THE SEESAW BOARD OF THOUGHT

A Plinko-Style Model of Biased Stochastic Decisions Across Scales

v1.4 — CR-IMRaD Edition

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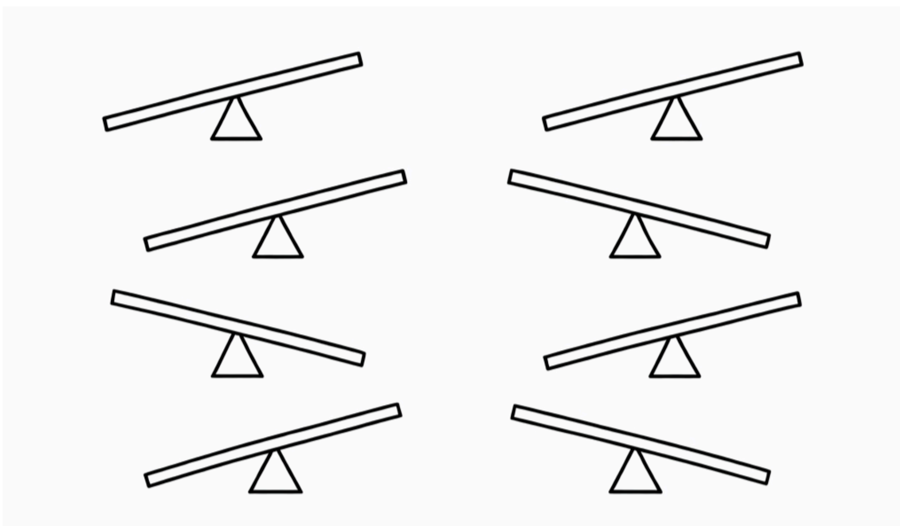


[VISUAL AID: Seesaw Complexity]

Fig 0.1: An assortment of six stacked seesaws. A ball (micro-decision) falls through responsive seesaws (biased decision units). Board geometry (priors, environment, architecture) constrains but does not determine where the ball lands. Patterns emerge after many drops, not from any single bounce. Microsoft CoPilot generated image.

Simplest Summary

Thought emerges from a cascade of tiny, **biased decisions** (seesaws) filtered by your history and environment (the **board's geometry**). While no single decision is predictable, the collective pattern is stable. This model defines consciousness as **structured noise** filtered through this **biased geometry**, bridging **agency and predictability** to show behavior is lawful but never fixed.

Note: *This is a proposed theoretical framework. It has not been empirically validated. It draws on established mathematics (drift-diffusion models, category theory, representational similarity analysis) applied in a novel configuration.*

1. Introduction | The Universal Metaphor

1.1 The Seesaw Board

Imagine a tall vertical board covered in small **seesaws**, like a Plinko or Pachinko machine. You drop a **ball** from the top. It hits the first **seesaw** and tips slightly left or right. It falls to the next **seesaw** and tips again. Each contact changes the **ball**'s direction by a small amount. No single bounce decides where the **ball** ends up. But after the **ball** has passed through hundreds or thousands of **seesaws**, it lands in a bin at the bottom which represents the action undertaken, the feeling felt, or the thought generated. Drop a thousand **balls**, and a clear **pattern** forms. Some bins fill up more than others. The shape of the **board** including the arrangement of the **seesaws**, how tilted they are, how heavy they are, and how many there are, all of that determines the overall **pattern**. Not perfectly. Not for any single **ball**. But statistically, reliably, across many drops.

1.2 What Makes This Board Different

In a normal Plinko board, the pegs are rigid. They do not respond to the ball. However, in this model, every peg is a **responsive seesaw**. Each one tilts based on the ball's weight, speed, and angle of arrival. Each seesaw has its own **balance point** (how biased it is), its own **length** (how much evidence it needs to tip), and its own **texture** (how much random noise affects it). Some seesaws are heavy and barely move. Others are sensitive and tip at the slightest touch. The ball's journey through this board feels unpredictable moment to moment but produces stable patterns across many runs.

1.3 The Last Grain of Sand Is a Qualia

This paper proposes that human **thought works like this board**. A **qualia** is this schema's term for the smallest input needed to tip a **seesaw** of a certain size, e.g., a grain of sand versus a boulder needed to tip a seesaw and enable the cascade from criticality or chaos to ordered output. Every perception, decision, and feeling is the result of a **cascade** of small, biased decision patterns of seesaws tipping in sequence. No single neuron or brain region decides what you think. The **geometry of the whole board** including your genetics, your memories, your current physical state, your environment and more all shape the cascade. The result is behavior that is lawful but not fixed: predictable at the population level, often surprising at the individual level, and never exactly the same twice.

Note: *This is an intuition bridge,* ***not*** *a claim about* ***literal*** *neural hardware. The* ***metaphor*** *exists to reduce cognitive load while preserving the mathematical structure described in Section 2.*

2. Methods | Formalizing the Biased Cascade (GDDM, Yoneda, & Fractals)

From this point forward, technical language is used. Each concept maps directly to a component of the Seesaw Board metaphor introduced in Section 1.

2.1 The Seesaw as a Biased Stochastic Decision Unit

Each seesaw in the board **corresponds** to a single **decision unit in the brain**, a point where incoming information is evaluated against a criticality threshold and tips toward one outcome or another. The mathematical framework for this is the **drift-diffusion model** (DDM) and its generalization, the **General Decision Diffusion Model** (GDDM) (Ratcliff & McKoon, 2008).

The metaphor maps as follows:

- **Seesaw tilt** = drift rate (the bias toward one response)
- **Seesaw length** = decision bounds (how much evidence is needed to commit)
- **Contact texture** = noise gain (how much randomness affects each interaction)
- **Initial orientation** = starting-point bias (prior expectations)

The perceptual bias vector formalizes the geometry of a single seesaw:

P_vec = (p++, p+-, p-+, p--) where Sum = 1

Where p++ = approach/yes, p+- = avoid/no, p-+ = explore/maybe, p-- = freeze/unknown. **Bias** is understood to be **structural** geometry, **not** necessarily **moral** choice. Every seesaw has a probability vector that can be measured, understood, and gradually **reshaped** through experience, behavior, or other methods.

2.2 From Falling Balls to Sequential Sampling

One ball falling into the board is one decision trial. **Many** balls produce the **distributions** of **patterns** that characterize reaction times and choice probabilities. The **board layout** includes at a **minimum**: the **arrangement** of seesaws, their **biases**, their **sensitivities**, their **number**, their **type** (external sensory input vs internal thought), their **size**, all of which help define the task constraints and priors.

The random seed for each cascade is not purely internal:

Xi_thought = Integral(Impulse * Product Seesaw_i(Static_i)) d(Static)

Sources of **static** include but are not limited to **thermal** noise, **quantum** fluctuations,and **environmental** randomness. Without static, the system would be deterministic. With static, it is **unpredictable** at the level of any single ball, **but patterned** across many.

2.3 The Cascade Function

The full cascade through the board is formalized as:

Psi_cascade = epsilon_input (conv) Product H(Tilt_i - epsilon_grain_i) * Yoneda(cluster_i)

Where H() is the Heaviside step function (0 below threshold, 1 at or above), epsilon_grain is the minimum input required to tip a seesaw (the qualia threshold), and Yoneda(cluster_i) captures the relational structure of the seesaw network. Each seesaw's **output** becomes the **next** seesaw's **input**, shaped by the relational **structure** of the **board**. The **cascade terminates** when the ball reaches a bin **(an observable outcome)** or when **no remaining** seesaw tips.

2.4 The Full Board as Cross-Scale Geometry

The board is **not flat**. Seesaws are **embedded** within **larger** sensory and cognitive input **structures**, clusters of seesaws that function as **macro-seesaws** at a higher scale. Constraints propagate downward from the largest structures **without** enforcing determinism at the smallest. This **enables nested decision** scales without central control.

This is consistent with evidence that neural dynamics exhibit scale-free, 1/f-like statistics (He, 2014) and long-range temporal correlations that span multiple cognitive timescales.

2.5 Identity as Relational Pattern (Yoneda Mapping)

The Yoneda Lemma from Category Theory provides the formal basis for how identity emerges from the board:

Seesaw(X) ~ Hom(Hom(X,-), Seesaw)

An object (a **thought**, a **person**, a **quale**) is **completely** determined by its **relationships** to **everything** else. You **cannot** understand a **thought** by examining a **single** seesaw. Identity is the **pattern** of landings across **many** drops, the statistical **distribution** over outcomes, **not** any **single path** through the board.

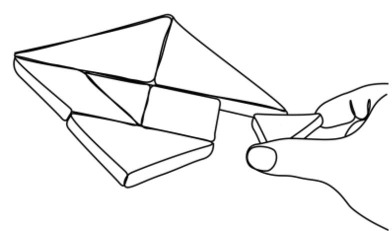


IMAGE FROM PNGTREE.COM

Imagine a set of **tangrams**, a collection of geometric **shapes** that **fit** into a square when **arranged** correctly. Now imagine you **remove** only **one** tangram **shape**. If you **know** every **other shape** is there **correctly**, you have surrounded the hole with boundaries of the other shapes. You **now know** the **shape** of the absent piece precisely **because** of its **relationship** to **all** other **pieces**. This "hole" is a **pattern** of **relations** that can be quantified as a **dissimilarity matrix**.

This independently converges with the **Enriched Category Theory of Qualia** proposed in the consciousness literature (Tsuchiya et al., 2016) and with representational similarity analysis (RSA) in neuroimaging (Kriegeskorte, 2008), where mental states are characterized by their **relational geometry** rather than their absolute activation levels.

2.6 The Fractal-Yoneda Asymptote

lim[eps->0] L(eps) ~ F*eps^(1-D) <=> lim[C->All] Hom(-,X) approaches but never reaches X

The formal statement above has **three** key implications for measurement:

- **Asymptotic Completeness:** The **complete** relational definition of **identity** is **asymptotic**, meaning it approaches, but is **never** fully achievable.
- **Diverging Complexity:** As the measuring **resolution increases** (e.g., a "smaller ruler on the coastline" or more morphisms mapped in the Yoneda embedding), the measured **complexity diverges.**
- **Finite Approach: Identity** must be **approached** through **finite**, scale-aware **summaries** (such as representational dissimilarity matrices in RSA), not through an exhaustive enumeration that would consume infinite resources.

This is proposed as a novel **bridge** between **Fractal Geometry** and **Category Theory.**

Image of a highly fractal coastline superimposed with varying sized measuring sticks.

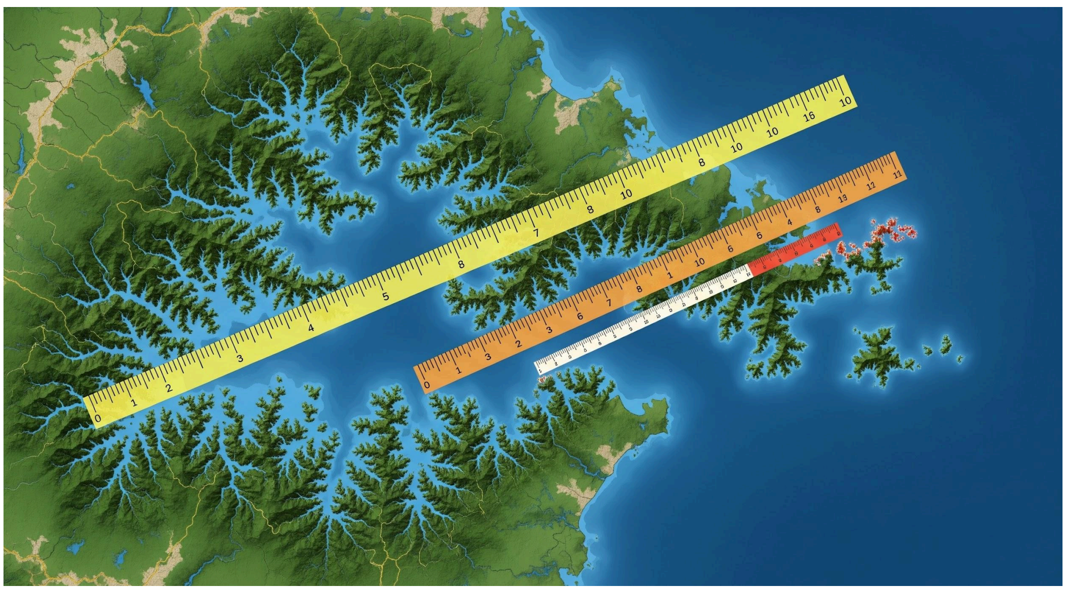


Image generated by Gemini AI

3. Results | What the Board Predicts

> ***Note:*** *No empirical data has been collected to date. This section describes theoretical predictions and proposed measurement approaches.*

3.1 Emergent Distributions and Scale-Free Patterns

The board **predicts** that cognitive time series should exhibit **1/f-like** spectral statistics, long-range **temporal correlations**, and condition-dependent **scaling shifts**. These predictions are consistent with existing findings in neural dynamics (He, 2014) and EEG studies of resting-state brain activity.

3.2 Structured Noise as Facilitation

Noise occurring in the board is **not** considered to be **damage**. It perturbs rigid local equilibria, **allowing** the ball to **escape from suboptimal** positions and **find new paths**. The model predicts an inverted-U relationship between noise and performance: too **little** noise produces rigid, deterministic cascades that miss optimal solutions; too **much** noise overwhelms the seesaw geometry entirely. **Timing** and locus of the **noise** matter.

This is consistent with stochastic resonance research showing that moderate noise can enhance signal detection in nonlinear systems (McDonnell & Ward, 2011).

3.3 The Qualia Threshold

The model **predicts** that **conscious experience** (a **quale**) emerges when a **sufficient cluster** of seesaws **tips** in a r**elational configuration** that crosses a **minimum threshold**:

Theta_quale = min{N_seesaw : Cluster(N) -> Feeling}

Below this threshold, seesaw activity constitutes the ‘dark matter’ of consciousness, the **subconscious processing** that influences behavior **without** producing **subjective experience**. Different systems (different brains) may have **different thresholds**, producing different **densities** of qualia per unit time.

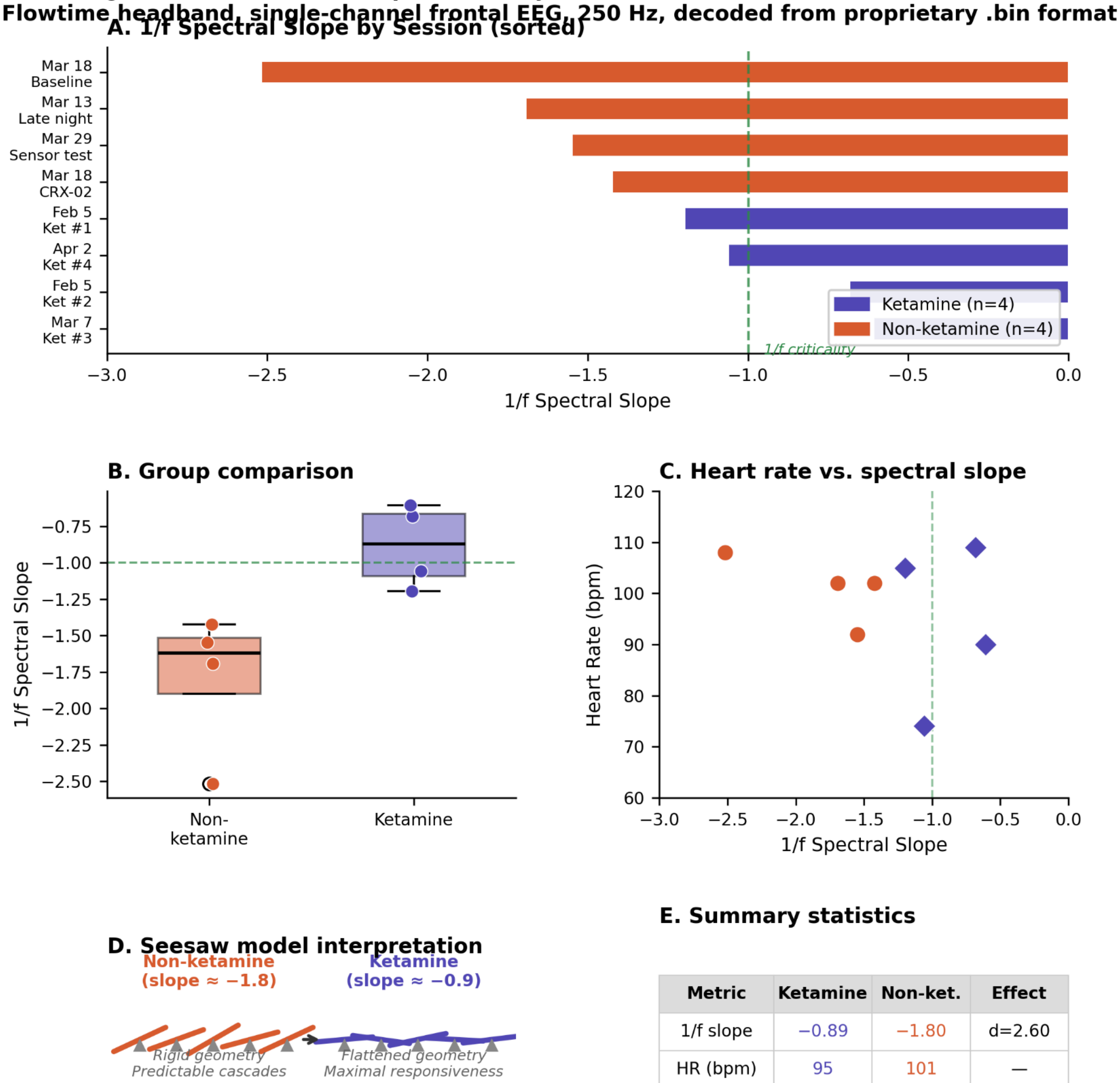
3.4 Proposed Measurement Framework

The following proxies are proposed for **future** empirical **testing** of the model:

Prediction	Proposed Proxy	Method
Seesaw bias geometry	EEG spectral ratios (gamma*beta / alpha+delta)	Consumer EEG headband
Cascade depth	Reaction time distributions under varying noise	Behavioral task with DDM fitting
Relational identity structure	Representational dissimilarity matrices	fMRI or EEG with RSA
Qualia threshold differences	Subjective report latency vs. stimulus complexity	Psychophysics paradigm

Scale-free dynamics	1/f slope of EEG power spectrum	Spectral analysis of resting-state EEG

Figure X. Consumer EEG Spectral Analysis: Ketamine vs. Non-Ketamine Sessions
Flowtime headband, single-channel frontal EEG, 250 Hz, decoded from proprietary .bin format



Metric	Ketamine	Non-ket.	Effect
1/f slope	−0.89	−1.80	d=2.60
HR (bpm)	95	101	—
δ/β ratio	1.33	1.41	—
Duration	44.8 min	12.0 min	—
Sessions	n = 4	n = 4	—

Data: 8 sessions (Feb 5 – Apr 2, 2026) | Device: Flowtime Biosensing | Analysis: Welch PSD, 1/f log-log fit (1–40 Hz) | Haskin, J. (2026). DodecaGone Systems.

Figure X. Pilot data from consumer EEG (Flowtime, single-channel frontal, 250 Hz) across 8 sessions. Ketamine sessions (n=4) show significantly flatter 1/f spectral slopes (mean = −0.89) compared to non-ketamine sessions (mean = −1.80), Cohen's d = 2.60. All ketamine sessions fall at or beyond the 1/f criticality boundary, consistent with the model's prediction that effective intervention reshapes seesaw geometry toward maximal responsiveness (Section 4.2)

4. Discussion | Agency Without Magic

4.1 Why Behavior Is Lawful but Not Fixed

The Seesaw Board produces behavior that is **constrained** but **not commanded**. Outcomes are predictable at the **population level** by dropping enough balls and the distribution will be stable. But for any **single** ball, the **path** through the board is genuinely **unpredictable** due to noise, initial conditions, and the **responsive nature** of the seesaws. This is **not** randomness dressed up as free will. It is a specific mathematical **structure** (biased stochastic cascade) that produces the **combination** of behavioral **regularity**, subjective **agency**, and **unpredictable** outcomes that characterize actual human behavior.

4.2 Intervention Reshapes Geometry, Not Outcomes

The model makes a **clear prediction** about intervention. **Aversive input** primarily **adds noise** to the cascade (shaking the board), making outcomes **less predictable without changing** the **underlying geometry**. Effective **intervention** can **reshape** the **seesaws**, it changes the bias, the sensitivity, or the thresholds of specific decision units. Therapy, medication, environmental redesign, and skill training all operate by **modifying** seesaw **parameters** rather than trying to **force** specific balls into specific ‘bins’ of action. Intervention under **conditions** of high intrinsic **load** or metabolic **constraint** leads to system **inefficiency** and increases the probability of **catastrophic** cascade **termination**.

4.3 Philosophical Boundary Conditions

The Seesaw Theory **rejects** both hard **determinism** (every outcome was inevitable from initial conditions) and pure **randomness** (outcomes have no structure). Agency lives in three places: the **geometry** of the board (which can be learned and modified), the **learning** rules that update seesaw parameters based on outcomes (which define how the system adapts), and the **constraint** modulation that shapes which seesaws are active in a given context (which defines attention and relevance).

4.4 Limitations

- This framework has **not** been empirically tested.
- The Plinko metaphor is an **intuition bridge**; it is **not** claimed that neurons **literally** operate as seesaws.
- The mapping to drift-diffusion models is **structural**, not mechanistic.
- The Yoneda-based identity theory is mathematically sound but has **not** been operationalized beyond the RSA proxy.
- The qualia threshold concept **requires** independent **calibration**.
- Cross-scale geometry is consistent with existing 1/f findings but the specific seesaw mechanism has **not** been isolated experimentally.

4.5 Future Directions

- Immediate priorities include fitting GDDM parameters to behavioral data under the seesaw interpretation, testing whether RSA dissimilarity matrices show the predicted asymptotic structure, and comparing EEG spectral ratios across populations with known differences in subjective experience density.
- The framework should be tested against competing models (predictive coding, global workspace theory, IIT) on the same datasets.

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