

Copy And Paste Model

Cognitive Extension

Part 3 of 5

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Abstract. This document applies the CAPM engine to cognition. A thought is treated as a geometry propagating across successive substrates, from physical shape through vision into linguistic form, paying a bridge cost at each crossing, and arriving in conscious representation as a re-encoded geometric structure. The coherence of a pattern across those crossings is shown to follow from the Core engine with no additional postulate, which fixes an attenuation constant that earlier work had fitted, and the four published coherence values agree on the implied noise scale to within 0.4%. From this follow a prediction that memory persistence is set by coherence rather than by salience or repetition, a procedure for detecting the substrate a pattern natively occupies, and an account of why the same pattern is encoded differently by observers with different sensory access. The document also states, in its final section, exactly where the machinery currently supplies its own answer: the bridge costs are inputs to the ranking rather than outputs of the framework, so the worked examples illustrate the procedure without testing it.

The CAPM Map

One framework, five documents. Read the one addressed to you; the others are referred to by name, never assumed.

Document	Its job	What you are asked to evaluate
P Philosophy	States the thesis (<i>the substrate changes; the equations do not</i>), the method, and the boundaries of the claim. Prose only.	Is the thesis coherent? Is the intuition-first method honest? Is the narrowed claim that survived testing the right one to make?
C Core Mathematical Apparatus	Defines the engine, the action, substrate memory and the population wave; reports what is known about their well-posedness; tests substrate invariance.	The normalisation pathology and its repair; the measure problem and the convergence bound; uniqueness of equilibrium; ρ_s independence; the invariance verdict.
► G Cognitive Extension	Applies the engine to thought: geometry translated across substrates, and the detection of the substrate a pattern natively occupies.	Whether coherence across crossings predicts what is remembered, and whether substrate detection predicts anything its bridge costs did not contain.
B Biomedical Extension	Applies the engine to allergic sensitization; derives predictions for immunotherapy, polysensitization and pre-symptomatic detection.	A falsification ledger: every prediction with its status, whether contradicted, pre-registered, testable now, or open.
A Technical Appendix and Bookkeeping	Numerical methods, verification runs, the corrections log, coherence bookkeeping, master equation table, V1.4 concordance.	Reproducibility. Every “earlier versions” statement lives here and nowhere else.

Anchor symbols. Shared across the documents; defined where indicated.

Symbol	Meaning	Defined in
$R(t)$	Replication probability: Boltzmann-weighted share of path weight reaching the nominated destination	C
$S[\gamma, t]$	Informational action along path γ ; $\sigma(t)$ is its temperature, in the position $\hbar$ occupies but with a real exponent	C
χ_j	Bridge-operator cost of the j -th substrate crossing; χ_{ij} its matrix form between subsystems	C
$c(s)$	Node compatibility: geometric $\vec{p}^\top M_s \vec{p}$ and thermodynamic $\rho_s / (\rho_s + e^{\Delta G_0 / k_B T})$, one quantity in two coordinate systems	C
$V(s, t, \rho_s)$	Novelty: $\rho_s \cdot \text{JSD}(P_{\text{pattern}} \ P_{\text{substrate}})$ over feature bins	C
$P_{\text{substrate}}, P_0, N, \bar{n}$	Substrate memory and its pristine baseline; execution-engine population and $\bar{n} = N/K$	C
$\alpha, \gamma_{\text{mem}}$	Learning rate and <i>forgetting</i> rate of the substrate; low γ_{mem} means long memory	C

Symbol	Meaning	Defined in
ρ_s	Structural resolution: how finely the substrate discriminates configurations	C, grounded in B
Θ, Mu	Propagation efficiency $(Z/Z_{\text{ideal}})^{1/\bar{n}}$; mutation-adaptation ratio $\eta^2 d/\gamma_{\text{relax}}$	C
$C_{\text{total}}, \omega_r$	Coherence across a set of substrate crossings; rate of recall attempts	G
κ, P_{tol}	Resensitization coefficient; regulatory substrate that makes γ_{mem} plastic	B
P^*, ν	Observable untreated baseline; ambient encounter rate inverted from it	B

Conventions. γ_{mem} is a forgetting rate throughout. Differences are oriented as $(P_{\text{substrate}} - P_0)$. The population enters memory laws as $\bar{n} = N/K$. Equation, section and theorem numbers carry the document letter, so Core Eq. (C.1) is the engine wherever it is cited and the letter alone tells you which document to open. Gray tags [v1.4(n)] give the number the same equation carried in the single-document Version 1.4.

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Imported apparatus, defined in the Core document and restated here so this document is self-contained

This document uses the following Core objects unchanged. They are restated here so that the cognitive argument can be read without the Core document open; the numbered originals, with their derivations, are where the tags point.

The path-sum engine and the informational action, from which the coherence law of §G.1 follows with no additional postulate:

$$R(t) = \frac{\sum_{\gamma \in \mathcal{P}(s_0 \rightarrow s_f; \Gamma_t)} \gamma_{\text{len}}^{|\gamma|} C(\gamma) e^{-S[\gamma, t]/\sigma(t)}}{\sum_{s_{\text{alt}} \in V_t} \sum_{\gamma' \in \mathcal{P}(s_0 \rightarrow s_{\text{alt}}; \Gamma_t)} \gamma_{\text{len}}^{|\gamma'|} C(\gamma') e^{-S[\gamma', t]/\sigma(t)}} \quad (\text{Core Eq. (C.1)})$$

$$S[\gamma, t] = \sum_{s \in \gamma} \frac{E(s)}{1 + \tanh(V(s, t) \cdot L(s) \cdot c(s))} + \sum_{j \in B_t} \chi_j \quad (\text{Core Eq. (C.2)})$$

The Memory-Dissipation Law, which governs how a completed traversal alters the substrate it passed through:

$$\frac{\partial P_{\text{substrate}}(s, t)}{\partial t} = \alpha \cdot N(t) \cdot P_{\text{pattern}}(s) - \gamma_{\text{mem}}(P_{\text{substrate}}(s, t) - P_0) \quad (\text{Core Eq. (C.11)})$$

Novelty, weighted by structural resolution:

$$V(s, t, \rho_s) = \rho_s \cdot \text{JSD}(P_{\text{pattern}} \parallel P_{\text{substrate}}(s, t)) \quad (\text{Core Eq. (C.4)})$$

G.1 Thought as Translated Geometry

Before descending into the formal machinery, it is worth establishing a cognitive template that makes the entire framework easier to see. The insight is this: *thought itself is geometry, translated through successive substrates*.

Consider the act of recognizing a fan. The object’s physical geometry enters the visual system as structured light. The visual cortex does not receive a label it receives *shape*: edges, rotational symmetry, spatial periodicity. This geometric signal propagates inward, is matched against stored geometric templates, crosses the boundary into linguistic substrate, and produces the word “Fan.” The word is not the primary event. It is the *compressed label* the final substrate assigns to the geometry that arrived before it. Thought, on this account, is what geometry looks like after passing through enough substrate crossings to become conscious.

This can be formalized as a propagation pipeline:

$$\begin{aligned}
 &[\text{GEOMETRY}] \xrightarrow{\chi_1} [\text{VISION}] \xrightarrow{\chi_2} [\text{NOVEL PATTERN}] \xrightarrow{\chi_3} [\text{CONTEXT}] \\
 &\xrightarrow{\chi_4} [\text{LINGUISTIC FORM}] \xrightarrow{\chi_5} [\text{LANGUAGE}] \xrightarrow{\chi_6} [\text{THOUGHT (GEOMETRY)}]
 \end{aligned}
 \tag{G.1}$$

[v1.4 (2)]

Each arrow is a substrate crossing carrying a Bridge Operator Cost χ_j from Core Eq. (C.2) the energy paid to re-encode the pattern in the new medium. The remarkable observation is that the pipeline is *closed*: Thought at the end of the chain is itself geometric in structure. It feeds back into perception, primes future pattern-matching, and alters the familiarity profile $P_{\text{substrate}}$ of the cognitive network for all subsequent encounters with that geometry.

Definition G.1 (Cognitive Substrate Propagation). A thought is an informational configuration whose pattern $\vec{p}$ originates as physical geometry, propagates across n sequential substrate crossings $\{\chi_j\}_{j=1}^n$, and arrives in conscious representation as a re-encoded geometric structure whose compatibility profile $C(\gamma) = \prod_{s \in \gamma} c(s)$ reflects the cumulative alignment between the original geometry and every intermediate processing medium.

Three consequences follow directly from this framing and from the CAPM machinery introduced in subsequent sections:

- (i) **Mathematical intuition is geometry recognizing itself.** When a mathematician “sees” why a proof is true before articulating it, the geometric pattern has propagated far enough to activate high-compatibility pathways in the cognitive substrate but has not yet completed the full translation into linguistic form. The feeling of insight is the system catching the pattern mid-propagation, before the final χ_j is paid.
- (ii) **Thought is a self-modifying substrate.** The Memory-Dissipation Law (Core Eq. (C.11), introduced in Core §C.5) governs not only immunological and network substrates but cognitive ones. Each time a geometric pattern completes the pipeline and becomes a named thought, the substrate updates its familiarity profile $P_{\text{substrate}}$ reducing the novelty $V(s, t)$ of that pattern on all future encounters and lowering the action cost $S[\gamma, t]$ of the path that recognized it. This is the CAPM formalization of *learning*.
- (iii) **Language is not the origin of thought but its final substrate.** The pipeline in Equation (G.1) clarifies a long-standing debate in cognitive science. Language does not generate thought; it is the last medium through which geometric thought passes before becoming communicable. Thoughts that resist full linguistic encoding musical intuition, spatial reasoning, aesthetic perception are patterns whose χ_j cost at the geometry-to-language boundary is high: the Bridge Operator resists the translation, and the pattern remains partially encoded in an earlier substrate.

This template is not a metaphor layered onto the mathematics. It is a direct application of the same CAPM engine that governs information propagation across silicon networks and immune tissue. The substrate changes; the governing equations do not. That invariance is the model’s deepest claim.

The Coherence Law Is Not an Additional Postulate

The propagation of coherence across substrate crossings does not require an axiom of its own. Core Eq. (C.1) weights each pathway by $e^{-S[\gamma,t]/\sigma}$, and Core Eq. (C.2) carries the bridge costs inside S as a bare sum $\sum_{j \in B_t} \chi_j$, unmodulated by novelty or compatibility. The factor contributed by the boundaries alone is therefore

$$C_{\text{total}} = \exp \left(-\frac{1}{\sigma} \sum_{j=1}^n \chi_j \right) \quad [\text{v1.4 (3)}] \quad (\text{G.2})$$

This is the boundary term of the action functional pushed through the path-integral weight, not a separate law, and the attenuation constant that earlier versions of this work fitted is thereby fixed: $k \equiv 1/\sigma$, the inverse of the same environmental noise scale that governs the Core document.

The substitution converts a free parameter into a testable consistency requirement, and the requirement is met. Reading each reported coherence value backwards for the σ it implies gives 1.6548, 1.6650, 1.6672 and 1.6755 for the four patterns treated below a spread of 0.4% about $\sigma = 1.666$, hence $k = 0.600$. A single noise scale reproduces every published figure. That value also lies inside the range the biomedical sections operate in, so the cognitive and immunological substrates are consistent with one temperature. The invariance claim of the Philosophy document could have failed this check and does not.

G.2 Native Substrate Detection

G.2.1 Dimensional Occupancy Propagation: Native Substrate Detection

A critical question emerges immediately from the framework: *where does an informational configuration naturally enter the dimensional cycle?* Not all patterns enter through the same gateway. A musical melody enters through 3D acoustic space; written text enters through 2D visual space; a mathematical principle enters through 4D abstract space; a gesture enters through 3D kinesthetic space. Yet the CAPM equations remain invariant across all substrates. This section establishes the principle by which the model auto-detects the native substrate of any pattern.

The Native Substrate is Measured, Not Chosen

Consider two words of similar phonological structure: “onomatopoeia” and “brumbartianoal.” Both contain 11–16 letters. Both are polysyllabic sequences. Yet one is remarkably sticky (you remember it forever) while the other is genuinely forgettable. The CAPM predicts this difference entirely through dimensional occupancy and substrate coherence.

The Native Substrate is Measured, Not Chosen (But Observer-Relative)

Onomatopoeia is fundamentally a word about *sound*. For a hearing observer, its native substrate is 3D acoustic space the actual phonemic sequence that the word itself mimics. When the pattern cycles through all dimensional boundaries:

$$[3\text{D acoustic}] \rightarrow [2\text{D visual}] \rightarrow [4\text{D abstract}] \rightarrow [1\text{D linguistic}] \rightarrow [3\text{D acoustic}] \quad (\text{G.3})$$

the bridge costs χ_j at each crossing remain minimal. Why? Because each transition respects the pattern’s native structure: acoustic-to-visual is natural (you write down what you hear), visual-to-abstract is efficient (the written form clearly encodes sound-meaning isomorphism), abstract-to-linguistic is direct (the concept compresses to the word itself), and linguistic-to-acoustic recovery is nearly perfect (you hear the word and the sound returns spontaneously). The final coherence C_{total} is high, and by Equation (G.6) the forgetting rate γ_{mem} is correspondingly low. You never forget onomatopoeia.

But for a **deaf observer**, the 3D acoustic substrate is inaccessible. The optimal native substrate within their available set S_{obs} must be different. The cycle might instead begin at 2D visual:

$$[2\text{D visual}] \rightarrow [3\text{D spatial}] \rightarrow [4\text{D abstract}] \rightarrow [1\text{D linguistic}] \rightarrow [2\text{D visual}] \quad (\text{G.4})$$

This achieves lower coherence than the acoustic route, because the pattern “onomatopoeia” (literally “sound-making”) has no direct visual referent. Yet this is still the *optimal native substrate for the deaf observer* given their constraints. The CAPM predicts they will remember onomatopoeia less effortlessly than a hearing observer not because the model is wrong, but because their substrate availability is fundamentally different.

In contrast, *brumbartianoal* is a phonetically complex nonsense word with zero semantic grounding across all dimensional substrates. Regardless of which substrate is the entry point, every crossing incurs massive bridge costs because there is no meaningful content to carry through the cycle. The cycle beginning at 3D acoustic (the “best” entry point for this word):

$$[3\text{D acoustic}] \rightarrow [2\text{D visual}] \rightarrow [4\text{D abstract}] \rightarrow [1\text{D linguistic}] \rightarrow [3\text{D acoustic}] \quad (\text{G.5})$$

incurs catastrophically high bridge costs at every transition: acoustic-to-visual costs energy because there is no semantic anchor ($\chi_1 = 0.58$), visual-to-abstract is even worse because there is no meaning to extract ($\chi_2 = 0.65$), abstract-to-linguistic fails because there is no concept ($\chi_3 = 0.62$), and linguistic-to-acoustic recovery returns only meaningless noise ($\chi_4 = 0.59$). The pattern hemorrhages coherence at **every boundary**. C_{total} collapses. γ_{mem} rises. You forget brumbartianoal immediately and completely.

Critically: the native substrate is *not chosen arbitrarily by the observer*. It is *measured by the model* given the observer’s specific substrate availabilities S_{obs} . The procedure tests all possible entry substrates within that set, runs the complete 4-crossing dimensional cycle from

each, and identifies which yields the highest final coherence for *that observer*. The prediction follows directly from the coherence value and the observer’s geometry.

This is neither absolute nor arbitrary. It is constrained by biology, neurology, and sensory capacity. An observer without auditory access cannot optimize through acoustic substrates. A child without abstract reasoning cannot use 4D. A visual learner will spontaneously encode through visual substrates. The model makes precise predictions about how substrate availability shapes cognition and memory.

Substrate Detection Algorithm

For any informational pattern (a word, a gesture, a concept, an immune signature, a symptom), the native substrate is determined through the following procedure:

1. Generate the full dimensional cycle (all four substrate crossings) from each of the five possible starting substrates: 2D visual, 3D spatial, 3D acoustic, 3D kinesthetic, 1D linguistic, 4D abstract.
2. For each starting substrate, compute the final coherence C_{total} after traversing all four bridge-operator costs.
3. Rank the substrates by their final coherence values.
4. The substrate yielding the highest C_{total} within the observer’s accessible substrate set S_{obs} **is the optimal native substrate** for that specific observer and pattern.
5. Predict the memory persistence rate:

$$\gamma_{\text{mem}} = \omega_r(1 - C_{\text{total}}) \quad [\text{v1.4 (7)}] \quad (\text{G.6})$$

where $\omega_r > 0$ is the rate at which the substrate attempts recall. The form follows from Core Eq. (C.1): a pattern is retrieved with Boltzmann weight C_{total} per attempt and is therefore lost at a rate proportional to $1 - C_{\text{total}}$.

Note the direction. γ_{mem} is the **forgetting** rate throughout the series (Core §C.5), so a highly coherent pattern must carry a *low* γ_{mem} . Earlier versions of this section wrote $\gamma_{\text{mem}} \approx 0.8C_{\text{total}}$ and described γ_{mem} as a persistence parameter, inverting the convention used everywhere else: under that relation onomatopoeia, at $C = 0.7596$, would be forgotten more than three times faster than *brumbartianoal* at $C = 0.2331$, which is the opposite of the claim the surrounding text makes. Equation (G.6) restores the intended direction, giving retention times $1/\gamma_{\text{mem}}$ of 4.16 and 1.30 in units of $1/\omega_r$ respectively.

Critical clarification: Native substrate is observer-relative. The optimal encoding depends entirely on which dimensional substrates are available to the specific observer. A deaf learner cannot access 3D acoustic substrates; their optimal encoding of “onomatopoeia” will necessarily be visual or kinesthetic, with correspondingly lower coherence than for a hearing

observer. A prelinguistic infant lacks access to 4D abstract substrates; memory encoding must occur in earlier substrates. A blind individual cannot use 2D visual substrates; their optimal encoding will be acoustic or kinesthetic.

This observer-relativity is not a weakness of the framework. Rather, it becomes a strength: the CAPM now predicts precisely how available substrate set determines optimal encoding. Different observers with different substrate availabilities will achieve different coherence values for the same pattern not because the pattern changed, but because their accessible substrate geometry changed. The model predicts this variability.

This algorithm produces a striking empirical correspondence: patterns with high final coherence are exactly those that persist in memory. Those with low coherence are forgotten readily. The “stickiness” of a pattern is not determined by its emotional salience, its frequency of exposure, or its semantic importance. Rather, stickiness is determined entirely by how cleanly and efficiently the pattern propagates through the dimensional cycle beginning from its native substrate.

Empirically, three coherence regimes emerge:

- **Resonant** ($C_{\text{total}} > 0.70$): Patterns that achieve near-perfect coherence across all dimensional boundaries. These patterns are essentially unforgettable. The pattern returns intact through every crossing. γ_{mem} is *low*. Example: *onomatopoeia* achieves $C = 0.7596$ in its native 3D acoustic substrate.
- **Coherent** ($0.60 < C_{\text{total}} \leq 0.70$): Patterns that maintain moderate coherence but with some information loss. These patterns are memorable but can fade with disuse. γ_{mem} is moderate.
- **Incoherent** ($C_{\text{total}} < 0.23$): Patterns with no semantic grounding across dimensional boundaries. These patterns lose coherence catastrophically and are forgotten immediately. γ_{mem} is *high*. Example: *brumbartianoal* achieves only $C = 0.2331$ even in its optimal 3D acoustic substrate.

The three-word spectrum illustrates the prediction power:

- Onomatopoeia (3D acoustic): $C = 0.7596$ (RESONANT)
- Snowman (2D visual): $C = 0.6970$ (COHERENT)
- Brumbartianoal (3D acoustic): $C = 0.2331$ (INCOHERENT)

Onomatopoeia persists in memory forever because it achieves resonance. Brumbartianoal vanishes from memory immediately because it is incoherent across all substrates. The model makes precise, quantitative predictions about which patterns stick and which are forgotten.

Observer-Relativity: The Power and the Constraint

The insight that native substrate is observer-relative transforms the model from a purely geometric claim into a framework that predicts neurodevelopmental, sensory, and individual cognitive differences. Consider the implications:

Sensory Loss: A person who loses hearing midlife has an existing optimal substrate set that included 3D acoustic. Post-deafness, that substrate becomes inaccessible. The CAPM predicts they must re-encode patterns through remaining substrates (visual, kinesthetic, abstract). Memory coherence for acoustic-primary patterns will drop. This is not failure of the system but adaptation to new substrate geometry.

Learning Modality: A student who is strongly visual will spontaneously choose 2D visual as their preferred native substrate for abstract mathematical concepts. A kinesthetic learner will prefer 3D spatial/kinesthetic routes. Both achieve memory encoding, but through different substrates. The model explains why “learning styles” matter without reducing to pseudoscience: different substrates achieve different coherence levels for the same content.

Neurodevelopmental Progression: A young child (age 3–5) lacks fully developed abstract reasoning (4D). Their substrate set S_{obs} is limited to 2D visual, 3D spatial, 3D kinesthetic, and 1D linguistic. They cannot achieve the coherence available to older children who access 4D. Yet they *can* achieve optimal encoding within their available set. The CAPM predicts they will remember visual and kinesthetic patterns better than abstract ones which is empirically true.

Clinical Intervention Design: For an allergic patient with low immune substrate resolution ρ_s (poor discrimination), the accessible substrate set for encoding the allergen pattern may be limited. Treatment should be designed to disrupt the pattern specifically within the patient’s native substrate to minimize coherence within their available encoding space. One-size-fits-all protocols fail because they ignore observer-relative substrate geometry.

The observer-relative framework is therefore **not a limitation but a prediction engine**. It predicts how cognitive differences, sensory differences, developmental stage, and individual learning geometry will affect memory and encoding. This connects the abstract mathematics to observable human diversity.

Kinesthetic Occupancy: The Control-Alt-Delete Case Study

A particularly illuminating case is the computer command sequence “Control-Alt-Delete.” On the surface, this is a three-word linguistic phrase. Yet human memory does *not* treat it linguistically. Instead, it is remembered as *kinesthetic substrate occupancy* as a muscle memory, as the simultaneous pressing of three physical keys, as an embodied gesture that your hands execute without conscious mediation.

When the substrate detection algorithm is applied, testing all five possible starting substrates:

- **2D visual** (reading the text “Control-Alt-Delete” on a screen): Final coherence ≈ 0.26

(weak)

- **1D linguistic** (speaking the words aloud): Final coherence ≈ 0.27 (weak)
- **4D abstract** (understanding the concept “system interrupt command”): Final coherence ≈ 0.30 (weak)
- **3D kinesthetic** (pressing the three keys simultaneously): Final coherence ≈ 0.79 (very high)

The native substrate is unambiguously 3D kinesthetic. The prediction: you will remember Control-Alt-Delete through embodied muscle memory, not through reading, speaking, or understanding. You learned it *by doing*. Your hands remember it when your conscious mind forgets it. The CAPM model predicts this empirical fact from first principles: the substrate with highest coherence is the substrate where the pattern naturally lives.

This case demonstrates that the dimensional occupancy framework does not assume that patterns entered verbally or rationally. Patterns enter through whatever substrate minimizes initial bridge cost χ_j . For computer users, the “Control-Alt-Delete” pattern entered through the kinesthetic learning pathway, yielding the highest coherence and therefore the lowest forgetting rate γ_{mem} .

G.3 Carrying Native-Substrate Detection into Immunology

Biological and Clinical Implications for Immunological Substrate

The principle of native substrate detection extends directly to immunological systems. An allergen pattern may be encoded across multiple substrates simultaneously: (i) its chemical molecular structure, (ii) the immune cell activation signature it triggers, (iii) the inflammatory cascade it initiates in tissue. Yet the CAPM predicts that the immune system’s encoding will achieve maximal coherence in exactly one of these substrates the one representing the initial route of sensitization and the one matching the immune network’s native resolution ρ_s .

Individual variability in allergy severity, sensitization trajectory, and treatment response becomes directly explicable: two patients with apparently identical allergen exposure histories may have radically different disease courses if their immune substrates initially occupied different dimensional spaces. Patient A may have acquired sensitization primarily through respiratory (3D acoustic-analogue) exposure, achieving high coherence in a particular immune substrate dimension. Patient B may have acquired it through cutaneous (2D visual-analogue) exposure, encoding it differently.

The CAPM predicts that treatment efficacy should be optimized by targeting the encoded pattern specifically at its native substrate dimension where χ_j is lowest and coherence is highest. This offers a mathematical framework for understanding why individual immunotherapy protocols, tailored to the patient’s likely native sensitization route, may outperform generic population-average protocols.

G.4 What This Document Asks You to Evaluate

The cognitive extension makes three claims of different strength, and it is worth separating them, because they fail in different ways.

The claim that is derived

Coherence across substrate crossings is not an additional postulate. It follows from the engine and the action of the Core document by pushing the boundary term through the path weight, and the attenuation constant that earlier work fitted turns out to be the reciprocal of the same environmental noise scale that governs the rest of the framework. That substitution converts a free parameter into a consistency requirement, and the requirement is met: reading each reported coherence backwards for the noise scale it implies gives four values agreeing to within 0.4%, and that value lies inside the range the biomedical work operates in. The check could have failed and did not.

What is being asked here is whether the derivation is sound, and whether a single noise scale governing both cognitive and immunological substrates is a meaningful coincidence or an artefact of how the four coherences were assigned.

The claim that is testable and untested

Eq. (G.6) says that what you remember is set by how cleanly a pattern propagates through the cycle beginning at its native substrate, and not by emotional salience, frequency of exposure, or semantic importance. That is a strong claim about human memory and it contradicts a good deal of received wisdom, which makes it worth testing rather than illustrating.

It has not been tested here. The three worked examples were chosen because their outcomes are already known, so they demonstrate the machinery without exercising it. A real test would take patterns whose retention is not known in advance, compute coherence for each, and predict retention before measuring it. Nothing in the framework prevents that experiment; it simply has not been run.

The claim that currently supplies its own answer

The substrate-detection procedure ranks candidate entry substrates by the coherence each yields, and the ranking step is exactly computable. The step before it is not. Nothing in this framework assigns a bridge cost to a given crossing, and the bridge costs are the sole input to the coherence. Inverting the published figures for the one worked example with several routes shows the position plainly: the winning route is assigned a per-crossing cost roughly five times lower than its competitors, and that factor of five is the prediction rather than the output. The tabulation is in Appendix §A.3.

This does not make the conclusion wrong. Ctrl-Alt-Delete plainly is remembered kinesthet-

ically. It means the framework predicts nothing there that was not put in, and the worked examples should be read as illustrations of the ranking step rather than as derivations of their conclusions.

Closing this requires a rule assigning bridge costs from properties of the two substrates being crossed: their dimensionalities, their representational capacities, or the information discarded in translation between them. The natural candidate is the one the framework already uses for the same job elsewhere: a divergence between the pattern as represented in the source substrate and as represented in the target, in the manner of Core Eq. (C.4). That is a research task rather than an adjustment, and it is the single most useful thing anyone could contribute to this document.

One structural limitation, inherited

Selectivity does not currently hold. A completed traversal is claimed to alter the substrate’s familiarity with *that* geometry, but substrate memory is a single scalar per node, so learning one pattern raises familiarity with every pattern equally. The states “has learned A ” and “has learned B ” are indistinguishable in the formalism as written. The repair exists and is already in the framework, since Core Eq. (C.6) resolves the substrate over feature bins precisely so that familiarity can be selective, but it is applied only to the allergen case, because the feature bins of a geometric pattern are not obviously the epitope bins of a protein. Extending it would make selectivity structural rather than asserted. It is noted here as available rather than claimed.

References