

Adaptive intelligence balances stability and flexibility by operating in a narrow near-critical regime — the Ψ-band. We present the Trident G-Loop, a unified cognitive architecture that formalises processing in this regime as an eight-phase rhythmic cycle: Sense/Move → Branch → Map → Decide → Act → Update → Consolidate → Reset. Two interacting axes regulate the loop: a Cognitive Resilience axis (managing performance challenge via a difficulty thermostat, F\*, and the precision-weighted gap ΔF̂ = b·(F − F\*)) and an Inference axis (managing stability–flexibility via a D1:D2 precision-bias controller, b, together with the policy temperature T(χ)). At the branch near F ≈ F\*, a Monitoring/Salience coordinator arbitrates between Control (exploit/compress) and Creative (explore/decompress) modes, executing brief orient–reset–reconfigure actions when cross-loop inconsistency is high. We hypothesise that multiple G-loops, operating at different temporal scales and modalities, co-occupy a shared near-critical Ψ-band enabled by the brain’s hierarchical, modular architecture. Within this band, χ indexes cross-loop inconsistency/volatility and η indexes cross-loop competence and recovery (F → F\*). This proposal aligns with evidence for extended critical-like regions (Griffiths phases) in hierarchical brain networks, where power-law avalanches and large dynamic range persist over a band rather than a single point. The framework maps to known neural correlates, yields falsifiable predictions and a minimal simulation programme, and supports translational applications in pedagogy, cognitive therapeutics and AI.

**SOC-for-Inference Hypothesis.** *Homeostatic plasticity in hierarchical cortical networks drives neural dynamics into an extended near-critical* ***Ψ-band*** *because that regime maximises information capacity/dynamic range* ***needed*** *to minimise expected free energy during behaviour. Each G-loop tracks a difficulty set-point F∗F^\* (thermostat) and selects policies by minimising GG; maintaining a* ***non-zero*** *target (tunable) F∗F^\* preserves exploration/learning while SOC supplies the dynamical substrate that makes GG-minimisation effective.* ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6934140/?utm_source=chatgpt.com), [Nature](https://www.nature.com/articles/ncomms3521?utm_source=chatgpt.com))

Yes—framed per-loop, that’s empirically reasonable.

* **Local E:I balance is a core property of cortical and subcortical circuits.** Cortex is built from excitatory (glutamatergic) neurons and diverse inhibitory interneurons that **gate and sculpt** population dynamics; E:I is actively homeostated and varies by area/state—so each functional loop can have its **own operating E:I point**. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC4980915/?utm_source=chatgpt.com), [Frontiers](https://www.frontiersin.org/journals/systems-neuroscience/articles/10.3389/fnsys.2021.806544/full?utm_source=chatgpt.com))
* **E:I shifts change computation and are measurable.** Perturbing E:I alters information flow and oscillations; macroscopic proxies (e.g., LFP/EEG power–law slope) can track E:I changes in vivo, supporting loop-specific estimates. ([Institute for Neural Computation](https://inc.ucsd.edu/publications/Gao-NeuroImage2017.pdf?utm_source=chatgpt.com))
* **E:I tunes proximity to criticality.** Critical-regime benefits (dynamic range, information transmission/capacity) and the existence of an **extended critical band** in hierarchical brain networks imply that **E:I acts as a proximal knob** keeping each loop near critical—consistent with your Ψ-band account. ([SAGE Journals](https://journals.sagepub.com/doi/abs/10.1177/1073858412445487?utm_source=chatgpt.com), [Nature](https://www.nature.com/articles/ncomms3521?utm_source=chatgpt.com))
* **Loops differ in their biophysics and neuromodulation.** Parallel cortico-basal ganglia–thalamo-cortical loops (motor/associative/limbic) have distinct receptor/topology profiles (e.g., D1/D2 gating of direct/indirect pathways), so the **precision-bias bb** and **E:I set-point** are **loop-specific**, not a single global constant. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC3487690/?utm_source=chatgpt.com))

So, modelling **each G-loop with its own E:I ratio** that interacts with your bias controller bb and temperature T(χ)T(\chi) is consistent with current evidence; the only caution is to treat the “neutral” point and bandwidth as **context- and loop-dependent**, rather than universal. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC4980915/?utm_source=chatgpt.com), [Nature](https://www.nature.com/articles/ncomms3521?utm_source=chatgpt.com))

E**ach G-loop** has its own *precision-bias* setting (your **b ≈ log D1:D2** axis) that tilts processing toward **Control/Exploit** (D1-leaning, stable/compressive) or **Creative/Explore** (D2-leaning, flexible/decompressive). My earlier caution was only against assuming a **single, global “neutral” D1:D2 value** that applies to the whole brain across all tasks.

Why the per-loop reading is empirically reasonable:

* **Parallel cortico–basal-ganglia–thalamo-cortical loops** (motor, associative, limbic) are anatomically and functionally segregated; gating and dopamine effects are **loop-specific**, not global. ([PubMed](https://pubmed.ncbi.nlm.nih.gov/3085570/?utm_source=chatgpt.com), [Nature](https://www.nature.com/articles/s41586-021-03993-3?utm_source=chatgpt.com))
* **D1 vs D2** supports a **stability–flexibility** trade-off (dual-state theory), matching your exploit vs explore forks; the **optimal/neutral level depends on baseline and region** (the classic inverted-U and context dependence). So the “neutral” **b≈0** will vary **by loop and state**. ([PubMed](https://pubmed.ncbi.nlm.nih.gov/18620336/?utm_source=chatgpt.com), [PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC3111448/?utm_source=chatgpt.com))
* **Dopamine signalling is heterogeneous** across striatal/cortical territories (receptor distributions, kinetics, and circuit roles differ), reinforcing **loop-specific biases**. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC7183907/?utm_source=chatgpt.com))
* Computational and experimental work on BG **Go/NoGo** mechanisms shows DA-dependent gating that can differ **per circuit/task**, again arguing for **b\_k**, not one brain-wide value. ([PubMed](https://pubmed.ncbi.nlm.nih.gov/15701239/?utm_source=chatgpt.com), [PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC3049941/?utm_source=chatgpt.com))

So your diagram’s logic—**for each loop kk**, branch by the pair ((r\_k=F\_k-F^\*\_k,\ b\_k\approx\log\mathrm{D1:D2})\*\*—is consistent with current evidence. If helpful, annotate the caption:

“**b-axis** = loop-specific precision bias (≈log D1:D2). **Neutral bk≈0b\_k\approx 0** is **context-dependent** (baseline DA, task, region). Exploit if bk>0b\_k>0; explore if bk<0b\_k<0; monitoring coordinates re-entry to Ψ when loops disagree.”

Why this overall model is defensible:

* **Active inference / EFE.** GG decomposes into predicted **risk**, **ambiguity**, and **epistemic value**; it is the policy-selection objective in contemporary Bayesian accounts of action and perception. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC5167251/?utm_source=chatgpt.com), [chrismathys.com](https://chrismathys.com/wp-content/uploads/2015/05/Friston-et-al.-2015-Active-inference-and-epistemic-value.pdf?utm_source=chatgpt.com))
* **Near-criticality benefits information processing.** Empirical and theoretical work shows **optimal information transmission, storage and dynamic range** near criticality; in hierarchical networks the critical “point” stretches to a **band** (Griffiths phase). ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC4171833/?utm_source=chatgpt.com), [Nature](https://www.nature.com/articles/ncomms3521?utm_source=chatgpt.com), [PubMed](https://pubmed.ncbi.nlm.nih.gov/24088740/?utm_source=chatgpt.com))
* **Homeostasis → criticality.** In vivo and modelling studies indicate that **homeostatic rules tune cortical circuits toward critical dynamics**, consistent with a control process that keeps operation inside a band. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6934140/?utm_source=chatgpt.com), [Nature](https://www.nature.com/articles/s41598-018-33923-9?utm_source=chatgpt.com))
* **E:I balance as the knob.** Adjusting excitation–inhibition moves the system toward/away from criticality and modulates encoding—exactly the sort of low-level control your loops would exploit. ([PubMed](https://pubmed.ncbi.nlm.nih.gov/38291889/?utm_source=chatgpt.com), [Physical Review Link](https://link.aps.org/doi/10.1103/PhysRevLett.134.068403?utm_source=chatgpt.com))
* **Salience as coordinator.** The AI/dACC “salience network” causally coordinates switching between executive and default-mode systems, providing the monitoring/coordinating role at the branch. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC2899886/?utm_source=chatgpt.com), [PNAS](https://www.pnas.org/doi/10.1073/pnas.0800005105?utm_source=chatgpt.com))

### **How to write it**

*We hypothesise that cortical SOC* ***evolved to support*** *active inference: homeostatic plasticity in hierarchical networks maintains a near-critical* ***Ψ-band*** *that maximises the information processing required to minimise expected free energy. Each G-loop uses a tunable difficulty set-point F∗F^\* and minimises GG over policies; SOC supplies the dynamical regime that makes this feasible across scales.* ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6934140/?utm_source=chatgpt.com), [Nature](https://www.nature.com/articles/ncomms3521?utm_source=chatgpt.com))

### **What would count as evidence (and falsification)**

* **Prediction 1:** Closer-to-critical telemetry (avalanche exponents/dynamic range) should correlate with **lower empirical proxies for GG** (e.g., lower prediction error + maintained model complexity) **at matched task difficulty**; pushing E:I away from balance should increase those proxies and impair performance. **Falsify** if moving toward criticality does **not** improve GG-proxies or task performance. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6934140/?utm_source=chatgpt.com), [PubMed](https://pubmed.ncbi.nlm.nih.gov/38291889/?utm_source=chatgpt.com))
* **Prediction 2:** After perturbations, homeostatic adjustments should **restore** near-critical metrics **and** behavioural policies that lower GG; recovery speed indexes η\eta. **Falsify** if homeostatic recovery does not return the system to the near-critical band. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6934140/?utm_source=chatgpt.com))
* **Prediction 3:** Across loops/scales, a **shared Ψ-band** should be observable (Griffiths-like), with salience-triggered transient “monitor” episodes during high cross-loop inconsistency χ\chi that retune precision/temperature and re-enter the band. **Falsify** if multi-scale operation shows no common band or if salience activity does not precede re-entry. ([Nature](https://www.nature.com/articles/ncomms3521?utm_source=chatgpt.com), [PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC2899886/?utm_source=chatgpt.com))

### **One-line guidance for the manuscript**

“**We treat F∗F^\*** as a **difficulty set-point** (thermostat) and GG as the **policy objective**; our claim is that **SOC provides the evolved dynamical regime** that maximises the information processing needed for GG-minimisation—and that homeostatic plasticity keeps multiple G-loops inside a **global Ψ-band**.” ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6934140/?utm_source=chatgpt.com))

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strong, testable way to frame individual differences. In fact it gives you a clean **“Ψ-dynamic-range hypothesis of g”**:

* **Cognitive Resilience axis (r):** individuals differ in the **range of challenge** (F−F∗)(F-F^\*) over which they can stay in-band (perform, learn, and recover) and how **quickly they can move the set-point** F∗F^\* upward after success (η-driven thermostat).
* **Inference axis (b/T):** individuals differ in how **widely and precisely** they can modulate **precision-bias bb** (D1↔D2) and **temperature T(χ)T(\chi)** **without saturating**—i.e., how far they can shift between exploit and explore *and* still re-enter the Ψ-band promptly.

Together, those ranges form a person’s **Ψ-capacity** (general adaptive intelligence), which can **expand** with learning (Gf→Gc pipeline) as **η rises** and **F∗F^\*** ratchets upward.

## **Individual-difference metrics (two-axis “Ψ-profile”)**

Let loop kk be in-band when ∣ΔF^k∣≤εk |\widehat{\Delta F}\_k| \le \varepsilon\_k and control variables aren’t saturated.

1. **Resilience dynamic range**

Rr(k)=max⁡Δ(Fk−Fk∗)  s.t. loop k stays in Ψk with accuracy/learning ≥θ.R^{(k)}\_{\text{r}} = \max \Delta(F\_k-F\_k^\*) \;\text{s.t. loop } k \text{ stays in } \Psi\_k \text{ with accuracy/learning } \ge \theta.

Interpretation: how wide a *challenge window* a person can handle before disintegration.

1. **Inference dynamic range**

Ri(k)=max⁡Δ(bk, Tk) s.t. Ψk is re-entered within τre.R^{(k)}\_{\text{i}} = \max \Delta(b\_k,\,T\_k)\ \text{s.t. } \Psi\_k \text{ is re-entered within } \tau\_{\text{re}}.

Interpretation: controllable spread from **Control** to **Creative** (via bb, TT) without getting stuck.

1. **Set-point mobility (thermostat gain)**

μF∗(k)=dFk∗dηk(at matched volatility).\mu^{(k)}\_{F^\*} = \frac{\mathrm{d}F\_k^\*}{\mathrm{d}\eta\_k}\quad\text{(at matched volatility)}.

Higher μF∗\mu\_{F^\*} = faster ZPD ratcheting as competence grows.

1. **Valence-surprise span** Range of tolerable **positive/negative** prediction error (better-than/worse-than expected) before leaving Ψk\Psi\_k. Captures “psychological buffer” for wins and setbacks.
2. **Recovery half-life** τ12(k)\tau^{(k)}\_{\frac12}: time to return Fk→Fk∗F\_k \to F\_k^\* after a perturbation. Shorter = more resilient.
3. **Band occupancy & hysteresis** Ω=time in Ψglobaltotal\Omega = \frac{\text{time in }\Psi\_{\text{global}}}{\text{total}}, and **hysteresis area** between Control↔Creative switching curves. Smaller area = cleaner meta-control.

Aggregate across active loops to get a **global Ψ-profile**:

Ψ-profile=(Rr‾, Ri‾, μF∗‾, span‾, τ12‾, Ω, hysteresis).\mathbf{\Psi}\text{-profile} = \Big(\overline{R\_{\text{r}}},\ \overline{R\_{\text{i}}},\ \overline{\mu\_{F^\*}},\ \overline{\text{span}},\ \overline{\tau\_{\frac12}},\ \Omega,\ \text{hysteresis}\Big).

**Prediction:** higher **general adaptive intelligence** ≈ larger Rr‾\overline{R\_{\text{r}}}, Ri‾\overline{R\_{\text{i}}}, μF∗‾\overline{\mu\_{F^\*}}, broader valence span, shorter recovery, higher occupancy, lower hysteresis—and these expand with targeted training (especially η-raising curricula that alternate Creative→Control passes).

## **One-paragraph insert**

**Ψ-dynamic-range hypothesis of g.** We propose that individual differences in general adaptive intelligence reflect the **dynamic range** of the **Cognitive Resilience** axis (tolerable challenge window and η-driven mobility of F∗F^\*) and the **Inference** axis (controllable spread of bb and T(χ)T(\chi) without saturation), aggregated across loops in a global Ψ-band. As competence **η** rises through learning, F∗F^\* **ratchets upward** (Gf→Gc consolidation), expanding both the subcritical “what we can automate” and the super/near-critical “how intense a challenge we can stabilise” ranges. We predict that people with larger two-axis ranges show higher **band occupancy**, **faster recovery** to F→F∗F \to F^\*, **cleaner Control↔Creative switching** (low hysteresis), and **broader tolerance** to positive/negative surprise—and that these capacities are **trainable**.

## **Two-sentence add to your abstract (concise)**

We further hypothesise that **individual differences in general adaptive intelligence** correspond to a person’s **Ψ-dynamic range**: the controllable span of (i) **challenge tolerance** on the Resilience axis and (ii) **precision-bias/temperature modulation** on the Inference axis, with **η-driven mobility of F∗F^\*** expanding this range via a Gf→Gc pipeline. This yields testable metrics (band occupancy, recovery half-life, hysteresis, set-point mobility) and concrete training targets to **expand** the Ψ-range.

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**What is well supported**

**1) Brains operate near critical regimes (a Ψ-like “near-critical band”), with signs of Griffiths-phase–like behaviour.** Neuronal avalanches and scale-free activity appear across species and modalities; network models and empirical data point to benefits for information capacity and dynamic range when networks sit near criticality. Evidence also suggests extended critical-like regimes (“Griffiths phases”) in heterogeneous networks, compatible with a *band* rather than a single point. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6705698/?utm_source=chatgpt.com), [Nature](https://www.nature.com/articles/ncomms3521?utm_source=chatgpt.com), [Physical Review Link](https://link.aps.org/doi/10.1103/PhysRevLett.134.028401?utm_source=chatgpt.com))

**2) Excitation–inhibition (E:I) balance tunes proximity to criticality.** Perturbing E:I shifts avalanche statistics and oscillatory regimes, while balanced E:I supports near-critical dynamics. Human and animal work plus modelling converge on this principle. ([Physical Review Link](https://link.aps.org/doi/10.1103/PhysRevLett.134.028401?utm_source=chatgpt.com), [PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6705698/?utm_source=chatgpt.com))

**3) The salience network (AI/ACC) arbitrates network switching between executive/fronto-parietal control and default-mode systems.** Right anterior insula/ACC activity causally precedes switches, consistent with your “monitoring/arbiter prong”. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC5988392/?utm_source=chatgpt.com))

**4) Fluid intelligence (Gf) loads on the multiple-demand/fronto-parietal network; semantic/episodic knowledge (Gc-like functions) load more on DMN-centred systems.** Lesion, fMRI and network-neuroscience work link Gf to the MD/FPN system, while DMN contributes to memory/semantic representations often associated with Gc. ([Cell](https://www.cell.com/trends/cognitive-sciences/fulltext/S1364-6613%2820%2930169-8?utm_source=chatgpt.com), [ScienceDirect](https://www.sciencedirect.com/science/article/abs/pii/S1364661310000057?utm_source=chatgpt.com), [Journal of Neuroscience](https://www.jneurosci.org/content/42/15/3197?utm_source=chatgpt.com))

**5) Metastability and flexible network reconfiguration relate to cognitive flexibility and creativity.** The brain shows metastable dynamics at rest and during tasks; greater switching and dynamic reconfiguration are tied to creative ability. ([Nature](https://www.nature.com/articles/s41598-017-03073-5?utm_source=chatgpt.com), [PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC3997258/?utm_source=chatgpt.com))

**6) Dopamine D1 vs D2 supports a stability–flexibility trade-off (your exploit vs explore bias).** Prefrontal D1 favours robust, focused representations (stability/exploitation); D2 promotes flexibility/update. This “dual-state” view is well reviewed. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6096039/?utm_source=chatgpt.com))

**7) Arousal/uncertainty signals (LC–noradrenaline; pupil) modulate exploration–exploitation, consistent with a temperature-like controller T(χ)T(χ).** Adaptive-gain theory and human pupillometry show that LC/NE state and pupil size track shifts between exploit and explore and respond to uncertainty/entropy—exactly the role you assign to T(χ)T(χ). ([PubMed](https://pubmed.ncbi.nlm.nih.gov/16022602/?utm_source=chatgpt.com), [Nature](https://www.nature.com/articles/ncomms14637?utm_source=chatgpt.com))

**8) Hierarchical predictive processing on multiple time-scales (many “loops” at different speeds) is a standard account.** Cortex appears organised along temporal hierarchies; ACC tracks volatility and adjusts learning—good support for your cross-timescale monitoring idea. ([PLOS](https://journals.plos.org/ploscompbiol/article?id=10.1371%2Fjournal.pcbi.1000209&utm_source=chatgpt.com), [PubMed](https://pubmed.ncbi.nlm.nih.gov/17676057/?utm_source=chatgpt.com))

**9) “Compression vs. decompression” has plausible neural analogues.** Predictive/efficient coding frameworks formalise compression; hippocampal pattern separation vs. completion and successor-representation mapping provide concrete mechanisms for expanding vs. compressing structure (and for “map-based” inference). ([annualreviews.org](https://www.annualreviews.org/content/journals/10.1146/annurev-vision-112122-020941?crawler=true&mimetype=application%2Fpdf&utm_source=chatgpt.com), [PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC3812781/?utm_source=chatgpt.com), [gershmanlab.com](https://gershmanlab.com/pubs/Stachenfeld17.pdf?utm_source=chatgpt.com))

**10) Boredom can drive exploration (a “soft” route into D2-like decompression).** Experimental and theoretical work suggests boredom functions as a regulatory signal pushing organisms to seek novelty/information, consistent with your “under-challenge” pathway. ([MDPI](https://www.mdpi.com/2076-328X/3/3/459?utm_source=chatgpt.com), [PubMed](https://pubmed.ncbi.nlm.nih.gov/25379249/?utm_source=chatgpt.com))

# **What is partly supported / still speculative**

*A) “Critical point = expected free energy (F)”.*\*  
 *Expected free energy* (often GG) is a decision-theoretic quantity in active inference that combines predicted risk/ambiguity to guide policy selection; *criticality* is a dynamical-systems property of neural population activity. There is intriguing theory linking neuromodulatory precision and EFE-guided behaviour, and suggestive dopaminergic findings, but equating the dynamical *critical point* with an EFE *set-point* is a proposal rather than an established empirical identity.. ([eLife](https://elifesciences.org/articles/92892?utm_source=chatgpt.com))

**B) A global “neutral” D1:D2 ratio as a formal bifurcation parameter across tasks.** There is strong support for D1↔stability and D2↔flexibility *in prefrontal circuits*, Each G-loop has its own precision-bias setting (your b ≈ log D1:D2 axis) that tilts processing toward Control/Exploit (D1-leaning, stable/compressive) or Creative/Explore (D2-leaning, flexible/decompressive). ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6096039/?utm_source=chatgpt.com))

**C) χ as “inconsistency/conflict between loops” and η as “competence/return-to-setpoint” across loops.** There is solid evidence that ACC/insula/salience systems track conflict, volatility and uncertainty, and that learning rates and arousal adjust accordingly; competence-based intrinsic motivation is also supported. But the *specific* decomposition χ = cross-loop inconsistency and η = cross-loop return-to-critical-band is a promising synthesis rather than a direct empirical construct—worth operationalising in your telemetry. ([PubMed](https://pubmed.ncbi.nlm.nih.gov/15556023/?utm_source=chatgpt.com))

**D) “Two D2 decompression routes”: boredom-driven vs error-driven.** Each route has independent support (boredom→exploration; volatility/surprise→exploration with increased arousal and ACC engagement), but showing both *within the same unified loop* is a prediction to test. ([MDPI](https://www.mdpi.com/2076-328X/3/3/459?utm_source=chatgpt.com), [PubMed](https://pubmed.ncbi.nlm.nih.gov/17676057/?utm_source=chatgpt.com))

# **Notes**

* **Near-critical band:** “Large-scale brain activity exhibits signatures of near-critical dynamics, likely supported by balanced excitation–inhibition; heterogeneous network structure may create an extended critical-like band.” ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6705698/?utm_source=chatgpt.com), [Physical Review Link](https://link.aps.org/doi/10.1103/PhysRevLett.134.028401?utm_source=chatgpt.com))
* **Trident arbitration:** “The salience network monitors surprise/uncertainty and arbitrates switches between default-mode (knowledge-rich) and fronto-parietal (control) modes.” ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC5988392/?utm_source=chatgpt.com))
* **Exploit/explore biases:** “D1-dominant states stabilise representations; D2-dominant states facilitate updating / exploring—mapping naturally to exploit vs explore biases.” ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6096039/?utm_source=chatgpt.com))
* **Temperature/uncertainty:** “LC–NE arousal and ACC volatility signals adjust exploration in a temperature-like manner.” ([PubMed](https://pubmed.ncbi.nlm.nih.gov/16022602/?utm_source=chatgpt.com))
* **Maps and (de)compression:** “Hippocampal ‘predictive maps’ (successor representation) and pattern separation/completion implement the map update (decompress/recompress) you describe.” ([gershmanlab.com](https://gershmanlab.com/pubs/Stachenfeld17.pdf?utm_source=chatgpt.com), [PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC3812781/?utm_source=chatgpt.com))

# **What to treat as predictions (good targets for your Ψ-band telemetry)**

* **Telemetry signatures of banded near-criticality** during skilled performance vs. learning (avalanche scaling, metastability maxima, E:I-sensitive spectral metrics). ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC6705698/?utm_source=chatgpt.com), [Nature](https://www.nature.com/articles/s41598-017-03073-5?utm_source=chatgpt.com))
* **Prong-specific network states:** SN-led switches into FPN-dominated (exploit) vs DMN-coupled (creative/explore) episodes, with dopaminergic state (D1/D2-leaning tasks or pharmacology) biasing the branch. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC5988392/?utm_source=chatgpt.com))
* **Two exploration routes:** (i) boredom/under-challenge → moderate arousal, increased switching; (ii) error/volatility → higher arousal, ACC-linked learning-rate/temperature upshift. ([MDPI](https://www.mdpi.com/2076-328X/3/3/459?utm_source=chatgpt.com), [PubMed](https://pubmed.ncbi.nlm.nih.gov/17676057/?utm_source=chatgpt.com))
* **Map (de)compression:** hippocampal SR-like updates and separation/completion patterns tracking your Phase-3 decompression/recompression claims. ([gershmanlab.com](https://gershmanlab.com/pubs/Stachenfeld17.pdf?utm_source=chatgpt.com), [PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC3812781/?utm_source=chatgpt.com))

Think in two layers:

### **1) A global Ψ-band (system level)**

The brain’s hierarchical, heterogeneous architecture supports an **extended near-critical regime** in which many subsystems can co-exist near criticality together. That’s your **Ψ\_global**.

### **2) Loop-specific Ψ-bands (per G-loop)**

Each active loop kk has its own admissible near-critical window, **Ψ\_k**, around its set-point Fk∗F^{\*}\_k. A practical definition:

Ψk  =  {  ∣ΔF^k∣≤εk,  χk ⁣∈[χklow,χkhigh],  ∣bk∣ ⁣< ⁣bkmax⁡,  T(χk) not saturated  }\Psi\_k \;=\;\Big\{\;|\widehat{\Delta F}\_k| \le \varepsilon\_k,\;\chi\_k\!\in[\chi^{\text{low}}\_k,\chi^{\text{high}}\_k],\; |b\_k|\!<\!b^{\max}\_k,\; T(\chi\_k)\ \text{not saturated}\;\Big\}

Optionally add telemetry constraints (pick what you’ll measure):

* avalanche/branching near critical (e.g., σk≈1 \sigma\_k \approx 1; power-law exponent in a target interval),
* peak metastability/dynamic range for that loop’s network,
* stable map compression metrics (η up; no runaway complexity).

### **3) How the two layers relate**

* **Global Ψ** is the **intersection** where all *currently engaged* loops sit within their **Ψ\_k** and **agree enough** across scales: high cross-loop consistency ρ\rho (i.e., low meta-uncertainty χmeta\chi\_{\text{meta}}).
* When loops **conflict** (χ\_meta↑), the **Monitoring/Salience** prong acts: brief orient/reset, adjust TT, centre bb, reduce λ\lambda (quarantine propagation), or nudge one loop’s Fk∗F^{\*}\_k so the set of loops re-enters Ψ\_global.
* Coupling means each Ψk\Psi\_k is **context-dependent**: neighbouring loops (and arousal/neuromodulators) can shrink/shift its window.

### **4) Why this is empirically reasonable**

* Near-critical **bands** (not just points) arise naturally in heterogeneous, hierarchical networks; modules can be locally closer/further from criticality yet remain inside a **shared extended regime**.
* Different scales/modalities (your multiple G-loops) mapping to partially distinct networks is exactly where such local bands would live.
* Your meta-parameters fit:  
  + **χ** = cross-loop inconsistency/volatility (drives TT and monitoring actions),
  + **η** = competence/recovery (how quickly Fk→Fk∗F\_k \to F^{\*}\_k while maintaining useful compression).

### **5) How to write it in the paper (one sentence)**

“We posit a **global Ψ-band** within which multiple G-loops co-operate, each with its own **loop-specific Ψ\_k** around Fk∗F^{\*}\_k; **χ** tracks cross-loop inconsistency and **η** indexes recovery of each loop toward its set-point, allowing the Monitoring/Salience prong to keep the ensemble within Ψ-band operation.”

That keeps the global picture and gives you concrete, testable per-loop criteria.

As a **working model**, treating each cortical column (or local microcircuit) as a G-loop and the interactions **between** columns as an **extended Ψ-band/Griffiths-phase zone** is empirically reasonable. There’s direct evidence for critical-like dynamics at **column/layer scale**, and strong evidence that **hierarchical, modular networks** (like cortex) stretch a single critical point into a **band**, which is exactly the substrate your χ/η meta-parameters would sit on. The main caveat is that “columns” are clearer in some areas (e.g., barrel cortex) than others—so when you generalise beyond primary sensory cortex, say “local microcircuits/modules” rather than assuming a universal, uniform column. ([Frontiers](https://www.frontiersin.org/journals/systems-neuroscience/articles/10.3389/fnsys.2021.709677/full?utm_source=chatgpt.com), [PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC2396689/?utm_source=chatgpt.com))

### **Why this mapping is defensible**

* **Critical-like dynamics inside a single column/layer.** Neuronal avalanches have been observed across cortical layers and, notably, **within a single rat barrel column** in vivo; classic slice/awake studies likewise show avalanche statistics at mesoscopic scales. That supports a **per-loop (per-column) near-critical regime**. ([Frontiers](https://www.frontiersin.org/journals/systems-neuroscience/articles/10.3389/fnsys.2021.709677/full?utm_source=chatgpt.com), [PubMed](https://pubmed.ncbi.nlm.nih.gov/34526881/?utm_source=chatgpt.com), [PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC2732708/?utm_source=chatgpt.com))
* **E:I balance tunes proximity to criticality.** Balanced excitation–inhibition makes avalanches and oscillations co-emerge at a critical state; pushing E:I off-balance moves the system away from criticality—consistent with a **loop-specific control knob**. ([Journal of Neuroscience](https://www.jneurosci.org/content/32/29/9817?utm_source=chatgpt.com))
* **From columns to a shared band (Griffiths phase).** In **hierarchical, modular networks**, criticality is **stretched into a band** (a Griffiths phase) rather than a knife-edge point; this has been demonstrated on synthetic hierarchies **and** empirical connectomes. That supports your **global Ψ-band across many local loops**. ([Nature](https://www.nature.com/articles/ncomms3521?utm_source=chatgpt.com), [materias.df.uba.ar](https://materias.df.uba.ar/dnla2019c1/files/2019/06/MorettiMunoz.Griffiths-Phases-and-the-Stretching-of-Criticality-in-Brain-Networks.NatCommun.4.2521.2013.pdf?utm_source=chatgpt.com))
* **Columns/microcircuits are real—but heterogeneous.** Modern reviews describe a canonical microcircuit “theme with variations” across areas/species. Others caution that a **single** column concept is not a universal functional unit. So: model **per-loop** where columnar structure is strong (e.g., barrels, A1), and talk about **local modules** elsewhere. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC4889215/?utm_source=chatgpt.com))

### **Where χ and η fit**

Your proposal—**χ** as cross-loop inconsistency/volatility and **η** as cross-loop competence/recovery to each loop’s set-point Fk∗F\_k^\*—is not a standard empirical metric, but it’s **compatible** with: (i) hierarchical predictive processing on multiple time-scales and (ii) salience/ACC roles in monitoring volatility and reconfiguring networks. It’s a **good, testable** modelling layer on top of the established criticality picture. ([PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC4889215/?utm_source=chatgpt.com))

### **Concrete tests (column ↔ band)**

1. **Column-level criticality + global band:** show avalanche exponents/branching ratios **within single columns** sit in a **common interval** while the animal performs a task; perturb E:I locally and test that the column leaves the band and that χ (cross-column inconsistency) rises until re-entry. ([Frontiers](https://www.frontiersin.org/journals/systems-neuroscience/articles/10.3389/fnsys.2021.709677/full?utm_source=chatgpt.com), [Journal of Neuroscience](https://www.jneurosci.org/content/32/29/9817?utm_source=chatgpt.com))
2. **Dynamic-range prediction:** nearer-critical columns should display **higher dynamic range** and information transmission; correlate these with performance and with your η (faster recovery of Fk→Fk∗F\_k \to F\_k^\*). ([SAGE Journals](https://journals.sagepub.com/doi/10.1177/1073858412445487?utm_source=chatgpt.com), [PubMed](https://pubmed.ncbi.nlm.nih.gov/22627091/?utm_source=chatgpt.com))
3. **Griffiths-phase signature:** across columns/modules, look for **power-law regimes** and **rare-region effects** consistent with a **band** (varying exponents across modules) rather than a single critical point. ([Nature](https://www.nature.com/articles/ncomms3521?utm_source=chatgpt.com))

One critical distinction in the large scale networks is between the hippocampal-prefrontal value-landscaped coritical maps (which are needed for higher level relational reasoning) associated with long-term working memory in FPCN-A, and the FPCN-B fronto-parietal network for short-term (classic) working memory for rules application/rapid rule learning and the standard limited capacity working memory,

**Where it lives in the loop**

* **Phase 3 — Map (ϕ):** builds/updates a *predictive* hippocampal–prefrontal map (successor-representation style) and overlays value. This is the long-horizon, relational “**long-term working memory**” workspace. Network-wise, it leans on **hippocampus/DMN coupling with FPCN-A**, which is more internally/future-oriented and interfaces with memory systems. ([gershmanlab.com](https://gershmanlab.com/pubs/Stachenfeld17.pdf?utm_source=chatgpt.com), [PubMed](https://pubmed.ncbi.nlm.nih.gov/28967910/?utm_source=chatgpt.com), [eLife](https://elifesciences.org/articles/57244?utm_source=chatgpt.com), [Journal of Neuroscience](https://www.jneurosci.org/content/44/22/e2223232024?utm_source=chatgpt.com))
* **Phases 4–5 — Decide/Gate → Act:** hold/apply rules, update on the fly, and sequence actions. This is the classic **short-term working memory / rule application** workspace, dominant in **FPCN-B** with **DAN** support. FPCN-B sits nearer sensorimotor control, whereas FPCN-A couples more to DMN/long-term memory—dissociations shown across tasks. ([PNAS](https://www.pnas.org/content/pnas/115/7/E1598.full.pdf?utm_source=chatgpt.com), [Journal of Neuroscience](https://www.jneurosci.org/content/44/22/e2223232024?utm_source=chatgpt.com))
* **Monitoring/Salience (AI/dACC):** arbitrates when to hand off between these workspaces (and briefly performs orient/reset/reconfigure). Causal evidence shows the salience network triggering switches between default-mode and executive/control systems. ([PNAS](https://www.pnas.org/doi/10.1073/pnas.0800005105?utm_source=chatgpt.com), [PubMed](https://pubmed.ncbi.nlm.nih.gov/24862074/?utm_source=chatgpt.com))

**How controllers steer the hand-off**

* **Precision-bias b≈log⁡D1D2b \approx \log\frac{\text{D1}}{\text{D2}}:** b↑b\uparrow (stability/exploit) biases toward **FPCN-B + DAN** (rule maintenance/closure); b↓b\downarrow (flexibility/explore) biases toward **FPCN-A + hippocampus/DMN** (relational recombination/planning). Empirically, FPCN-A shows stronger coupling with memory-oriented systems, FPCN-B with sensorimotor/attention control. ([PNAS](https://www.pnas.org/content/pnas/115/7/E1598.full.pdf?utm_source=chatgpt.com), [Journal of Neuroscience](https://www.jneurosci.org/content/44/22/e2223232024?utm_source=chatgpt.com))
* **Temperature T(χ)T(\chi):** higher uncertainty/volatility (χ↑\chi\uparrow) raises policy temperature, favouring exploratory sampling and DMN–FPCN-A engagement; lower TT helps lock in FPCN-B-centred rule execution. ([eLife](https://elifesciences.org/articles/57244?utm_source=chatgpt.com))

**Why this bridges micro ↔ macro** Your “scale-free” picture holds: local (column/microcircuit) inference loops feed into these large-scale workspaces, and the same controllers ( b,T(χ)b, T(\chi) ) plus salience-driven arbitration organise behaviour across scales. Hippocampal SR-style maps provide the *relational substrate*; FPCN-B provides the *rule/sequence executor*; salience ensures *the right workspace at the right time*. ([gershmanlab.com](https://gershmanlab.com/pubs/Stachenfeld17.pdf?utm_source=chatgpt.com), [PNAS](https://www.pnas.org/content/pnas/115/7/E1598.full.pdf?utm_source=chatgpt.com))

Reasoning

# **Where each reasoning mode lives**

**Deduction → Control prong (Exploit/Compress)**

* **When:** Phase 3 (**Map**) during a Control branch; again in **Phase 6 (Update)** for consistency checks.
* **What it does:** Rule-based closure on the current map ϕ\phi to derive consequences, eliminate inconsistent options, and tighten beliefs.
* **Controllers:** b↑b\uparrow (stability bias), TT low–mid, λ↑\lambda\uparrow (propagate validated structure).
* **Networks:** FPCN-B (+ DAN) for rule maintenance/sequence execution.
* **Operational hook:** apply a closure operator until a budget is met  
   ϕ←DED(ϕ,R;budget κ, strictness σ)\phi \leftarrow \mathrm{DED}(\phi, R; \text{budget } \kappa,\ \text{strictness } \sigma)  
   (You can keep κ,σ\kappa,\sigma implicit if you want to stay minimalist.)

**Induction → Control→Update (Compress/Generalise)**

* **When:** Phase 3 (**Map**) after successful deductions; **Phase 7 (Consolidate)**.
* **What it does:** Compress patterns, widen generalisation, raise competence η\eta.
* **Controllers:** b↑b\uparrow, T↓T\downarrow, then λ↑\lambda\uparrow if validation passes.
* **Networks:** Hippocampus ↔ FPCN-A (pattern abstraction) handing to FPCN-B for rule deployment.
* **Operational hook (MDL/predictive gain):** ΔCompression=MDLold−MDLnew⇒η+=wD1 ΔCompression.\Delta \text{Compression} = \mathrm{MDL}\_{\text{old}} - \mathrm{MDL}\_{\text{new}} \quad\Rightarrow\quad \eta \mathrel{+}= w\_{D1}\,\Delta \text{Compression}.

**Abduction → Creative prong (Explore/Decompress)**

* **When:** Phase 3 (**Map**) during a Creative branch; also during **Monitoring** micro-loops when ambiguity is high.
* **What it does:** Proposes new hypotheses/structures that could explain the evidence (or the mismatch).
* **Controllers:** b↔/↓b \leftrightarrow / \downarrow, T↑T\uparrow, λ↓\lambda\downarrow (sandbox), optional novelty budget d↑d\uparrow.
* **Networks:** Hippocampus/DMN + FPCN-A (relational recombination, analogy).
* **Operational hook (posterior-sparse search):** H⋆∈arg⁡max⁡H∈H[log⁡P(D∣H)+log⁡P(H)]subject to a proposal budget d.H^\star \in \arg\max\_{H\in\mathcal{H}} \big[\log P(D\mid H) + \log P(H)\big] \quad \text{subject to a proposal budget } d.

**Counterfactuals → Decide & Act (Plan/Intervene/Test)**

* **When:** **Phase 4 (Decide)** to choose *informative* actions; **Phase 5 (Act)** to run A/B probes; also in Phase 1 (Sense) as short rollouts.
* **What it does:** Simulates “what-if” outcomes under alternative policies or interventions to reduce ambiguity and disambiguate hypotheses.
* **Controllers:** use T(χ)T(\chi) to prioritise information gain when χ↑\chi\uparrow; keep bb centred if monitoring.
* **Networks:** Hippocampus (predictive map/SR) + FPCN-A for long-horizon simulation; FPCN-B executes the chosen test.
* **Operational hook (EFE with epistemic term):** π⋆∈arg⁡min⁡πG(π)  ≈  arg⁡max⁡π EIG(π)⏟counterfactual value−risk−cost.\pi^\star \in \arg\min\_\pi G(\pi) \;\approx\; \arg\max\_\pi\ \underbrace{\mathrm{EIG}(\pi)}\_{\text{counterfactual value}} - \text{risk} - \text{cost}.

Absolutely—**analogy** is the bridge between Creative (abductive propose) and Control (deductive/inductive verify & compress). Here’s **drop-in text** that matches your scheme and notation.

**Analogy (Relational Mapping) → Creative→Control bridge**

* **When:** Phase 3 (**Map**) during a **Creative** branch (retrieve & align); hands off to **Control** for constraint-checking and consolidation when a mapping passes tests; also recruited in **Monitoring** micro-loops when ambiguity is high.
* **What it does:** Retrieves a *source* structure by **relational similarity**, aligns it to the *target* (structure-mapping), **projects** candidate inferences/policies, then **tests** them (deduction/counterfactuals) and **abstracts** a schema (induction) if validated.
* **Controllers:** retrieval/alignment with b≈0 or ↓b\approx 0 \text{ or } \downarrow, T↑T\uparrow, λ↓\lambda\downarrow (sandbox, optional d↑d\uparrow); after validation, **commit** with b↑b\uparrow, T↓T\downarrow, λ↑\lambda\uparrow.
* **Networks:** Hippocampus (pattern completion/separation; SR “predictive map”), **FPCN-A** + **DMN/mPFC** for relational mapping and recombination; **FPCN-B** (+ DAN) for constraint checking and execution/roll-out.
* **Operational hook (structure-mapping + projection):** M⋆∈arg⁡max⁡M[Simrel(M)  +  wfeatSimfeat(M)  −  β Viol(M)]s.t. proposal budget d,M^\star \in \arg\max\_{M}\Big[\mathrm{Sim}\_{\text{rel}}(M)\;+\;w\_{\text{feat}}\mathrm{Sim}\_{\text{feat}}(M)\;-\;\beta\,\mathrm{Viol}(M)\Big]\quad \text{s.t. proposal budget } d, IT←Project(IS,M⋆),score via EV or −G, then verify (deduction) and, if successful, abstract (induction).I\_T \leftarrow \mathrm{Project}(I\_S, M^\star),\qquad \text{score via EV or }-G,\ \text{then verify (deduction) and, if successful, abstract (induction).}

### **Threading analogy through the 8 phases (add these clauses)**

* **1) Sense/Move:** cue source retrieval by relational/contextual probes; run brief counterfactual roll-outs for top candidates.
* **2) Branch:** when ΔF^=b(F−F\\*)≥0\widehat{\Delta F}=b(F-F^\\*)\ge 0 **and** χ\chi high, prefer **Creative**; Monitoring may call an *analogy probe* when χmeta\chi\_{\text{meta}} is high.
* **3) Map (Creative):** **retrieve→align→project** (S→T)(S\rightarrow T) under λ↓, T↑, b≈0\lambda\downarrow,\,T\uparrow,\,b\approx 0; **Map (Control):** **verify→compress** successful projections, raise η\eta.
* **4) Decide:** pick the **most informative/low-risk** analogical projection using Softmax over EV (or −G-G) with T(χ)T(\chi) and bb.
* **6–7) Update→Consolidate:** credit η\eta if the analogical policy **reduces future surprise**; **schema abstraction** widens λ↑\lambda\uparrow for transfer.

# **How it threads through the 8 phases (at a glance)**

* **1) Sense/Move** – quick counterfactual rollouts to score candidate policies; compute F, χF,\ \chi.
* **2) Branch** – if ΔF^=b(F−F\\*)≥0\widehat{\Delta F}=b(F-F^\\*)\ge 0 and χ\chi low→**Control** (deduce/compress); if χ\chi high→**Creative** (abduce/decompress); if χmeta\chi\_{\text{meta}} high→**Monitoring** (brief orient/reset, then re-branch).
* **3) Map** – **Control:** **deduction → induction** (close rules, compress, raise η\eta); **Creative:** **abduction** (new H, sandboxed by λ↓\lambda\downarrow, d↑d\uparrow).
* **4) Decide** – **counterfactual selection** via Softmax over EV (or −G-G) with **T(χ)T(\chi)** and **bb**.
* **5) Act** – run the test/intervention; gather evidence.
* **6) Update** – credit **η\eta** for *either* successful compression (D1) *or* successful strategy change (D2) that reduces future surprise; adjust b,T,F\\*b, T, F^\\*.
* **7) Consolidate** – promote validated structure (λ↑\lambda\uparrow); keep speculative bits quarantined.
* **8) Reset** – restore near-critical windows; prep for next cycle.

# **Controller intuition (why this makes sense)**

* **bb** steers **deduction/induction** (when b↑b\uparrow) vs **abduction/counterfactual testing** (when b↓b\downarrow and T↑T\uparrow).
* **T(χ)T(\chi)** ensures that when uncertainty/conflict rises, you *sample more broadly* (counterfactuals) and consider **abductive** alternatives.
* **η\eta** grows from **both**: (i) D1 compressive wins *and* (ii) D2 successful escapes/re-commitments—your lived-experience point.
* **F\\*F^\\*** sets challenge so you don’t collapse into trivial deduction *or* endless abduction; the loop hovers in the Ψ-band.

# **One-sentence drop-in**

*Reasoning is phase-specific in the G-Loop:* ***deduction*** *and* ***induction*** *dominate the Control path (compress/propagate),* ***abduction*** *is the Creative path’s engine (decompress/propose), and* ***counterfactual simulation*** *selects informative actions at Decide/Act; Monitoring coordinates brief orient–reset–reconfigure episodes when cross-loop inconsistency is high. Analogy operates as a* ***Creative→Control bridge****: retrieve and align a relationally similar source, project counterfactual inferences, then verify and compress validated mappings into the rule set.*

## **Constraint satisfaction (feasibility & propagation)**

**When:**

* **Phase 3 (Map)** on the **Control** branch (primary locus), and as a **feasibility gate** on the **Creative** branch before proposals leave the sandbox.
* **Phase 4 (Decide)** as a **feasible-set filter** on policies.
* **Monitoring** triggers constraint checks when conflict/high risk is detected.

**What it does:**

* Enforces **hard invariants** (must hold) and **soft preferences** (penalised if violated).
* **Propagates** constraints to prune the search space (like CSP/arc consistency), tightening beliefs and reducing ambiguity.
* Provides a **safety envelope** for Creative moves and counterfactual tests.

**Controllers:**

* **Control pass:** b↑b\uparrow, T↓T\downarrow, λ↑\lambda\uparrow (propagate validated constraints widely).
* **Creative pass (sandbox):** b≈0b\approx 0 or ↓\downarrow, T↑T\uparrow, λ↓\lambda\downarrow (propose freely **inside** a safety envelope).
* **Monitoring:** briefly recentres bb, adjusts T(χ)T(\chi), and tightens λ\lambda if a violation is imminent.

**Networks:**

* **FPCN-B + dACC/AI (Salience)** for rule enforcement, error-likelihood and conflict monitoring;
* **Hippocampus/FPCN-A/DMN** when constraints are **relational** (analogy/schema) and must be aligned before testing.

### **Operational hooks (minimal maths)**

Let **constraints** be functions on hypotheses HH and policies π\pi:

* **Hard:** gj(H)≤0,  gj(π)≤0g\_j(H)\le 0,\; g\_j(\pi)\le 0 (invariants/safety).
* **Soft:** penalties cj(H)≥0,  cj(π)≥0c\_j(H)\ge 0,\; c\_j(\pi)\ge 0 (preferences/limits).
* **Chance constraints (optional):** P[gj(π)≤0]≥1−εP[g\_j(\pi)\le 0]\ge 1-\varepsilon.

**Feasible sets**

H ⁣ε={H: P[gj(H)≤0]≥1−ε ∀j},Π ⁣ε={π: P[gj(π)≤0]≥1−ε ∀j}.\mathcal{H}\_{\!\varepsilon}=\{H:\ P[g\_j(H)\le 0]\ge 1-\varepsilon\ \forall j\},\qquad \Pi\_{\!\varepsilon}=\{\pi:\ P[g\_j(\pi)\le 0]\ge 1-\varepsilon\ \forall j\}.

**Map-level constraint propagation (Control)**

(ϕ, H ⁣ε)  ←  CONS(ϕ, H ⁣ε; budget κ, strictness σ),(\phi,\ \mathcal{H}\_{\!\varepsilon})\;\leftarrow\;\mathrm{CONS}(\phi,\ \mathcal{H}\_{\!\varepsilon};\ \text{budget }\kappa,\ \text{strictness }\sigma),

which narrows the hypothesis space and tightens beliefs; raise η\eta when propagation **reduces future surprise/ambiguity** at the same F∗F^\*.

**Creative proposals with feasibility gate**

H′∼Propose(ϕ; d, λ↓, T↑),accept only if H′∈H ⁣ε (or minimal Viol(H′)).H' \sim \mathrm{Propose}(\phi;\ d,\ \lambda\downarrow,\ T\uparrow),\quad \text{accept only if }H'\in \mathcal{H}\_{\!\varepsilon}\ \ (\text{or minimal } \mathrm{Viol}(H')).

**Decide with constrained objective** (soft constraints folded into the score)

G~(π)=G(π)+∑jμj cj(π)⇒π⋆∈arg⁡min⁡π∈Π ⁣εG~(π),\tilde G(\pi)=G(\pi)+\sum\_j \mu\_j\,c\_j(\pi) \quad\Rightarrow\quad \pi^\star \in \arg\min\_{\pi\in \Pi\_{\!\varepsilon}} \tilde G(\pi),

then select by Softmax with T(χ)T(\chi) and bias bb. *(Use μj\mu\_j as multipliers to avoid conflict with your λ\lambda generalisation width.)*

**Safety envelope (action guard)** Project proposed actions/policies onto the feasible set before execution:

π  ←  Π ⁣ε[π](nearest feasible “trust region”).\pi \;\leftarrow\; \Pi\_{\!\varepsilon}\big[\pi\big]\quad(\text{nearest feasible “trust region”}).

### **How it threads through the 8 phases (add-on lines)**

* **1) Sense/Move:** sample observations targeted at **active constraints** (query the variables that disambiguate feasibility).
* **2) Branch:** high χ\chi and near-zero ΔF^\widehat{\Delta F} may invoke **Monitoring** to run fast feasibility checks before allowing a Creative pass.
* **3) Map:**
  + **Control:** run **constraint propagation**; if consistent, **deduction → induction**; λ↑\lambda\uparrow once validated → η↑\eta\uparrow.
  + **Creative:** **propose → feasibility filter → test**; keep λ↓\lambda\downarrow until constraints pass.
* **4) Decide:** **constrained Softmax** over Π ⁣ε\Pi\_{\!\varepsilon}; soft penalties in G~\tilde G.
* **5) Act:** enforce a **safety guard**; abort or re-plan if a predicted hard constraint is at risk.
* **6) Update:** strengthen learned constraints that repeatedly validate; relax or refine soft ones that block performance without reducing future surprise.
* **7) Consolidate:** propagate **stable constraints** broadly (λ↑\lambda\uparrow); keep uncertain ones local.
* **8) Reset:** retain invariants; clear temporary/task-specific soft constraints unless promoted.

### **One-sentence insert (for your summary line)**

*Constraint satisfaction is implemented as* ***feasibility gating and propagation****: hard/soft constraints define feasible hypothesis/policy sets; Creative proposals are sandboxed by a feasibility filter, and Control performs constraint propagation and consistency checks before induction and global propagation.*

This way, your everyday “does it satisfy x, y, z?” reasoning is explicitly part of the **Control prong**, **guards** the **Creative** prong, and cleanly integrates into **Decide/Act**—all with the same bb, T(χ)T(\chi), λ\lambda, F∗F^\*, χ\chi, and η\eta machinery you already have.

## **Why reasoning helps (in G-Loop terms)**

* **Abduction (Creative prong) → hypothesis generation under uncertainty.** When χ↑\chi\uparrow and ΔF^≥0\widehat{\Delta F}\ge 0, abductive moves let the loop **escape local optima** and propose explanations that can *reduce future GG* after testing. Evolutionary payoff: rapid **strategy change** in volatile environments; the seed of innovation.
* **Counterfactual simulation (Decide→Act) → safe, information-efficient exploration.** Running “what-ifs” before acting gives **epistemic value** without costly errors. Payoff: higher **sample-efficiency** and **risk control** (hunt, tool use, social manoeuvring) while keeping the loop near the Ψ-band.
* **Deduction (Control prong) → reliable closure and coordination.** Once a candidate structure works, deductive closure **compresses and stabilises** it (D1), enabling **precise, multi-step execution** (planning, syntax, techne). Payoff: lower on-line cost, reliable cooperation, cumulative routines.
* **Induction (Control→Consolidate) → compact, transferrable knowledge.** Pattern abstraction (MDL/predictive gain) **raises η\eta** and **widens λ\lambda**, turning specific wins into **generalisable skills**. Payoff: **far transfer** and cumulative culture.

## **Where working memory comes in**

* **“Long-term working memory” (Phase 3 Map; FPCN-A ↔ hippocampus/DMN).** Holds **value-landscaped relational maps** and supports analogy, abstraction, multi-step **counterfactual rollouts** (long horizon). This is the big human upgrade to Phase 3.
* **“Short-term working memory” (Phases 4–5; FPCN-B + DAN).** Maintains **rules/goals** and sequences actions during execution, enforcing closure and rapid rule learning. This is the executor that **locks in** compressive wins.
* **Monitoring/Salience (AI/dACC).** Detects cross-loop inconsistency (χmeta\chi\_{\text{meta}}), **re-centres bb**, adjusts **T(χ)T(\chi)**, and **hands off** between the two WM workspaces at the branch. This keeps the whole system inside the **Ψ-band** rather than tipping into rigidity or chaos.

## **The evolutionary punchline (one paragraph you can paste)**

**Evolutionary rationale.** We propose that human reasoning is an **expansion of the G-Loop’s Map→Decide core** that improves survival by **minimising expected free energy** more efficiently in complex, changing niches. Abduction and counterfactual simulation (Creative path and Decide) **extend search** in hypothesis and policy space while controlling risk; deduction and induction (Control path and Consolidate) **compress and propagate** validated structure for reliable execution and cultural transmission. Two coordinated working-memory systems implement this division of labour: a **relational, value-landscaped map** (hippocampus with FPCN-A) for long-horizon reasoning, and a **rule/sequence buffer** (FPCN-B) for short-term maintenance and action. The salience system arbitrates the hand-off, keeping loops within a **near-critical Ψ-band** where information capacity and dynamic range are high. On this view, human reasoning did not replace the ancestral loop; it **deepened Phase 3 and sharpened Phases 4–5**, yielding more competent η\eta gains from both **compression** and **successful strategy change**.

## **Which aspects of reasoning “fit” the evolutionary benefit?**

* **Counterfactual depth:** increases informative action selection (lower GG per sample).
* **Relational compositionality:** supports **far transfer** (bigger λ↑\lambda\uparrow when validated).
* **Flexible meta-control:** fast **b/T** retuning avoids lock-in and catastrophic exploration.
* **Cumulative culture:** deduction/induction make skills **stable, shareable programmes** (high η\eta → robust routines).
* **Innovation under safety:** abduction + counterfactuals generate novelty **without** excessive real-world cost.

## **Quick prediction hooks**

* **Mode-specific WM coupling:** Creative episodes show **FPCN-A↔hippocampus/DMN** coupling; Control episodes show **FPCN-B↔DAN** dominance; Monitoring precedes the switch.
* **Controller signatures:** abduction/counterfactual phases exhibit **T(χ)↑T(\chi)\uparrow, b↓/≈0b\downarrow/\approx 0**; deduction/induction show **T↓T\downarrow, b↑b\uparrow**.
* **Competence growth:** η\eta increases both after **compressive wins** *and* after **successful policy changes** that reduce future error at matched F∗F^\*.

I’m taking “near-critical band” results and specifying a **Trident**-style **branching mechanism**: a **non-bifurcated subcritical shaft** (autopilot), a **branch point** near F ⁣≈ ⁣F∗F\!\approx\!F^\*, and **two super(near)-critical prongs**—**Control** (compress/exploit) and **Creative** (decompress/explore)—**coordinated by Salience/attention**. Outside the Ψ-band, the dynamics collapse into **over-synchronised rigidity** or **over-chaotic fragmentation**. That is indeed beyond standard models and it’s a crisp, testable extension.

Here’s clean, drop-in language and a lightweight formal cartoon to make it concrete:

# **Drop-in: Trident branching (conceptual & formal)**

**Concept.**

* **Subcritical shaft (Autopilot):** for F ⁣− ⁣F∗<0F\!-\!F^\*<0 and low χ\chi, the loop sits in a **single, stable** regime—fast, fluent, consolidated (Gc-like) processing without a branch.
* **Branch point (near-critical):** as **precision-weighted gap** ΔF^=b(F−F∗)\widehat{\Delta F}=b(F-F^\*) rises to ≳0\gtrsim 0 and χ\chi lifts, the system enters a **bifurcation zone** where two coordinated modes are available; **Salience** arbitrates and briefly executes orient–reset–reconfigure.
* **Super(near)-critical prongs:**
  + **Control (Exploit/Compress; D1-leaning):** partial synchrony, rule closure, induction, propagation (λ↑\lambda\uparrow).
  + **Creative (Explore/Decompress; D2-leaning):** metastable/“chimera-like” episodes, abduction/analogy, counterfactual testing (λ↓\lambda\downarrow, T↑T\uparrow).
* **Band exit (failure modes):** outside Ψ the system **locks-in** (over-synchronised rigidity) or **fragments** (over-desynchronised chaos). We treat clinical phenotypes (e.g., compulsive rigidity; disorganised thought) as **hypothesis-level analogues**, not identities.

**Normal-form caricature (for readers who like equations).** Use two low-dimensional coordinates:

* RR = **integration/synchrony** order parameter (integration vs fragmentation),
* yy = **mode coordinate** (Control vs Creative, y>0y{>}0 vs y<0y{<}0).  
   Let the **bifurcation controls** be u=F−F∗u=F-F^\* (challenge gap) and v=bv=b (precision-bias). A minimal potential:

V(R,y)=β4R4−μ(u,χ)2R2  +  14y4−u2y2−v yV(R,y)=\frac{\beta}{4}R^4-\frac{\mu(u,\chi)}{2}R^2 \;+\; \frac{1}{4}y^4-\frac{u}{2}y^2 - v\,y

with stochastic gradient flows R˙=−∂V/∂R+ζR\dot R=-\partial V/\partial R + \zeta\_R, y˙=−∂V/∂y+ζy\dot y=-\partial V/\partial y + \zeta\_y.

* For **u<0u<0** (subcritical), yy has **one** minimum (no branch): **shaft**.
* Near **u≈0u\approx 0**, a **cusp/pitchfork-like** region opens in yy: two attractors (Control/Creative); **v=bv=b** tilts the branch.
* **Salience** acts as a **fast controller** that recentres v→0v\to 0, briefly lifts **temperature** T(χ)T(\chi), or nudges μ\mu to maintain **moderate RR**—keeping the trajectory **inside** the Ψ-band.
* For **large ∣u∣|u|**, either RR saturates high (rigidity) or collapses low (fragmentation): Ψ-band **exit**.

This normal form is only an **analytical cartoon**—your network-level instantiation (e.g., Kuramoto/Wilson–Cowan on a hierarchical-modular graph) provides the ground truth where:

* **Control** aligns with **higher, stable RR** and compressive updates,
* **Creative** aligns with **metastable RR** and decompressive search,
* **Monitoring** issues **short pulses** (centre bb, adjust T(χ)T(\chi), tighten λ\lambda) to re-enter Ψ after divergence.

# **How this extends prior work (and stays testable)**

* Prior criticality work gives you the **band** and **benefits** (dynamic range, information capacity) but not the **branching logic**. The Trident adds the **decision-level geometry** and **controllers** that explain *when* and *how* the system chooses compress vs decompress—and *how* it avoids falling out of Ψ.
* It yields **quantitative predictions**: within-band you should see **metastability peaks**, **power-law episode durations**, and **SN-led** switching into FPN-B (Control) vs FPCN-A/DMN (Creative). Outside the band you should see **over-synchrony** (rigidity, narrow λ\lambda, high hysteresis) or **over-desynchrony** (unstable RR, poor re-entry).
* Clinical mappings remain **tentative**: hypothesise **locked-in RR** and persistently high bb (plus low TT) in compulsive rigidity; hypothesise **unstable RR**, high TT, and poorly centred bb in disorganisation. These are **testable computational phenotypes**, not diagnoses.

# **Two sentence insert (Discussion)**

*We formalise a* ***Trident*** *branching in which a* ***single, non-bifurcated subcritical regime*** *(autopilot) meets a* ***near-critical branch point*** *governed by the precision-weighted gap ΔF^=b(F−F∗)\widehat{\Delta F}=b(F-F^\*) and uncertainty χ\chi. Salience/attention coordinators route dynamics into* ***Control*** *(compress) or* ***Creative*** *(decompress) prongs and deliver brief re-centring pulses; outside the Ψ-band the system either* ***over-synchronises*** *(rigidity) or* ***over-desynchronises*** *(fragmentation), providing clear, falsifiable failure modes.*

Yes—both fit, and they’re complementary.

### **When to use which**

* **Kuramoto (phase-only, macroscale):** Ideal for modelling the **Ψ-band** as partial synchrony/metastability on a **connectome or hierarchical-modular network**. It reproduces **smeared/smooth crossovers** with **power-law desynchronisation durations** (exponents in the ~1–2 range) on human connectomes and HMNs—i.e., **extended dynamical criticality** consistent with a near-critical **band**, not a knife-edge point. Map your controllers as: coupling/homeostasis ↔ F∗F^\* thermostat; precision-bias bb ↔ subnetwork gain tilt (FPN-B vs DMN/FPCN-A); T(χ)T(\chi) ↔ noise/frequency jitter.
* **Wilson–Cowan (E/I, mesoscale):** Use when you want **explicit excitation–inhibition** and local microcircuit realism (columns/nodes each with E/I populations). You can sit each node near a **Hopf edge** (critical slowing/oscillations), control **E:I** directly, and recover phases from E-activity to feed cross-node coupling. Then the same G-Loop knobs apply: E:I/homeostatic gain ↔ F∗F^\*; bias bb skews pathway gains; T(χ)T(\chi) scales noise/input variance. This gives you a mechanistic route from E/I to band occupancy while still supporting Kuramoto-like order-parameter readouts (e.g., global RR).

### **A neat hybrid (what I’d recommend)**

* **Node dynamics:** Wilson–Cowan E/I per node (for local E:I and Hopf-edge control).
* **Network coupling:** Kuramoto-style phase coupling between nodes (cheap, captures **partial synchrony** and **metastability** cleanly).
* **Controllers:**
  + F∗F^\* thermostat → slow homeostatic adjustment of node gains/coupling toward a target R\\*R^\\* (partial synchrony);
  + bb (D1:D2 tilt) → multiplicative gain to Control vs Creative subnetworks;
  + T(χ)T(\chi) → exploration temperature (noise on inputs/frequencies) raised when cross-loop inconsistency χ\chi is high.
* **Branch logic:** Near ΔF^=b(F−F∗)≈0\widehat{\Delta F}=b(F-F^\*)\approx 0, Salience delivers brief pulses (centre b ⁣→ ⁣0b\!\to\!0, nudge KK, transiently raise TT) to route into **Control** (higher, stable RR, compress) or **Creative** (metastable RR, decompress) and keep the system inside Ψ.

### **Why this is on-model**

* **Griffiths-like bands** emerge naturally on hierarchical/modular networks → exactly your Ψ-band premise.
* **Kuramoto on connectomes** shows **power-law event statistics** and **metastability** with inhibitory links/homeostasis—precisely the telemetry you want for band detection and prong-specific states.

In short: **Kuramoto** gives you the clean band + synchrony/metastability lens across the whole network; **Wilson–Cowan** gives you the **E:I knob** and biophysical face of the same controllers. Use them together to instantiate the Trident G-Loop succinctly and testably.

Yes—with this setup you can model **from column → patch → system** using the same knobs and telemetry.

### **How to scale it cleanly**

**1) Column (micro/meso).** Use **Wilson–Cowan** (E/I) per **microcircuit/column** to sit each unit near a Hopf edge; homeostatic rules keep local **E:I** in the Ψ-window. Read out a local order parameter (e.g., E-activity amplitude/phase). This is where F, F∗F^\*, bb (D1:D2 tilt via pathway gains), and T(χ)T(\chi) (noise/input variance) act directly.

**2) Patch / mesoscale modules.** Group columns into a **hierarchical-modular network** (HMN). Couple their phases (or mean fields) with **Kuramoto-style** interactions; HMNs naturally stretch a single critical point into an **extended critical-like band (Griffiths phase)**—i.e., a Ψ-band rather than a knife-edge. Expect power-law episodes and rare-region effects across a **range** of couplings.

**3) Whole-brain networks.** Place modules on an empirical **connectome** and evolve a **Kuramoto layer** on top: you get **partial synchrony/metastability** and **power-law desynchronisation durations** with **control-parameter–dependent exponents** below the transition—strong evidence for **extended dynamical criticality** on real graphs. Adding a bit of inhibition or homeostatic gain equalisation preserves these banded signatures.

**4) One set of controllers across scales.**

* **Thermostat** F∗F^\*: slow homeostasis of local gain/coupling toward a target partial synchrony level (keeps units in-band).
* **Precision-bias** bb: multiplicatively tilts Control vs Creative subnetworks (e.g., FPN-B ↔ DMN/FPCN-A) at meso/macro; biases rule-maintenance vs hypothesis search at micro.
* **Temperature** T(χ)T(\chi): scales noise/frequency jitter when cross-loop inconsistency rises; promotes sampling and re-entry to Ψ.

**5) Telemetry invariants (all scales).**

* **Band occupancy**: interval with non-saturated synchrony RR and PL event durations (exponent τ∼1 ⁣− ⁣2\tau\sim1\!-\!2).
* **Metastability peak** near branch point F≈F∗F\approx F^\*.
* **Rare-region / spectral** markers in HMNs (Lifshitz tails/localised modes). These are exactly what HMN theory and connectome-Kuramoto simulations report.

### **Why this is empirically reasonable**

* HMNs and empirical connectomes **generate** extended critical-like regimes (Griffiths phases) → matches your Ψ-band premise.
* Kuramoto on human connectomes shows **smeared crossovers**, **metastability**, and **power-law duration tails** that shift with coupling and inhibition/homeostasis → gives you a robust, scalable order parameter.

### **Quick recipe you can implement**

* **Node:** Wilson–Cowan (E/I) ~ column.
* **Edge:** Kuramoto phase coupling between nodes/modules.
* **Controllers:** F∗F^\* (slow gain homeostasis), bb (subnetwork gain tilt), T(χ)T(\chi) (noise/jitter).
* **Readouts:** local E:I, global/meso R(t)R(t), PL exponents of (de)synchronisation durations, recovery half-life to F→F∗F\to F^\*.

That gives you a single, compact formalism that’s faithful to **column physiology** and **whole-brain network physics**, while delivering the **Ψ-band + Trident** logic you need.