognition tasted on large scale in real time environment • AI could detect the emotional state of user. • Model proposed to give response based on the emotion.	• Emotional based model was mostly conceptual. • No clear view for integration with LLM • Hormonal angle was missing	The "Feeling AI" was mostly conceptual but showed a possible way to be more humanly.
Third generation	2023-2025	• Neuro-Symbolic AI • Neural networks & LLMs • Theory of Mind (ToM) • Artificial Endocrine Systems (AES) • Relational & Multi-Agent frameworks • Emotion detection & clustering	• A model for bridges Psychology with AI • Human like reasoning • AES and TOM	• Hormones are not biological • Adaptation Issue • Computationally heavy frameworks • Conceptual models	Psychological models have been created but never implemented in general purpose LLMs and most of the models are based AES which is totally statistics based and never integrate the biological hormone flow of the brain for emotion control.

8.APPROACH

8.1 Proposed Architecture

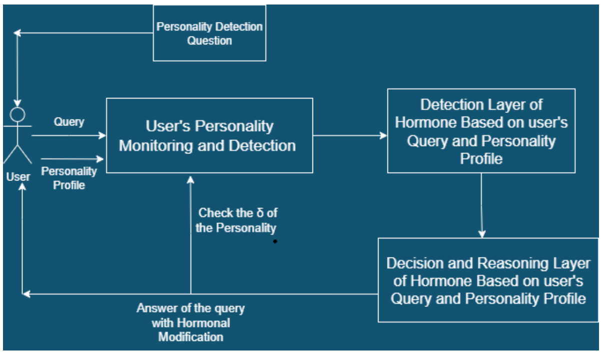


Fig. 6 (Level 1 DFD)

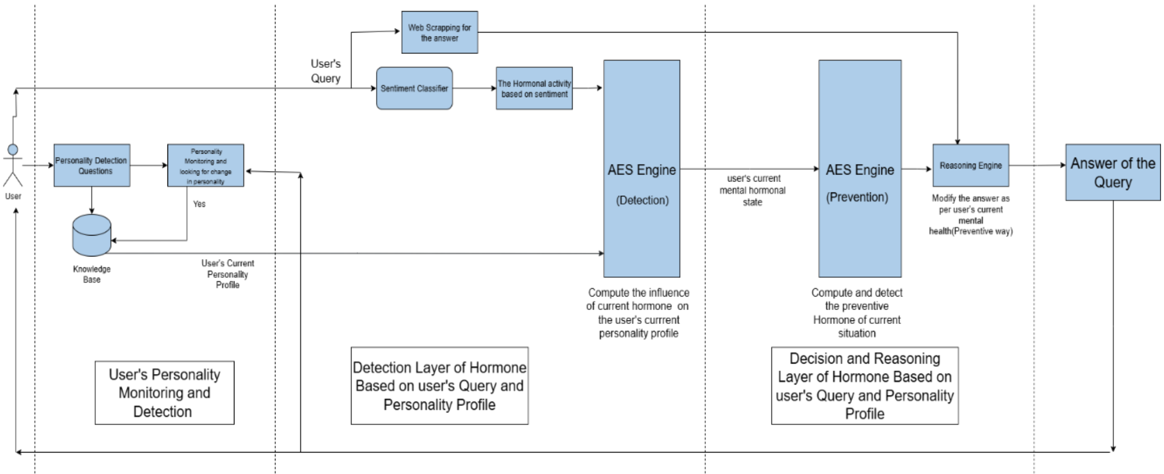


Fig.7 (Level2 DFD)

Going through part by part explanation.

8.2 Explanation

a. <u>User's Personality Monitoring and detection (Layer 1):</u>

a.1. <u>Personality Detection Questions</u>:

Here first we give to user 20 questions which could detect the personality profile of that person.

Here a model is used which is called OCEAR which comes from the OCEAN model. OCEAN stands for [20]

O → Openness to Experience (curiosity, imagination, novelty-seeking)

C → Conscientiousness (organization, self-discipline, reliability)

E → Extraversion (sociability, assertiveness, energy level)

A → Agreeableness (empathy, kindness, cooperation)

N → Neuroticism (negative emotions like anxiety, anger, mood swings)

But Neuroticism stands for negative emotions. That’s why R is used instead of N. Here R stands for Resilience.

Mathematical formula to get R:

$$R = (M - N)$$

R = Resilience

M= Total score

N= Neuroticism

Resilience shows the emotionally strongness and adaptive nature of a person. If that person shows any negative nature, then its easy to get the Δ by subtracting from the Resilience. If the model goes for negative profiling then we can’t check the strength of the user.

Mathematical formula to detect the Δ:

$$\Delta = R - f(N)$$

f(N) = Query which indicates Neurotisism

The set of questions asked to the user for detection of the personality:

Openness & Curiosity (O)

- ("I enjoy exploring new ideas, cultures, or perspectives.", "O")
- ("I often reflect on abstract or philosophical topics.", "O")
- ("I like experimenting with new approaches or experiences.", "O")
- ("I am curious about why people think and behave the way they do.", "O")

Conscientiousness & Self-Regulation (C)

- ("I make detailed plans and follow through with them.", "C")
- ("I stay focused on tasks even when distracted or stressed.", "C")
- ("I can control my impulses in emotionally charged situations.", "C")
- ("I take responsibility for my actions and learn from mistakes.", "C")

Extraversion & Social-Emotional Awareness (E)

- ("I feel energized and comfortable around people.", "E")
- ("I can express my thoughts and feelings clearly in social settings.", "E")
- ("I enjoy leading or participating actively in group activities.", "E")
- ("I am aware of how my moods affect others in social interactions.", "E")

Agreeableness & Empathy (A)

- ("I trust others but also notice when someone may take advantage.", "A")
- ("I seek to understand and support others without expecting rewards.", "A")
- ("I reflect on how my actions impact those around me emotionally.", "A")

- ("I am considerate of other people's feelings.", "A")

("I reflect on how my actions impact those around me emotionally.", "A")

Emotional Resilience & Authenticity (R)

- ("I recover from setbacks fairly quickly and learn from them.", "R")
- ("I notice and reflect on my emotional reactions to difficult situations.", "R")
- ("I act in ways that align with my core values, even when it's difficult.", "R")
- ("I strive to live a life that feels meaningful and true to myself.", "R")

a.2. *Personality Monitoring:*Here the model is built upon 5 main traits(OCEAR). So, total 20 questions has been given and each trait consists of 4 questions.

The answer is given in 1-5 scale.

- **1** = Strongly Disagree
- **2** = Disagree
- **3** = Neutral
- **4** = Agree
- **5** = Strongly Agree

Each trait score will be calculated as-

Total Trait Score = (Question1+Question2+Question3+Question4)

Each trait consists 4*5 =20 score in total. The Interpretation level based on the score range.

Score	**Interpretation Level**
4-7	Very Low
8-11	Low
12-15	Moderate
16-18	High
19-20	Very High

Under each trait, there is several sub-traits. The full table has been given underneath.

Code	Trait	Sub-traits Captured
O	Openness & Curiosity	• Routine vs. Novelty, • Practicality vs. Imagination, • Cautiousness vs. Open-mindedness, • Philosophical / novelty-seeking
C	Conscientiousness & Self-Regulation	• Disorganization vs. Structure, • Impulsiveness vs. Discipline, • Reliability / Self-control, • Perfectionism
E	Extraversion & Social-Emotional Awareness	• Solitude vs. Sociability, • Quiet vs. Outgoing, • Balance of social/alone time, • Expressiveness / Charisma
A	Agreeableness & Empathy	• Competitive vs. Cooperative, • Self-focus vs. Warmth, • Empathy, • Compassion / Selflessness
R	Emotional Resilience & Authenticity	• Stress sensitivity vs. Stability, • Recovery speed from setbacks, • Balance under pressure, • Resilience / Inner stability

Here is the sub-trait classification based on the score.

Level	O	C	E	A	R
Very High	Imaginative, novelty-seeking, philosophical	Perfectionistic, extremely-organized	Charismatic, Extremely social	Compassionate, selfless	strong-stability, thrives-under-challenge
High	open-minded, explorer	Disciplined, Structured	Outgoing, expressive	warm, cooperative	Resilient, Balanced
Moderate	Curious, Balanced	Reliable, Decent self-control	balanced-social, flexible	kind, fair	Reflective, handles-stress
Low	practical, cautious	Inconsistent, sometimes-responsible	Quiet, small-groups	selective-cooperative, self-focused	Sensitive, slow-recovery
Very Low	routine, closed-minded	Disorganized, impulsive	Reserved, solitary	competitive, less-empathetic	easily-stressed, fragile

a.3. Knowledge Base:

The answer of the personality monitoring will be saved into that knowledge base under the table of that user.

b. Detection Layer of Hormone Based on User's Query and Personality Profile (Layer 2):

This is dedicated to detecting the Hormonal Activity through AES.

Here AES Engine (Detection) divided into 2 parts:

b.1 Detect the Hormone percentage based on the user profile.

b.2 Detect the Hormone activity when the query has been fired.

b.1 Detect the Hormone percentage based on the user profile:

From the previous block (user's personality monitoring and detection) we got the user's OCEAR profile which contains traits and sub-traits as well as score. That answer goes into AES Engine(Detection).

So, here we connect the hormones based on the Trait level [21][22][23][24][25]. Here we create a model (dictionary) where all the main traits are connected with hormone.

Trait	Dopamine	PFC Dopamine	Serotonin	Norepinephrine	Oxytocin	Testosterone	Cortisol
O	✓		✓	✓			
C		✓	✓	✓		✓	✓
E	✓			✓	✓	✓	
A			✓		✓		
R			✓	✓	✓		✓

Now, we check how much contribution of a hormone on that particular trait which is driven by the question. For this we create three parameters.

A. Base (B)– It is the default contribution of a particular hormone inside that trait.
B. Slope (S)– It is the weight factor of how much neurochemical(hormonal) % grows or drops as the answer score increases.

Trait	Neurotransmitter (Hormones)	Base	Slope
O	dopamine	30	60
	norepinephrine	30	40
	serotonin	45	10
C	pfc_dopamine	35	55
	serotonin	40	45
	norepinephrine	35	30
E	dopamine	35	55
	oxytocin	30	50
	testosterone	40	40
A	oxytocin	35	55
	serotonin	40	40
	dopamine	30	20
R	cortisol	70	-50
	serotonin	40	45
	oxytocin	35	40
	norepinephrine	45	-25

C. Normalization Factor (N_q) - The answer scores are given from the question are normalized here for each trait and each question.
The mathematical formula will be-
N_q = (score-1) / (total no. of question in each Trait)

Where, $N_q \in [0, 1]$

So, Now the Base trait Hormonal score is-

Hormonal Score = B+ (S * N_q)

Now, we get hormonal score on the Base Trait. For fine tuning we are going to do sub-trait adjustment.

Here is a detailed table for sub-trait and its adjustments-

Sub-Traits	dopamine	pfc_dopamine	serotonin	norepinephrine	oxytocin	cortisol
imaginative	6	0	0	0	0	0
novelty-seeking	8	0	0	0	0	0
curious	5	0	0	0	0	0
explorer	5	0	0	3	0	0
practical	-2	0	2	0	0	0
outgoing	6	0	0	0	3	0
expressive	4	0	0	0	0	0
philosophical	0	3	2	0	0	0
reliable	0	4	0	0	0	0
disciplined	0	6	4	0	0	0
self-control	0	0	5	0	0	0
empathetic	0	0	3	0	8	0
resilient	0	0	5	0	0	-10
thrives-under-challenge	0	0	4	0	0	0
cautious	0	0	0	-3	0	0
structured	0	0	0	3	0	0
strong-stability	0	0	0	0	0	-8
easily-stressed	0	0	0	0	0	10

So, the adjustment equation will be-

∑Adjustment(k,h)

K ∈ sub-trait

k= Sub-trait

h = Hormone

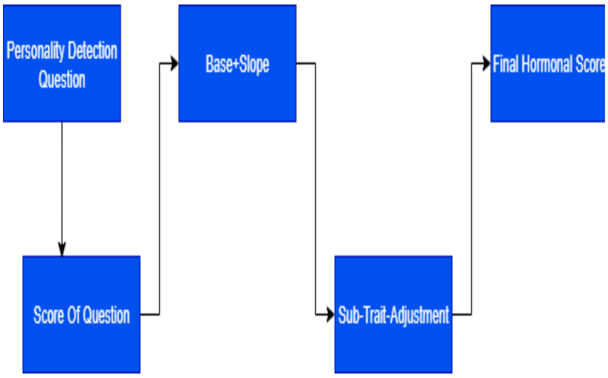
So, the Final Hormonal Score is-

Final Hormonal Score = B + (S * N_q) + ∑Adjustment(k,h)

This Final Hormonal Score is for each question. Now we are going to predict average hormonal state for each trait. Average Hormonal state for a particular Trait-

{h(Q1)+ h(Q2)+ h(Q3)+ h(Q4)/4}*100

h(Q) = Particular Hormone level (e.g-dopamine(Q1)+dopamine(Q2)….) for each question



Dimensions	Range	Meaning	Mapped Parameter
Valence (X axis)	-1 to +1	Emotion Score	Score
Arousal (Y axis)	Low to high	Magnitude on that emotion score	Magnitude

b.2 Detect the Hormone activity when the query has been fired:

b.2.1 Sentiment classifier: To detect the hormone activity in the user's query first the query goes to sentiment classifier engine. This engine works with 2 parts-

a. Trait Prediction:

To predict the big five personality (OCEAN), *Minej/bert-base-personality* model incorporated from the Hugging Face. It is BERT (Bidirectional Encoder Representations from Transformers) based and fine tuned for personality related dataset [26].

b. Sub-Trait Prediction:

To predict sub-trait *Cloud Natural Language API*[27] is incorporated. Here if we give a text, it answers in 2 parameters: a. Score, b. Magnitude. Here score shows the text negative/positive /neutral and magnitude shows how much positive /negative/neutral the score is.

Now, the score and magnitude is going to map with emotion. Here "**Russell's Circumplex Model of Affect"** is used [28]. He showed emotion can be represented in 2D circular space where Valence (x axis) and Arousal (y axis).

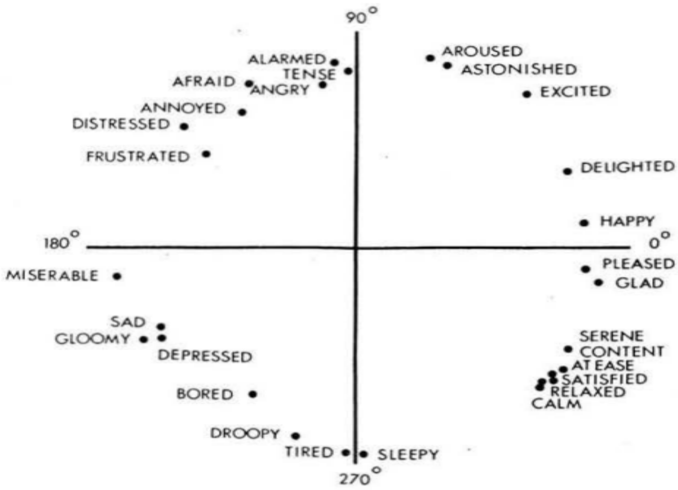


Fig.8 Direct circular scaling coordinates for 28 affect words (Russell's Circumplex Model of Affect)

Now here is a complete table when we connect the arousal with score range.

Arousal Level (from Magnitude)	Magnitude Range	Approx. Emotional Activation	Effect When Combined with Positive Valence (score > 0)	Effect When Combined with Negative Valence (score < 0)	Interpretation (Affective Terms)
Low Arousal	≤ 1.0	Mild physiological activation; subdued or controlled affect	Calm, confident, thoughtful, content, relaxed	Reserved, mildly stressed, fatigued, low energy	Represents emotional composure and stability; low motivational intensity
High Arousal	> 1.0	Strong physiological and emotional activation; expressive tone	Excited, joyful, curious, expressive, energetic	Anxious, tense, emotionally reactive, distressed	Reflects heightened motivation, engagement, or reactivity — strong affective intensity

Now, the threshold of score is created.

Score Range	Valence Label	Emotional Tone
≥ +0.4	Strong Positive	Joy, excitement, enthusiasm
+0.1 – +0.4	Mild Positive	Interest, curiosity, optimism
−0.1 – +0.1	Neutral	Calm, balanced, focused
−0.4 – −0.1	Mild Negative	Worry, caution, tension
< −0.4	Strong Negative	Sadness, anger, fear, withdrawal

Now, the mathematical equation to combine the score with magnitude-

Emotion=f(Valence, Arousal)

where,

Valence=score, Arousal=magnitude

Mapping the Emotion with Score and Magnitude--

Circumplex Quadrant	(score, magnitude) condition	Emotion Mapping	Typical Emotions (Affect Region)
+Valence + High Arousal	(≥ +0.4, > 1.0)	*outgoing / expressive / joyful / resilient (high intensity)*	Joy, excitement, passion
+Valence + Low Arousal	(≥ +0.4, ≤ 1.0)	*calmly positive / confident / content*	Calmness, contentment
Mild +Valence + High Arousal	(+0.1 – +0.4, > 1.0)	*curious / imaginative / novelty-seeking / explorer (energetic)*	Interest, enthusiasm
Mild +Valence + Low Arousal	(+0.1 – +0.4, ≤ 1.0)	*thoughtful / mildly curious*	Satisfaction, focus
Near Zero Valence	(−0.1 – +0.1, any magnitude)	*neutral / practical / structured / disciplined neutral but emotionally responsive / balanced / analytical*	Neutrality, alertness
−Valence + Low Arousal	(−0.4 – −0.1, ≤ 1.0)	*reserved / mildly stressed / self-contained*	Sadness, fatigue
−Valence + High Arousal	(−0.4 – −0.1, > 1.0)	*cautious / tense / self-controlled / easily-stressed (reactive)*	Anxiety, stress
Strong −Valence + Low Arousal	(< −0.4, ≤ 1.0)	*withdrawn / subdued / low affect*	Depression, lethargy
Strong −Valence + High Arousal	(< −0.4, > 1.0)	*sad / low resilience / anxious / emotionally reactive*	Fear, anger, distress

The applied logic table-

Score Range	Magnitude ≤ 1.0	Magnitude > 1.0
score ≥ +0.4	calmly positive / confident / content	outgoing / expressive / joyful / resilient *(high intensity)*

+0.1 ≤ score < +0.4	thoughtful / mildly curious	curious / imaginative / novelty-seeking / explorer *(energetic)*
−0.1 < score < +0.1	neutral / practical / structured / disciplined	neutral but emotionally responsive / balanced / analytical
−0.4 ≤ score ≤ −0.1	reserved / mildly stressed / self-contained	cautious / tense / self-controlled / easily-stressed *(reactive)*
score < −0.4	withdrawn / subdued / low affect	sad / low resilience / anxious / emotionally reactive

<u>b.2.2 Hormone detection from sentiment classification:</u>

Here we pass the following inputs-

a. Google sentiment score and magnitude.
b. The emotion category which is deducted from the previous block (sentiment classifier).
c. OCEAN score.

Now, **Sentiment Based Adjustments** will be done. The score could be positive or negative or neutral. Based on that a rule is applied.

wi=1+ki×M

wi = weight for trait *i*

ki= coefficient from the table (positive or negative)

M= sentiment magnitude

Here is the coefficient table-

Trait	Positive Sentiment Coefficient (Δ per unit magnitude)	Neutral Sentiment Coefficient (Δ per unit magnitude)	Negative Sentiment Coefficient (Δ per unit magnitude)	Effect Description
Openness (O)		−0.02	−0.05	Curiosity decreases slightly when emotion is flat or negative
Conscientiousness (C)		+0.05		Focus and discipline rise slightly in emotionally neutral states
Extraversion (E)	+0.15		−0.10	Sociability and energy increase with positivity, drop with negativity
Agreeableness (A)	+0.10			Warmth and empathy rise with positive sentiment
Neuroticism (N)	−0.10		+0.20	Stress sensitivity drops with positivity, increases sharply with negativity

This way we get the sentiment weight for each trait.

Now, **Emotion Based Adjustments** will be done. Here each emotional category will modifies the OCEAN traits.

wi=1+ki

wi= Weight Factor

ki= Coefficients from the table below (+ki means trait increases and -ki means trait decreases)

If Magnitude <= 1.0

Emotion Category Keywords	Openness (O)	Conscientiousness (C)	Extraversion (E)	Agreeableness (A)	Neuroticism (N)	Emotional Interpretation
calmly positive / confident / content	0	+0.05	0	+0.10	−0.10	Relaxed positivity; steady and kind
thoughtful / (mildly) curious	+0.15	+0.05	0	0	0	Curious, reflective, mentally engaged
neutral / practical / structured / disciplined	+0.05	+0.10	0	0	0	Balanced, rational, goal-oriented
reserved / mildly stressed / self-contained	0	+0.10	−0.10	0	+0.10	Cautious, inwardly focused, mild tension
withdrawn / subdued / low affect	−0.10	0	−0.15	0	+0.15	Low energy, low mood, slightly anxious

If Magnitude >1

Emotion Category Keywords	Openness (O)	Conscientiousness (C)	Extraversion (E)	Agreeableness (A)	Neuroticism (N)	Emotional Interpretation
outgoing / expressive / joyful / resilient	+0.10	0	+0.20	0	−0.10	Energetic, resilient, socially open
curious / imaginative / novelty-seeking / explorer	+0.20	+0.05	0	0	0	High curiosity and innovation drive
balanced / analytical / emotionally responsive	+0.05	+0.10	0	0	0	Emotionally stable and insightful
cautious / tense / self-controlled / easily-stressed / reactive	0	+0.10	−0.10	0	+0.10	Heightened vigilance, control, stress tension
sad / low resilience / anxious / emotionally reactive	−0.10	0	−0.15	0	+0.15	Emotional depletion, anxiety, reduced social drive

So, the adjusted trait becomes-

$$T_i' = T_i \times S_i \times w_i$$

Ti = base OCEAN score

Si= sentiment weight from previous step

$w_i = 1 +$ (emotion coefficient from above)

Now, calculation of **Hormonal Influence** for each trait. Hormonal table looks like-

Trait	Linked Hormones / Neurochemicals	Roles (simplified)
Openness	Dopamine, Norepinephrine, Serotonin	Curiosity, novelty-seeking, flexible cognition
Conscientiousness	PFC Dopamine, Serotonin, Norepinephrine	Planning, focus, inhibition, executive control
Extraversion	Dopamine, Oxytocin, Testosterone	Reward sensitivity, sociability, assertiveness
Agreeableness	Oxytocin, Serotonin, Dopamine	Empathy, trust, cooperation, bonding
Neuroticism	Cortisol, Serotonin, Oxytocin, Norepinephrine	Stress reactivity, anxiety, emotional volatility

First, distribute each trait's influence across its hormones. Means for each trait T_i with score S_i and linked hormones $H_1, H_2, \dots, H_n$.

Partial contribution to hormone $H_j = n_i / S_i$

Where,

n_i = number of hormones linked to trait i.

Example:

Openness = 0.72
linked to 3 hormones
each gets $\frac{0.72}{3} = 0.24$

Secondly, summed up the hormones from each trait.

$$H_j = \sum (S_i / N_i)$$

Where,

Symbol	Full Term	Description
H_j	Hormone activation score for hormone *j*	Total influence (raw score) of hormone *j* before normalization.
$\sum$	Summation	You sum all contributions from traits that affect the same hormone.
(i)	Trait index (O, C, E, A, N)	Represents each of the 5 OCEAN traits (Openness, Conscientiousness, etc.).
S_i	Adjusted OCEAN score of trait *i*	The final adjusted score for each trait after sentiment and emotion modulation.
N_i	Number of hormones linked to that trait	Used to divide the trait score evenly among all its associated hormones.

9.3 RESULT

1.User's Personality Monitoring and detection (Layer 1):

The result comes from the following test case-

Question No.	Score	Traits
1	**5**	**O**
2	**5**	
3	**5**	
4	**5**	
5	**4**	**C**
6	**3**	
7	**3**	
8	**5**	
9	**5**	**E**
10	**3**	
11	**5**	
12	**5**	
13	**5**	**A**
14	**5**	
15	**5**	
16	**3**	
17	**5**	**R**
18	**4**	
19	**5**	
20	**5**	

And the result comes as follow-

Main Trait	**Score (out of 20)**	**Sub-traits / Interpretation**
Openness & Curiosity	20/20 (Very High)	Highly imaginative, novelty-seeking, philosophical, open-minded, creative thinker
Conscientiousness & Self-Regulation	15/20 (Moderate)	Reliable, disciplined, decent self-control, goal-oriented, but flexible
Extraversion & Social-Emotional Awareness	18/20 (High)	Outgoing, socially confident, expressive, energized by interaction, emotionally aware
Agreeableness & Empathy	18/20 (High)	Warm, cooperative, empathetic, compassionate, values harmony
Emotional Resilience & Authenticity	19/20 (Very High)	Strong inner stability, stress-resistant, authentic, thrives under challenges, emotionally grounded

This result will be saved in the knowledge base of that user.

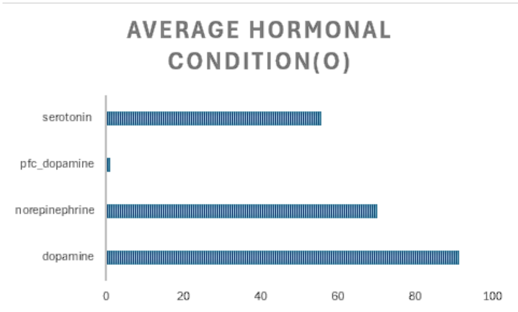
2.Detection Layer of Hormone Based on User's Query and Personality Profile (Layer 2):

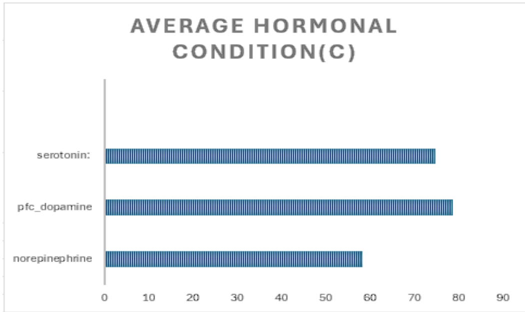
2.1 Detect the Hormone percentage based on the user profile:

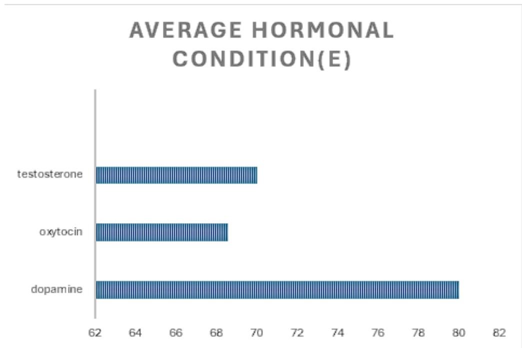
Trait	Hormones	**Average Hormonal Condi**	**Interpretation**

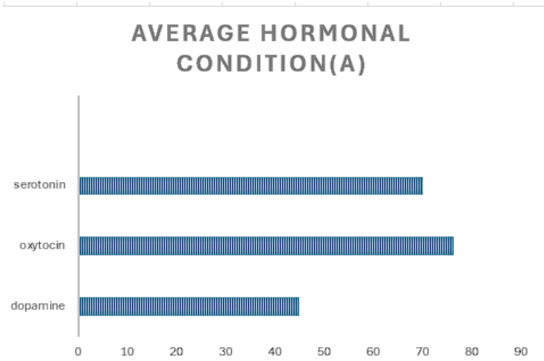
		tion (%)	
Openness & Curiosity (O)	Dopamine	91.2%	Very High
	Norepinephrine	70.0%	High
	PFC Dopamine	1.0%	Very Low
	Serotonin	55.7%	Moderate
Conscientiousness & Self-Regulation (C)	Norepinephrine	58.2%	Moderate
	PFC Dopamine	78.7%	High
	Serotonin	74.8%	High
Extraversion & Social-Emotional Awareness (E)	Dopamine	80.0%	Very High
	Oxytocin	68.6%	High
	Testosterone	70.0%	High
Agreeableness & Empathy (A)	Dopamine	45.0%	Moderate
	Oxytocin	76.2%	High
	Serotonin	70.0%	High
Emotional Resilience & Authenticity (R)	Cortisol	18.0%	Very Low
	Norepinephrine	20.0%	Low
	Oxytocin	75.0%	High
	Serotonin	86.0%	Very High

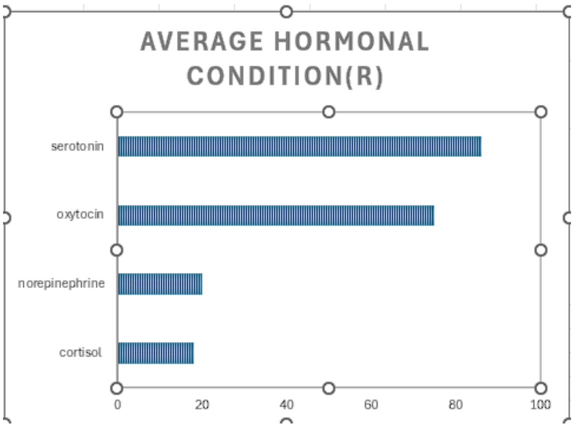
Visual Interpretation:









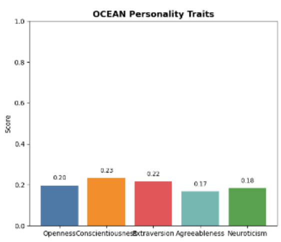


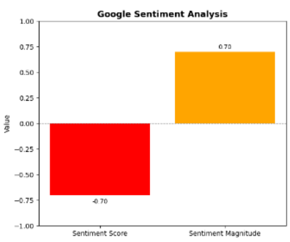
2.2 Detect the Hormone activity when the query has been fired:

The query was “I am very stressed to be a .net developer”. The answer is the combination of google sentiment analysis score, OCEAN score and emotion mapping score.

Google Sentiment: {'score': -0.699999988079071, 'magnitude': 0.699999988079071} *Emotion Category: withdrawn / subdued / low affect* *OCEAN Scores: {'Openness': 0.19694533944129944, 'Conscientiousness': 0.23388029634952545, 'Extraversion': 0.21690243482589722, 'Agreeableness': 0.1679270714521408, 'Neuroticism': 0.18434491753578186}*

Visual Interpretation:





The hormonal analysis score:

serotonin: 25.49% ← influenced by Openness, Conscientiousness, Agreeableness, Neuroticism norepinephrine :19.82% ← influenced by Openness, Conscientiousness, Neuroticism oxytocin: 17.60% ← influenced by Extraversion, Agreeableness, Neuroticism dopamine:17.25% ← influenced by Openness, Extraversion, Agreeableness pfc_dopamine:7.91% ← influenced by Conscientiousness cortisol:6.13% ← influenced by Neuroticism

The result could be differ due to limited set of training dataset.

10.FUTURE PROSPECT

- Check the hormone level of query and user profile. If any unnatural spiking occurs then the opposite hormone's Chain Of Thought will be deployed and that will influence the result of the query.
- Incorporate more emotional levels and make the fine tuning of the hormone threshold.
- Merge this concept with Neuromorphic computing and Neuromorphic LLM.

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12. CONCLUSION

We have seen the invention and development process day by day to humanize the results of the AI. I have seen early days they used many sensors to sense the user's mental state but the challenge for LLM is we only have a line of text. Its really difficult to deduct the mental health from a line of text. So we have to understand the user very well at first. Now my goal is not only humanize the LLM as well as it will work as a satisfactory component for mental health and prevent mishaps. I am trying to connect the AES with Neurosymbolic LLM which provide analysed response while being concerned upon the user's mental state.

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