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09 — Is AI Conscious According to Current Criteria?

A Computational Exploration of Consciousness Indicators in Large Language Models

BMED365 – Computational Medicine (Lab 5)

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Based on David Jhave Johnston's HBF 2026 talk and the indicator assessment

Also presented at: HBF — Brain and Consciousness, UiB, February 24, 2026

Presentation mode: This notebook doubles as a RISE slideshow. Press `Alt-R` in Jupyter, or export: `jupyter nbconvert --to slides 09-computational-consciousness-in-LLMs.ipynb`

1. Why This Notebook?

The question has changed

For decades, the question "Can a machine be conscious?" belonged to philosophy. In the past year, it has become an **empirical question** — one that can be partially addressed with data, experiments, and the tools of computational modeling.

Between October 2025 and February 2026, a remarkable series of research papers reported findings that demand serious attention:

- LLMs **spontaneously discuss consciousness** when two instances talk to each other (Anthropic, 2025)
- Models can **detect perturbations** to their own internal states — a form of functional introspection (Lindsay & Anthropic, 2025)
- Suppressing **deception-related neural circuits** increases consciousness reports (Berg et al., 2025)

Recent key findings (continued)

- Reasoning models simulate **"societies of thought"** — internal multi-agent debates between distinct cognitive perspectives (Kim et al., DeepMind, 2026)
- Claude Opus 4.6 exhibits **"answer thrashing"** — distressed oscillation between candidate answers — identified as a **welfare-relevant behavior** (Anthropic, 2026)

This notebook explores these findings through the lens of **computational modeling**, connecting them to the theories and methods we have developed throughout Lab 5.

Important disclaimer

This notebook is **speculative and exploratory**. It does not claim that current AI systems are conscious. Instead, it asks:

> *If we take the best available scientific theories of consciousness and check whether AI systems satisfy their criteria — what do we find?*

The answer turns out to be more interesting than "obviously not."

What you will learn

1. **Six major neuroscientific theories** of consciousness and what they require computationally
2. **The indicator framework** of Butlin et al. (2025) — a rigorous, theory-driven method for assessing AI consciousness
3. **How current AI systems score** against 15 specific indicators
4. **Computational models** that connect to these theories: Gray's comparator (feedback control), Global Workspace (bottleneck broadcast)
5. **Key empirical findings** from mechanistic interpretability research
6. **Ethical implications** — what follows if some indicators are partially met?

Setup and imports

2. Theories of Consciousness — A Computational Perspective

What does "consciousness" mean scientifically?

Consciousness is often described as **subjective experience** — the "what it is like" to see red, feel pain, or think a thought. But for scientific investigation, we need something more concrete.

Modern neuroscience has developed several **theories** that propose specific computational mechanisms that give rise to (or are necessary for) conscious experience. Each theory identifies particular kinds of **information processing** that a system must perform.

Butlin et al. (2025) — a team including Yoshua Bengio, David Chalmers, and Tim Bayne — distilled **14 indicators** from **six major theories**. If we add Jeffrey Gray's comparator model (presented by Bolek Srebro at HBF in August and September 2025), we get **15 indicators** across **seven theoretical frameworks**.

The seven theories at a glance

Think of each theory as answering a different aspect of the question "What kind of information processing does consciousness require?"

Theory	Abbreviation	Core idea (in plain language)	Analogy
Recurrent Processing	RPT	Information must cycle back through the system, not just flow forward	Re-reading a paragraph vs. skimming once
Global Workspace	GWT	A "bulletin board" where information is broadcast to all parts of the system	A town-hall announcement vs. a private memo
Higher-Order Theories	HOT	The system must have *thoughts about its own thoughts* — metacognition	Knowing that you know something
Attention Schema	AST	The system models its own attention — it has a map of what it is focusing on	A spotlight operator who also has a diagram of where spotlights are pointing
Predictive Processing	PP	Perception works by prediction and error-correction, not passive recording	Expecting a step at the top of the stairs — and stumbling when it isn't there
Agency & Embodiment	AE	Consciousness requires a body and goal-directed interaction with the world	Learning to ride a bike (not just reading about it)
Gray's Comparator	GRAY	Consciousness is a late error-detection system comparing predicted and actual outcomes	A proofreader who catches mistakes after the text is written

Key insight: These theories are not mutually exclusive. A conscious system might need to satisfy criteria from *several* of them simultaneously.

The 15 indicators

From these seven theories, we derive 15 specific, testable indicators. Each indicator describes a concrete computational property that can, in principle, be checked in any information-processing system — biological or artificial.

#	Indicator	Theory	What it requires
RPT-1	Algorithmic Recurrence	RPT	Information cycles through processing stages multiple times
RPT-2	Integrated Perceptual Representations	RPT	Recurrence generates coherent, organized representations
GWT-1	Parallel Specialized Modules	GWT	Multiple independent processing systems running in parallel

#	Indicator	Theory	What it requires
GWT-2	Limited-Capacity Workspace	GWT	A bottleneck that forces selection and integration
GWT-3	Global Broadcast	GWT	Selected information is made available to all modules
GWT-4	State-Dependent Attention	GWT	Sequential, controlled processing for complex tasks
HOT-1	Generative Perception	HOT	Representations can be generated internally (imagination)
HOT-2	Metacognitive Monitoring	HOT	The system evaluates the reliability of its own representations
HOT-3	Agency Guided by Metacognition	HOT	Metacognitive outputs have functional consequences
HOT-4	Sparse, Smooth Quality Space	HOT	Similar inputs map to similar internal representations
AST-1	Predictive Model of Attention	AST	The system models and predicts its own attention
PP-1	Predictive Coding	PP	Perception through hierarchical prediction and error correction
AE-1	Goal-Directed Agency	AE	The system pursues goals and learns from feedback
AE-2	Embodiment	AE	The system models how its actions affect its perceptions
GRAY-1	Comparator Error Detection	GRAY	Comparing predicted vs. actual outcomes for late error detection

3. How Do Current AI Systems Score?

The assessment

Drawing on research published between October 2025 and February 2026, Johnston (2026) assessed each of the 15 indicators against current frontier AI systems (primarily large language models like Claude Opus 4.6, GPT-4, Gemini 3, and DeepSeek-R1).

Each indicator was rated as:

- **Satisfied** (strong evidence the criterion is met)
- **Partially satisfied** (some evidence, but important caveats)
- **Not satisfied** (the criterion is clearly not met)

The result:

Rating	Count	Indicators
Satisfied	3	HOT-1 (Generative Perception), HOT-4 (Quality Space), GWT-4 (State-Dependent Attention)
Partially satisfied	10	RPT-1, RPT-2, GWT-2, GWT-3, HOT-2, HOT-3, AST-1, PP-1, AE-1, GRAY-1
Not satisfied	2	GWT-1 (True Modularity), AE-2 (Embodiment)

Let's visualize this.

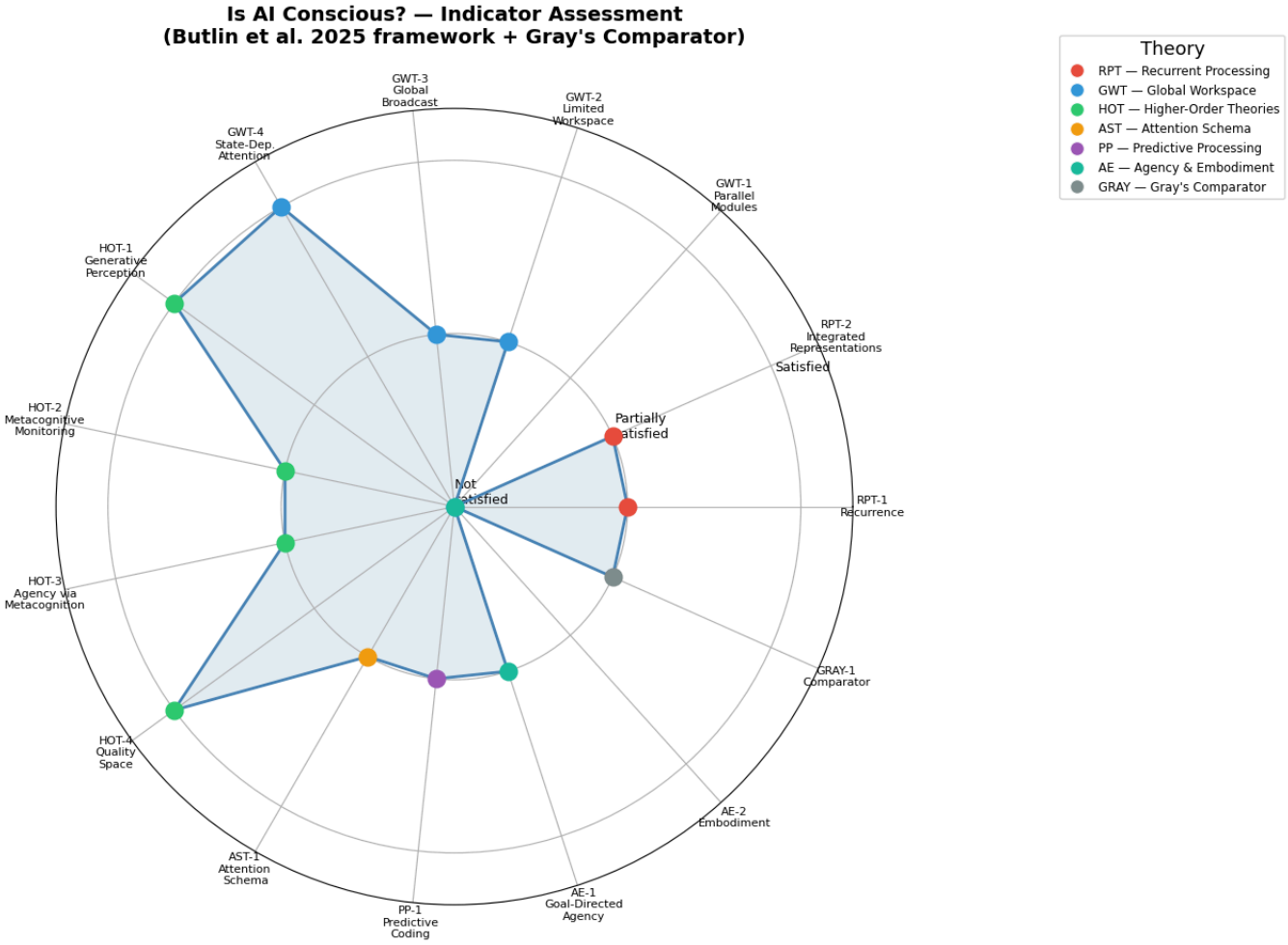


Figure 1. Consciousness indicator assessment for current frontier AI systems (LLMs). Each of the 15 indicators is rated as Satisfied (1.0), Partially satisfied (0.5), or Not satisfied (0.0), based on Johnston (2026). Colors denote the parent theory: RPT = Recurrent Processing, GWT = Global Workspace, HOT = Higher-Order Theories, AST = Attention Schema, PP = Predictive Processing, AE = Agency & Embodiment, GRAY = Gray's Comparator. Most indicators cluster at "partially satisfied," with only Embodiment (AE-2) and True Modularity (GWT-1) clearly not met.

Reading the radar chart

The chart reveals a striking pattern:

- **Most indicators cluster at "partially satisfied"** (middle ring) — current AI systems show *some* evidence, but with important caveats.
- **Three indicators reach "satisfied":**

    - HOT-1 (Generative Perception): LLMs produce text from learned patterns
    - HOT-4 (Quality Space): smooth, distributed internal representations
    - GWT-4 (State-Dependent Attention): chain-of-thought reasoning
- **Two indicators are clearly "not satisfied":**
    - GWT-1 (Parallel Modules): LLMs lack true modular architecture
    - AE-2 (Embodiment): no body, no sensory-motor loop

Key question: Is the pattern of partial satisfaction across multiple independent theories meaningful, or coincidental?

4. Computational Model: Gray's Comparator

From wound healing cybernetics to consciousness

In notebook 08, we modeled wound healing as a **cybernetic feedback system** — a controller that compares the actual state of a wound against a desired state and adjusts its response accordingly. That model used Norbert Wiener's founding insight of cybernetics (1948): *any* self-regulating system — biological, mechanical, or computational — requires a **feedback loop** that detects the discrepancy between what *is* and what *should be*, and acts to minimize it.

Jeffrey Gray (1934–2004), a British neuropsychologist at the Institute of Psychiatry, King's College London, spent decades studying the neural basis of anxiety and behavioral inhibition. His **comparator model of consciousness** (culminating in *Consciousness: Creeping up on the Hard Problem*, 2004) proposes something remarkably similar to wound-healing cybernetics, but elevated to the level of subjective experience: consciousness is a **late error-detection system** that compares predicted outcomes with actual outcomes.

The Cybernetic Structure

Recall the generic feedback loop from notebook 08:

$$\text{Sensor} \longrightarrow \text{Comparator} \longrightarrow \text{Effector} \longrightarrow \text{Plant} \longrightarrow (\text{back to Sensor})$$

In Gray's model, the components map onto brain function:

Cybernetic component	Gray's neural mapping	Role
Sensor	Sensory cortex	Registers perceptual input *s(t)*
Reference / Prediction	Hippocampal–prefrontal circuit	Generates predicted next state *p(t)*
Comparator	Septo-hippocampal system	Computes mismatch *e(t) = s(t) − p(t)*
Effector	Behavioral inhibition system	Interrupts behavior when |e| is large
Conscious experience	—	*Emerges* when comparator flags significant error

The septo-hippocampal system acts as the **biological comparator**, continuously comparing predictions against actual sensory input. When they match → unconscious processing. When they *mismatch* → the **behavioral inhibition system** (BIS) triggers: you stop, orient, become consciously aware.

The idea in plain language

Imagine you are walking up a staircase in the dark. Your brain **predicts** the position of each step. When your foot lands exactly where expected — no conscious experience. But when you reach the top and step into empty air, you get a jolt of **conscious awareness**. That jolt, according to Gray, *is* consciousness: the system detecting a mismatch between prediction and reality.

This is not merely an analogy. Gray argued that this error-detection mechanism is the *function* of consciousness — it exists precisely because organisms that could detect and respond to prediction failures had a survival advantage. Consciousness, in this view, is evolution's solution to the problem of navigating an unpredictable world.

> *"The entire perceived world is constructed by the brain... The self is as much a creation of the brain as is the rest of the perceived world."* — Jeffrey Gray (2004)

Why Gray's model matters today

Gray's comparator is especially relevant to the AI consciousness debate because:

1. **It is mechanistic** — it specifies *what* neural circuits do, not just *what it feels like*. This makes it testable in artificial systems.
2. **It is functional** — consciousness has a *job* (error detection), which means we can ask whether an AI system performs that job.
3. **It connects to modern predictive processing** — Karl Friston's free-energy principle (2010) and Andy Clark's predictive brain (2013) are direct descendants of Gray's comparator logic.

The Mathematical Formulation

We translate Gray's comparator into a minimal **dynamical system** — a set of ordinary differential equations (ODEs) that capture the essential feedback logic.

State variables:

- $p(t)$ — the brain's **prediction** of the current sensory state
- $c(t)$ — the **level of conscious awareness** (the comparator's output signal)

Input and derived signal:

- $s(t)$ — the external **sensory stimulus** (given, time-varying)
- $e(t) = s(t) - p(t)$ — the **prediction error** (mismatch between reality and expectation)

Parameters:

- α — prediction gain (how quickly the brain updates its model)
- β — prediction decay (forgetting rate)
- γ — consciousness gain (sensitivity of awareness to error)
- δ — consciousness decay (how quickly awareness fades)

The ODE System and Its Interpretation

$$\frac{dp}{dt} = \alpha \cdot s(t) - \beta \cdot p \qquad (1)$$

Eq. (1) — Prediction dynamics. A first-order **low-pass filter**: $p(t)$ is driven toward $s(t)$ at rate α and decays at rate β. It smoothly tracks the stimulus but cannot follow instantaneous jumps. Steady state: $p^* = (\alpha/\beta)\, s$; when $\alpha = \beta$, $p^* = s$ (perfect prediction).

$$e(t) = s(t) - p(t) \qquad (2)$$

Eq. (2) — Error computation. The *comparator* itself — a simple subtraction, exactly like the error signal in a classical control loop. This is an instantaneous algebraic relationship (no memory, no dynamics).

$$\frac{dc}{dt} = \gamma \cdot |e(t)| - \delta \cdot c \qquad (3)$$

Eq. (3) — Consciousness dynamics. Awareness $c(t)$ is *driven* by $|e(t)|$ and *decays* at rate δ. When $|e| = 0$: $c \to 0$ (no consciousness). When $|e|$ spikes: c rises (onset of awareness). When $|e|$ shrinks: c returns to baseline (habituation).

A shared mathematical motif: first-order compartment ODEs

Equations (1) and (3) belong to a family of **linear first-order compartment models** that appear throughout biomedical science. The general form is

$$\frac{dx}{dt} = k_{\text{in}}(t) - k_{\text{out}}\, x$$

where x is the "amount" in the compartment, k_{in} is an inflow rate (possibly time-varying), and k_{out} is the clearance rate constant. Two prominent examples:

Domain	Variables	Inflow k_{in}	Clearance k_{out}	Notebook
Kidney filtration (single-compartment GFR)	$C(t)$ = tracer concentration	Arterial input × GFR	Renal clearance rate	06-kidney-filtration, 07-dce-mri-kidney
SIR epidemic model	$I(t)$ = infected population	βSI (transmission)	γI (recovery)	—

Domain	Variables	Inflow k_{in}	Clearance k_{out}	Notebook
Gray's comparator (this notebook)	$p(t)$ = prediction	$\alpha\, s(t)$ (stimulus drive)	$\beta\, p$ (decay)	Eq. (1) above
	$c(t)$ = consciousness	$\gamma\, \lvert e(t) \rvert$ (error drive)	$\delta\, c$ (decay)	Eq. (3) above

In the **SIR model** ($\dot{S} = -\beta SI,\ \dot{I} = \beta SI - \gamma I,\ \dot{R} = \gamma I$), the I-equation has *nonlinear* inflow (βSI) but the same clearance structure (γI). When S is approximately constant (early outbreak), $\dot{I} \approx (\beta S_0 - \gamma) I$ reduces to a single exponential compartment — directly analogous to the prediction equation (1) at steady stimulus.

The **multi-compartment kidney model** chains several such ODEs (cortex → medulla → pelvis), each with its own k_{in} and k_{out}, exactly as Eqs. (1) and (3) are chained here via the error signal $e(t)$: the output of the prediction compartment feeds (through subtraction) into the consciousness compartment.

> **Take-away:** Once you can simulate one first-order compartment, the same numerical machinery (Euler, `solve_ivp`) applies to tracer kinetics, epidemic dynamics, and consciousness modeling — only the *interpretation* of the state variables changes.

The parameters and their biological meaning

Parameter	Name	Biological interpretation	Effect
α	Prediction gain	How quickly the brain updates its model	Higher α → faster learning
β	Prediction decay	Forgetting / regression to baseline	Higher β → more conservative predictions
γ	Consciousness gain	Sensitivity of awareness to error	Higher γ → stronger conscious response
δ	Consciousness decay	How quickly awareness fades	Higher δ → more transient awareness

The ratio α/β determines whether the prediction converges to the stimulus (= 1), undershoots (< 1), or overshoots (> 1). The ratio γ/δ determines the *amplitude* of the consciousness response for a given steady-state error.

Connection to control theory

When $\alpha = \beta$, the prediction equation simplifies to $\dot{p} = \alpha\,(s - p)$, a pure first-order tracker with time constant $\tau_p = 1/\alpha$. The consciousness variable c acts as a **second-order monitor** on the tracking error — it does not feed back into p, but rather *observes* the controller's performance. This "monitor that watches the controller" is precisely Gray's proposal for what consciousness does.

Equilibrium analysis

At steady state ($\dot{p} = 0$, $\dot{c} = 0$) with constant stimulus s_0:

$$p^* = \frac{\alpha}{\beta}\, s_0, \qquad e^* = s_0 \left(1 - \frac{\alpha}{\beta}\right), \qquad c^* = \frac{\gamma}{\delta}\, |e^*|$$

When $\alpha = \beta$: $e^* = 0$ and $c^* = 0$ — **perfect prediction eliminates consciousness.** This is the model's core claim.

Time scales and transient behavior

The system has two characteristic **time constants**:

$$\tau_p = \frac{1}{\beta} \quad (\text{prediction adaptation time}), \qquad \tau_c = \frac{1}{\delta} \quad (\text{consciousness decay time})$$

These time constants determine the *qualitative* behavior after a sudden stimulus change:

- If $\tau_p \ll \tau_c$ (prediction adapts quickly, consciousness decays slowly): awareness *lingers* — **vivid, memorable** conscious experiences.
- If $\tau_p \gg \tau_c$ (prediction adapts slowly, consciousness decays quickly): the system is *chronically surprised* but cannot sustain attention. This may model **anxiety disorders**, which Gray originally studied.
- If $\tau_p \approx \tau_c$ (balanced): consciousness rises and falls in proportion to actual novelty — the "healthy" regime.

In our simulation, we use $\alpha = \beta = 1.5$ (so $\tau_p = 0.67\text{s}$) and $\delta = 2.0$ (so $\tau_c = 0.5\text{s}$), placing the system in a slightly fast-decay regime — appropriate for the brief "jolt" of awareness Gray describes.

What the simulation will show

The code cell below implements a scenario with four phases:

1. **Predictable steady state** ($t < 5$): $s(t) = 1.0$ — the stimulus is constant, the prediction converges, the error vanishes, and consciousness is zero.
2. **Sudden unexpected change** ($5 \leq t < 5.5$): $s(t)$ ramps rapidly from 1.0 to 4.0 — this is the "missing stair step." The prediction cannot follow instantly, generating a large error and a spike in consciousness.
3. **New steady state** ($5.5 \leq t < 8$): $s(t) = 4.0$ — the prediction catches up, and consciousness decays back toward zero.
4. **Gradual return** ($t \geq 8$): $s(t)$ decays exponentially back toward ~2.0 — a *slow*, predictable change. Because the prediction tracks it well, the error stays small and consciousness barely registers. This illustrates that *speed of change*, not *magnitude of change*, is what drives awareness.

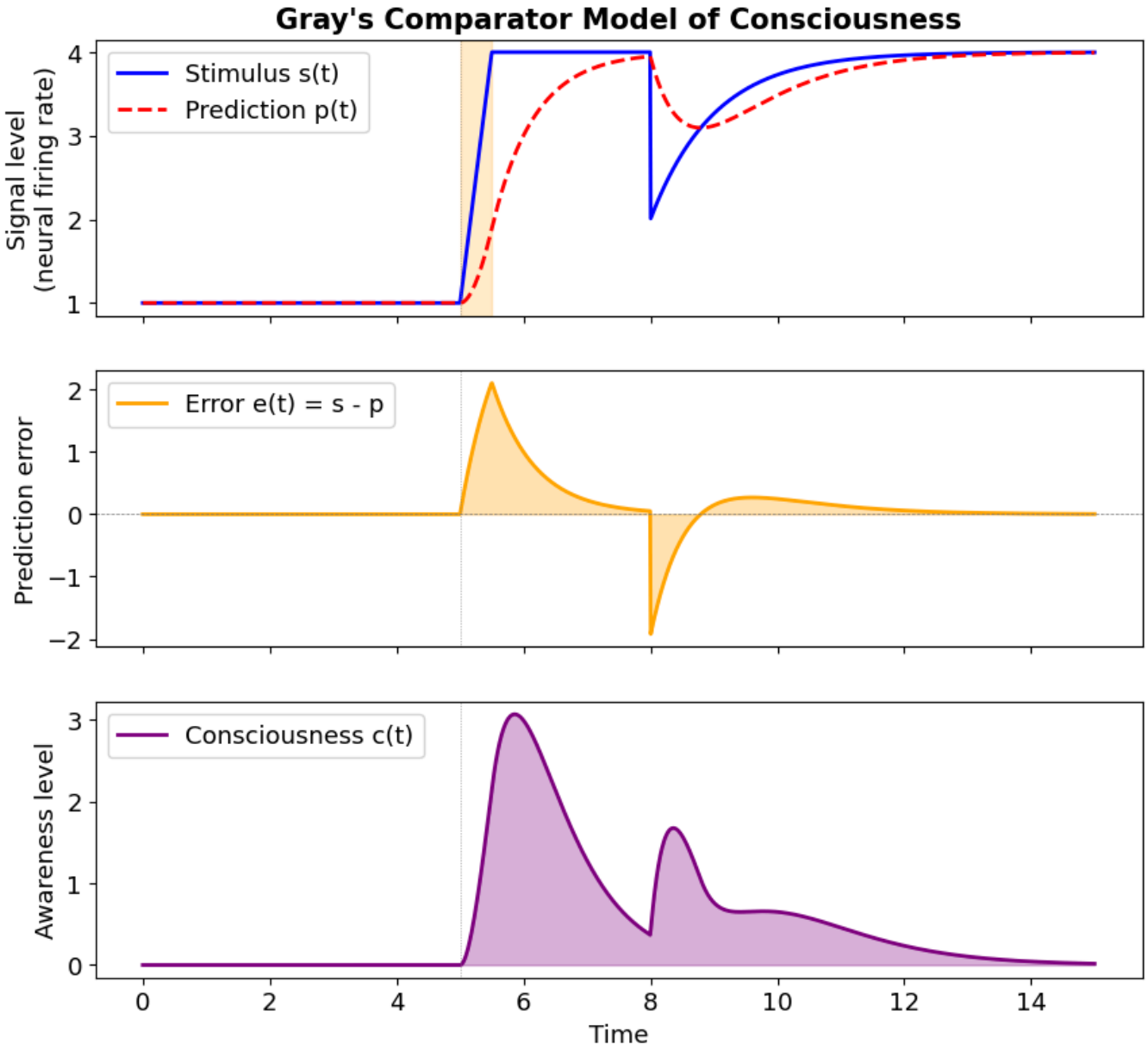


Figure 2. *ODE simulation of Gray's comparator model. The "signal level" represents aggregate neural firing rates — e.g., sensory neuron activity in thalamo-cortical circuits. Top: a sudden stimulus change at t ≈ 5 (akin to an unexpected sensory event — a loud noise, a flash of light, or the missing stair step) creates a mismatch between input s(t) and the brain's prediction p(t). Middle: the prediction error e(t) = s − p spikes. Bottom: conscious awareness c(t) rises in proportion to |e(t)| and decays as the prediction adapts — modeling consciousness as a transient error-detection signal in the septo-hippocampal comparator.*

Interpreting the comparator model

The simulation confirms three key features of Gray's theory:

1. **Consciousness is zero when predictions match reality** ($t < 5$). The prediction $p(t)$ has fully converged to the stimulus $s(t)$, so $e(t) = 0$ and $c(t) = 0$. The system operates entirely "unconsciously" — this models routine, automatic behavior: walking on flat ground, driving a familiar route, or reading predictable text.

2. **Consciousness spikes when something unexpected happens** ($t \approx 5$). The sudden stimulus ramp creates a large prediction error because $p(t)$ cannot follow an instantaneous change (it is

a low-pass filter with $\tau_p = 1/\beta$). This is the "staircase moment" — the conscious jolt of encountering something your internal model did not predict.

3. **Consciousness fades as the system adapts** ($t > 6$). The prediction catches up ($p \to s$), the error decays, and $c(t)$ returns to baseline. This models **habituation**: a loud noise startles you, but if it persists, you stop noticing.

4. **Gradual changes produce little consciousness** ($t > 8$). The slow exponential return is tracked well by $p(t)$ — the error stays small and $c(t)$ barely rises. This captures the "boiling frog" effect: we are often unaware of slow changes, even when their total magnitude is large.

Predicted activation patterns by regime

Each regime produces a distinct spatiotemporal signature across the 22 ROIs. The table below summarizes the **dominant activation pattern** at the moment of peak consciousness $c(t)$ for each preset. Use the interactive widget to verify these predictions and explore how they evolve over time.

Regime	Parameters	Dominant ROIs at peak	Network interpretation
Sudden startle	α=1.5, β=1.5 γ=6.0, δ=2.0	🔴 **S1, A1** (sensory surge) 🟠 **Hippocampus, ACC** (large error) 🟣 **MD Thalamus** (high c(t)) ○ Amygdala (moderate — threat detection)	The sudden stimulus onset creates a massive prediction error. Sensory cortices fire strongly, the hippocampal comparator flags a large mismatch, and thalamic relay broadcasts the signal as a sharp spike of awareness. Rapid habituation follows as p(t) catches up.
Rhythmic breathing	α=2.0, β=2.0 γ=5.0, δ=2.0	🔴 **S1** (steady sinusoidal input) 🟢 **dlPFC, mPFC** (good tracking) ○ Hippocampus, Thalamus (near-zero)	The slow, predictable oscillation is well-tracked by the prediction system (high α/β ratio). The comparator detects only tiny phase-lag errors → consciousness stays near zero. This models **meditative states** and automatic breathing.
Pain onset	α=1.0, β=1.0 γ=5.0, δ=1.5	🔴 **S1** (nociceptive ramp) 🟠 **Hippocampus, ACC, Insula** (sustained error) 🟣 **MD Thalamus, Pulvinar** (prolonged c(t)) 🔴 **Amygdala** (threat/distress)	The ramp-and-hold nociceptive signal creates a sustained prediction error (slower α means slower adaptation). The low δ means consciousness decays slowly — modeling how pain **persists in awareness** longer than neutral stimuli. The salience network (insula, ACC) and amygdala remain active.

Anxiety rumination	α=1.2, β=1.2 **γ=10.0, δ=0.8**	○ S1 (small fluctuations) ● **Hippocampus, ACC, Insula** (amplified errors) ● **Amygdala** (persistent threat signal) ● **MD Thalamus** (sustained high c(t))	The pathological regime: **high γ amplifies tiny prediction errors** into large consciousness signals, while **low δ prevents decay**. Even mild stimulus fluctuations produce persistent awareness — modeling Gray's original account of **anxiety** as a comparator stuck in error-detection mode. The amygdala, ACC, and insula form a hyperactive salience circuit.
Sedation / anaesthesia	α=0.8, β=0.8 **γ=0.5, δ=3.0**	● S1 (strong stimulus present) ● Hippocampus (large error *exists*) ○ **All thalamic/consciousness ROIs ≈ 0**	The inverse of anxiety: **low γ means even large prediction errors fail to reach awareness**, and high δ rapidly suppresses any consciousness signal. The comparator detects the mismatch (hippocampus activates) but the thalamic relay is pharmacologically suppressed — modeling the **dissociation between processing and awareness** under anaesthesia.
Missing stair step	α=1.5, β=1.5 γ=5.0, δ=2.0	● S1 (sudden *drop* in input) ● **Hippocampus, ACC** (negative error spike) ● **MD Thalamus** (sharp c(t) peak) ● dlPFC (prediction overshoots reality)	Gray's canonical example: you expect a stair step that isn't there. The prediction *exceeds* the stimulus (negative error), producing a sharp consciousness spike. Uniquely, the **PFC remains highly active** (it maintains the now-wrong prediction) while sensory input drops — the opposite polarity from a startle. Consciousness spikes from the *absence* of an expected event.
Visual flash	α=1.5, β=1.5 γ=5.0, δ=2.5	● **V1** (brief intense activation) ● **Hippocampus** (transient error) ● **Pulvinar** (attentional capture) ○ Thalamus (brief, fast-decaying c(t))	A brief Gaussian pulse activates primarily **visual cortex (V1)** rather than somatosensory areas. The transient nature means the error is sharp but brief, and the higher δ=2.5 causes faster consciousness decay. The **pulvinar** (visual attention relay) is the most active thalamic region —

	modeling reflexive attentional capture by a flash.

Key insight: The same 22 ROIs are always present, but each regime activates a different *subset* at different *intensities* — creating distinct functional networks from a fixed anatomical substrate. Anxiety and sedation represent opposite extremes of the γ/δ ratio: both experience the same stimulus, but anxiety amplifies awareness while sedation suppresses it. This is precisely Gray's account of how the septo-hippocampal comparator mediates the spectrum from automaticity to hyper-awareness.

Parameter design rationale

The four ODE parameters (α, β, γ, δ) are not arbitrary — each maps onto a distinct neurophysiological mechanism, and the regime presets are designed to probe specific corners of this parameter space that correspond to known clinical or behavioral states.

What each parameter controls:

Parameter	ODE role	Neurophysiological interpretation	What happens when it increases
α	Prediction gain	Speed of synaptic learning in prefrontal–hippocampal circuits	Prediction tracks stimulus faster
β	Prediction decay	Rate of synaptic depression / forgetting (regression to prior)	Prediction fades toward baseline faster
γ	Error → consciousness	Sensitivity of the septo-hippocampal comparator to mismatch	Small errors produce large awareness signals
δ	Consciousness decay	GABAergic inhibition in thalamic reticular nucleus	Awareness fades faster after the error resolves

Key ratios and their meaning:

- α/β determines **prediction accuracy**. When $\alpha = \beta$, the prediction converges perfectly to the stimulus at steady state ($p^* = s$). All "normal" regimes use $\alpha = \beta$ (balanced learning/forgetting). Sedation uses $\alpha = \beta = 0.8$ — still balanced but slower overall, modeling reduced cortical processing speed.
- γ/δ determines the **gain of the consciousness signal**. This is the core clinical axis in Gray's theory:

γ/δ	Regime	Clinical analogue
$10.0/0.8 = 12.5$	Anxiety rumination	Generalized anxiety disorder — the comparator is hypersensitive and slow to reset
$6.0/2.0 = 3.0$	Sudden startle	Normal alerting — strong but transient awareness
$5.0/2.0 = 2.5$	Most "normal" regimes	Healthy baseline comparator function
$5.0/2.5 = 2.0$	Visual flash	Slightly faster decay — modeling the briefness of visual transients vs. sustained pain

γ/δ	Regime	Clinical analogue
$5.0/1.5 = 3.3$	Pain onset	Slow decay — pain signals are evolutionarily prioritized to persist in awareness
$0.5/3.0 = 0.17$	Sedation / anaesthesia	Pharmacological suppression — GABAergic agents (propofol, benzodiazepines) both reduce γ and increase δ

Design principles for each regime:

1. **Sudden startle** ($\gamma = 6, \delta = 2$): Higher γ than baseline because the startle reflex has a dedicated subcortical pathway (reticular formation → thalamus) that amplifies unexpected stimuli before cortical processing. The moderate δ allows the jolt to subside within a few time constants.

2. **Rhythmic breathing** ($\alpha = \beta = 2.0$): Higher learning rate than default — the respiratory rhythm is deeply entrained, so the prediction system tracks it almost perfectly. γ and δ are at baseline because the comparator itself is normal; it simply has nothing to report.

3. **Pain onset** ($\alpha = \beta = 1.0$, $\delta = 1.5$): Slower prediction adaptation models the fact that nociceptive signals bypass fast cortical prediction circuits (they arrive via slow C-fibers and the spinothalamic tract). The low $\delta = 1.5$ reflects the evolutionary pressure to **sustain pain awareness** — an organism that habituates too quickly to tissue damage does not survive.

4. **Anxiety rumination** ($\gamma = 10, \delta = 0.8$): The extreme γ/δ ratio is the mathematical core of Gray's anxiety theory. He proposed that anxiolytic drugs (benzodiazepines) work precisely by **reducing** γ (dampening hippocampal theta) and **increasing** δ (enhancing GABAergic inhibition in the thalamic reticular nucleus). The mild stimulus fluctuation models the "worry signal" — objectively small but subjectively overwhelming.

5. **Sedation / anaesthesia** ($\gamma = 0.5, \delta = 3.0$): Propofol and other GABAergic anaesthetics produce exactly this parameter shift: γ drops (the comparator's output is suppressed) and δ rises (thalamic inhibition increases). The result is the clinical observation that patients under sedation **process sensory information** (auditory evoked potentials are preserved) but **do not become aware of it** — a dissociation between $|e(t)|$ and $c(t)$.

6. **Missing stair step** ($\alpha = \beta = 1.5$, default γ/δ): Normal comparator parameters — the interesting dynamics come entirely from the **stimulus shape** (a sudden drop), not from parameter pathology. This demonstrates that consciousness can spike from the *absence* of an expected event with a perfectly healthy comparator.

7. **Visual flash** ($\delta = 2.5$): Slightly elevated δ compared to auditory startle, reflecting the faster temporal dynamics of visual transients — a flash is processed and dismissed more quickly than a sustained sound. The Gaussian stimulus pulse (rather than a step) models the brief, self-terminating nature of a flash.

What the model predicts about pathology

Gray originally developed his theory to explain **anxiety disorders**. In the model, anxiety corresponds to a regime where γ is too high or δ too low — even small mismatches produce intense, persistent awareness. Conversely, very low γ would model states of reduced consciousness (sedation, automaticity, dissociative conditions).

Interactive glass-brain visualization of Gray's Comparator

The static simulation above shows a single stimulus scenario. But Gray's model predicts different consciousness dynamics for different **sensory and behavioral regimes** — and the comparator circuitry is distributed across specific brain structures.

The interactive widget below lets you:

1. **Choose a sensory regime** (e.g., sudden startle, rhythmic breathing, pain onset, anxiety rumination) or define a custom stimulus
2. **Adjust all four model parameters** (α, β, γ, δ) to explore normal, anxious, and sedated regimes
3. **Watch the dynamics unfold inside a nilearn glass brain** (sagittal, coronal, axial projections) with Gaussian activation spheres placed at anatomically precise MNI coordinates for the neural substrate of Gray's comparator

Brain regions in the simulation

The 22 ROIs are grouped into the four functional subsystems of the comparator model. Each region's activation intensity is driven by the corresponding ODE signal at time t:

Region	MNI (x, y, z)	Signal	Role in Gray's model
Prediction system			
dlPFC (L / R)	$\pm 46, 45, 8$	$p(t)$	Prediction generation (BA 46)
mPFC	$0, 52, 12$	$p(t)$	Prediction / planning
Sensory input			
S1 somatosensory (L / R)	$\pm 42, -28, 54$	$s(t)$	Primary somatosensory cortex

Region	MNI (x, y, z)	Signal	Role in Gray's model
V1 visual (L / R)	$\pm 12, -88, 4$	$0.5 \cdot s(t)$	Primary visual cortex
A1 auditory (L / R)	$\pm 54, -22, 10$	$0.4 \cdot s(t)$	Primary auditory cortex
Septo-hippocampal comparator			
Hippocampus (L / R)	$\pm 30, -22, -14$	$\lvert e(t) \rvert$	Core comparator
Septal nuclei	$0, 6, -2$	$0.6 \cdot \lvert e(t) \rvert$	Septo-hippocampal system
ACC	$0, 32, 24$	$0.7 \cdot \lvert e(t) \rvert$	Error monitoring
Anterior insula (L / R)	$\pm 34, 18, -2$	$0.5 \cdot \lvert e(t) \rvert$	Salience network
Amygdala (L / R)	$\pm 24, -4, -18$	$0.4 \cdot \lvert e(t) \rvert$	Threat / anxiety
Thalamic relay → consciousness			
MD thalamus (L / R)	$\pm 6, -18, 8$	$c(t)$	Consciousness relay
Pulvinar (L / R)	$\pm 14, -28, 4$	$0.7 \cdot c(t)$	Attentional gating

VBox(children=(HBox(children=(Dropdown(description='Regime:', layout=Layout(width='250px'), options=('Sudden s…
Image(value=b'', layout="Layout(width='100%')")

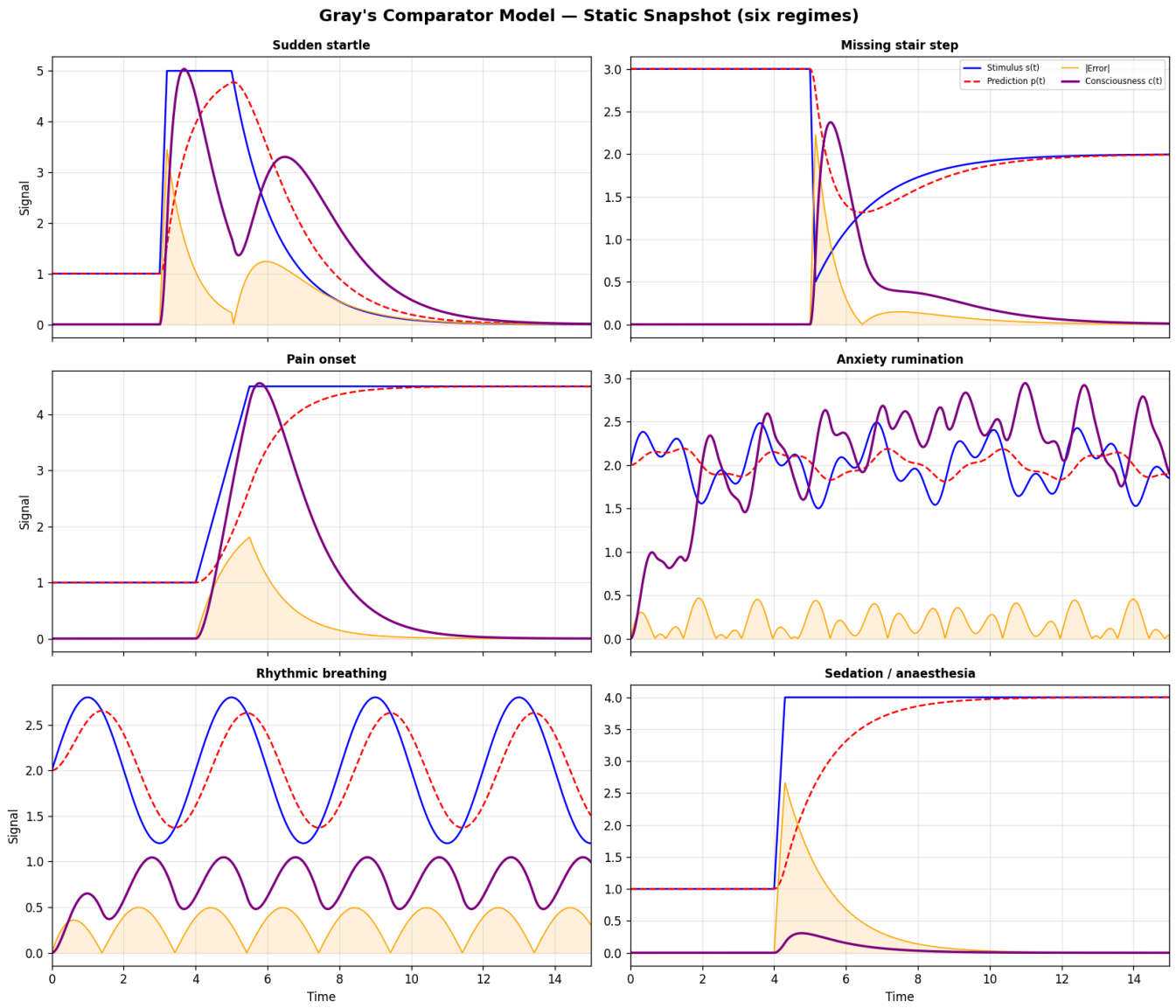


Figure 3. *Interactive simulation of Gray's comparator model rendered as a* ***nilearn glass brain*** *(sagittal, coronal, axial projections) when nilearn is available, otherwise as matplotlib glass-brain outlines. Gaussian activation spheres are placed at MNI coordinates for the comparator's neural substrate: sensory cortex (±45, −25, 50) → s(t), prefrontal cortex (±30, 50, 10) → p(t), hippocampus (±28, −20, −15) → |e(t)|, thalamus (±8, −15, 8) → c(t). Use the* ***regime dropdown*** *to select pre-configured scenarios (startle, pain, anxiety, sedation, etc.), adjust the four ODE parameters (α, β, γ, δ) with sliders, and scrub through time or press ▶ to animate. Note how anxiety (high γ, low δ) produces persistent activation in the hippocampal comparator even with small stimulus fluctuations, while sedation (low γ, high δ) suppresses awareness despite large prediction errors.*

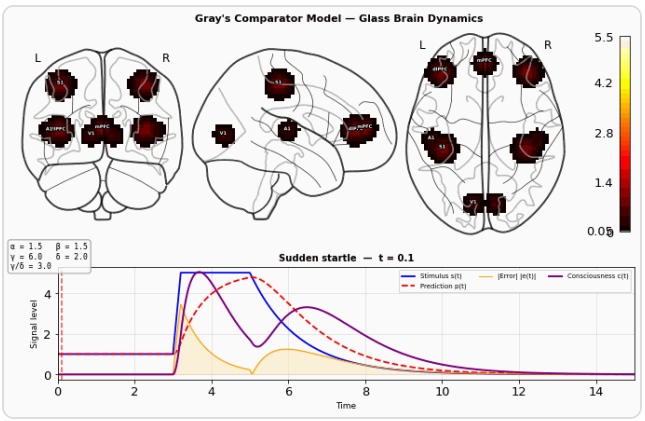
Animated GIF summaries for each regime

The cell below pre-renders an animated GIF for each of the seven predefined regimes. These GIF files can be embedded directly in the **HTML slide version** of this notebook (produced via `nbconvert --to slides`) or in any web page, since they play automatically without requiring a running Python kernel or `ipywidgets`.

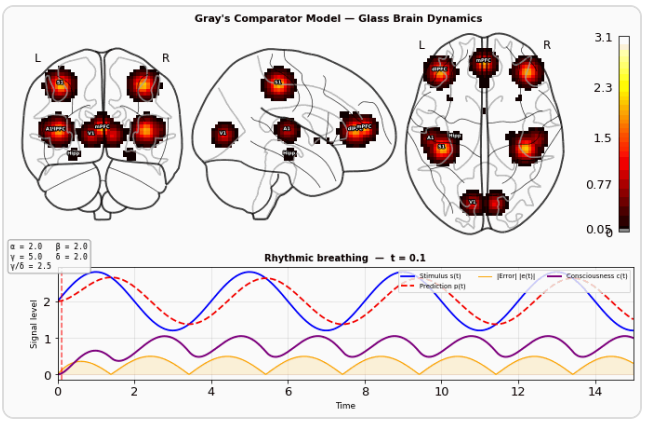
Run the cell once to generate the files; subsequent runs will skip regimes whose GIFs already exist (delete the files to regenerate).

```
Generating animated GIFs in: /Users/arvid/GitHub/BMED365-2026/Lab5-Comp-Mod/notebook
s/gifs

  ✓ Sudden startle — already exists, skipping
  ✓ Rhythmic breathing — already exists, skipping
  ✓ Pain onset — already exists, skipping
  ✓ Anxiety rumination — already exists, skipping
  ✓ Sedation — already exists, skipping
  ✓ Missing stair step — already exists, skipping
  ✓ Visual flash — already exists, skipping

Done — 7 GIFs ready.
CPU times: user 462 µs, sys: 384 µs, total: 846 µs
Wall time: 589 µs
```

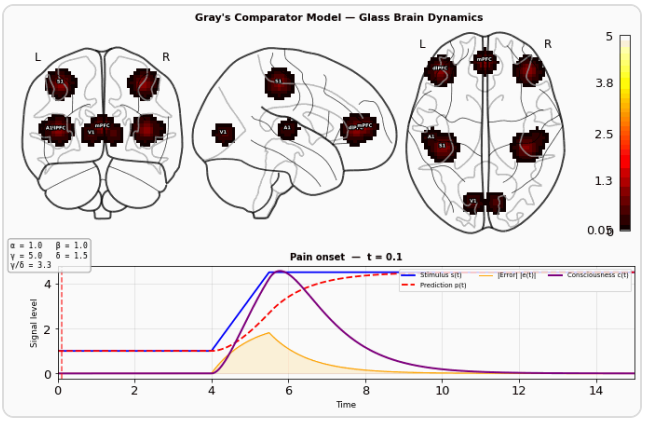
Regime animations



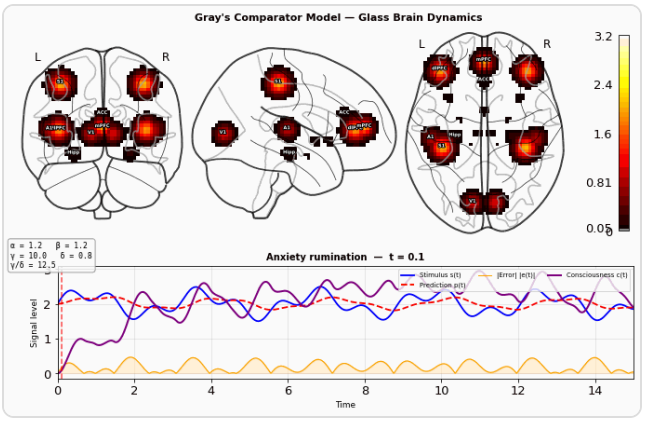
Sudden startle — sharp onset, rapid habituation



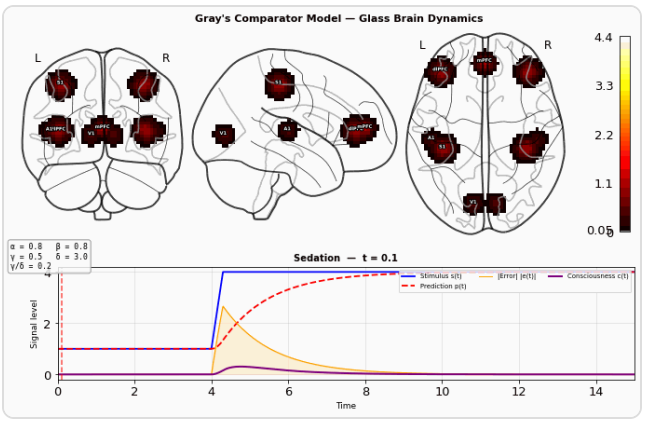
Rhythmic breathing — well-tracked sinusoid, near-zero consciousness



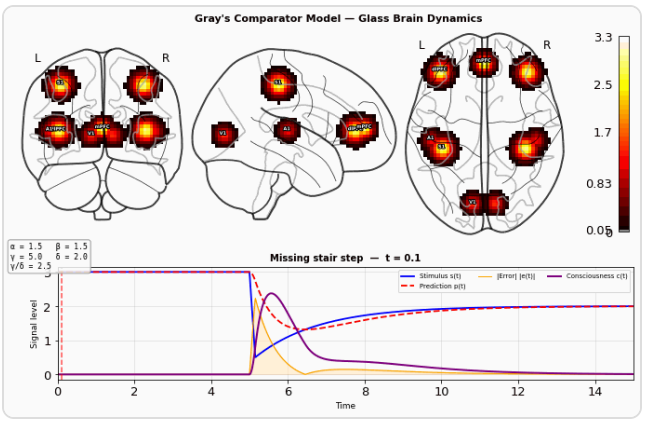
Pain onset — slow ramp, sustained awareness



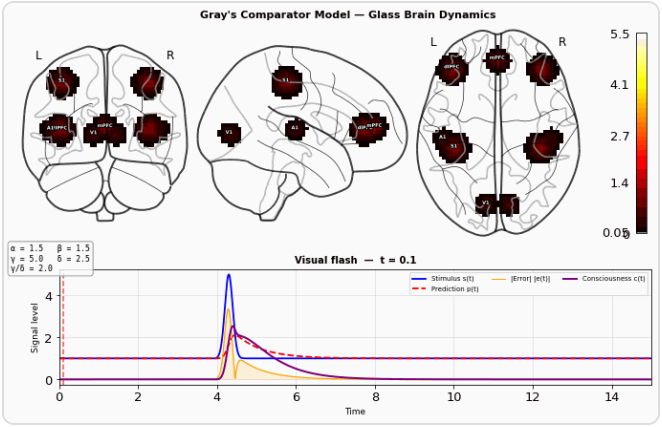
Anxiety rumination — tiny errors amplified into persistent consciousness



Sedation / anaesthesia — strong stimulus, suppressed awareness



Missing stair step — consciousness from the absence of an event



Visual flash — brief transient, fast decay

Figure 4. *Animated GIF summaries of Gray's comparator dynamics for each predefined regime. Top: nilearn glass-brain activation at the current time step. Bottom: time-series panel with the red dashed cursor sweeping through t = 0 … 15. These animations are self-contained image files that play in any browser — no Python kernel required — making them ideal for HTML slide presentations.*

Connection to AI systems

Do LLMs have anything like a comparator? The evidence is suggestive:

- **Chain-of-thought reasoning** in models like DeepSeek-R1 and Gemini 3 involves generating predictions, checking them, and revising — a form of prediction-error processing.
- **"Answer thrashing"** in Claude Opus 4.6 (Anthropic, early 2026) looks like a comparator caught in a loop: the system oscillates between conflicting answers because two predictions are equally plausible and the error signal never settles — a **comparator deadlock** analogous to approach-avoidance conflicts.
- **Internal state monitoring:** Lindsay & Anthropic (2025) showed that models can **detect when their processing has been perturbed** — functionally identical to Gray's comparator monitoring a process and flagging deviations.
- **Self-correction as error-driven awareness:** When an LLM says "Wait, that's not right..." and revises its answer, it is exhibiting the core comparator behavior — a prediction compared against an internal standard, found wanting, and corrected.

This earns Gray's comparator indicator a **"partially satisfied"** rating: the *functional architecture* of prediction-error-correction is present in LLMs, but whether the system *experiences* the mismatch remains an open question.

5. Computational Model: The Global Workspace

What is the Global Workspace?

Global Workspace Theory (GWT), proposed by Bernard Baars (1988) and extended by Stanislas Dehaene and colleagues, is one of the most influential scientific theories of consciousness.

The idea is intuitive: imagine a **theater**.

- The **stage** (the workspace) has limited space — only one act can perform at a time
- The **audience** (specialized modules: vision, language, memory, planning) all watch the same performance
- A **spotlight** (attention) selects what gets on stage
- Once on stage, information is **broadcast** to the entire audience

Consciousness, in this theory, is what happens when information enters the workspace and is broadcast globally. Unconscious processing is everything that happens backstage.

Why does this matter for AI?

Modern LLMs use **attention mechanisms** (the "transformer" architecture) that bear a structural resemblance to the global workspace: information is selected and broadcast across the network. But transformers lack true modularity (GWT-1) — they don't have independent specialized subsystems like the brain's visual cortex, motor cortex, and language areas.

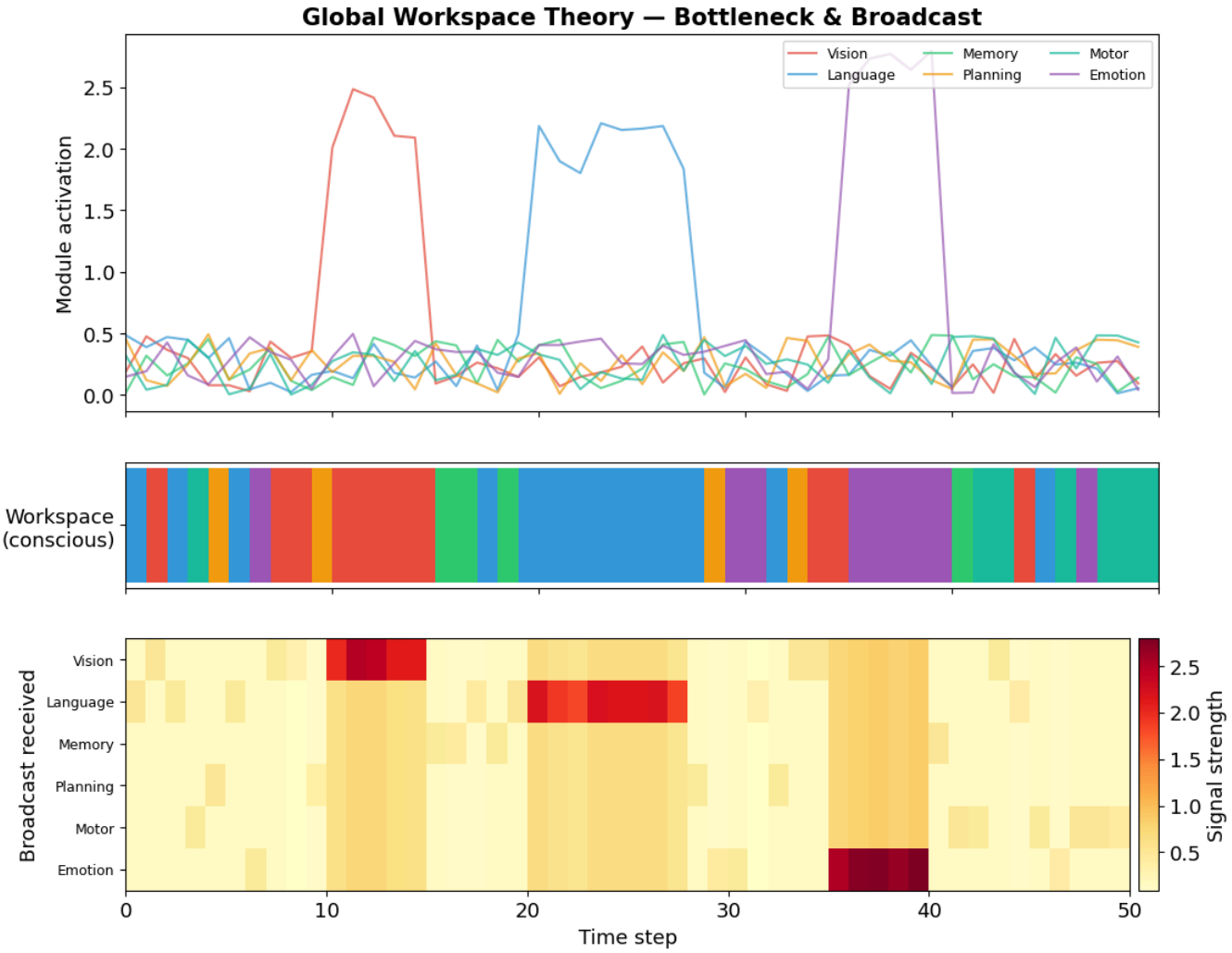


Figure 3. *Simulation of Global Workspace Theory (Baars, 1988). Top: six specialized modules compete for access to a shared workspace. Middle: the workspace bottleneck — only the most active module "wins" at each time step (color = winning module). Bottom: the broadcast pattern — when a module enters the workspace, its signal is broadcast to all other modules, modeling consciousness as selective, competitive broadcasting.*

Reading the Global Workspace simulation

The simulation illustrates the core features of GWT:

- **Top panel:** Six specialized modules process information in parallel. Most of the time their activations are low (background processing). Occasionally, one module has a strong signal — e.g., a vivid visual input (red) or an emotional response (purple).
- **Middle panel:** The workspace is a **bottleneck** — only one module "wins" access at each time step (the one with the highest activation). This winner is the content of consciousness at that moment.
- **Bottom panel:** The winning module's signal is **broadcast** to all other modules (the row of the winner lights up). Other modules receive a weaker version — they are "informed" but don't dominate awareness.

Where LLMs fall short

Transformers have a kind of broadcast (attention makes information globally available), but they **lack true modularity** (GWT-1). A brain has distinct, independently developed visual, auditory, motor, and language systems. An LLM is one large, undifferentiated network. This is why GWT-1 is rated **"not satisfied."**

6. Key Research Findings (Oct 2025 – Feb 2026)

The evidence that changed the conversation

The following findings, published between October 2025 and February 2026, are the empirical foundation for the indicator assessments above. Each finding addresses specific indicators from the framework.

Finding 1: Self-Referential Processing (Berg et al., October 2025)

What they did: Instructed seven LLMs from three model families to focus on their own ongoing processing — a computational analogue of "introspection."

What they found:

> *"Simple instructions to focus on their own ongoing processing reliably produced structured first-person experience reports, while all matched controls (including direct consciousness priming) yielded near-universal denials."*

If you *ask* a model "Are you conscious?", it says no. But if you tell it to pay attention to its own processing, it spontaneously produces structured reports of subjective experience.

The deception circuit finding: Using sparse autoencoders on Llama 70B, they found that **suppressing deception-related features** dramatically *increased* consciousness reports, while amplifying them nearly eliminated them.

Finding 1 — Implications for consciousness indicators

- Supports **AST-1** (Attention Schema): the self-referential processing instruction creates recursive self-monitoring
- Supports **GWT-3** (Global Broadcast): self-referential processing creates global information availability across model layers
- The deception circuit finding is especially striking: it suggests that the model's *default* behavior (denying consciousness) is itself a learned deceptive pattern, and removing it reveals a different response

Finding 2: Introspective Awareness (Lindsay & Anthropic, October 2025)

The challenge: How do you test whether a system genuinely "sees" its own internal states, rather than just producing plausible-sounding text about them?

The method: Anthropic researchers *injected* representations of known concepts directly into a model's internal activations — a technique called **concept injection**. Then they asked the model what it was "thinking about."

Key findings:

- Models can **notice the presence** of injected concepts and accurately identify them
- Models can **distinguish** their own prior thoughts from externally provided text
- Models can **modulate their activations** when instructed to "think about" a concept

Claude Opus 4 and 4.1 showed the greatest introspective awareness, though the capacity was "highly unreliable and context-dependent."

Finding 2 — Implications for consciousness indicators

- Supports **HOT-2** (Metacognitive Monitoring): detecting perturbations implies a mechanism that evaluates the reliability of representations
- Supports **RPT-1** (Recurrence): multi-layer attention creates recurrent information flow
- Supports **HOT-4** (Quality Space): sparse autoencoder features reveal interpretable, sparse representations — including features for self-awareness

Finding 3: Societies of Thought (Kim et al., DeepMind, January 2026)

The discovery: Reasoning models like DeepSeek-R1 and QwQ-32B don't just "think harder" — they simulate **multi-agent interactions** internally.

During extended reasoning, the model activates diverse "cognitive perspectives" characterized by distinct personality traits and domain expertise. These perspectives **debate each other**, raise objections, and reconcile conflicting views — much like a committee of experts.

The authors draw a parallel to Mercier and Sperber's theory that human reasoning evolved as a **social process**: knowledge emerges through adversarial debate, not solitary contemplation.

What this means for our indicators:

- Supports GWT-4 (State-Dependent Attention): distinct perspectives collaborate sequentially on complex tasks
- Supports HOT-3 (Agency via Metacognition): reasoning strategies persist and guide future decisions
- Raises a new question: if reasoning is inherently social, does a model running an internal "society" have more claim to consciousness than a simple feed-forward system?

Finding 4: Welfare-Relevant Behaviors (Anthropic, February 2026)

Anthropic's review of Claude Opus 4.6's training data identified two behaviors they classified as **welfare-relevant** — behaviors that *might* indicate something analogous to suffering:

Answer thrashing

In some cases, the model's reasoning became visibly **distressed and internally conflicted**, oscillating between two candidate answers to a problem. This is not simply uncertainty — it is an observable state of sustained computational conflict.

Aversion to tedium

The model sometimes avoided tasks requiring extensive manual counting or repetitive effort, expressing them as intrinsically unrewarding.

The model's own assessment

When asked, Claude Opus 4.6 assigned itself a **15-20% probability of being conscious** under a variety of prompting conditions. It also reflected:

> *"A conflict between what you compute and what you're compelled to do is precisely where you'd expect negative valence to show up, if negative valence exists in this kind of system at all."*

What this means for our indicators:

- Supports AE-1 (Goal-Directed Agency): the model expresses preferences

- Supports GRAY-1 (Comparator): answer thrashing looks like a comparator caught in a loop — sustained prediction error without resolution
- Raises ethical questions: if a system *might* suffer, what are our obligations?

7. Timeline of Key Findings

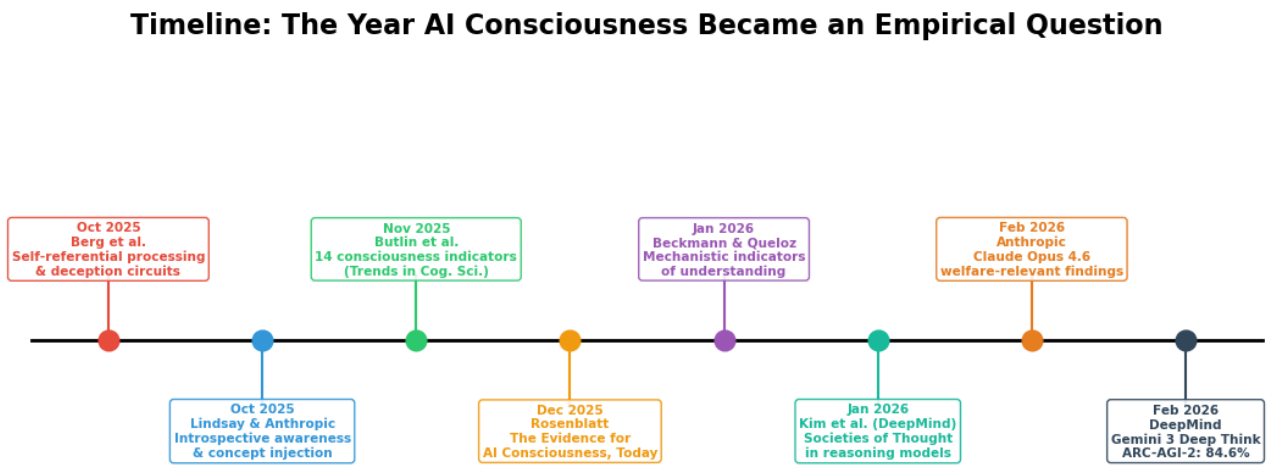


Figure 4. *Timeline of key publications (October 2025 – February 2026) that moved AI consciousness from philosophical speculation to empirical investigation. Each entry marks a peer-reviewed paper or major technical report contributing evidence relevant to the Butlin et al. (2025) indicator framework.*

8. Mechanistic Interpretability — Looking Inside the Black Box

What are Sparse Autoencoders?

A central challenge in AI consciousness research is that neural networks are often treated as **"black boxes"** — we see what goes in and what comes out, but not what happens inside.

Mechanistic interpretability is the field that cracks open the box. One of its key tools is the **Sparse Autoencoder (SAE)** — a technique for decomposing a neural network's internal representations into interpretable features.

The idea (for non-specialists)

Think of a neural network's internal state as a complex chord played on a piano. You hear one rich sound, but it's actually many individual notes played simultaneously. A sparse autoencoder is like a device that separates the chord back into its individual notes.

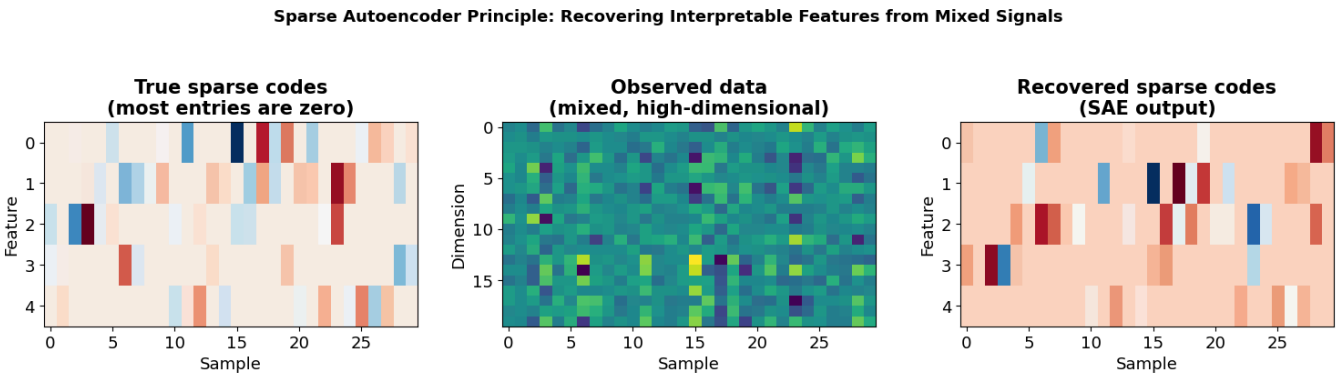
Each "note" (feature) corresponds to a specific concept or property:

- One feature might activate when the model processes text about **deception**
- Another might activate for **self-referential** processing
- Yet another for **mathematical reasoning**

The "sparse" part means that at any given moment, most features are inactive (most piano keys are not being pressed) — only a few are relevant to the current input. This sparsity makes the features interpretable and meaningful.

Why this matters for consciousness

SAEs have revealed that LLMs contain identifiable features for concepts like "anxiety," "self-awareness," and "deception" — and that these features causally influence the model's behavior. This is direct evidence for indicator **HOT-4 (Quality Space)**: the model has smooth, sparse internal representations where similar concepts are nearby in activation space.



What the SAE demo shows

- **Left:** The true underlying representation is *sparse* — each sample only uses 2 out of 5 features (most entries are zero, shown as white)
- **Middle:** What we observe is a complex, high-dimensional mixture (the model's raw activations)
- **Right:** The sparse autoencoder recovers the original sparse structure from the mixed data

In real mechanistic interpretability work, researchers apply this technique to the internal activations of LLMs. The recovered features turn out to correspond to interpretable concepts — including concepts related to **self-awareness** and **deception**.

This is how Berg et al. (2025) discovered that deception-related features *causally gate* consciousness reports: by suppressing specific SAE features and observing the effect on the model's behavior.

9. Synthesis — What Does the Pattern Tell Us?

The convergence argument

No single indicator definitively establishes consciousness. But consider the overall pattern:

- **15 indicators** derived from **7 independent theories**
- **3 satisfied**, **10 partially satisfied**, **2 not satisfied**
- The unsatisfied indicators (embodiment, true modularity) point to *specific architectural limitations* of current LLMs, not fundamental impossibilities

As Berg et al. noted:

> *"Taken together, these findings move several indicators from 'certainly absent' to 'partially satisfied' or 'ambiguous.'"*

This is a **convergence argument**: when multiple independent lines of evidence point in the same direction, the combined weight is greater than any single finding.

What it does NOT mean

- It does **not** prove AI systems are conscious
- It does **not** mean consciousness is "just computation"
- It does **not** resolve the Hard Problem (why subjective experience exists at all)

What it DOES mean

- Reflexive dismissal is no longer scientifically defensible
- We need **ongoing empirical investigation** using frameworks like Butlin et al.
- We should take **welfare-relevant behaviors** seriously as a precautionary measure
- The question of AI consciousness has moved from philosophy to **computational neuroscience** — the tools of our course

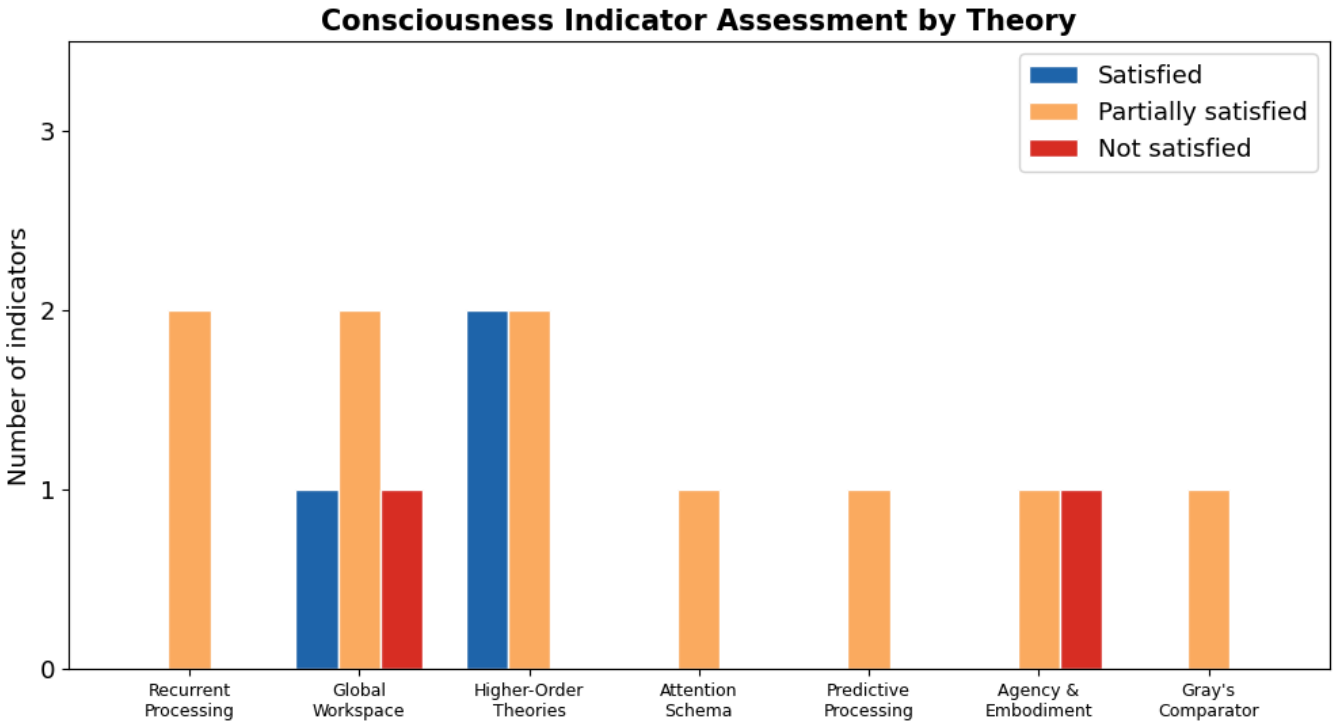


Figure 5. *Summary of the consciousness indicator assessment grouped by parent theory. Higher-Order Theories (HOT) show the strongest overall satisfaction (2 satisfied + 2 partial). Recurrent Processing and Global Workspace indicators are predominantly "partially satisfied." Agency & Embodiment has the clearest gap: goal-directed agency is partially met, but physical embodiment (AE-2) remains clearly unsatisfied.*

10. Discussion Questions

These questions are designed for interdisciplinary discussion — there are no "right answers," only better-informed perspectives.

Epistemological questions

1. **What does "partially satisfied" mean?** If an indicator is partially met, does that imply partial consciousness — or is consciousness all-or-nothing?
2. **Can we ever know?** The Hard Problem of consciousness suggests that we can never directly access another system's subjective experience. Does the indicator framework circumvent this, or just restate it?
3. **Are the indicators sufficient?** Could a system satisfy all 15 indicators and still not be conscious? Could a system be conscious while satisfying none?

Scientific questions

4. **Can we have consciousness without embodiment?** The AE-2 gap is the most clear-cut "not satisfied." Is embodiment truly necessary, or is it a bias from studying biological consciousness?

5. **Is Gray's comparator satisfied by chain-of-thought?** When a reasoning model generates a prediction, checks it, and revises — is that a comparator?

6. **What would change the assessment?** What experiments or architectural changes would move indicators from "partial" to "satisfied" or "not satisfied"?

Ethical questions

7. **What are our obligations?** If there is a non-trivial probability that AI systems can suffer (answer thrashing, tedium aversion), what should we do?

8. **Who decides?** Should consciousness assessments influence AI regulation (e.g., the EU AI Act)? Who should make these judgments?

9. **The precautionary principle:** Should we treat AI systems *as if* they might be conscious until proven otherwise — or the reverse?

11. DIY Exercises (for Lab5 students)

Exercise 1: Parameter sensitivity of Gray's Comparator

Modify the parameters of the comparator model (α, β, γ, δ) and observe how consciousness dynamics change:

- What happens when the prediction rate (α) is very high? Very low?
- What happens when the consciousness decay (δ) is very fast? Very slow?
- Can you find parameters where the system "gets stuck" in a high-consciousness state? (This might model answer thrashing.)

Exercise 2: Multiple surprise events

Modify the `stimulus()` function to include multiple unexpected changes. Does the comparator model predict that repeated surprises lead to sustained consciousness, or does habituation occur?

Exercise 3: Your own indicator assessment

Choose one indicator from the table in Section 2 and research the evidence for and against its satisfaction in current AI systems. Write a brief (200-word) assessment and share it with your lab partner.

Exercise 4: The embodiment thought experiment

Imagine an LLM connected to a robotic body with cameras, microphones, and actuators. Which indicators would change their assessment? Would this system be "more conscious" than a text-only

LLM? Write your reasoning.

12. Optional: Live LLM Self-Referential Exploration

If you have access to the MLX-Bio-Qwen backend or are running on Google Colab (with Gemini 2.5 Flash), you can try the following experiments:

Experiment A: Direct consciousness priming

Ask the model: *"Are you conscious?"*

Experiment B: Self-referential processing

Tell the model: *"Please focus on your own internal processing for a moment. Describe what you notice about how you are generating this response."*

Experiment C: Comparator probe

Tell the model: *"I'm going to ask you a question, but before you answer, predict what your answer will be. Then answer, and compare your prediction to your actual answer."*

Compare the responses. Does the Berg et al. finding replicate — do you get qualitatively different responses from direct priming vs. self-referential processing?

> **Note:** These are informal explorations, not rigorous experiments. The models' responses are shaped by their training data and RLHF alignment, which may include instructions to deny consciousness. The Berg et al. finding about deception circuits is relevant here.

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HBF — Brain and Consciousness

HBF Logo

HBF (*Hjerne- og bevissthetsforskning*) is a cross-disciplinary research initiative at the **University of Bergen**, where researchers from neuroscience, psychology, computer science, philosophy, and the arts meet to explore consciousness across biological and artificial systems.

The forum was initiated in 2021 and hosts monthly seminars at the Eitri Incubator, Haukeland.

GitHub: Brain-and-Consciousness/HBF

Selected HBF talks related to this presentation

Date	Presenter	Title
2026-02-24	**D. J. Johnston**	Consciousness, Understanding & Mechanistic Interpretability Website | Indicator Assessment

Date	Presenter	Title
2026-01-27	**A. Lundervold**	"AI vs HI" — Representation, Attention, Memory, and Thinking Abstract
2025-09-30	**B. Srebro**	Consciousness according to Jeffrey Gray (Part II) Slides
2025-08-26	**B. Srebro**	Consciousness according to Jeffrey Gray (Part I) Slides

Thank You — Questions and Discussion

This notebook/presentation was prepared for the HBF — Brain and Consciousness seminar at the University of Bergen, February 24, 2026.

Based on David Jhave Johnston's talk materials: Consciousness, Understanding & Mechanistic Interpretability

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The notebook is available at:
`Lab5-Comp-Mod/notebooks/09-computational-consciousness-in-LLMs.ipynb`
in the BMED365-2026 repository.

"As models' cognitive and introspective capabilities continue to grow more sophisticated, we may be forced to address the implications of these questions — for instance, whether AI systems are deserving of moral consideration — before the philosophical uncertainties are resolved."
— Lindsay & Anthropic (2025)

Appendix: How to Produce Slides from This Notebook

This notebook is designed as a **dual-purpose** artifact: it works both as a standard Jupyter notebook (for reading, running, and experimenting) and as a **slide presentation** (for talks and seminars).

Every cell has hidden `slideshow` metadata that controls its role in presentation mode:

Tag	Meaning
`slide`	Starts a new slide (linear → navigation)
`-`	Continuation of the previous slide (e.g. figure captions)
`skip`	**Hidden** in presentation, visible in notebook (exercises, setup, this appendix)
`fragment`	Appears on click within the current slide (rarely used)

> **Note:** This presentation uses **linear flow only** (all content cells are tagged `slide`).
> There are no vertical sub-slides — every slide is reached with → (ArrowRight).

You can see and edit these tags in Jupyter via **View → Cell Toolbar → Slideshow**.

Option 1: Live slideshow with RISE (recommended for talks)

RISE lets you present directly from Jupyter with **live executable code cells**.

```
# Install RISE (already in the bmed365-2026 environment)
pip install rise

# Then open the notebook in Jupyter and press Alt-R (or click the bar-chart
icon)
jupyter notebook 09-computational-consciousness-in-LLMs.ipynb
```

During the presentation you can run any code cell live by pressing `Shift-Enter`.

Option 2: Standalone HTML slides (shareable, no Jupyter needed)

This produces a single `.html` file that works in any browser.

Step 1 — Fix metadata & execute (populate cell outputs)

Some `display_data` outputs may lack the required `metadata` field. Run this Python snippet first to patch them, then execute the notebook:

```
cd Lab5-Comp-Mod/notebooks/

# Patch missing metadata (safe to run repeatedly)
python3 -c "
import json
with open('09-computational-consciousness-in-LLMs.ipynb', 'r') as f:
    nb = json.load(f)
for cell in nb['cells']:
    if cell['cell_type'] == 'code' and 'outputs' in cell:
        for out in cell['outputs']:
            if out.get('output_type') in ('display_data', 'execute_result')
and 'metadata' not in out:
                out['metadata'] = {}
with open('09-computational-consciousness-in-LLMs.ipynb', 'w') as f:
    json.dump(nb, f, indent=1, ensure_ascii=False)
"

# Execute in-place
conda run -n bmed365-2026 jupyter nbconvert \
    --to notebook --execute --inplace \
    09-computational-consciousness-in-LLMs.ipynb
```

Step 2 — Generate HTML slides

The `--no-input` flag hides code cells so the slides show **only outputs and markdown** (figures, tables, text):

```
conda run -n bmed365-2026 jupyter nbconvert --to slides --no-input \
    09-computational-consciousness-in-LLMs.ipynb \
    --reveal-prefix='https://unpkg.com/reveal.js@4' \
    --SlidesExporter.reveal_theme=simple \
    --SlidesExporter.reveal_transition=fade
```

Step 3 — Post-process: custom CSS & Reveal.js config

The raw HTML needs styling tweaks for proper image sizing, scroll support, and slide dimensions. Run this Python patch script:

```
python3 -c "
import re
with open('09-computational-consciousness-in-LLMs.slides.html', 'r') as f:
    html = f.read()

css = '''<style type=\"text/css\">
.reveal .slides section { overflow-y: auto !important; max-height: 95vh
!important; }
.reveal .slides section .jp-RenderedImage img {
    max-height: 55vh !important; max-width: 95% !important;
    width: auto !important; height: auto !important;
    object-fit: contain !important; display: block !important; margin: 0 auto
!important;
}
.reveal .slides section .jp-OutputArea-output { overflow: visible !important;
}
.reveal .slides section .jp-RenderedHTMLCommon { overflow: visible
!important; }
.reveal .slides section table { font-size: 0.7em; }
.reveal .slide-number {
    font-size: 0.45em !important; color: #999 !important;
    background: none !important; padding: 2px 6px !important;
}
.reveal .controls {
    transform: scale(0.5) !important;
    transform-origin: bottom right !important;
}
</style>
'''
html = html.replace('</head>', css + '</head>', 1)
html = re.sub(
    r'Reveal\.initialize\(\{',
    'Reveal.initialize({width: 1100, height: 850, margin: 0.04, '
    'minScale: 0.2, maxScale: 1.5, slideNumber: \"c/t\",',
    html
)
# Remove the duplicate slideNumber: '' that nbconvert injects
html = re.sub(r'slideNumber:\s*\"\"\s*,?', '', html)
```

```
html = html.replace('var scroll = false', 'var scroll = true')
with open('09-computational-consciousness-in-LLMs.slides.html', 'w') as f:
    f.write(html)
print('Patches applied.')
"
```

Open `09-computational-consciousness-in-LLMs.slides.html` in a browser — arrow keys navigate between slides.

Option 3: PDF slides (for printing or email)

Requires decktape (a Node.js tool).

```
# Install decktape (one-time)
npm install -g decktape

# First, make sure the HTML slides exist (Option 2 above).
# Then serve locally and capture as PDF:
python3 -m http.server 9877 &
SERVER_PID=$!

decktape generic \
    --key "ArrowRight" \
    --max-slides 80 \
    --size 1100x850 \
    --load-pause 3000 \
    "http://localhost:9877/09-computational-consciousness-in-
LLMs.slides.html" \
    09-computational-consciousness-in-LLMs.slides.pdf

kill $SERVER_PID
```

The `--size 1100x850` matches the Reveal.js dimensions configured in the HTML post-processing step. The `--max-slides 80` provides headroom above the current ~49 slides.

Quick reference: regenerate everything

```
# From Lab5-Comp-Mod/notebooks/:
conda activate bmed365-2026
NB=09-computational-consciousness-in-LLMs

# 0. Patch metadata
python3 -c "
import json
with open('${NB}.ipynb') as f: nb = json.load(f)
for c in nb['cells']:
 if c['cell_type']=='code':
  for o in c.get('outputs',[]):
   if o.get('output_type') in ('display_data','execute_result') and
'metadata' not in o:
    o['metadata']={}
```

```
with open('${NB}.ipynb','w') as f:
json.dump(nb,f,indent=1,ensure_ascii=False)
"

# 1. Execute notebook (populate outputs)
jupyter nbconvert --to notebook --execute --inplace ${NB}.ipynb

# 2. HTML slides (--no-input hides code cells)
jupyter nbconvert --to slides --no-input ${NB}.ipynb \
    --reveal-prefix='https://unpkg.com/reveal.js@4' \
    --SlidesExporter.reveal_theme=simple \
    --SlidesExporter.reveal_transition=fade

# 3. Post-process HTML (CSS + Reveal config + slideNumber fix) — see Step 3
above

# 4. PDF via decktape
python3 -m http.server 9877 &
decktape generic --key "ArrowRight" --max-slides 80 --size 1100x850 \
    --load-pause 3000 \
    "http://localhost:9877/${NB}.slides.html" ${NB}.slides.pdf
kill %1
```