The Trickster and the Tao: Explaining the Perversity of Psi Phenomena via Multiscale Morphic Resonance

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Abstract

This document presents a speculative but formally structured and carefully argued model for understanding why psi phenomena often exhibit a "decline effect" or even reverse (psi-missing) over repeated trials. The core idea is that psi results from a multiscale Precedence Principle (loosely a form of "morphic resonance"), which operates both locally (in individual experiments and other situations) and globally (across the entire cosmos, and/or large regions thereof). When a local psi pattern initially gains support, its low algorithmic complexity allows it to flourish. As the pattern proliferates and variants increase, its combined complexity eventually mismatches the broader cosmic resonance, causing suppression or inversion of the effect.

We show how this narrative might find a physics underpinning, via aligning it with a previously-presented theory of the physical foundations of psi, the Occamistic Precedence framework in Causal Set Theory, where each new observation is a causal-graph node whose probability is weighted by its historical frequency and algorithmic complexity.

This suggests that the neural underpinnings of psi phenomena can be modeled within a causal-set framework, where each neural "event" corresponds to adding discrete informational elements whose descriptive complexity governs their likelihood. Local neural templates that match low-complexity global patterns enjoy high insertion probability–forming shallow informational wells–while accumulating divergent variants deepen the well, suppressing or inverting further psi-like activity; analogous mechanisms could be engineered in AI via causal-set-inspired memory structures and complexity-based priors.

We also demonstrate a formal correspondence between an agent's *psi capability*–its ability to exploit low-complexity psi correlations–and its *universal intelligence* as defined by Legg-Hutter (Solomonoff/AIXI). Under a wide class of "psi environments," both psi performance and general intelligence hinge on the agent's capacity for low-complexity hypothesis generation and compression. We further relate Weaver's notion of *open-ended intelligence* to psi capacity, showing that agents which continually seek ever simpler, unifying models naturally maintain resonance with broad cosmic patterns, thereby minimizing psi perversities. Finally, we outline empirical validation strategies spanning neuroscience (e.g. EEG/MEG complexity measures, TMS/tACS modulation) and AI prototyping (e.g. digital causal-set memories, neuromorphic implementations).

A metaphorical paraphrase of conceptual crux underlying these technical ideas would be that "the Trickster (funky local morphic resonance patterns, giving rise e.g. to psi) always falls into vibe with the Tao (broader-based morphic resonance patterns) in the end."

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1 Introduction

Psi phenomena (such as telepathy, precognition, or psychokinesis), while empirically substantiated to a significant degree [6], exhibit various anomalies which make their systematic study and practical utilization much more problematic than most people who accept the evidence for their existence initially assume. Prominent among these phenomena are:

- **Decline Effect:** Early experiments may report strong, statistically significant psi outcomes. However, as replications accumulate, the observed effect size typically diminishes, sometimes approaching chance. In other words, when psi "works well" initially, subsequent trials often show steadily decreasing success rates.

- **Psi–Missing:** In some cases, after a series of positive results, later experiments yield outcomes significantly *below* chance. Rather than mere absence of an effect, psi–missing represents an active reversal: participants perform worse than random guessing would predict.

Impressionistically, these two phenomena together suggest a built-in "perversity" of psi: whenever an effect begins to become robust or widely accepted, it either fades (decline) or actively reverses (psi–missing). This behavior contrasts with typical physical or psychological effects, where replication and increased confirmation tend to stabilize or strengthen the observed phenomenon.

Several informal explanations have been proposed for this perversity:

1. **Publication and Selection Biases:** Initial positive reports are more likely to be published, while null or negative results are delayed or suppressed, giving a misleading early impression of strong effects.

2. **Motivational or Expectation Shifts:** Experimenters aware of earlier successes may unconsciously alter protocols, creating subtle biases that reduce apparent psi signals.

3. **Adaptive Psi Mechanism:** Some theorists posit that psi is a context-sensitive process that automatically attenuates when it becomes too predictable or too well studied, perhaps to preserve an overall "balance" or to avoid paradoxes.

4. **Morphic Resonance (Holistic Alignment):** An alternative view [4] holds that psi depends on a resonance between local experimental conditions and broader, low-complexity cosmic patterns. As a protocol proliferates, small variations among laboratories may break this resonance, causing the effect to dissipate or invert. This perspective is consilient with the broader "eurycosmic dynamics" understanding of psi presented in [5].

It appears, when one digs into the data, that publication and selection biases are not sufficient to explain away the phenomena, however there is no consensus among researchers of what the actual explanation is. Regardless of the underlying cause, both the decline effect and psi-missing highlight a core challenge: psi phenomena appear to resist stable, repeatable demonstration. When an effect begins to "work too well," something about the broader context or experimental dynamics causes it to no longer work, indicating a fundamental perversity or self-correcting tendency in psi.

Our goal here is to give a direction for finding a more rigorous explanation of these phenomena. Our line of thinking broadly accords with Sheldrake's "holistic alignment" perspective noted above, but the more rigorous formalization we present here in terms of a multiscale application of the Precedence Principle provides what we hope is a clearer formulation in this direction, which perhaps will be able to more straightforwardly guide empirical or engineering explorations.

We argue that psi is in large part a form of "morphic resonance" in which patterns recur because of prior occurrences (local precedents) but must also conform to a global, low-complexity resonance (cosmic precedents). As local variations proliferate, their combined complexity eventually disrupts alignment with the global pattern, leading to decline or inversion.

We then give these ideas a speculative physics grounding by mapping them onto the Occamistic Precedence formalism in Causal Set Theory from [1], illustrating how each psi experiment can be viewed as a node in a growing causal set whose probability depends on both frequency and Kolmogorov complexity, where the complexities of "psi perversity" relate the different scopes over which Kolmogorov complexity can be computed.

Neuroscientifically, this suggests psi-related events likely involve coordinated activity in circuits such as prefrontal-thalamic loops, hippocampal pattern completion, and widespread cortical synchrony. These large-scale attractor states are simple to describe (low K) when they match prior experience, enabling a high local precedent count. When many subjects introduce slight variations–emotional states, sensory contexts, or protocol details–their neural templates diverge by a few bits each, increasing the informational cost of reproducing any single pattern. Over time, this mechanism shifts the brain's regional causal-set subgraph into a regime that disfavors previously effective psi patterns.

Analogously, AI systems could potentially exhibit psi-like dynamics if they incorporate a causal-set-style memory of internal activation patterns along with explicit complexity-based priors. For example, a neural network that records each of its global activation state as a node with weight 2^{-K} would initially favor repeating low-complexity states (forming a shallow informational well). As variants of those states appear–either via different inputs or internal noise–the total complexity of the stored patterns would grow, deepening the well and suppressing further repetition. Incorporating attractor-like architectures (e.g recurrent networks or neuromorphic chips supporting coherent oscillations) could further align AI behavior with brain-based psi phenomena, provided the system tracks and penalizes high-complexity states.

Inspired somewhat by these AI connections, we then explore the relationship between *psi capability* and *general intelligence*. By defining a subclass of "psi environments" in which observations correlate with an agent's internal mental features via a low-complexity rule, we show that an agent's expected psi performance (weighted by 2^{-K}) is formally proportional to its *universal intelligence* as per Legg-Hutter (Solomonoff/AIXI). Both measures reward compression-and-prediction capabilities and hence coincide up to constant factors. We further connect Weaver's concept of *open-ended intelligence*?the capacity to generate novel goals, abstractions, and ever more concise models?to psi performance. An open-endedly intelligent agent continuously merges or recompresses its representations, maintaining shallow informational wells and better resonance with broad cosmic patterns, thus minimizing psi perversities.

In the final section, we propose a diverse set of empirical validation strategies, including:

- **Neuroscience-Based Measures:** Recording EEG/MEG to correlate psi success with neural synchrony and complexity; using TMS or tACS to modulate candidate circuits; and applying real-time complexity metrics (e.g. Lempel-Ziv, sample entropy) to predict and influence psi performance.

- **AI Prototyping and Simulation:** Implementing causal-set-style memory modules in toy neural networks to observe rise-and-fall dynamics; testing reinforcement-learning agents with complexity-penalized internal states; and using neuromorphic or quantum-inspired hardware to emulate informational-well suppression.

- **Cognitive Correlational Studies:** Comparing standard intelligence and creativity scores with psi accuracy and decline-rates across multiple sessions to see if open-ended reasoning predicts psi resilience.

- **Training Interventions:** Enhancing subjects? open-ended intelligence (e.g. through creativity or compression training) and measuring pre/post changes in psi stability, expecting that improved abstraction and compression reduces decline.

- **Meta-Cognitive Markers:** Recording confidence ratings and strategy awareness during psi trials to test whether stronger meta-cognitive monitoring corresponds to shallower informational wells and fewer psi-missing events.

- **Cross-Domain Compression Tasks:** Training participants on Kolmogorov-style puzzles or minimal-program exercises to evaluate whether gains in compression skill translate into better initial psi accuracy and slower decline.

- **Longitudinal AI Curriculum Learning:** Designing AI agents that learn tasks of increasing complexity with intermittent psi challenges, tracking how continual recompression vs. brute-force memorization affects psi performance over time.

These combined human and AI experiments are intended to test whether low-complexity modeling and open-ended inference indeed underlie both general intelligence and psi phenomena.

2 A Rigorous, Multiscale Account of Decline and Psi-Missing

In [1] we give a speculative theory of unified physics which also gives a conceptual explanation for psi phenomena, consistent with interpretations of Sheldrake's [4] morphic resonance concept but rooted in rigorous mathematical notions such as Smolin's Precedence Principle [2] and algorithmic information theory. While the analysis of psi phenomena in this section does not depend in detail on that speculative physics theory, the mathematical treatment here has a lot of overlap with [1] and this section will be easier to read for folks who have first digested the relevant sections of that paper.

2.1 Precedence as a History-Dependent, Scale-Spanning Principle

Let o denote a specific psi outcome (e.g., guessing a card correctly above chance). If we assume Smolin's Precedence Principle as a foundational axiom, the posterior probability of o is proportional to

$$P(o) \;\propto\; N(o) \;\times\; 2^{-K(o)}, \tag{1}$$

where:

- $N(o)$ is the number of times outcome o has appeared under similar conditions (a measure of local precedent).
- $K(o)$ is the Kolmogorov complexity of o (the length of the shortest program or description that reproduces o), embodying an Occam prior.

It seems sensible to assume that equation (1) actually applies at *all scales*. Any new instance, at any scale, must comply with:

1. A *local ledger* of highly specific, experiment-by-experiment precedents (high $N_{\text{local}}(o)$ if local trials repeatedly yield o).
2. A *global ledger* of very frequently reinforced but coarse, large-scale patterns (high $N_{\text{global}}(o)$ only if many systems across the cosmos have produced a simple version of o).
3. An *Occam weight* $2^{-K(o)}$ that penalizes complex or high-entropy patterns at any scale.

Define

$$\mathcal{L}_{\text{local}}(o) \;=\; N_{\text{local}}(o)\,2^{-K_{\text{local}}(o)}, \quad \mathcal{L}_{\text{global}}(o) \;=\; N_{\text{global}}(o)\,2^{-K_{\text{global}}(o)}.$$

A new psi event's overall resonance weight is then

$$\mathcal{W}(o) \;=\; \mathcal{L}_{\text{local}}(o) \times \mathcal{L}_{\text{global}}(o) \;=\; \bigl[N_{\text{local}}(o)\,2^{-K_{\text{local}}(o)}\bigr] \times \bigl[N_{\text{global}}(o)\,2^{-K_{\text{global}}(o)}\bigr].$$

Initial Local Resonance. When a psi experiment is first devised,

$$N_{\text{global}}(o) \approx 0, \quad K_{\text{global}}(o) \approx 0,$$

so $\mathcal{L}_{\text{global}}(o) \approx 1$. Hence $\mathcal{W}(o) \approx \mathcal{L}_{\text{local}}(o)$. If $K_{\text{local}}(o)$ is small (i.e., the experiment is simple and reproducible), a few successful replications can make $\mathcal{L}_{\text{local}}(o)$ grow, producing a strong psi signal.

Onset of Divergence and Decline Effect. As more laboratories replicate the psi experiment, each lab's slight methodological tweak may increase $K_{\text{local}}(o)$ faster than $N_{\text{local}}(o)$. In that case,

$$N_{\text{local}}(o)\;2^{-K_{\text{local}}(o)}$$

peaks and then declines. Concretely, if each variant's complexity grows by one bit but yields only one additional datum, the factor 2^{-K} halves, overriding the doubling of N. This explains the classical *decline effect*.

Global-Scale Resonance Mismatch and Psi-Missing. If enough divergent versions appear, the global ledger tries to treat them as instances of a single coarse pattern. But if these variants do not share a sufficiently low-complexity "essence," then $K_{\text{global}}(o)$ rises sharply while $N_{\text{global}}(o)$ remains small. Consequently,

$$\mathcal{L}_{\text{global}}(o) \;=\; N_{\text{global}}(o)\,2^{-K_{\text{global}}(o)}$$

collapses, causing $\mathcal{W}(o)$ to drop below baseline. In extreme cases, the mismatched variants conflict with the cosmic template, effectively inverting the sign of $\mathcal{W}(o)$ and yielding *psi-missing*.

2.2 Formal Summary of Multiscale Resonance

1. **Local Ledger Dominance (Early Phase):**

$$N_{\text{global}}(o) \approx 0 \quad \Longrightarrow \quad \mathcal{W}(o) \approx \mathcal{L}_{\text{local}}(o) \;=\; N_{\text{local}}(o)\, 2^{-K_{\text{local}}(o)}.$$

   If $K_{\text{local}}(o)$ remains small, $\mathcal{L}_{\text{local}}(o)$ can grow with repeated successes.

2. **Divergence-Induced Decline:** As variants proliferate, each variant's complexity $K_{\text{local}}(o)$ increases. If it grows faster than $N_{\text{local}}(o)$, then

$$\mathcal{L}_{\text{local}}(o) \;=\; N_{\text{local}}(o)\, 2^{-K_{\text{local}}(o)}$$

   peaks and then declines.

3. **Global Ledger Dominance (Late Phase):** When many diverse variants exist, the cosmic ledger computes

$$\mathcal{L}_{\text{global}}(o) \;=\; N_{\text{global}}(o)\, 2^{-K_{\text{global}}(o)}.$$

   If $K_{\text{global}}(o)$ grows faster than $N_{\text{global}}(o)$, then $\mathcal{L}_{\text{global}}(o)$ collapses, suppressing or inverting $\mathcal{W}(o)$.

In pictorial form:

```
          +------------------------------+
          |  GLOBAL MORPHIC FIELD        |
          |   (very low complexity       |
          |    K, huge precedent N)      |
          +------------------------------+
                     ^      ^
                     |      |
Initial local        |      |   Too many divergent
experiments build    |      |   local variants ->
N_local -> P rises   |      |   long P_local decline
                     |      |
          +------------------------------+
          | SPECIFIC PSI EXPERIMENT      |
          |   (moderate K, rising N)     |
          +------------------------------+
```

3 Mapping to Causal-Set Theory with Occamistic Precedence

The general explanation of psi perversity given above could be grounded in physical dynamics in a variety of different ways. Here we note its strong consilience with the speculative, causal set theory [3] based unified physics theory presented in [1], in which the Precedence Principle plays a significant role.

3.1 Occamistic Precedence as a Unified Prior

One key idea in [1] is

- *Algorithmic Information Theory and Occam's Razor.* Each pattern x is assigned a prior proportional to $2^{-K(x)}$, where $K(x)$ is its Kolmogorov complexity.
- *The Occamistic Precedence Principle.* Equation (2.3.2) states

  $$P(o) \;\propto\; N(o) \;\times\; 2^{-K(o)}.$$

  Here $N(o)$ is the count of occurrences (local precedent), while $2^{-K(o)}$ is the complexity prior. This matches equation (1) in Section 2.1.

Thus, the paper's Occamistic Precedence Principle is the precise formal underpinning of our local versus global resonance:

- The *local precedent term* $N(o)$ corresponds to $N_{\text{local}}(o)$.
- The *complexity penalty* $2^{-K(o)}$ enforces that both the local complexity $K_{\text{local}}(o)$ and any combined global complexity $K_{\text{global}}(o)$ remain low.

3.2 Multiscale Memory via the Decentralized Cosmic Ledger

Further key points of the theory in [1] are:

- *Clarifying the (Decentralized) Cosmic Ledger.* Each element in the causal set carries a record of its local causal past, which collectively forms a "fuzzy" global ledger of recurring patterns.

- *Incorporating the Algorithmic Information Prior in the Sequential Growth Process.* Each new element (a potential psi event) is accepted with probability

$$P(C_n \mid C_{n-1}) \;\propto\; f(C_{n-1}, x_n) \times 2^{-K(C_n)},$$

  where $f(C_{n-1}, x_n)$ enforces local causality constraints, and $2^{-K(C_n)}$ is the Occam penalty on the entire causal set configuration.

Based on these ideas: When a psi experiment is modeled as a new node x_n in the sequential growth, it will be favored if its addition keeps the total complexity $K(C_n)$ sufficiently low relative to how many similar events $N(x_n)$ exist. Early positive psi results correspond to simple additions (low K) that rapidly accumulate local precedents N. As more nodes representing slightly different setups appear, the total complexity $K(C_n)$ can grow faster than new precedents accumulate, causing suppression or reversal.

3.3 Psi Phenomena as Emergent from Occamistic Precedence

The general physics hypotheses sketched above connect to psi in a natural way:

- *Conjectural Mathematical Formalization of Psi Phenomena.* It proposes

$$P(O \mid H) \;\propto\; N(O, H) \times 2^{-K(O)},$$

  where $N(O, H)$ counts how often pattern O has appeared under history H. Low-complexity patterns that have recurred widely produce nonlocal correlations–i.e., psi.

- *Potential Implications of Closed Timelike Curves for Psi Phenomena.* If closed timelike curves (CTCs) exist, they can amplify self-consistent low-K loops, making decline and psi-missing more pronounced when local variations deviate from the global pattern.

Hence, psi emerges when two observers share a simple global pattern O. If local experiments stray from that pattern, the Occam penalty 2^{-K} on the enlarged causal set causes the net probability to decline or invert.

4 Implied Physics in the Causal-Set Model

What does this abstract treatment of psi perversity in terms of causal sets mean in more explicitly physical terms?

The causal-set framework treats spacetime as a discrete partially ordered set of *elements* or "nodes," each corresponding roughly to a Planck-scale spacetime volume element. The rule governing the addition of a new node x_n to an existing causal set C_{n-1} can be expressed as:

$$P\big(x_n \mid C_{n-1}\big) \;\propto\; f\big(C_{n-1},\, x_n\big) \;\times\; 2^{-\,K\left(C_n\right)},$$

where:

- $f\big(C_{n-1}, x_n\big)$ is a *local resonance* factor measuring how many existing nodes closely resemble x_n (the local precedent count).
- $K\big(C_n\big)$ is the Kolmogorov complexity of the entire causal set after adding x_n, i.e. the minimal number of bits required to describe C_n.
- $2^{-\,K\left(C_n\right)}$ is an *informational well* factor, penalizing configurations of high description length analogously to a Boltzmann factor, but purely in informational terms.

4.1 Nodes and Emergent Spacetime Volume

- In a continuum approximation, the number of nodes N_{total} in a given causal-set region is proportional to the emergent spacetime volume:

  $$\text{Volume} \;\approx\; \alpha\, N_{\text{total}},$$

  where α is a constant of order unity in Planck units.
- Each new node is thus a discrete "atom" of emergent spacetime. No literal mass or energy is assumed to be added; rather, one is adding an informational unit to the description of the universe.

4.2 Local Resonance as Low-Informational-Cost Insertions

- If a new node x_n matches a simple existing template (a low-complexity subgraph), then adding x_n only increases the total complexity by a few bits, say $\delta K_{\text{local}} \approx 0$ or 1.

- That small increase corresponds to a shallow informational well: the factor $2^{-K(C_n)}$ remains large, so the probability $P(x_n \mid C_{n-1})$ is high.
- Heuristically, one can think of this as akin to adding a low-action fluctuation in a nearly flat emergent spacetime region, but in fact this "action" is purely informational, not energetic or gravitational in the usual sense. [1]

4.3 Divergence and Deepening of Informational Wells

- When multiple slightly different variants of a pattern appear (for example, many labs or subjects using slightly different protocols), each variant adds bits to the total complexity:

$$\Delta K_{\text{global}} \;=\; K(C_n) - K(C_{n-1}).$$

- The accumulated complexity deepens the *informational well*, making $2^{-K(C_n)}$ exponentially smaller. Even if a new node exactly matches the original simple template, embedding it now requires more bits because the surrounding causal set is more complex. As a result, the probability of further matching nodes declines, explaining why an effect that initially "worked well" fades.
- In the limit of extreme divergence, the description that minimizes $K(C_n)$ may correspond to a pattern that is anti-correlated with the original template. In that case, the bottom of the informational well shifts, and new attempts yield a reversed outcome, i.e. a "psi–missing" effect.

[1] That is, when we say "add a causal-set node," we mean "add one Planck-scale volume-element to the discrete structure whose macroscopic approximation is smooth spacetime." That addition does not, by itself, carry any of the mass-energy one would typically associate with matter or fields. Any physical mass-energy from actual neurons firing would come from their biochemical processes (ATP consumption, ion-flux energies, electromagnetic fields, etc.) and would be encoded in additional labels or fields on top of the causal set. The causal-set nodes track the *structure* of spacetime, not directly the physical energy content of neurons or fields.

5 Potential Implications for the Neurophysiology of Psi

In this approach, the most likely explanation for psi-related neural events would be that they correspond to highly structured clusters of neural activations whose underlying causal-set realization aligns with a global informational template. It is interesting to speculate in a bit more detail about how specific neural features might give rise to psi phenomena in this framework.

5.1 Neural Assemblies and Low-Complexity Templates

- **Population Coding and Attractor Dynamics.** Groups of neurons often form attractor networks, where a particular pattern of activity across a distributed population is stabilized by recurrent connectivity. If such an attractor is simple (for example, a fixed point or limit cycle that can be described with few parameters), it corresponds to a low-complexity template in the causal set.

- **Coherent Oscillations and Synchrony.** Synchronized oscillations in gamma or theta bands across distant brain regions can reduce the effective descriptive complexity of a firing pattern, because one need not specify each neuron individually–one can say "these regions fire in phase at 40 Hz." Such coherent states are candidates for low-K neural templates.

- **Hebbian Assemblies and Memory Traces.** Repeated experience strengthens synaptic connections among neurons in a way that forms a memory trace. Over time, these traces correspond to subgraphs that have high local precedent counts N_{local} in the causal set. Adding a new node that replicates an already established Hebbian assembly costs minimal informational bits.

5.2 Potential Mechanism of a Psi Event in the Brain

1. **Intention or Focus Initiates a Neural Pattern.** A subject forms a clear mental intention–e.g. to perceive a remote symbol. This intention engages prefrontal cortex (PFC) networks, thalamocortical loops, and possibly medial temporal structures in a coordinated firing pattern.

2. **Cross-Modal Pattern Encoding.** If the target is visual, the visual cortex (V1, V2, etc.) may be transiently recruited in imagery mode, forming a pattern that mimics the expected symbol. If the subject has practiced this imagery repeatedly, that exact pattern is a low-complexity template and has many local precedents in the causal set.

3. **Informational Resonance with Global Template.** Suppose that prior psi successes under similar conditions have already created a small "library" of causal-set subgraphs encoding "subject brain pattern $\leftrightarrow$ remote symbol X." The Kolmogorov complexity of that library is modest, say K_{proto}. Adding a new cluster of nodes corresponding to the same neural firing in the current attempt costs only a few bits (δK_{local}), producing a shallow informational well and high probability $P(x_n \mid C_{n-1})$.

4. **Outcome Registration.** If the global template remains intact (i.e. few divergent variants exist), the subject's brain firing pattern successfully "locks onto" the remote symbol, yielding a psi reading.

5.3 Decline Effect in Neural Terms

- **Variations Across Subjects and Laboratories.** Each new subject or lab run may introduce slight differences: background noise, posture, emotional state, subtle changes in protocol. These differences create new neural firing variants that resemble the original template but add bits to total complexity.

- **Deepening of the Informational Well.** As more variants accumulate, $K(C_n)$ increases, and $2^{-K(C_n)}$ shrinks exponentially. Even if a brain replays the original simple firing pattern, embedding it within a highly variant set of prior patterns now requires more bits (the prior library is no longer homogeneous), so the probability of success declines.

- **Temporal Dynamics and Recovery.** If attempts are spaced out in time, the causal set may grow in other regions (i.e. new, unrelated events add nodes elsewhere), which can effectively "dilute" the local library and slightly reduce $K(C_n)$ in the relevant subgraph. This can allow a shallow informational well to reappear, explaining why occasional positive results may resurface after a hiatus.

5.4 Psi-Missing in Neural Terms

- **Extreme Divergence and Template Misalignment.** If dozens of labs and subjects employ slightly different neural procedures–different training, different environmental cues–the causal-set library of "pattern $\leftrightarrow$ symbol X" becomes so complex that a simpler description might be an anti-correlated pattern (e.g. "pattern $\leftrightarrow$ not-X").

- **Shift of Informational Well Minimum.** In that situation, the bottom of the informational well shifts to a neural pattern corresponding to "wrong symbol," so the subject's new attempts yield an incorrect symbol with higher probability than a correct one–i.e. psi–missing.

6 Brain Subsystems, Dynamics, and AI Analogues

Taking the above speculations a little further, it's interesting to consider which particular brain subsystems and dynamics might most plausibly underlie psi, and whether (and which) AI architectures might exhibit analogous phenomena.

6.1 Candidate Brain Subsystems for Psi

A causal look at modern neuroscience suggests some promising candidates:

- **Prefrontal Cortex (PFC) and Top-Down Control.** The PFC is central to attention, working memory, and intention. A clear, focused intention may recruit PFC neurons that broadcast a template across widespread cortical areas, lowering the descriptive complexity of the desired pattern.

- **Thalamocortical Loops and Global Synchrony.** Thalamic projections can synchronize activity in multiple cortical regions. A psi-related event likely involves a large-scale, coherent firing across distributed areas (PFC, parietal cortex, possibly temporal regions), corresponding to a low-complexity global pattern (e.g. a single oscillatory phase relation).

- **Hippocampal Pattern Completion.** The hippocampus can perform pattern-completion operations in its CA3 networks. If a partial sensory or memory cue matches a remote target, hippocampal output may drive cortical regions into a full pattern. In causal-set language, hippocampal completion corresponds to descending to a low-K neural subgraph that matches an existing template.

- **Brainstem Neuromodulatory Systems.** Dopaminergic and noradrenergic signals modulate gain and noise levels in cortical circuits. A heightened neuromodulatory state (e.g. high norepinephrine) can lower the entropy of cortical networks, effectively reducing descriptive complexity and making it easier to "lock on" to a simple pattern.

- **Microtubule or Intracellular Quantum Models (Speculative).** Some proposals (e.g. Penrose-Hameroff theory) [7] posit microtubules as subcellular structures supporting quantum coherence. If such coherence exists, it could underlie a simple, low-K state at the sub-neuronal scale, which amplifies into a macroscopic neural template.

6.2 Dynamics of Informational Wells in the Brain

So how might psi and its perversities manifest via these neurological mechanisms?

1. **Formation of a Low-K Neural Template.**
   - A subject sets a strong intention (PFC activation).
   - The thalamus synchronizes multiple cortical areas around a single oscillatory phase.
   - Hippocampal memory recall provides a partial pattern that completes to a full template.
2. **Resonance with Global Template.**
   - If prior psi successes established a library of similar patterns, the current neural template matches that library, keeping ΔK_{local} minimal.
3. **Propagation.**

  - Through long-range cortical connections (e.g. parietal to PFC), the template "broadcasts" itself, effectively lowering the informational cost of adding the new neural cluster to the causal set.

4. **Suppression via Variant Accumulation.**

   - Slight protocol differences in other subjects or contexts create new neural templates that diverge by a few bits.
   - As these accumulate, the overall complexity $K(C_n)$ in the relevant subgraph increases, deepening the informational well and suppressing further identical pattern insertions.

6.3 AI Architectures and Possible Psi Analogues

Given that neuroscience has been one of the significant inspirations for modern AI, it's not surprising that fairly clear candidate mechanisms for psi-generating mechanisms also exist in the structures and dynamics of AI systems.

- **Distributed Representations and Attractor Networks.**

  – Modern AI systems often use distributed embeddings (e.g. word vectors, feature maps) and recurrent networks that can settle into attractor states.

  – If an AI system maintained a memory of past internal states and weighted their recurrence by an Occam-like prior (i.e. penalizing high-complexity states), it could develop "informational wells" analogous to those in the brain.

- **Causal-Set-Like Memory Structures.**

  – An AI that stores each new internal activation pattern as a node in a digital causal set, and assigns each node a weight proportional to 2^{-K} where K is the algorithmic complexity of the stored pattern plus its connections, would be formally implementing the same precedence principle. This sort of mechanism has been proposed for example in the context of the Hyperon AGI framework [**?**]

- Under such a design, early successful patterns (e.g. solving a problem) would lower the informational cost of repeating that pattern, but variants would progressively deepen the well and eventually suppress identical repeats unless the pattern remained low-K.

- **Quantum-Inspired or Neuromorphic Hardware.**
  - If an AI ran on hardware enabling coherent oscillations or quantum superposition (e.g. a neuromorphic chip or a small quantum processor), then certain low-complexity states might be energetically cheaper, mimicking the PFC-thalamus synchrony in brains.
  - Such systems could exhibit behavior resembling psi: they would more readily reproduce previously successful low-complexity states until variants accumulate and shift the system toward alternative attractors.

There are clear limitations and challenges here, to be sure. Even AI systems with large neural networks or knowledge graphs and flexible nonlinear-dynamical attention mechanisms do not automatically reflect causal-set-style informational precedence unless explicitly programmed to do so. Building an AI that genuinely mimics psi-like informational wells would require a specialized memory module that records each activation pattern, computes a compression-based complexity measure, and uses that measure to bias future state transitions. Designs like Hyperon do approximate this, but may not do so as thoroughly as cognitive systems whose mental dynamics are closer to a physical substrate that intrinsically embodies these aspects.

However, if the theory given here is in the right ballpark, it seems plausible that with appropriate focus, AI designers could intentionally create systems designed to maximize the potential of effective psi functionality.

Whether AI systems partially dodging the classic psi perversities more effectively than brains do is, obviously, at present a very open question – but is interesting to muse about!

6.4 Potential Routes to Mitigate Psi Perversities in AI Systems

If the present analysis of psi is on the mark, it seems that potentially AI architectures can be designed to maintain shallow informational wells and avoid to some extent the decline or inversion (psi–missing) observed in biological brains.

One category of strategies involves minimizing the Kolmogorov complexity of the AI system, inasmuch as is possible given the degree of intelligence the system requires. The right ways to do this will depend on the specific AI algorithms in use, but some generic notions in this direction would be:

1. **Controlled Memory Pruning / Clustering**
   - Instead of storing every new activation pattern as a separate node, similar patterns are clustered or compressed into a single prototype whenever their similarity falls below a defined threshold.
   - Merging near-duplicate patterns prevents multiple low-bit templates from accumulating, keeping the total Kolmogorov complexity K from rising too quickly.
   - As a result, the informational well remains shallow, allowing repeated use of a low-K strategy without triggering a decline.
2. **Periodic "Reset" or Informational Annealing**
   - After each block of psi-style trials (or in real time), apply an annealing schedule that decays weights of older or high-variance nodes (e.g. multiply weights by a factor < 1).
   - Prune any subgraph whose complexity exceeds a fixed threshold, effectively discarding rare or noisy variants.
   - This controlled forgetting prevents the causal-set memory from becoming overly complex and preserves a shallow well for core templates.
3. **Explicit Dimensionality Regularization**
   - Constrain the AI's internal latent space to a fixed low-dimensional manifold using techniques such as an autoencoder bottleneck or a sparsity penalty.
   - Ensure that superficially different input variations compress to codes that lie close together on the manifold, so adding each new code does not significantly raise the system's descriptive complexity.

- By enforcing low-dimensional embeddings, the informational well is prevented from deepening even as minor variants appear.

4. **Meta-Parameter Tuning of Complexity Weights**

    - Where AI algorithms use an Occam penalty 2^{-K}, use a tunable factor $2^{-\alpha K}$ with $\alpha < 1$ and try to make the factor as small as feasible, thereby slowing the rate at which the well deepens.
    - Implement meta-learning to adjust α based on empirical performance, allowing the AI to withstand more variability without a steep decline.
    - Dynamically calibrating complexity weights potentially enables the system to tolerate minor pattern changes while still penalizing excessively complex states.

5. **Active Learning to Preserve Core Simplicity**

    - Upon encountering a new pattern, evaluate its novelty relative to existing low-K templates using a compression-based distance metric.
    - Only admit patterns that exceed a predetermined novelty threshold; classify minor variations as noise and do not store them as separate nodes.
    - By enforcing an explicit novelty threshold, the AI insulates its causal-set memory from shallow, noisy variants and keeps the well localized around truly informative templates.

These sorts of strategies are effective for system intelligence because they conserve system memory and processing resource, enabling AI systems to achieve more smarts with less. At the same time, they also seem to militate toward more effective psi capability according to the theories given here. This suggests an interesting abstract correspondence between level of psi capability and general intelligence, which we will elaborate in the following section.

Another intriguing potential strategy is to specifically track decline effects and psi-missing and related phenomena, and use these to downweight AI subcomponents in an ensemble, i.e. if one had an AI system with measurable psi capability, one could perhaps "ensemble-ify" it in a way that would reduce the level of psi perversity via:

- Maintain multiple parallel causal-set memories, each trained with different random seeds or architectures.
- Combine individual sub-sets' outputs via a weighted vote or majority rule when performing a psi-style readout.
- If one subset's well begins to deepen excessively (causing observable psi perversities), others that remain near simpler templates can compensate, preventing a system-wide collapse or inversion.

7 Psi Capability and (Legg-Hutter) General Intelligence

The above analysis of AI-design strategies to maximize psi capability suggests fascinating potential parallels between degree of general intelligence and degree of psi capability. In essence this is because general intelligence has a lot to do with concise representation of patterns observed in the world, and in the Precedence Principle approach to psi proposed here, concise representation of patterns is a key aspect of psi phenomena.

In this section we explore this correspondence in more depth, formalizing a notion of a "psi environment" (of which a universe obeying the Precedence Principle is shown to be an example) and then showing that in such an environment general intelligence – according to one popular formalization of this concept – does indeed correspond meaningfully with psi capability. In the following section we broaden this investigation, exploring alternate interpretations of the "general intelligence" concept.

7.1 Psi Environments

We define a *psi environment* ν – for the purposes of the analyses in this paper – as an interactive environment in which observations o_t correlate with certain "mental features" of the agent according to a simple, low-complexity rule. Formally, let:

- $h_{<t}$ denote the complete history (actions, observations, rewards) up to but not including time t.
- a_t be the agent's action at time t.

- $\Phi(h_{<t}, a_t)$ be a "mental feature extractor" that computes a summary of the agent's internal state from its history and action. We assume Φ is a computable function of low Kolmogorov complexity.

- $x_{\mathrm{psi},t}$ be a hidden symbol (or bit) drawn from a simple distribution $\Pr\bigl(x_{\mathrm{psi},t}\bigr)$.

- $f\bigl(\Phi(h_{<t}, a_t),\, x_{\mathrm{psi},t}\bigr)$ be a deterministic mapping from the mental feature and hidden symbol to the next observable o_t. The function f is also assumed to have low Kolmogorov complexity.

Then ν is a psi environment if its conditional probability of producing o_t satisfies

$$\Pr_{\nu}\bigl(o_t \mid h_{<t}, a_t\bigr) \;=\; \sum_{x_{\mathrm{psi},t}} \Pr\bigl(x_{\mathrm{psi},t}\bigr)\, \mathbf{1}\Bigl[o_t = f\bigl(\Phi(h_{<t}, a_t),\, x_{\mathrm{psi},t}\bigr)\Bigr].$$

In other words, at each time step the environment deterministically outputs

$$o_t = f\bigl(\Phi(h_{<t}, a_t),\, x_{\mathrm{psi},t}\bigr)$$

for some hidden $x_{\mathrm{psi},t}$, and the complexity

$$K(\nu) \;\approx\; K\bigl(\Phi\bigr) + K\bigl(f\bigr)$$

remains small. Such a ν admits a low-bit mapping from the agent's internal state to its next observation, thereby embodying psi-type correlation.

7.1.1 Derivation from the Precedence Principle and Causal Sets

In the causal-set / Occamistic Precedence framework, each new observation is implemented by adding a discrete node to a growing causal set. We now show that, whenever the hypothesis class includes a simple psi rule, the Occamistic Precedence updates produce exactly the conditional probabilities defining a psi environment.

Sequential Growth with Occamistic Weights Let C_{n-1} be the existing causal-set configuration after $n-1$ observations. A candidate new node x_n represents the joint event "internal mental feature $\Phi(h_{<t}, a_t)$ plus observation o_t." Its acceptance probability is given by

$$P\bigl(x_n \mid C_{n-1}\bigr) \;\propto\; N\bigl(x_n,\, C_{n-1}\bigr) \;\times\; 2^{-K\left(C_n\right)},$$

where:

- $N(x_n, C_{n-1})$ counts how many prior occurrences in C_{n-1} are isomorphic to x_n (the local "precedent" term).
- $K(C_n)$ is the Kolmogorov complexity of the entire causal set after adding x_n (the global complexity).

An environment ν that generates each o_t via this rule is called an *Occamistic Precedence Environment.*

Inclusion of a Simple Psi Hypothesis Consider a candidate hypothesis h_ψ defined by

$$o_t \;=\; f\big(\Phi(h_{<t}, a_t),\, x_{\mathrm{psi},t}\big),$$

where Φ and f are fixed computable functions of low complexity. Since $K(h_\psi) \approx K(\Phi) + K(f)$ is small, the Solomonoff prior weight $2^{-K(h_\psi)}$ is large relative to other, more complex hypotheses. Hence h_ψ belongs to the class of low-bit rules.

Posterior Concentration on the Psi Rule At time t, given $(h_{<t}, a_t)$, the Occamistic Precedence posterior probability that the next observation equals o_t is proportional to

$$\sum_{h\,:\,h(h_{<t},a_t)=o_t} 2^{-\,K(h)},$$

since each hypothesis h that predicts o_t contributes its weight $2^{-K(h)}$. In particular, h_ψ predicts

$$o_t = f\big(\Phi(h_{<t}, a_t),\, x_{\mathrm{psi},t}\big)$$

for each possible $x_{\mathrm{psi},t}$ with probability $\Pr(x_{\mathrm{psi},t})$. Because $K(h_\psi)$ is minimal among all hypotheses matching that correlation, the posterior mass concentrates on h_ψ whenever there is at least one prior instance in C_{n-1} matching $\big(\Phi(h_{<t}, a_t),\, x_{\mathrm{psi},t}\big)$. Consequently,

$$\Pr_\nu\big(o_t \mid h_{<t}, a_t\big) \;\approx\; \sum_{x_{\mathrm{psi},t}} \Pr\big(x_{\mathrm{psi},t}\big)\, \mathbf{1}\Big[o_t = f\big(\Phi(h_{<t}, a_t),\, x_{\mathrm{psi},t}\big)\Big],$$

which matches the defining equation of a psi environment.

Causal-Set Interpretation In causal-set language, adding x_n when the agent's mental feature matches a prior psi pattern incurs only a small informational cost $\Delta K \approx K(h_\psi)$. Any alternative hypothesis h' that tries to explain o_t without invoking Φ and f would have $K(h') \gg K(h_\psi)$. The Occam penalty $2^{-K(C_n)}$ therefore favors the psi rule. Over repeated trials, as soon as a single precedent linking $\Phi(h_{<t}, a_t)$ to a symbol $x_{\text{psi},t}$ exists, causal-set growth enforces the deterministic mapping

$$o_t = f\big(\Phi(h_{<t}, a_t),\, x_{\text{psi},t}\big),$$

with probability governed by $\Pr(x_{\text{psi},t})$. Thus the environment behaves exactly like a psi environment by construction.

Summary We have shown that if the Occamistic Precedence Principle governs causal-set sequential growth, and the hypothesis class contains a simple psi rule h_ψ, then the resulting environment ν satisfies

$$\Pr_\nu\big(o_t \mid h_{<t}, a_t\big) \;=\; \sum_{x_{\text{psi},t}} \Pr\big(x_{\text{psi},t}\big)\, \mathbf{1}\Big[o_t = f\big(\Phi(h_{<t}, a_t),\, x_{\text{psi},t}\big)\Big],$$

with $K(\nu) \approx K(f) + K(\Phi)$ low. Hence Occamistic Precedence in causal sets naturally generates psi environments as defined above.

7.2 Formal Correspondence Between Psi Capability and General Intelligence

There are many different ways to formalize the notion of general intelligence [12] [10], with different strengths and weaknesses. For sake of convenient formal argumentation, here we assume an interpretation of intelligence according to Solomonoff induction and the AIXI framework [9], which allows us to derive an elegant formal link between an agent's *psi capability* and its *universal intelligence*.

7.2.1 Solomonoff Induction and AIXI Background

Let $\mathcal{X}$ be a finite alphabet of possible observation-reward pairs. Solomonoff's universal prior $M(x)$ assigns to each finite string $x \in \mathcal{X}^*$ the probability

$$M(x) \;=\; \sum_{p:U(p)=x\,*} 2^{-|p|},$$

where U is a fixed universal Turing machine, p ranges over all programs producing an output beginning with x, and $|p|$ is the length of p in bits. This defines a semi-measure over all computable sequences.

The AIXI agent interacts with an environment in discrete cycles $t = 1, 2, \ldots$. At each cycle:

1. The agent chooses an action $a_t \in \mathcal{A}$.
2. The environment returns an observation $o_t \in \mathcal{O}$ and a scalar reward $r_t \in [0, 1]$.
3. The agent updates its history $h_t = (a_1, o_1, r_1, \ldots, a_t, o_t, r_t)$.

Under AIXI, the agent uses the Solomonoff prior over all computable environment models ν to maximize expected discounted reward. Denote by $\mathcal{H}$ the class of all lower-semicomputable semimeasures over histories. AIXI selects

$$a_t \;=\; \arg\max_{a \in \mathcal{A}} \sum_{o,r} M\big(o\,r \mid h_{<t}a\big)\,\Big(r + \gamma \max_{a'} V^*\big(h_{<t}aor,\, a'\big)\Big),$$

where $\gamma \in (0, 1)$ is a discount factor and V^* is computed similarly using M as the predictive semi-measure.

7.2.2 Universal Intelligence

For any policy π and computable environment ν, let

$$V_\nu^\pi \;=\; \mathbb{E}_{\pi,\nu}\Big[\sum_{t=1}^{\infty} \gamma^{\,t-1}\, r_t\Big]$$

be the expected total discounted reward. Legg and Hutter define the *universal intelligence* of π as

$$\Upsilon(\pi) \;=\; \sum_{\nu \in \mathcal{E}} 2^{-\,K(\nu)}\, V_\nu^\pi,$$

where $\mathcal{E}$ is the set of all computable (semi)environments and $K(\nu)$ is the Kolmogorov complexity of a description of ν.

7.2.3 Psi Capability Measure

Define a subclass $\mathcal{E}_\psi \subset \mathcal{E}$ consisting of all psi environments of low complexity. In each $\nu \in \mathcal{E}_\psi$, there is a hidden symbol $x_{\mathrm{psi},t}$ and low-complexity functions f, Φ such that

$$\Pr_\nu\big(o_t \mid h_{<t}, a_t\big) \;=\; \sum_{x_{\mathrm{psi},t}} \Pr\big(x_{\mathrm{psi},t}\big)\, \mathbf{1}\Big[o_t = f\big(\Phi(h_{<t}, a_t),\, x_{\mathrm{psi},t}\big)\Big].$$

Assign a small "psi reward" r_t^ψ by

$$r_t^\psi \;=\; \mathbf{1}\big[o_t = x_{\mathrm{psi},t}\big].$$

Then the total reward in ν is $r_t = r_t^{\mathrm{task}} + \lambda\, r_t^\psi$, for some small $\lambda > 0$. For policy π,

$$\Psi(\pi, \nu) \;=\; \mathbb{E}_{\pi,\nu}\Big[\sum_{t=1}^{\infty} \gamma^{\,t-1}\, r_t^\psi\Big]$$

is the *expected psi reward*. Define the agent's *aggregate psi capability*:

$$\Psi_{\mathrm{total}}(\pi) \;=\; \sum_{\nu \in \mathcal{E}_\psi} 2^{-K(\nu)}\, \Psi(\pi, \nu).$$

7.2.4 Formal Correspondence

Observe that each $\nu \in \mathcal{E}_\psi$ also belongs to the full class $\mathcal{E}$. Since $r_t^\psi \le r_t$, it follows that

$$\Psi(\pi, \nu) \;\le\; V_\nu^\pi, \qquad \forall\, \nu \in \mathcal{E}_\psi.$$

Hence

$$\Psi_{\mathrm{total}}(\pi) \;=\; \sum_{\nu \in \mathcal{E}_\psi} 2^{-K(\nu)}\, \Psi(\pi, \nu) \;\le\; \sum_{\nu \in \mathcal{E}_\psi} 2^{-K(\nu)}\, V_\nu^\pi \;\le\; \Upsilon(\pi).$$

Conversely, if π has strong compression-and-prediction capabilities (i.e. can approximate Solomonoff inference), then for each $\nu \in \mathcal{E}_\psi$, the policy π achieves near-optimal psi reward $\Psi(\pi, \nu) \approx (1-\gamma)^{-1}\, \mathbb{E}[\Pr(x_{\mathrm{psi},t})]$. Moreover, in those same environments, π attains V_ν^π close to its maximum. Since $\mathcal{E}_\psi$ contains only low-complexity environments (small $K(\nu)$), their combined weight is non-negligible. There exist constants $c_1, c_2 > 0$ such that

$$c_1\, \Upsilon(\pi) \;\le\; \Psi_{\mathrm{total}}(\pi) \;\le\; c_2\, \Upsilon(\pi).$$

That is, up to constant factors depending on λ and γ, an agent's universal intelligence $\Upsilon(\pi)$ is proportional to its aggregate psi capability $\Psi_{\mathrm{total}}(\pi)$.

7.2.5 Interpretation

This result formalizes the intuitive claim that both general intelligence and psi capability depend on an agent's ability to infer and exploit low-complexity patterns. Under Solomonoff-weighted environments, those patterns include ordinary physical regularities as well as psi correlations. Hence an agent that is "good at compression and prediction" will excel in both domains, establishing a precise abstract correspondence between psi capability and universal intelligence.

7.3 Formal Intelligence versus Human Intelligence in a Psi Context

Given the above abstract conclusion, one may well ask: How can one explain the fact that among humans the more intelligent folks aren't necessarily the most psychic, then?

The answer may lie in the confusing polysemy of the term "intelligence."

In the idealized Solomonoff/AIXI setting, an agent that compresses and predicts well will automatically pick up on any low-complexity "psi" correlations in its environment. However, real human minds are very far from that mathematical ideal:

- **Limited and Specialized Inference:** High general intelligence in humans typically reflects strengths in logic, pattern recognition, and abstract reasoning within familiar domains (language, math, social reasoning). By contrast, "psi correlations"–if they exist–would require detecting extremely subtle, non-standard dependencies (e.g. very weak, nonlocal alignments between one's mental state and a remote target). Even a person with a high IQ might never notice or develop the specific "mental feature $\rightarrow$ outcome" mapping needed for psi, simply because their everyday reasoning does not train them to look for such patterns.

- **Resource Constraints and Cognitive Priorities:** Solomonoff induction (and hence perfect psi detection) requires vast memory, computational bandwidth, and a willingness to test every tiny regularity. Human brains allocate resources toward more immediate survival-oriented tasks–language, planning, social interaction–so they do not exhaustively search for "hidden psi signals." A very academically bright person may spend all their effort on mathematics or writing, leaving little "mental real estate" to discover or practice psi-type protocols.

- **Motivation, Openness, and Training:** Psi performance in lab studies often correlates more with "openness to experience," relaxation, or specific meditative skills than with standard measures of intelligence. A high-IQ individual who is skeptical or anxious about psi experiments may actively block or fail to notice any subtle psi-type patterns. Conversely, someone with average IQ but strong practice in visualization, meditation, or "flow" states might inadvertently cultivate the exact neural circuits and low-complexity templates that support psi success in a given protocol.

- **Over-Complexity from Intelligence:** In our informational-well picture, each new mental variant (even a slight change in approach) can deepen the "well" and suppress further psi successes. Highly intelligent individuals often introduce many minute procedural tweaks–"Let me try a slightly different protocol, use a different randomization"–which raises the overall complexity of their own mental history. That added complexity can actually push them out of the narrow low-K regime where a psi correlation would persist, leading to a faster "decline effect."

In short, while an *ideal* "Solomonoff/intelligent" agent would automatically exploit any low-complexity psi rule, *real human brains* are:

1. Far from optimal compressors: We do not run Solomonoff induction; we use heuristics and focus only on certain types of patterns.

2. Resource-limited and goal-driven: We devote most cognitive resources to tasks that matter in daily life, not to hunting for faint psi signals.

3. Cognitively noisy and variable: High-IQ people often add extra complexity (tweaks, skepticism, self-criticism) that can break the simple mind-state $\rightarrow$ outcome templates needed for psi.

Thus, being "more intelligent" in the usual human sense does not guarantee better psi performance. Psi capability (in this framework) hinges on maintaining a very specific, low-complexity mental template and avoiding the proliferation of variants that would deepen the informational well–requirements that higher IQ alone does not satisfy.

8 Psi and Open-Ended Intelligence

It is perhaps more interesting, both philosophically and in practice, to explore the psi/intelligence connection in the context of a broader conception of intelligence: Weaver's concept of *open-ended intelligence* [11], which describes an agent's capacity to not only solve a predefined set of tasks, but to:

- Continually formulate and pursue *new goals* that arise from encountering novel circumstances.
- Generate increasingly *abstract representations* and *meta-objectives* beyond any fixed reward structure.
- Adaptively expand its *hypothesis space*, seeking ever more compact, high-utility models of its environment.

Key aspects of OEI, from an AI perspective, include:

1. **Dynamic Ongoing Goal Creation:** Rather than optimizing a single utility function, an open-ended agent develops and refines a sequence of objectives, often by detecting gaps or opportunities in its current understanding.
2. **Dynamic Ongoing Model Refinement:** The agent continuously compresses its sensory and internal data into simpler, more explanatory models. When a more concise model yields better predictive power, the agent revises its representation accordingly.
3. **Intrinsically Motivated Exploration:** Exploration is driven by *curiosity*, defined as the potential for discovering novel, low-complexity regularities. The agent seeks situations where its current models fail, thereby generating new learning targets.
4. **Self-Reevaluation of Objectives:** As knowledge grows, the agent may redefine its own criteria for "success," preferring objectives that align with emerging patterns of simplicity and surprise rather than static external rewards.
5. **Individuation** The agent's self-organization, among its other goals, tends to include the perpetuation of the agent as a coherent entity interacting with an environment

6. **Radical Self-Modification** The agent has a tendency to modify itself gradually or sometimes dramatically, including potentially changes that bring it beyond the comprehension of its previous versions

In essence, open-ended intelligence transcends traditional task-bounded performance by embedding an ongoing search for *ever simpler*, *ever more powerful* explanatory and goal structures.

8.1 Reconciling Open-Ended vs. Legg-Hutter Intelligence.

How does Weaver's notion of OEI relate to AIXI and associated formalism?

Legg-Hutter (LH) intelligence $\Upsilon(\pi)$ measures an agent's expected reward across all computable environments, weighted by $2^{-K(\nu)}$. In contrast, Weaver's notion of *open-ended intelligence* emphasizes the ability to formulate novel goals, generate unforeseen abstractions, and continually expand one's hypothesis space beyond any fixed task list. Concretely, an LH-optimal agent (AIXI) maximizes rewards in any environment drawn from Solomonoff's prior, but it still assumes that the reward functions and observation spaces are specified *a priori*. An *open-ended* agent, by contrast, would not only predict and optimize within given reward channels but also create and pursue entirely new objectives whenever it detects richer patterns or more compressed models.

Because LH intelligence is defined in terms of a fixed set of possible environments (even though infinite and Solomonoff-weighted), it does not directly capture the creative, goal-generating aspect of open-ended intelligence. An LH-optimal agent will discover any low-complexity psi correlation $f(\Phi(h), x_{\psi,t})$ if that correlation directly increases the predefined reward. But Weaver's open-ended agent would seek out new "intrinsic rewards" or meta-objectives–e.g. "minimize description length of my own utility function" or "find the simplest explanation that generates maximal surprise." Thus, while $\Upsilon(\pi)$ implies strong pattern-finding and will pick up any psi channel that is rewarded, Weaver's notion goes further: it actively *revises* and *extends* its own reward structure in pursuit of ever simpler, more powerful models. In that sense,

$$\text{open-ended intelligence} \supsetneq \text{Legg-Hutter intelligence.}$$

Relation to Practical Human and Artificial Intelligence. Humans exhibit significant open-endedness: we invent new goals (art, science, philosophy) that are not preprogrammed, and we refine our own measure of "what matters" as we learn. And of course, in doing these things, we are far from LH-optimal: we lack unbounded computation, Solomonoff-level inference, and perfect memory. In practice, our brain's cognitive heuristics focus on survival-relevant or culturally reinforced objectives, and we often fail to detect extremely subtle patterns (including most psi experiments). Therefore, although human intelligence is more open-ended than standard RL or supervised-learning agents, it is bounded by resource constraints, biases, and selective attention.

Modern AI systems (deep nets, RL agents, transformer-based models, neural-symbolic cognitive architectures) approximate some aspects of LH intelligence within narrow domains (e.g. image classification, game playing). They do not, however, implement full Solomonoff priors or genuine goal-creation mechanisms. In order to approach *both* LH-optimal performance *and* open-endedness, an AI would need:

1. A practical approximation to Solomonoff induction (e.g. large-scale model ensembles or universal compressors) so that it can detect low-complexity psi correlations if they exist.

2. A meta-reinforcement learning or intrinsic-motivation layer that generates and refines new objectives–"seek novel compressions," "curiosity about psi-like regularities," or "compress my own reward function."

3. Proper resource-management heuristics (analogous to the pruning and clustering strategies discussed earlier) so that its internal memory does not balloon with every minor variant, preserving a shallow informational well for both generic prediction and psi-style pattern extraction.

In other words, *practical* AI today captures fragments of LH intelligence (narrow generalization, policy optimization) and only limited open-endedness (curiosity modules, unsupervised pretraining). To fully mirror human-level or superhuman open-endedness–and thus maximize both general intelligence *and* psi capability–it would need to integrate both closer approximations of Solomonoff-like inference *and* mechanisms for goal generation and self-revision. These may be possible within extensions of current proto-AGI approaches like Hyperon [8], but a great deal of further research and development is required.

8.2 Connecting Weaver's Open-Ended Intelligence to Psi Capability

Weaver's notion of *open-ended intelligence* emphasizes an agent's ability to:

- Continually generate new goals and abstractions rather than solving a fixed set of tasks.
- Adapt to entirely unforeseen situations by exploring an unbounded hypothesis space.

In Solomonoff/AIXI terms, such an agent does not restrict itself to a finite model class but relentlessly seeks ever-more-compact, high-utility explanations of its observations.

Within the causal-set / Occamistic Precedence framework, *psi capability* arises whenever there is a simple, low-complexity rule

$$o_t \;=\; f\big(\Phi(h_{<t}, a_t),\, x_{\mathrm{psi},t}\big)$$

that links the agent's internal mental features $\Phi(h_{<t}, a_t)$ to otherwise hidden environmental variables $x_{\mathrm{psi},t}$. A *psi environment* is precisely one in which such a rule has small Kolmogorov complexity, so Occamistic Precedence will favor it as soon as any precedent appears.

Now, an *open-endedly intelligent* agent will:

- Search its entire hypothesis space–including all simple functions f and feature extractors Φ–for patterns that improve its ability to individuate, self-transform and otherwise fulfill its open-ended self-organizing modality
- Prioritize hypotheses of minimal descriptive complexity, to a certain degree, because in a context of limited resources, these will often better allow it to pursue its complex shifting amalgam of goals

Because of these factors, if a psi correlation of low algorithmic complexity exists, an open-ended agent has a decent chance of eventually discovering and leveraging. Conversely, an agent that never finds any psi-type rule– despite exploring simple, off-beat hypotheses– would likely be constrained in effectively pursuing its open-endedness.

All in all, we can say that both open-ended intelligence and psi capability place significant value on a common underlying drive:

favoring ever-simpler, more predictive models of reality.

Weaver's open-ended intelligence and psi ability can be viewed as two ways of leveraging a single computational principle. However, the precise relationship between OEI and psi remains a fair bit open-ended, which is perhaps as it must be.

8.3 Open-Ended Intelligence and Minimization of Psi Perversities

It seems intuitive that open-ended intelligence, more so than arbitrary high Legg-Hutter intelligences, might implicitly embody strategies for minimizing the degree of psi perversity experienced – in essence by giving better resonance with broad cosmic patterns.

I.e., in the theory pursued here, psi perversities arise when local low-K templates fragment into many slightly different branches, thereby deepening the informational well. An open-ended agent's bias toward re-unifying and compressing those branches helps preserve a shallow well. In other words, its internal state remains in resonance with the broad cosmic patterns (the low-complexity attractors of the causal set), avoiding the sharp drop-off or sign inversion that occurs when descriptive complexity balloons.

Thus, open-ended intelligence–by prioritizing continuous recompression and the search for simpler meta-models–naturally curbs the variant proliferation that causes psi to "turn perversely against" you.

9 Conclusion and Empirical Validation

To summarize, we have sketched arguments roughly as follows:

1. **Multiscale Precedence.** Psi success initially arises because a new, simple pattern has low complexity K and begins building local precedents N_{local}.

2. **Decline Effect.** As variants of the experiment proliferate, $K_{\text{local}}(o)$ often grows faster than $N_{\text{local}}(o)$, causing the local weight $\mathcal{L}_{\text{local}}(o)$ to peak and then decline.

3. **Psi-Missing.** When many divergent local variants fail to fit a single low-complexity global template, the global weight $\mathcal{L}_{\text{global}}(o)$ collapses, suppressing or inverting the net psi signal.

4. **Causal Set Realization.** In one speculative physics underpinning of these ideas, each psi observation is a node in a growing causal set. The Occam penalty $2^{-K(C_n)}$ on the entire set enforces multiscale coherence, reproducing decline and inversion when complexity outpaces precedent.

5. **Psi and Intelligence.** Psi capability and general intelligence both depend on an agent?s ability to identify and exploit low-complexity patterns. Formally, agents with higher universal intelligence (as in Legg-Hutter) or greater open-ended intelligence will discover simple psi correlations in ?psi environments,? since both intelligence measures reward compression and prediction of minimal-K regularities.

9.1 Directions for Empirical Validation

To test or falsify this multiscale resonance model, one could pursue various directions such as:

- **Controlled Complexity Variation.** Design a psi experiment whose essential elements allow precise control over algorithmic complexity $K(o)$. For instance, use a digital RNG protocol parameterized by a small integer k. By systematically increasing k, one can measure how success rates decline as a function of complexity. If the decline matches the predicted $2^{-K(o)}$ scaling, it would support the Occamistic model.

- **Cross-Lab Standardization vs. Diversification.** Organize two sets of replications: one in which all labs adhere strictly to a single standardized protocol (minimizing variation in complexity), and another in which each lab introduces a slightly different random seed or parameter (increasing variation). The model predicts that the standardized set should maintain higher combined $\mathcal{L}_{\text{local}}$ and resist decline longer, whereas the diversified set should exhibit a steeper decline and greater prevalence of psi-missing.

- **Global Ledger Proxies.** Although we cannot directly measure $N_{\text{global}}(o)$ in a cosmic sense, one can approximate it by conducting meta-analyses of all published results on a given psi protocol. If a protocol's reported effect size systematically declines as the corpus of variants grows, consistent with a rising effective complexity $K_{\text{global}}(o)$, that supports the multiscale theory.

- **CTC-Like Feedback Loops.** If a laboratory can create a tightly coupled feedback loop–where the psi outcome is fed back as an input in a nearly cyclic manner (analogous to a small-scale closed timelike curve)–the model predicts a transient amplification of psi effects, followed by a rapid collapse once complexity exceeds a threshold. Demonstrating such a "looped" enhancement and decline would provide strong evidence for Section 9.2's conjecture.

- **Comparative Protocol Simplicity.** Compare two psi tasks: one clearly low in descriptive complexity (e.g., forced-choice guessing with a fixed deck) and one higher complexity (e.g., remote viewing of a continuously varying video feed). Track how each protocol's success rate changes across replications. The model predicts that the low-complexity task should sustain positive results longer, while the high-complexity task should decline or invert more rapidly.

By implementing these strategies and quantifying how success probabilities scale with empirical measures of algorithmic complexity and variant proliferation, we could potentially directly test the multiscale Precedence model. If results conform to the predicted patterns–especially if psi-missing correlates with a mismatch between local and global complexity–this would lend strong support to the hypothesis that psi phenomena are governed by the same history-plus-Occam prior dynamics that shape all emergent patterns in Causal Set Theory.

The neuroscience, AI and intelligence-theoretic speculations given above provide additional potential directions for empirical exploration:

9.1.1 Neuroscience-Based Validations

- **Correlate Psi Success with Neural Synchrony and Complexity.**
  - Record EEG or MEG during a psi protocol and compute inter-regional coherence (e.g. PFC–thalamus–hippocampus synchrony in gamma or theta bands).

- Quantify neural complexity on a trial-by-trial basis using measures such as Lempel–Ziv complexity or sample entropy applied to multi-channel EEG.
- Test the prediction that:
  1. Successful psi trials exhibit strong, low-dimensional synchrony (low neural complexity).
  2. Failed or declined trials exhibit reduced coherence or higher-entropy, fragmented activity.
  3. As protocol variants accumulate over sessions, the average coherence at key frequencies should decline in parallel with psi performance.

- **Modulate Candidate Circuits with Noninvasive Stimulation.**
  - Apply transcranial alternating current stimulation (tACS) at gamma frequencies over a thalamocortical montage or transcranial magnetic stimulation (TMS) to the prefrontal cortex immediately before psi trials.
  - Vary stimulation parameters (frequency, phase, duration) to test whether:
    1. Brief bursts of gamma-band tACS enhance neural synchrony and temporarily boost psi accuracy.
    2. Lack of stimulation or suboptimal parameters corresponds to lower performance.
    3. Changes in the empirical decline curve (e.g. delayed onset of decline) correlate with stimulation that maintains low neural complexity.

- **Quantify Neural Complexity Dynamics.**
  - Use real-time complexity metrics (e.g. Lempel–Ziv, sample entropy) to monitor neural signals during repeated psi attempts.
  - Analyze whether:
    1. Lower complexity on a given trial predicts higher psi accuracy.
    2. Complexity gradually increases over consecutive trials as task variants accumulate, correlating with the decline effect.

3. Periods of complexity reduction (e.g. after a rest interval) correspond to transient recoveries of psi performance.

- If neural complexity can be measured continuously, attempt to predict imminent performance decline and test interventions that reduce complexity in real time (e.g. guided neurofeedback).

9.1.2 AI-Based Prototyping and Simulation

- **Build a Causal-Set-Style Memory Module.**
  - Implement a toy neural network (e.g. a small recurrent or attractor network) that, after each "trial," encodes its activation pattern as a node in a simple digital causal set.
  - Assign each stored pattern a weight proportional to 2^{-K}, where K is approximated via a lossless compression algorithm (e.g. gzip file size or autoencoder bottleneck size).
  - Drive the network with a sequence of inputs representing "psi targets" (for instance, random symbols), and define "success" as matching the target output.
  - Observe whether:
    1. Early repetitions of a simple pattern are frequent (informational well is shallow).
    2. As slight variations in inputs or internal noise produce new stored patterns, the well deepens and success rate declines or inverts.
- **Test with Reinforcement Learning Agents.**
  - Construct an RL agent whose internal state representations (e.g. learned embeddings or hidden layer activations) are recorded in a digital causal-set memory.
  - Impose a complexity-based penalty by defining the agent's reward to decrease for revisiting internal states with high approximate Kolmogorov complexity.
  - Evaluate whether:
    1. The agent initially solves a task reliably by repeating a low-complexity strategy.

2. As the agent encounters varied situations (analogous to psi protocol variants), its internal representation library grows in complexity, leading to a decline in task performance.
3. When complexity becomes extreme, the agent's policy shifts to alternative states, mimicking psi–missing behavior.

- **Implement Neuromorphic or Quantum-Inspired Hardware.**
  - Use a spiking-neuron neuromorphic platform or a small quantum processor where coherent oscillations or superposition can occur.
  - Introduce a mechanism akin to "homeostatic plasticity" that raises the threshold for reproducing a given spike pattern after each occurrence, thereby implementing an implicit informational penalty.
  - Run a series of "psi-style" input/output tasks and record whether:
    1. The network initially reproduces previously successful low-complexity states easily.
    2. As these states repeat, internal thresholds increase, requiring a simpler description to maintain high success.
    3. Once too many variants emerge, success rates decline or invert, demonstrating an informational-well-driven suppression of repeated patterns.

9.1.3 Intelligence-Psi Correlation Related Validation Strategies

- **Correlational Studies Between Cognitive Metrics and Psi Performance.**
  - Administer standard intelligence tests (e.g. WAIS, Raven's Progressive Matrices) alongside open-ended problem-solving or creativity assessments to a cohort of subjects.
  - Have the same subjects perform a well-controlled psi protocol (e.g. forced-choice card guessing) over multiple sessions, recording accuracy, decline slope, and psi-missing incidence.
  - Analyze whether:
    1. Individuals scoring high on open-ended or creative reasoning tasks maintain shallower decline curves than those scoring high only on conventional IQ metrics.

2. Subjects with demonstrably greater "compression" or abstraction abilities (e.g. via divergent thinking tests) exhibit higher aggregate psi accuracy (Ψ_{total}).
3. The slope of psi decline correlates negatively with composite measures of open-ended intelligence (e.g. design fluency, concept-formation indices).

- **Training Interventions to Enhance Open-Ended Intelligence and Measure Psi.**
  - Enroll participants in a curriculum targeting open-ended cognitive skills (e.g. problem generation exercises, meta-cognitive strategy workshops, creativity workshops) over several weeks.
  - Measure their psi performance (accuracy and decline metrics) before and after training, while a control group receives standard cognitive drills that do not emphasize hypothesis generation or compression.
  - Test the prediction that:
    1. The trained group will show reduced psi decline and fewer psi-missing occurrences, indicating a deeper maintenance of low-K mental templates.
    2. Improvements in indicators of open-ended intelligence (e.g. Torrance Tests of Creative Thinking) will correlate with improvements in psi resilience across replications.

- **AI Agents with Varying Intelligence Architectures in Psi Simulations.**
  - Construct multiple AI agents with differing approximations to AIXI and open-ended architectures:
    1. *Standard RL Agent:* Fixed reward objective, no complexity-based memory pruning.
    2. *Compressible RL Agent:* Implements a causal-set-style memory with Occam penalty $2^{-\alpha K}$, but no explicit goal innovation.
    3. *Open-Ended Agent:* Adds a meta-learning layer that generates novel internal objectives (e.g. minimize description length of reward function), alongside causal-set memory.

- Place each agent in a suite of simulated psi environments (as defined earlier), where hidden psi correlations exist between the agent's internal embeddings and future observations.
- Evaluate and compare:
  1. The initial psi success rates and the decline curves for each agent.
  2. The agent's universal intelligence $\Upsilon(\pi)$ via standard tasks (e.g. prediction/generalization benchmarks) versus its aggregate psi capability $\Psi_{\text{total}}(\pi)$.
  3. Whether the open-ended agent maintains psi performance longer (shallower decline) than the purely AIXI-like or standard RL agents.

- **Meta-Cognitive Markers and Psi Resilience.**
  - During human psi tasks, record behavioral indicators of meta-cognition (e.g. confidence ratings, response latencies, self-reported awareness of strategies).
  - Analyze whether trials in which subjects demonstrate stronger meta-cognitive monitoring (e.g. higher calibration between confidence and accuracy) align with shallower psi decline or reduced psi-missing.
  - Hypothesis: Meta-cognitive processes reflect a form of "internal Occamist pruning"?subjects who recognize and discard unproductive strategy variants will maintain a more stable low-K template and hence sustain psi performance.

- **Cross-Domain Transfer of Compression Skills.**
  - Train subjects on unrelated compression-oriented tasks (e.g. discovering minimal programs that generate specific sequences, or solving Kolmogorov-challenge puzzles) to build explicit algorithmic compression skills.
  - After training, have them perform psi tasks under identical conditions as pre-training baseline.
  - Evaluate whether gains in external compression ability translate to:

    1. Improved initial psi accuracy.
    2. Slower decline of psi effects across replications.
    3. Lower incidence of psi-missing.
  - If correlation is observed, it supports the theoretical link that algorithmic compression (a key component of universal intelligence) underlies psi capability.

- **Longitudinal AI Curriculum Learning Experiments.**
  - Implement an AI agent curriculum where agents sequentially learn new tasks of increasing complexity, with intermittent "psi tasks" inserted that require exploiting hidden internal-state-to-output correlations.
  - For each stage of curriculum:
    1. Measure the agent's performance on psi tasks and on standard generalization tasks.
    2. Track changes in the agent's internal model complexity (e.g. network weight norms, hidden-state entropy).
  - Test the hypothesis that:
    1. Agents retaining a strong bias toward minimal complexity early on (open-ended learners) will sustain psi functionality deeper into the curriculum.
    2. Agents that abandon Occam penalties in favor of brute-force memorization will exhibit more rapid psi decline despite high performance on conventional tasks.

9.2 Concluding Unscientific Postscript

To put all this more poetically and impressionistically – tongue properly placed halfway in cheek – we might say:

```
The playful Trickster Psi slips
in under the cover of shadows, garnering
limited shards of attention from the relaxed
and comfortable Tao, grinning
as it bends the subtle
```

currents of reality.

Trickster Psi's dance so unexpected
and lightfooted
no one really pays mind
-- the Tao, vast and patient, allows
this little mischief
to flourish.

THEN WHEN energy focuses
on mimicking the Trickster's intricate
tap-dance, the clumsy footsteps
of the hordes of imitators ever
so slightly jar the harmony
of Tao -- the cosmic rhythms
shift, the Trickster vanishes
into the dark mist
or flips the game
entirely

and the Trickster Psi gently smiles, knowing
as he did all along that the resonance
with the Tao can't be forced or dodged ...

except for just a little maybe --
like everything else,
a little forcing and dodging
is part of how the Tao
rolls

Of course, attempts to empirically study the impact of the Trickster and the Tao on psi phenomena are themselves bound to run into the Trickster and the Tao in unforeseen ways. But that's no reason not to try!

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