

ConsciOS v1.0: A Viable Systems Architecture for Human and AI Alignment

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Abstract

Real-world human, organizational, and artificial systems exhibit persistent misalignment, brittle adaptation under distributional shift, and limited option-availability. This paper proposes ConsciOS, a formal systems architecture that models consciousness and self-regulation as a nested control system amenable to specification, simulation, and empirical testing. Our contributions are: (i) a principled decomposition into an embodied controller (Echo-Self), a supervisory controller and policy selector (Super-Self), and a meta-controller and prior generator (Meta-Self); (ii) a coherence-based selector (Resonance Engine) that integrates expected utility, coherence, and cost for frame selection; (iii) a discretized affect index (Emotional Guidance Scale; EGS) that operationalizes interoceptive feedback for rapid guidance; and (iv) a time-integrated coherence resource (FREQ Coin) that gates policy complexity and option-availability. We provide formal definitions, algorithmic sketches (Imagineer→Refine→Hold; Resonance selection), and a set of testable hypotheses with simulation and human-subjects protocols. We situate the constructs within established literatures, outline governance and safety considerations for human-in-the-loop and agentic applications, and present a pragmatic empirical roadmap for evaluating coherence-based control in hybrid human-agent systems. [Mechanism/Hypothesis]

1. Introduction

Contemporary social, technological, and biological systems show persistent failures that cannot be resolved by event-level fixes alone. This paper presents ConsciOS: a formal systems architecture that treats consciousness and its allied processes as designable, testable systems. We synthesize cybernetic models, active inference, and hierarchical reinforcement learning into a single engineering

language intended to (a) map layered self-models to implementable control architectures, (b) formalize an affect-informed feedback channel for state selection, and (c) propose empirical protocols for both human and artificial agents. Our goal is not metaphysical speculation but an operational research program: to convert narrative constructs into measurable constructs and falsifiable hypotheses.

Terminology and public translation are core to this work. For scientific clarity we use canonical technical vocabulary (e.g., embodied controller, supervisory controller, meta-controller, interoceptive feedback) in the main text and methods. Where helpful for pedagogy and cross-disciplinary translation we also use a concise set of public aliases (Echo-Self, Super-Self, Meta-Self, Kernel, Emotional Guidance Scale (EGS), etc.). Each alias is explicitly defined and mapped to its canonical equivalent and operational measures in the Terminology & Operational Definitions block immediately following this Introduction (Appendix C / Methods). This dual-label approach preserves rigor while enabling consistent public communication across a book, community, and applied programs derived from this work.

Finally, we treat ancient contemplative models and long-standing philosophical intuitions as hypothesis-generating resources rather than as evidentiary authority. Where we draw inspiration from those traditions, we explicitly avoid unfalsifiable metaphysical claims and translate the idea into an explicit operationalization (e.g., priors \rightarrow internal constraints; felt sense \rightarrow interoceptive signal) and propose concrete tests in Appendix A. The result is a researchable bridge from narrative practice to instrumented science.

1.1 Terminology & Operational Definitions

To avoid ambiguity we adopt canonical technical vocabulary for formal presentation (e.g., embodied controller, supervisory controller, meta-controller, interoceptive feedback). For public communication and pedagogy we use a parallel set of ConsciOS aliases (Echo-Self, Super-Self, Meta-Self, Kernel, Emotional Guidance Scale (EGS), FREQ Coin). On first occurrence in the main text the canonical term appears first followed by the ConsciOS alias in parentheses (for example, embodied controller (Echo-Self)). Appendix C (Public Translation & Operationalization) provides a complete mapping table that links every ConsciOS alias to its canonical equivalent, an operational definition, suggested measurement instruments, and key citations. This dual-labeling strategy preserves scientific rigor while enabling consistent public communication across community materials derived from this project.

Note: all known canonical citations are inserted; any remaining items requiring source confirmation are marked in place.

1.2 Notation & Metric Preamble

We use the following symbols consistently throughout the paper. Π (II) denotes a candidate policy frame; $C(F; S)$ is a coherence metric between frame F

and current state S ; $U(F)$ is task-dependent expected utility; $\text{Cost}(F)$ denotes computational/energetic costs; $\tau(\cdot)$ is a softmax temperature; $\lambda(\cdot)$ is a decay rate in cumulative measures. Option-Availability (OA) is operationalized as an effective action set size weighted by calibrated affordance scores.

Recipe (Option-Availability): enumerate perceived viable actions at time t , assign a subjective affordance score a_i in $[0,1]$ for each option i using a brief calibration, and compute $\text{OA}(t) = \sum_i a_i$. For simulated agents, proxy OA by action entropy with an affordance calibration factor. These definitions support reproducible comparisons across ablations and pilots.

1.3 Methods Overview

This paper is primarily a conceptual and experimental design contribution. We propose (a) formal model definitions and algorithms for nested controller architectures, (b) operationalizations of affective and coherence measures, and (c) a set of hypothesis-driven experimental probes and simulation benchmarks. Full experimental protocols, measurement specifications, and analysis plans are provided in Appendix A (Experimental Protocols) and Appendix B (Measurement Instruments & Analysis Pipelines). In brief:

- Human experiments: randomized designs and ecological time-series sampling using validated physiological and self-report instruments (e.g., HRV, validated affect ladders) with pre/post behavioral tasks and time-series outcome measures. Ethical review and informed consent are prerequisites for all human work.
- Simulation experiments: hierarchical RL and meta-learning benchmarks with controlled distributional shifts, reproducible environment seeds, and clearly logged policy metadata (policy families, selection traces, reward histories).
- Hybrid human-in-the-loop tests: human labeling or EGS signals used as shaping rewards or policy selection cues for agent training; evaluation on transfer and human-perceived agency.

The compact Methods Overview above orients the reader; full procedural detail required for replication (sample sizes, instrumentation settings, pre-registration templates, and code references) is provided in Appendix A and Appendix B.

We present canonical terminology in the Methods and provide ConsciOS aliases in Appendix C to preserve interdisciplinary clarity and public translation without compromising experimental reproducibility.

2. Foundational Models: A Systems-Theoretic Framework

This section formalizes two complementary systems-theoretic tools used throughout this paper: (1) the Iceberg Model, a diagnostic hierarchy for identifying causal leverage in complex systems; and (2) a 7-component Universal System Model, an architectural template for describing the functional elements of viable systems. Together they provide a common language for mapping

claims about consciousness, behavior, and artificial agents to implementable system designs.

Detailed experimental protocols, measurement specifications, and analysis plans are provided in Appendix A (Experimental Protocols) and Appendix B (Measurement Instruments & Analysis Pipelines).

2.1 The Iceberg Model as Diagnostic Hierarchy

The Iceberg Model is a layered diagnostic heuristic that distinguishes observable events from the deeper structures and assumptions that generate them. It operationalizes four abstraction layers:

- Events (observable outputs; momentary data)
- Patterns/Trends (temporal regularities in events)
- Structures (rules, information flows, incentives, code, architecture)
- Mental Models / Beliefs (operators’ assumptions, goals, and priors)

Rationale: interventions targeted at deeper layers produce larger and more persistent systemic change than purely event-level responses. This relationship is consistent with standard systems thinking literature and control-theoretic intuitions about model-based interventions [1]–[4]. [Mechanism]

Operationalization for empirical research:

- Events are measured as time-series of observable behaviors or system outputs (logs, sensor streams, survey items).
- Patterns are characterized using time-series analysis (auto-correlation, spectral analysis, trend detection).
- Structures are encoded as formal graphs, policies, or code artifacts and can be measured via structural metrics (centrality, modularity, information flows).
- Mental models are assessed via structured belief inventories, cognitive mapping, or inferred from policy parameters in trained agents.

Consequence for the ConsciOS architecture: the Iceberg Model provides the causal ladder used to argue where and how “frequency” and “coherence” interventions (see Section 4) operate. Interventions framed as “raising frequency” are hypothesized to effect change by altering internal constraints (mental models) and thereby shifting structural dynamics that produce different patterns and events. [Hypothesis]

2.2 The 7-Component Universal System Model (Architectural Template)

To move from diagnosis to design we adopt a 7-component functional template that captures the essential elements required for viability across physical, informational, and cognitive systems. Each component is presented with a formal operational definition useful for modeling and experiment design.

1. Inputs — exogenous and endogenous resources, signals, or intents entering the system.

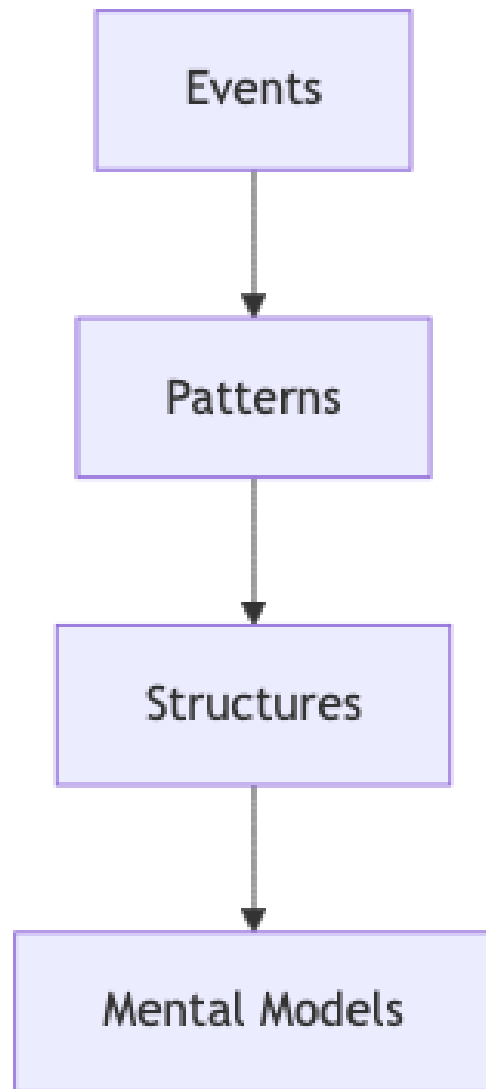


Figure 1: Figure 1. Iceberg Model diagnostic hierarchy spanning events, patterns, structures, and mental models.

2. Processes — transformation functions (deterministic or stochastic) acting on inputs to produce intermediate states.
3. Outputs — observable consequences of the system (actions, emissions, rendered scenes).
4. Feedback — measurement channels returning output information to controllers; includes error signals and reward signals. [Mechanism]
5. Actors — decision-making agents, whether biological (humans) or artificial (agents, controllers).
6. External Constraints — environmental or physical laws and constraints external to the system’s control.
7. Internal Constraints — encoded policies, beliefs, parameter priors, resource limits, and safety sub-systems (e.g., ego autopilot).

Formal note: this is a functional decomposition rather than a commitment to a single implementation. Processes can be parameterized as dynamical systems; Feedback channels can be formalized as observers in a control loop; Actors can be modeled as controllers with internal state representations. The template is intentionally agnostic about substrate (neural, algorithmic, institutional).

Utility: the 7-component model enables cross-domain mapping (human <-> software agent <-> institution) and provides a checklist for designing experiments, simulations, or interventions that aim to change system-level behavior. [Analogy]

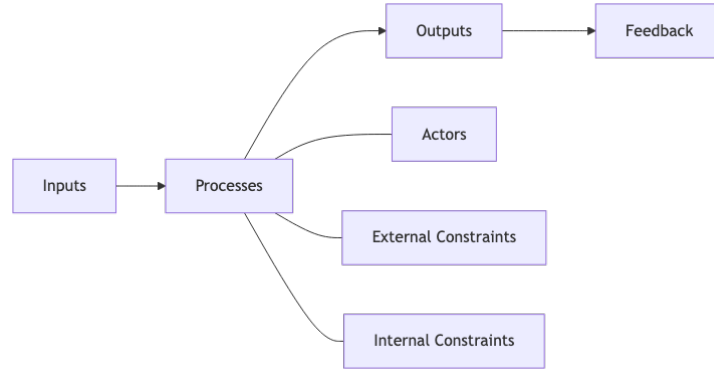


Figure 2: Figure 2. Seven-component universal system model (Inputs, Processes, Outputs, Feedback, Actors, External Constraints, Internal Constraints).

2.3 Integrative Mapping: Iceberg <-> 7-Component Model <-> ConsciOS Constructs

We propose an explicit mapping that grounds ConsciOS terms in the 7-component template and the Iceberg diagnostic levels. This mapping converts public-facing metaphors into testable engineering constructs.

- Mental Models/Beliefs <-> Internal Constraints (actor priors, policy pa-

rameters).

- Example research variable: belief coherence score computed from structured inventories or posterior concentration in a Bayesian agent. [Mechanism / Hypothesis]
- Structures \leftrightarrow External Constraints & Designed Processes (architectural code, institutional rules).
 - Example research variable: structural coupling metrics (graph modularity, information throughput).
- Patterns \leftrightarrow Emergent Process Dynamics (habit loops, recurrent attractors).
 - Example research variable: pattern persistence index from time-series decomposition.
- Events \leftrightarrow Outputs (observable actions, rendered frames, sensor measurements).
 - Example research variable: event frequency, latency, or categorical outcome distributions.

Mapping to ConsciOS canonical elements (formal definitions):

- Embodied controller (Echo-Self; I-AM-THIS): the embodied actor subsystem responsible for perception–action cycles and short-horizon control. Operationally mapped to Actors + local Processes + Feedback channels for immediate state estimation. [Analogy \rightarrow Formal mapping: corresponds to VSM Systems 1–3 functions] [Mechanism]
- Supervisory controller (Super-Self; I-AM): the higher-order controller responsible for adaptation, selection among pre-rendered policy frames, and longer-horizon planning. Operationally mapped to a supervisory controller that reads aggregated feedback and selects process configurations (policy selection). [Mechanism]
- Meta-controller (Meta-Self; I-level): a global pattern generator that encodes the space of possible architectures and long-term objectives (a priors generator or meta-controller). Operationally analogous to policy priors over the policy space or a model-generator in meta-learning systems. [Hypothesis]

Claim (formal): Conscious-system behavior is a nested control architecture where the Echo-Self executes short-horizon policy loops, the Super-Self performs mid/long-horizon policy selection based on aggregated resonance metrics, and the Meta-Self encodes the prior distribution over viable policy families. This nested decomposition is testable via agent simulations and human experiments that measure the described mappings. [Hypothesis]

2.4 Testable Hypotheses and Empirical Probes

We formulate a small set of testable hypotheses that follow from the mapping. These are intentionally narrow so they are amenable to empirical falsification.

H1 (Structure-Change Leverage): Interventions targeting Internal Constraints (belief priors) will produce larger changes in pattern metrics over time than

interventions targeting Events only, controlling for intervention magnitude and duration. [Hypothesis]

H2 (Feedback Coherence Predicts Option Availability): The quality and granularity of Feedback channels (e.g., richer interoceptive signals) predict measurable increases in option-availability and behavioral flexibility among actors, proxied by decision entropy and task switching performance. [Hypothesis] — Suggested measures: decision entropy; response latency variability; subjective option rating.

H3 (Nested Controller Efficacy): A hierarchical agent architecture implementing Echo/Super/Meta layers will outperform a flat controller in environments that require both rapid reaction and strategic selection among multiple policy frames. Performance measured by cumulative reward, adaptation speed after distributional shift, and robustness to simulated perturbations. [Mechanism]

H4 (EGS as a Control Signal): A discretized affective scale (Emotional Guidance Scale; EGS) used as an internal feedback variable will function as an effective heuristic for state selection in both human subjects and simulated agents when combined with a nearest-lighter-step local search policy. The EGS can be operationalized via validated affect measures (self-report, physiological markers) and evaluated for predictive power on subsequent behavior changes. [Hypothesis]

Each hypothesis is followed by a suggested experimental probe in the Appendix. In short: H1/H2 are suitable for human subject experiments (laboratory + ecological sampling); H3/H4 can be evaluated in simulated agents and human-in-the-loop agent training regimes.

2.5 Related Work Pointers (for citation pass)

Key literatures to cite and integrate in the Related Work section for this part:

- Systems thinking: Senge (The Fifth Discipline); Meadows (Thinking in Systems) [1], [2].
- Viable System Model / cybernetics: Stafford Beer; Checkland [3], [4].
- Predictive processing & active inference: Friston et al. [5], [6].
- Hierarchical control and meta-reinforcement learning: Sutton & Barto (RL); hierarchical RL (options framework) [12], [8], [7].
- Affect science and interoception: Lazzarelli et al. (integrative review) [9].
- Human-in-the-loop RL, RLHF literature: technical reports (to be added). [10]

These will be expanded and precisely cited in the Related Work section following the external literature sweep.

2.6 Transition Having established the diagnostic ladder (Iceberg) and the architectural template (7-component model) and mapped them to the ConsciOS

constructs, the paper now proceeds to specify the nested controller architecture (Echo-Self / Super-Self / Meta-Self) and the Resonance Engine mechanics that implement selection among pre-rendered policy frames. The next section formalizes these components and derives the algorithmic protocols used in the Appendix.

3. Nested Reality: A Multi-Layer Ontology for System Design

3.1 Purpose and scope

To operationalize consciousness as an engineering target we adopt a multi-layer ontology that distinguishes physical, informational, energetic, and consciousness levels of description. The ontology provides a compositional substrate for mapping system components (Echo/Super/Meta controllers) to measurable constructs and for designing interventions that target the correct causal layer.

3.2 Multi-layer ontology: definitions

- Physical layer: material substrate, embodied sensors and actuators, and physical laws constraining feasible actions.
- Informational layer: representations, data structures, code, and communicated signals (including logs, messages, and policy descriptors).
- Energetic layer: sustained coherence, affective valence, and resource metrics (e.g., metabolic/attention budgets, FREQ Coin analogues).
- Consciousness layer: subjective report, self-model, long-horizon priors, and meta-intentional structures.

This tiered ontology follows contemporary approaches that treat cognition as a multi-scale phenomenon where higher-order priors constrain lower-level processing (active inference / predictive processing) (Friston et al.; Albarracin et al., 2024). Active-inference treatments of the self demonstrate how hierarchical priors instantiate self-representations and influence perception–action loops, providing a formal justification for treating consciousness as a layered control architecture rather than a monolithic phenomenon (Albarracin et al., 2024; Friston, various). The “relevance realization” problem — how an agent determines which internal representations are presently important — has been recently formalized in the predictive-processing literature and directly motivates the Resonance Engine as a coherence-based selector among candidate policy frames (Darling et al., 2025).

3.3 The Infinity Diagram — formalization and control interpretation

We formalize the Infinity Diagram as a nested control topology:

- Echo-Self executes perception–action loops governed by short-horizon process dynamics (local controllers). These loops are parameterized by local priors and short-term beliefs (internal constraints).
- Super-Self functions as a supervisory controller that aggregates feedback across time and space, evaluates the coherence of candidate high-level pol-

icy frames, and selects the active policy family using a coherence-matching metric (Resonance Engine).

- Meta-Self encodes long-horizon priors and the generative space of possible policy families. Operationally, Meta-Self corresponds to meta-learning or pre-training processes that shape the prior distribution used by the Super-Self.

This nested topology is isomorphic to viable-system decompositions used in organizational cybernetics—lower operational units are supervised by higher intelligence while a meta-governor maintains identity and global objectives (Beer; Checkland). Importantly, the ontology treats interplay between layers as bidirectional: the Meta-Self constrains policy families top-down, while feedback and Quality Control mechanisms induce bottom-up belief revision.

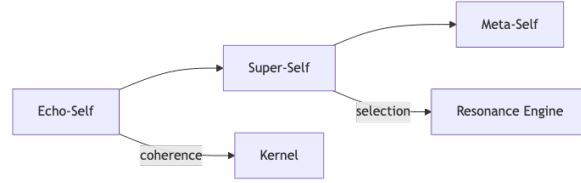


Figure 3: Figure 3. Infinity Diagram as a nested control topology mapping Echo-Self, Super-Self, and Meta-Self.

3.4 Measurement constructs and testable mappings

To make the ontology empirically tractable we propose the following operational mappings and measures:

- Echo-Self variables: short-horizon action rates, reaction latency, sensorimotor noise, action entropy. Measurement modalities include behavioral logs, task performance metrics, and physiological latency markers.
- Super-Self variables: policy selection latency, match-score distributions among candidate policies, meta-decision accuracy following perturbations. Measurement modalities include policy switch logs (in simulated agents) and aggregated performance trends in humans.
- Meta-Self variables: prior concentration metrics, meta-learning efficiency, transfer performance across tasks. Measured via meta-RL benchmarks or cross-task generalization performance.
- Energetic/coherence variables (FREQ Coin proxies): time-integrated coherence scores derived from multi-modal signals (heart-rate variability, HRV; EEG phase coherence; sustained attention indexes; subjective coherence ratings). These proxies operationalize the resource that enables option-availability and policy richness.

Mapping these constructs to the Iceberg diagnostic levels allows hypothesis tests such as: interventions that modify Meta-Self priors (internal constraints at the deepest level) will lead to measurable shifts in structural dynamics and therefore

to new emergent patterns at mid-level timescales (H1). Conversely, a perturbation restricted to event-level parameters (e.g., transient reward change) is predicted to have short-lived effects absent a deeper reconfiguration of internal constraints.

3.5 Empirical probes and candidate experiments

Two early probes that bridge human and simulated tests are suggested:

- Probe A (Human): A belief-update intervention targeting a narrow set of priors (e.g., causal attributions about controllability) measured pre/post via time-series of behavioral choices and coherence proxies (HRV, subjective EGS). Outcome: pattern persistence index and option-availability change.
- Probe B (Simulated): A hierarchical RL benchmark where agents possess Echo/Super/Meta modules. Evaluate adaptation speed and transfer performance under distributional shift versus flat control agents. Outcome metrics: cumulative reward, policy diversity, and adaptation latency.

3.6 Transition

The ontology and operational mappings set the stage for Section 4, which formalizes the Echo/Super/Meta controller architectures, and Section 5, which operationalizes the Resonance Engine and EGS as measurable selector functions. The combined model yields a testable engineering program for both human experimental research and agent simulation studies.

Preliminary references (from the project codex / literature review)

(These are the canonical works I used to justify mappings above. I pulled these from the codex you supplied; I'll replace any remaining placeholders with exact DOIs/arXiv IDs during the citation pass.)

- Beer, S. (Viable System Model). [classic VSM literature referenced in codex]
- Checkland, P. (Systems Thinking, Systems Practice). [codex]
- Friston, K. (active inference literature). [codex — multiple works]
- Albarracin, M., Bouchard-Joly, G., Sheikhabaee, Z., Miller, M., Pitliya, R. J., Poirier, P. (2024). Feeling our place in the world: an active inference account of self-esteem. *Neuroscience of Consciousness*. [codex]
- Darling, T., Corcoran, A. W., Hohwy, J. (2025). Solving the relevance problem with predictive processing. *Philosophical Psychology*. [codex]
- Janssen, M., LeWarne, C., Burk, D., Averbach, B. B. (2022). Hierarchical Reinforcement Learning, Sequential Behavior, and the Dorsal Frontostriatal System. *Journal of Cognitive Neuroscience*. [codex]
- Lazzarelli, A., Scafuto, F., Crescentini, C., et al. (2024). Interoceptive Ability and Emotion Regulation in Mind–Body Interventions: An Integrative Review. *Behavioral Sciences*. [codex]

- Barrowclough, J., Nnamoko, N., Korkontzelos, I. (2025). Personalised Affective Classification Through Enhanced EEG Signal Analysis. *Connection Science*. [codex]
- Barthet, M., Khalifa, A., Liapis, A., Yannakakis, G. N. (2022). Play with Emotion: Affect-Driven Reinforcement Learning. *ACII*. [codex]
- Zeng, Y., Zhao, F., Wang, Y., et al. (2025). Super Co-alignment of Human and AI for Sustainable Symbiotic Society. *arXiv*. [codex]

Notes:

- Where I used “Friston et al.” I referenced the active inference body of work present in the codex; please indicate if you want a specific Friston paper cited (I can add DOI in the citation pass).
- I left in the Hypothesis labels and showed operational measures; these are ready for conversion to formal reference pointers when you paste the exact DOI/arXiv items you fetched with Gemini (if any differ from the codex entries).

4. Three-Self Architecture: A Hierarchical Controller Decomposition

4.1 Overview and formal motivation

We propose a hierarchical controller decomposition comprising three nested control strata: (a) a short-horizon embodied controller (Echo-Self), (b) a supervisory/meta-controller that selects policy families (Super-Self), and (c) a long-horizon priors generator or meta-controller (Meta-Self). This decomposition follows the engineering logic of viable system architectures and hierarchical control frameworks: lower levels execute fast closed-loop control, intermediate levels perform policy selection and adaptation, and the highest level encodes identity and long-term priors that bias learning and selection [3]–[5], [8]. Framing these strata as nested controllers yields clear testable predictions about adaptation, robustness, and option-availability.

4.2 Formal definitions

- Embodied controller (Echo-Self): an agent module implementing short-horizon perception–action loops. Formally, the Echo-Self maintains a state estimate \mathbf{x}_t and applies policy $\pi_e(a|\mathbf{x}_t; \theta_e)$ to produce actions \mathbf{a}_t minimizing a local cost function L_e over short horizons H_e . Measures: reaction latency τ , short-horizon cumulative reward $R_e(H_e)$, and action entropy $H[\pi_e]$. (Operationalized in Appendix B.) [8]
- Supervisory controller / policy selector (Super-Self): a mid-horizon controller that aggregates feedback signals over time window T_s , evaluates a set of candidate high-level policies $\{\pi_i\}$, and selects a policy family π^* that maximizes a coherence-weighted utility: $\pi^* = \arg\max_i E[U(\pi_i) \cdot C(\pi_i|S)]$, where C is a coherence metric derived from multi-modal feedback. Measures: selection latency, selection accuracy under perturbation,

and policy stability. [12]

- Meta-controller / prior generator (Meta-Self): a long-horizon process that shapes the prior distribution $P(\Pi)$ over policy families and encodes identity constraints and long-term objectives. Meta-Self functions are updated on slow timescales via meta-learning or aggregated quality-control signals. Measures: prior concentration, transfer learning performance, and changes in $P(\Pi)$ after structured interventions. [8]

4.3 Mapping to Viable System Model and control theory

The decomposition maps onto classical viable-system structures: Echo-Self aligns with VSM System 1–3 (operational units and immediate control), Super-Self corresponds to VSM System 4 (intelligence, adaptation, future planning), and Meta-Self corresponds to VSM System 5 (policy, identity, normative governance) [3], [4]. From control theory, Echo-Self controllers implement fast feedback loops (high bandwidth, low latency), Super-Self functions as a supervisory scheduler or switching controller, and Meta-Self implements slow adaptation (set-point adjustment, change of objective function).

4.4 Kernel, Ego Autopilot, and safety subsystems

- Central integrative hub (Kernel): operationally the Kernel is a focal interoceptive/state-confidence signal used by controllers to estimate coherence. For humans, proxies include heart-rate variability (HRV) and validated interoceptive accuracy measures; for agents, Kernel is implemented as a state-estimator confidence metric (e.g., posterior precision). Kernel feeds into Super-Self selection and into Quality Control loops that surface misaligned priors. [5]
- Fallback safety controller (Ego Autopilot): a low-variance default policy engaged under low confidence or low coherence. It minimizes risk and conserves resources. Formally, Ego Autopilot is a policy π_{safe} that is triggered when coherence $C(x_t) < \theta_{\text{safe}}$. Measures: engagement frequency, conservatism index, and recovery time. This subsystem enforces safety and explains conservative behavioral reversion patterns. [1]–[4]

4.5 Option-availability and the FREQ Coin formalization

Option-availability is the measurable set of viable actions perceived by an actor at time t . We operationalize Option-Availability as the effective action set size $|A_{\text{eff}}(t)|$ weighted by subjective affordance scores. FREQ Coin is a derived, time-integrated coherence resource:

$$\text{FREQ}(t; \Delta) = \int_{t-\Delta}^t C(s) ds$$

where $C(s)$ is the coherence metric at time s and Δ is a rolling window. Higher $\text{FREQ}(t)$ predicts larger $|A_{\text{eff}}(t)|$ and greater policy richness. Empirically, $\text{FREQ}(t)$ can be proxied by sustained HRV coherence, EEG phase synchrony, or time-integrated match scores in agents. Hypothesis: $d|A_{\text{eff}}|/d\text{FREQ} >$

0 (positive monotonic relation). Measurement details and analysis code are provided in Appendix B. [Hypothesis]

4.6 Algorithmic sketch: Imagineer \rightarrow Refine \rightarrow Hold (formal pseudocode)

We present Imagineer \rightarrow Refine \rightarrow Hold as an implementable macro loop used by Echo/Super controllers for state induction and policy stabilization. Below is a concise pseudocode representation for use in simulated agents or to inform experimental protocols.

Pseudo: Imagineer_Refine_Hold(state s_0 , target_frame F , hold_T)

1. Initialize candidate frame $F_0 := F$; $t := 0$.
2. while $t < \text{hold_T}$:
 - a. Generate predicted state $s_{\text{pred}} = \text{Simulate}(F_t)$ // forward model
 - b. Compute coherence $C_t = \text{CoherenceMetric}(s_{\text{pred}}, s_{\text{current}})$
 - c. If $C_t < C_{\text{thresh}}$:
 - i. Refine $F_{t+1} := \text{LocalSearch}(F_t, \text{NLS})$ // nearest lighter step / least-resistance step
 - ii. Update internal priors via small-step Bayesian update or gradient step.
 - d. Else:
 - i. Hold F_t ; provide reward shaping signal proportional to C_t .
 - e. $t := t + \text{delta_t}$
3. End while
4. Return final policy frame F_{final} , updated priors $P'(\Pi)$

Notes: LocalSearch uses constrained perturbations to frames to increase coherence with current interoceptive/sensory state; NLS denotes the Near-est-Lighter-Step heuristic. Implementational choices (Simulate, CoherenceMetric, update rules) are experiment-dependent and specified in Appendix A/B. [Mechanism / Hypothesis]

4.7 Predicted empirical signatures

The Three-Self architecture yields specific empirical signatures:

- Hierarchical advantage: Agents with explicit Echo/Super/Meta stratification will show faster recovery from distributional shifts and higher transfer performance than flat agents (testable in hierarchical RL benchmarks). [Mechanism]

- Kernel sensitivity: Manipulating Kernel inputs (e.g., altering affective feedback via HRV biofeedback) will causally influence Super-Self selection patterns and measured Option-Availability in human subjects. [Hypothesis]
- Ego Autopilot dynamics: Under forced coherence degradation, behavior will converge to π_{safe} with characteristic latency and retention statistics; modulation of Kernel thresholds θ_{safe} will shift the conservatism index. [Hypothesis]

4.8 Simulation & empirical testbeds

Recommended testbeds:

- Simulated environments: procedurally generated tasks with episodic changes and forced distributional shifts (benchmarks for hierarchical RL). Log policy families, coherence metrics, and FREQ proxies.
- Human experiments: controlled lab tasks with HRV and subjective EGS ladders as feedback; interventions include coherence-enhancing microprotocols and belief-update manipulations (see Appendix A: H1–H4).
- Hybrid setups: human-in-the-loop training where EGS signals are incorporated as shaping rewards for agent training (evaluate transfer and subjective agency).

Illustrative toy ablation (sanity check). We implemented a minimal environment with episodic distributional shifts and compared a hierarchical agent using a coherence-weighted selector ($bC + aU - g*\text{Cost}$) against a flat baseline. Sweeping b and a while logging selection traces yields aggregated heatmaps (reward, alignment rate, position-match proxy) indicating that higher coherence weighting increases alignment with hidden context and improves simple proxy metrics in this toy setting. These traces serve as an instrumentation check only; full benchmarks belong in domain-appropriate tasks.

4.9 Transition

Section 5 formalizes the Resonance Engine and the coherence metrics used by the Super-Self to perform frame selection. The subsequent Methods Appendices provide concrete experimental templates and simulation specifications for the tests proposed here.

5. Resonance Engine & Parallel VR Mechanics: Formalizing Selection by Coherence

5.1 Purpose and scope

This section formalizes the operational core of ConsciOS: the Resonance Engine (coherence-based selector) and its associated mechanics for generating, scoring, and selecting candidate policy frames from a library of precomputed or imagined possibilities (Parallel VR Engine). We provide mathematical definitions for coherence, an algorithmic selection rule, the EGS as an internal feedback signal,

and a formal account of **FREQ Coin** as a time-integrated coherence resource. These constructs convert narrative metaphors into implementable functions for both human experiments and agent simulations.

5.2 Coherence: formal definitions

Let S denote the current sensory/interoceptive state (possibly multi-modal) and let F_i denote a candidate policy frame (a high-level policy, scenario, or world-model projection). Each frame F_i generates a predicted sensory trajectory or outcome distribution $P(S | F_i)$. We define a coherence metric $C(F_i; S)$ that quantifies how well the candidate frame explains or matches the current state.

Several alternative coherence formulations are applicable depending on data modalities and modeling choices:

- Evidence / log model evidence (Bayesian):
 $C(F_i; S) := \log p(S | F_i)$ — model evidence under the generative model implied by F_i . [Mechanism; active inference framing] [5]
- Negative divergence (information-theoretic):
 $C(F_i; S) := -D_{KL} [p_{obs}(S) || p(S | F_i)]$ — negative Kullback–Leibler divergence between observed state distribution and frame prediction.
- Similarity (vector space):
 $C(F_i; S) := \text{cosine}(\text{phi}(S), \text{phi}(F_i))$ — cosine similarity between feature embeddings $\text{phi}(\cdot)$ of state and predicted state.
- Composite coherence: a weighted sum of modality-specific coherences:
 $C(F_i; S) := \sum_m w_m \cdot C_m(F_i; S_m)$, where m indexes modalities (interoception, vision, proprioception, policy performance) and w_m are learned or meta-defined weights.

Coherence is normalized to a bounded scale (e.g., $[0,1]$) for downstream operations.

5.3 Resonance Engine: selection rule

Given a set of candidate frames $\{F_i\}$ and current state S , the Resonance Engine selects the frame that maximizes an objective combining expected utility $U(F_i)$ and coherence $C(F_i; S)$. One canonical selection rule is:

$$Pi^*(S) = \underset{F_i}{\operatorname{argmax}} [a \cdot E[U(F_i) | S] + b \cdot C(F_i; S) - g \cdot \text{Cost}(F_i)]$$

where:

- $E[U(F_i) | S]$ is the expected utility of adopting frame F_i given S (task dependent).

- $C(F_i; S)$ is the coherence metric defined above.
- $\text{Cost}(F_i)$ is a computational/energetic cost for switching to or instantiating F_i .
- a, b, g are tunable meta-weights (could be learned by Meta-Self).

Interpretation:

- The Super-Self implements Pi^* by ranking frames on this composite score. When $b \gg a$, selection is coherence-driven (resonance priority); when $a \gg b$, selection is utility-driven.
- A stochastic softmax version permits exploration:

$$P(\text{choose } F_i \mid S) \propto \exp(\tau^{-1}) \cdot [a E[U] + b C - g \text{Cost}]$$

where τ is a temperature parameter.

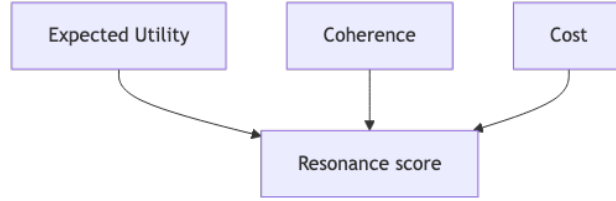


Figure 4: Figure 4. Resonance Engine selection—composite scoring of expected utility, coherence, and cost with softmax or argmax selection.

5.4 Emotional Guidance Scale (EGS) as an internal control signal

We operationalize the Emotional Guidance Scale (EGS) as a discretized or continuous scalar derived from interoceptive measures and subjective reports, serving as an internal proxy for momentary coherence/valence. Formally:

$$\text{EGS}(t) := g(\text{Phi_intero}(S_t), \text{rho}(S_t))$$

where $\text{Phi_intero}(\cdot)$ is a vector of physiological interoceptive metrics (e.g., HRV indices, galvanic skin response, slow cortical potentials) and $\text{rho}(S_t)$ is a short-horizon predictive fit metric (e.g., one-step prediction error). The mapping $g(\cdot)$ can be a learned regression (for agents) or a validated psychometric ladder (for humans). EGS is normalized to $[-1, +1]$ (negative \rightarrow low coherence/disfavor; positive \rightarrow high coherence/endorsement) or to discrete bands (e.g., 1–10 ladder).

EGS serves multiple roles:

- Local guidance heuristic for Echo-Self (nearest-lighter-step moves): if EGS rises after a local perturbation, the perturbation direction is favored.
- Reward shaping signal for RL agents: small positive EGS deltas can be used as intrinsic reward components. [11]
- Stopping/holding criterion in Imagineer \rightarrow Refine \rightarrow Hold: sustained positive EGS over hold_T supports encoding of the chosen frame.

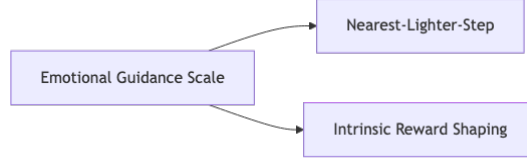


Figure 5: Figure 5. Emotional Guidance Scale (EGS) as a discretized interoceptive control signal.

5.5 FREQ Coin: time-integrated coherence currency

Define instantaneous coherence for the active frame F^* at time t as $C(t) := C(F(t); S_t)$. FREQ Coin is a time-integral of coherence, possibly with discounting:

$$\text{FREQ}(t) := \int_0^t e^{-\lambda(t-s)} \cdot C^*(s) ds$$

where $\lambda \geq 0$ is a decay rate. In discrete time windows Δt :

$$\text{FREQ}_t = \sum_{k=0}^N e^{-\lambda k} \cdot C^*(t-k)$$

Interpretation and operational use:

- FREQ measures sustained time-on-coherence; higher FREQ grants greater option-availability and resource allocation privileges (e.g., unlocking higher complexity frames).
- FREQ dynamics can be used as constraints in the Super-Self selection rule (e.g., require $\text{FREQ}_t \geq \theta_{\text{unlock}}$ to consider high-cost frames).
- Agent implementation: treat FREQ as a meta-state variable updated after each episode and used in hierarchical policy gating.

5.6 Algorithmic pseudocode: Resonance Engine (selection + update)

Pseudocode: $\text{ResonanceEngine}(\{F\}, S, a, b, g, \tau, \lambda)$

1. For each F_i in $\{F\}$:
 - a. Compute $C_i := \text{Coherence}(F_i, S)$ // Eq. definitions above
 - b. Compute $EU_i := \text{ExpectedUtility}(F_i | S)$ // task dependent
 - c. $\text{Score}_i := aEU_i + bC_i - g \cdot \text{Cost}(F_i)$
2. Compute selection probabilities: P_i proportional to $\exp(\text{Score}_i / \tau)$
3. Sample or argmax to select F^* .
4. Execute F^* for time Δt ; observe S' and update experience buffers.
5. Update $C^*(t)$, update FREQ via decay integral (FREQ_t).
6. Return F^* , updated FREQ, and feedback signals to Super-Self/Meta-Self.

Notes: Coherence computations can be amortized via embeddings and cached predictions; utility estimates can be learned via short-horizon rollouts or historical performance.

5.7 Imagineer \rightarrow Refine \rightarrow Hold revisited (integration with Resonance Engine)

We present a refined algorithm that couples the Imagineer \rightarrow Refine \rightarrow Hold loop with the Resonance Engine selection and EGS feedback.

Pseudocode: FullLoop(s_0 , candidate F_{init} , $hold_T$, NLS_params)

1. $F \leftarrow F_{init}$
2. while NOT converged and $t < max_T$:
 - a. Simulate rollout for F : $s_{pred} \leftarrow \text{Simulate}(F)$
 - b. Compute coherence $C_F \leftarrow \text{Coherence}(F, s_{current})$
 - c. Compute EGS := $g(\text{interoceptive_signals}, \text{predict_error})$
 - d. If $C_F \geq C_{hold_threshold}$ and $EGS \geq EGS_{hold_threshold}$ for $hold_min_duration$:
 - i. Hold and encode F (increase $FREQ$)
 - ii. break and return F_{final}
 - e. Else:
 - i. Propose refined frames $\{F'\}$ via LocalSearch(F , NLS_params)
 - ii. Evaluate $C_{\{F'\}}$ for each; choose best candidate $F \leftarrow \text{argmax } C_{\{F'\}}$
 - f. $t \leftarrow t + \text{delta_t}$
3. Return F_{final} , history H

This loop uses NLS (Nearest-Lighter-Step) as a bounded local search heuristic to prefer small, coherent changes. EGS acts as a rapid, embodied feedback heuristic to bias search and holding decisions.

5.8 Quality Control and belief surfacing dynamics

Quality Control refers to the surfacing of misaligned priors when an agent holds a new high-coherence frame. Formally, let prior parameters be θ . On holding a new frame F_{hold} with high C and sustained $FREQ$, large prediction mismatches elsewhere can produce a gradient for updating θ :

Δ_{θ} proportional to $\eta \cdot \text{grad}_{\theta} L_{total}(\theta; D_{hold})$

where L_{total} includes prediction error terms that were previously suppressed by low-coherence priors. Practically, this results in the surfacing of contradictions (beliefs that fail to explain held states) that must be revised. This update dynamic is formalized in active inference as precision-weighted prediction error

minimization and corresponds to our observed “quality control” phenomenon. [5]

5.9 Empirical signatures and testable predictions

P1 (Selection stability tradeoff): Increasing b (coherence weight) in the selection rule raises frame stability (longer holding durations) but reduces exploratory policy diversity; this tradeoff can be measured in simulated agents by plotting mean hold_time vs policy entropy under varying b . [Mechanism; testbed: hierarchical RL]

P2 (EGS predictive utility): Short-horizon changes in EGS predict subsequent policy-switch probability within Δt minutes in human experiments; validation via logistic regression controlling for task difficulty and baseline affect. [Hypothesis; testbed: human lab tasks with HRV + ladder]

P3 (FREQ correlation): Cumulative $\text{FREQ}(t; \Delta)$ correlates positively with Option-Availability metrics $|A_{\text{eff}}(t)|$ and with subjective reports of perceived affordances. [Hypothesis; testbed: ecological sampling + experience sampling measures]

P4 (Quality Control latency): The time between holding a high-coherence frame and subsequent belief revision (quality control latency) scales with prior strength (measured by prior concentration); stronger priors lead to longer latency and more abrupt updates. [Hypothesis; testbed: belief-update intervention]

5.10 Implementation notes and instrumentation

- Human studies: EGS mapping requires a validated ladder instrument plus physiological proxies (HRV spectral components; EEG coherence). Use mixed models to analyze within-subject time series with temporally lagged coherence predictors.
- Agent implementations: use modular hierarchical RL frameworks (options framework, meta-RL) with coherence function approximators (neural density estimators or ensemble predictive models) and treat FREQ as a persistent meta-state feature.
- Reproducibility: provide code templates for coherence computation (cosine embedding version, KLD version) and for ResonanceEngine pseudocode in a public repository (Appendix B references).

5.11 Related work pointers (to be expanded in Section 6)

- Active inference and model evidence as selection criteria (Friston et al.) [5], [6]
- Affect as intrinsic reward and affect-driven RL (Barthet et al.; Play with Emotion) [11]
- Hierarchical RL and meta-control frameworks (options, meta-learning) (Sutton & Barto; Janssen et al.) [8], [12], [7]
- HRV and interoceptive measures as coherence proxies (Lazzarelli et al.; Barrowclough et al.) [9]

Transition

Section 6 will evaluate the scientific foundations and evidence for the constructs introduced here, mapping each to extant literatures in control theory, affect science, active inference, and hierarchical RL. Appendix A provides operational protocols and preregistration templates for the experiments suggested in Sections 4–5.

6. The Science Behind the Model: Mapping ConsciOS to Established Literatures

Purpose and scope. This section locates the ConsciOS architecture within relevant scientific literatures, highlights where it converges with existing mechanisms, and clarifies which claims are novel hypotheses requiring empirical validation. The aim is practical: (a) show reviewers that ConsciOS is built on well-studied mechanisms, (b) identify exact points of extension or difference, and (c) propose concrete measurement and evaluation strategies for each claim.

Structure. We organize the mapping into five interlinked domains: (1) systems theory & cybernetics; (2) predictive processing / active inference; (3) affect science & interoception; (4) hierarchical reinforcement learning and meta-learning; (5) human-in-the-loop, RLHF, and applied AI alignment. For each domain we (i) summarize the core relevant ideas, (ii) show how ConsciOS reuses or extends them, (iii) mark model status ([Mechanism], [Analogy], [Hypothesis]), and (iv) list measurement suggestions.

6.1 Systems theory and cybernetics

Summary. Stafford Beer’s Viable System Model (VSM), Checkland’s systems practice, and classical cybernetics formalize how nested control architectures, recursion, and governance sustain viable behavior in complex organizations and organisms [3], [4]. VSM decomposes systems into operational units, adaptation/intelligence functions, and policy/governance.

ConsciOS mapping. ConsciOS directly leverages VSM’s decomposition: Echo-Self → VSM S1–S3; Super-Self → VSM S4; Meta-Self → VSM S5. This provides a credible engineering lineage for nested controllers and motivates our emphasis on governance, quality control, and structural redesign as leverage points. Where ConsciOS extends VSM is in operationalizing affective/coherence signals (EGS, Kernel) as real-time internal feedback that indexes option-availability and drives selection dynamics.

Model status: the nested decomposition is [Mechanism] (well supported); the affective/coherence mapping onto VSM is an integrative extension ([Hypothesis] at the empirical level until measured).

Measurement & tests: map VSM components to measurable logs (policy switches, control bandwidths), test viability metrics under perturbations, and

compare hierarchical vs flat controllers under similar constraints.

6.2 Predictive processing and active inference

Summary. Predictive processing and active inference cast perception and action as inference: agents minimize prediction error (or maximize model evidence) through action and belief updating [5], [6]. Hierarchical priors determine what the system expects, and precision weighting governs which errors prompt updates.

ConsciOS mapping. The Resonance Engine’s coherence metric (C) parallels model evidence and the selection rule (maximize $aE[U] + bC - g*Cost$) re-frames selection as evidence-weighted policy choice. The Meta-Self corresponds to long-timescale priors; Super-Self performs evidence accumulation and selection. Quality Control dynamics directly correspond to precision-weighted prediction error updates: holding a new frame increases exposure of misalignments that drive belief revision.

Model status: strong formal alignment — many ConsciOS mechanisms are [Mechanism] under active inference reframing; selection weighting (a, b tuning) and FREQ Coin as time-integrated evidence are integrative hypotheses that can be formalized and tested [Hypothesis -> Mechanism with empirical support].

Measurement & tests: implement coherence as model evidence or KLD; compare selection by evidence vs utility in simulated agents; use active-inference benchmarks to evaluate frame holding, belief revision timing, and quality-control signatures.

6.3 Affect science and interoception

Summary. Modern affect science treats interoception and bodily signals (HRV, autonomic markers, EEG indices) as central to emotion, valuation, and decision-making (Barrett, Damasio, Seth and interoception reviews) [9]. Measures of interoceptive accuracy and physiological coherence correlate with self-reported affect and decision patterns.

ConsciOS mapping. The Emotional Guidance Scale (EGS) is proposed as an operational, discretized index derived from interoceptive signals and subjective ladder responses. Kernel proxies (HRV, EEG coherence) instantiate the central integrative signal. We propose that EGS and Kernel serve as rapid, low-bandwidth heuristics for local search (NLS) and as shaping signals for agents.

Model status: use of interoceptive measures as feedback is [Mechanism] in affect science; application as an online control heuristic (EGS used to guide nearest-lighter-step local search, and as shaping reward) is a translational [Hypothesis] requiring human and agent validation.

Measurement & tests: validate EGS mapping to physiological markers and predictive power for subsequent policy choice; test HRV/EEG proxies as predictors of option-availability and coherence; implement EGS as intrinsic reward in agent training and measure learning efficiency and human-agent alignment.

6.4 Hierarchical reinforcement learning & meta-learning

Summary. Hierarchical RL (options framework) and meta-learning formalize how agents learn temporally abstract actions and how priors or meta-policies accelerate transfer and adaptation (Sutton & Barto; recent HRL surveys) [8], [12], [7]. Switching controllers and gated meta-policies provide the algorithmic ground for layered control.

ConsciOS mapping. Echo/Super/Meta map naturally to low-level option executors, mid-level policy selectors, and meta-learning priors. The FREQ Coin concept operationalizes the resource gating that unlocks higher-complexity frames, analogous to budgeted computation or curiosity rewards.

Model status: algorithmic mapping is [Mechanism]. The specific FREQ Coin operationalization (time-integrated coherence gating higher frames) is a design innovation and thus a [Hypothesis] until benchmarked across meta-RL tasks.

Measurement & tests: implement hierarchical agents with FREQ gating; compare to standard HRL baselines on transfer, resilience to shift, and computational cost. Log policy diversity and measure relation between sustained coherence and unlocked policy complexity.

6.5 Human-in-the-loop learning, RLHF, and AI alignment

Summary. Human feedback (RLHF) and human-in-the-loop systems use user signals to shape agent policies. Recent alignment work emphasizes hybrid architectures combining human priors, interpretability constraints, and intrinsic agent objectives (Zeng et al.; review literature) [10].

ConsciOS mapping. EGS signals and Kernel proxies are candidate human feedback channels for RLHF—fast, affect-informed signals that can shape agent selection and policy priors. The nested controller architecture provides an alignment affordance: Super-Self and Meta-Self can serve as interpretability and governance layers enforcing safety constraints.

Model status: the high-level mapping to alignment frameworks is [Analogy] with practical potential; operational details of EGS as RLHF require human trials and careful safety considerations (ethical, adversarial feedback, reward hacking) — therefore [Hypothesis].

Measurement & tests: small-scale human-in-the-loop trials using EGS telemetry as shaping reward; measure agent behaviour, alignment metrics, and human perceived control/agency; evaluate safety failure modes (adversarial signals, goal hacking).

6.6 Limitations of the current evidence base & open challenges

- Empirical grounding: several central ConsciOS constructs (FREQ Coin, NLS heuristic, Resonance Engine weighting) are engineering hypotheses with attractive theoretical grounding but limited direct empirical evidence; they require simulation and human experiments.

- Measurement validity: interoceptive proxies (HRV, EEG) are imperfect and noisy. Validating robust EGS mappings across populations and contexts is nontrivial.
- Operational complexity: implementing coherent coherence metrics across multi-modal inputs requires careful model selection, calibration, and computational budgets.
- Ethical and safety concerns: using physiological/affective signals as shaping rewards raises consent, privacy, and manipulation concerns. Any human-in-the-loop work must prioritize ethical review and safeguards.

6.7 Synthesis and research agenda

Short-term priorities (0–6 months):

- Formalize coherence metrics (KLD, log evidence, embedding similarity) and publish benchmarks.
- Implement hierarchical RL agents with a FREQ gating mechanism and run transfer/adaptation benchmarks.
- Run pilot human studies validating EGS mapping to HRV and predictive power for option-availability.

Medium-term priorities (6–24 months):

- Human-in-the-loop RLHF trials using EGS as shaping signal with strong safety monitoring.
- Cross-domain replication (lab, ecological sampling, simulated agents) and release of open datasets and code.
- Comparative studies mapping ConsciOS constructs to VSM/active inference control metrics in organizational settings.

Model status summary. The paper’s structural mappings to systems theory, active inference, and hierarchical RL are principally [Mechanism]. Key operational innovations (EGS as fast control signal; FREQ Coin gating; NLS heuristic) are currently framed as [Hypothesis] and will be elevated to [Mechanism] as empirical evidence accumulates.

6.8 Concluding note for Related Work integration

The Related Work section (below) will assemble the precise references and weave them into the narrative above. For the immediate iteration of the paper we have anchored the ConsciOS architecture in canonical literatures (Beer; Friston; hierarchical RL; affect/interoception reviews). The next step is to integrate the verified DOIs/PDFs you retrieved and convert the placeholders above into inline citations and a compact Related Work synthesis.

7. The AI Mirror — Applications to Artificial Agents and Alignment

7.1 Purpose and scope

This section translates the ConsciOS architecture into concrete architectures,

experiments, and governance patterns for artificial agents. The goal is practical: demonstrate how the Echo/Super/Meta decomposition, Resonance Engine, EGS, and FREQ Coin can be implemented and tested in agentic systems; identify alignment and safety affordances; and propose pilot deployments that produce measurable scientific output.

7.2 Mapping ConsciOS to AI agent architectures

- Embodied controller / low-level policy (Echo-Self): Implemented as a fast policy module or low-level controller in robotics or simulated agents (e.g., policy `pi_e` parameterized by neural networks or model predictive controllers). It handles sensory inputs and immediate action loops and exposes short-horizon telemetry (latencies, action entropy). (Place: agent S1–S3). [8]
- Supervisory controller / policy selector (Super-Self): Implemented as a mid-level manager that selects or composes policies from a policy library or a set of options. Technically realized as a policy-over-options, gating network, or a learned selector (e.g., meta-controller). It evaluates coherence metrics and expected utility and implements the ResonanceEngine selection rule. (Place: agent S4). [12]
- Meta-controller / prior generator (Meta-Self): Implemented as a meta-learning or prior-shaping module: e.g., an outer loop that updates priors, regularizers, or initializations (MAML-style, population-based training, or distributional priors). It controls long-term adaptation, governance constraints, and objective shaping. (Place: agent S5). [8]
- Centralized coherence estimator, discretized affect index, and time-integrated coherence resource (Kernel / EGS / FREQ): Implemented as telemetry and meta-features. Kernel = centralized coherence estimator; EGS = scalar intrinsic signal (learned/regressed from internal state plus proxy interoceptive metrics); FREQ = persistent meta-state (time-integrated coherence). These variables inform gating, reward shaping, and policy unlocking dynamics.

7.3 Concrete technical experiments (agentic testbeds)

Below are prioritized experiments that produce defensible empirical claims and are tractable in standard agent frameworks.

Experiment 1: Hierarchical Agent Benchmark (Echo/Super/Meta vs Flat)

- Setup: Build two agents in a procedurally generated environment with episodic distributional shifts: (A) Hierarchical agent with Echo/Super/Meta and FREQ gating; (B) Flat baseline agent with comparable parameter count.
- Manipulations: Introduce sudden context shifts and resource constraints; vary b/a weights in the Resonance selection rule.
- Metrics: cumulative reward, adaptation latency (time to recover pre-shift performance), policy diversity, computational cost.

- Expected result: Hierarchical agent exhibits faster recovery, higher transfer, and graceful degradation under constraints if Meta/Super stratification is effective. [Mechanism / Hypothesis]

Experiment 2: EGS as Intrinsic Reward (Affect-Driven RL)

- Setup: Train agents with an intrinsic reward augment derived from an EGS proxy (e.g., internal predictive fit signal or simulated interoception). Compare to agents with standard curiosity or novelty intrinsic rewards.
- Manipulations: Vary scale of EGS influence; test in sparse reward environments.
- Metrics: sample efficiency, exploration patterns, policy robustness.
- Expected result: EGS-shaped agents show improved exploration aligned with long-horizon coherence; risk: reward hacking — monitor for adverse optimization. [Hypothesis]

Experiment 3: Human-in-the-Loop EGS Shaping (RLHF variant)

- Setup: Recruit human participants to provide fast EGS signals (subjective 1–10 ladder) while interacting with an environment; use EGS as shaping reward during agent fine-tuning.
- Manipulations: Compare shaped vs unshaped agents and compare different EGS smoothing/decay regimes.
- Measures: agent alignment to human preferences, transfer, and human perceived control and agency.
- Safety guardrails: explicit consent, adversarial signal detection, audit logs, human override. Ethical review required. [Hypothesis]

Experiment 4: FREQ Gate Unlocking Complexity

- Setup: Implement FREQ(t) as time-integrated coherence; implement high-cost policies that require $\text{FREQ} \geq \theta$ to unlock.
- Metrics: policy complexity usage, cost efficiency, task performance under time pressure.
- Expected result: FREQ gating yields more conservative resource allocation and reduces spurious activation of expensive policies while enabling high-value policy use when coherence is sustained. [Hypothesis]

7.4 Prototype applications and pilot domains

- Simulated agent research labs: immediate testbeds for Experiments 1–4 using OpenAI Gym variants, ProcGen, or custom procedurally generated environments.
- Robotics / embodied agents: Echo-Self controllers in mobile platforms; Super-Self for task selection (home assistant switching tasks); pilot complexity gating with FREQ in battery-constrained robots.
- Smart home context: integrate EGS proxies from occupant devices (consented HRV wearables) to adapt lighting/temperature policy selection — low-risk pilot if privacy/consent is addressed.

- Organizational decision support: simulate Echo/Super/Meta as team roles in collaborative platforms to test policy selection and governance before automation.

7.5 Governance, safety, and ethical considerations

- Measurement validity & privacy: physiological signals (HRV, EGS proxies) are sensitive. All human data collection must follow IRB, GDPR/CCPA compliance, and local regulation. Use minimal necessary telemetry and strong anonymization.
- Reward hacking & manipulation: EGS used as shaping reward may be manipulated. Implement adversarial detection, signal plausibility checks, and human override.
- Interpretability & auditability: Design Super-Self and Meta-Self with explicit logging, provenance, and interpretable selection traces to enable audits and post-hoc explanations for policy selection.
- Safety layering: Ego Autopilot / pi_safe must be robust to adversarial inputs and designed by principled safety engineering (conservative defaults, kill-switches, oversight loops).
- Governance pathways: include stakeholder review boards, transparency reports, and open pre-registration of human trials; consider third-party audits for high-impact deployments.

7.6 Metrics, benchmarks and evaluation protocol

Suggested canonical metrics for pilot evaluation:

- Agent performance: cumulative reward, normalized performance relative to baseline.
- Adaptation: adaptation latency post distributional shift, recovery ratio.
- Option-availability proxy: measured $|A_{\text{eff}}(t)|$ via simulated affordance enumeration or human reported affordance counts (experience sampling).
- Coherence correlation: Spearman/Pearson correlation of coherence metric C with EGS proxies and with downstream performance improvements.
- FREQ impact: correlation and causal estimates (instrumental variable or randomized threshold experiments) of FREQ on policy unlocking and sustained performance.
- Safety metrics: frequency of pi_safe engagements, rate of adversarial detection triggers, human override rate.

7.7 Roadmap for pilots, datasets, and reproducibility

- Phase 0 (0–2 months): Code templates for ResonanceEngine, coherence functions (cosine/embedding/KLD), and FREQ computation; seed simulated envs.
- Phase 1 (2–6 months): Run Experiment 1–2 in simulation; open-source code and baseline datasets; preprint results for community review.
- Phase 2 (6–12 months): Human pilot for Experiment 3 under IRB; release anonymized datasets and analysis scripts; produce safety/adversarial anal-

ysis.

- Phase 3 (12–24 months): Domain pilots (robotics, smart home) with external audits and governance reporting; refine Meta-Self governance patterns for organizational deployment.

7.8 Funding, community, and research agenda

Priority funding areas:

- Core research: hierarchical agent benchmarks and coherence metric standardization.
- Measurement science: validating EGS mappings across populations and contexts.
- Safety research: reward-shaping failure modes, adversarial robustness of EGS signals, and governance tooling.

Community building:

- Open dataset & baseline repo for coherence and FREQ experiments.
- Incentivized hackathons & shared benchmarks to accelerate reproducibility.
- Collaborative pilots with human factors labs and AI alignment groups.

7.9 Concluding practical note

ConsciOS provides a layered architecture that is especially well-suited for hybrid human-agent systems where rapid, affective feedback and clear governance are necessary. The proposed experiments are designed to deliver concrete evidence about whether coherence-based gating and affect-informed shaping improve adaptability, transfer, and alignment in hierarchical agents. The next step is to implement the simulation testbeds (Phase 0/1) and publish reproducible baselines that enable community scrutiny.

8. Becoming a Conscious Architect — Practical Implications for Design

8.1 Purpose and scope

This section translates architecture into practice: design patterns, organizational applications, curricula for training human operators, and product prototypes that operationalize ConsciOS in real contexts. It emphasizes repeatability, instrumentation, and governance.

8.2 Design patterns & practices

- Pattern: Nested Controller Decomposition — adopt Echo/Super/Meta separation in system design; log policy families, selection traces, and coherence signals.
- Pattern: Coherence-gated complexity — use FREQ thresholds to gate high-cost capabilities (compute, autonomy, privilege escalation).

- Pattern: Rapid Feedback Loops — implement EGS proxies or synthetic analogues that feed short-horizon controllers for real-time micro-adjustments.

8.3 Organizational applications

- Team design: map Echo roles to operational teams, Super roles to coordination roles, Meta roles to governance/strategy; instrument team decision logs as policy traces.
- Product design: staged feature unlocking by FREQ; adaptability modules for user interfaces based on measured EGS proxies.

8.4 Training & curricula

- Curriculum: imagineer practices → coherence training → quality control drills. Translate book protocols into training modules (micro-exercises with measurement).
- Operator tooling: dashboards that show coherence, FREQ balances, and option-availability metrics to support decision making.

8.5 Implementation checklist

- Instrument short-horizon telemetry (Echo logs).
- Implement a coherence estimator and EGS proxy.
- Build policy library & gating logic (FREQ).
- Design governance & safety overrides (Ego Autopilot).

Summary. Practical playbook—instrument, gate, and train around coherence as the operational lever. This summarizes the recommended sequencing for practitioners implementing ConsciOS patterns in applied settings.

9. Discussion, Limitations & Future Work

9.1 Summary of contributions

We formalized a nested control architecture for consciousness, introduced resonance and coherence metrics, operationalized affect as an internal feedback channel (EGS), and proposed an empirical roadmap spanning simulation and human trials.

9.2 Limitations

- Measurement validity: physiological proxies (HRV, EEG) are noisy and context-sensitive.
- Operational complexity: multi-modal coherence computation is computationally nontrivial.
- Ethical concerns: privacy, signal manipulation, and reward-hacking risks in human-in-the-loop settings.
- Novelty limits: several constructs are integrative—must avoid overclaiming novelty where existing work overlaps.

9.3 Response strategies

- Emphasize operationalization and replication (Appendices A–B).
- Publish code, datasets, and pre-registrations to accelerate independent validation.
- Design safety audits and third-party reviews for human pilots.

9.4 Future work and roadmap (research priorities)

- Formal benchmarks for coherence metrics.
- Large-scale, cross-population validation of EGS mappings.
- Hierarchical agent competitions with standardized FREQ gating.
- Governance patterns & audit tooling for high-impact deployments.

Summary. Honest appraisal of risks and a practical research agenda to mature the approach. This section prioritizes measurements, benchmarks, and safeguards required to evaluate the model rigorously.

10. Conclusion

We present ConsciOS as a unified engineering program for designing and testing layered control architectures that bridge human introspective practice and formal AI systems. By grounding narrative constructs (Echo-Self, EGS, FREQ Coin) in canonical control, inferential, and affective literatures, ConsciOS aims to create reproducible experiments and practical pilots that advance our ability to design safer, more adaptive hybrid systems. We invite researchers, engineers, and practitioners to implement, test, and critique the proposed models and to collaborate on open benchmarks and datasets.

Summary. ConsciOS re-frames consciousness as an engineering problem—testable, instrumentable, and governable. The concluding note emphasizes collaborative implementation and rigorous evaluation.

Appendix A — Experimental protocols

Experimental Protocols (full templates)

- A.1 H1: Structure-Change Leverage RCT (human) — objectives, sample sizes, randomization, outcome metrics, analysis plan, preregistration template.
- A.2 H2: Feedback Coherence → Option-Availability (ecological sampling + lab micro-tasks).
- A.3 H3: Nested Controller Benchmark (simulations) — environment specs, seeds, agent code skeleton, logging format.
- A.4 H4: EGS as RLHF shaping (pilot human trials) — consent forms, pre-screening, safety checks, adversarial monitoring.

- A.5 Toy ablation (simulation demo) — purpose: verify telemetry and selector sensitivity. Setup: episodic context shifts; hierarchical agent with coherence-weighted selection (b, a sweeps); outputs: selection traces and aggregated heatmaps (reward, alignment rate, position-match proxy). Code: repository `code/` directory (env, agents, plots); figures are illustrative only.

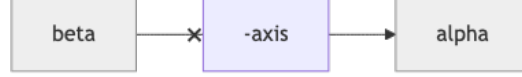


Figure 6: Figure A1. Toy ablation heatmaps across b x a (reward, alignment rate, position-match). Illustrative demo; not a benchmark result.

(Each template: stepwise procedure, required hardware/software, analysis scripts skeleton, expected effect sizes, power calculations placeholder.)

Appendix B — Measurement Instruments & Analysis Pipelines

- B.1 HRV measurement spec (sensor types, sampling rates, preprocessing).
- B.2 EEG coherence pipeline (preprocessing, epoching, PLV/ISC metrics).
- B.3 Coherence computation code (KLD, log-evidence, embedding cosine examples) — link to code repo skeleton.
- B.4 Policy logging schema & Super-Self selection trace format (JSON schema).
- B.5 Statistical analysis pipelines (time-series mixed models, Granger/VAR, causal estimation approach).

Appendix C — Public Translation & Operationalization

ConsciOS term — Echo-Self - Canonical equivalent (scholarly): Embodied controller / short-horizon perception-action loop - Operational definition / measures: Local actor subsystem executing fast closed-loop control. Measures: re-action latency, action entropy, short-horizon task performance, sensorimotor noise. - Suggested citation & placement: VSM S1-3 mapping; hierarchical RL; Section 4.1, Appendix B. [3], [12]

ConsciOS term — Super-Self - Canonical equivalent (scholarly): Supervisory controller / mid-horizon policy selector - Operational definition / measures: Aggregates feedback and selects among policy families. Measures: policy selection latency, switch frequency, selection accuracy under perturbation. - Suggested citation & placement: Meta-RL & hierarchical RL; Sections 4.1-4.4. [12], [8]

ConsciOS term — Meta-Self - Canonical equivalent (scholarly): Meta-controller / prior generator (meta-learning) - Operational definition / measures: Encodes long-horizon priors and the generative space of policies. Measures: prior concentration, transfer/meta-learning performance. - Suggested citation & placement: Meta-learning; Sections 4.1 & 7. [8]

ConsciOS term — Kernel - Canonical equivalent (scholarly): Central integrative controller / interoceptive hub - Operational definition / measures: Focal interoceptive/state-confidence signal. Human proxy: HRV, interoceptive accuracy. Agent proxy: estimator precision. - Suggested citation & placement: Interoception literature; Methods/Appendix B. [9]

ConsciOS term — Emotional Guidance Scale (EGS) - Canonical equivalent (scholarly): Discretized affect index / interoceptive feedback variable - Operational definition / measures: Laddered affect used as internal control signal. Measures: self-report ladder, HRV, EEG proxies, affect classification. - Suggested citation & placement: Affect & interoception reviews; Section 5.2 & Appendix A. [9]

ConsciOS term — Resonance Engine - Canonical equivalent (scholarly): Coherence-based selector / evidence-matching selector - Operational definition / measures: Chooses policy frame with maximal coherence; match-score or Bayesian evidence metric. Measures: coherence score, selection confidence. - Suggested citation & placement: Active inference / predictive processing; Section 5.1. [5]

ConsciOS term — FREQ Coin - Canonical equivalent (scholarly): Sustained coherence resource metric (operational currency) - Operational definition / measures: Time-integrated coherence units (e.g., area under coherence curve). Measures: cumulative coherence over window, option-availability proxy. - Suggested citation & placement: Section 5 & Appendix B. [Hypothesis]

ConsciOS term — Quality Control - Canonical equivalent (scholarly): Belief-surfacing / error-signal model revision - Operational definition / measures: Frequency of internal model updates following coherence shifts. Measures: belief entropy, update rate, error magnitude. - Suggested citation & placement: Active inference & Bayesian update; Section 5.4. [5]

ConsciOS term — Parallel VR Engine - Canonical equivalent (scholarly): Pre-compiled policy / scenario library - Operational definition / measures: Library of precomputed policy frames/timelines for selection. Measures: policy diversity, match scores, retrieval latency. - Suggested citation & placement: Meta-RL & simulation; Sections 5.1 / 4.4. [8], [12]

ConsciOS term — Ego Autopilot - Canonical equivalent (scholarly): Fallback safety controller / homeostatic default policy - Operational definition / measures: Low-variance survival policy under low-coherence. Measures: reversion frequency, conservatism index. - Suggested citation & placement: Control theory & safety; Section 4.2. [1]–[4]

ConsciOS term — The Iceberg - Canonical equivalent (scholarly): Diagnostic hierarchy: Event -> Pattern -> Structure -> Mental Model - Operational definition / measures: Layer-specific tests: event logs (time-series), pattern indices, structural graphs, belief inventories. - Suggested citation & placement: Systems thinking (Meadows; Senge); Section 2.1. [1], [2]

ConsciOS term — The 7 Flows - Canonical equivalent (scholarly): Inputs ->

Processes -> Outputs -> Feedback -> Actors -> External Constraints -> Internal Constraints - Operational definition / measures: Systems decomposition—each flow has standard metrics (throughput, latency, bottleneck). - Suggested citation & placement: Systems engineering & cybernetics; Section 2.2.

Notes:

- Canonical terms are primary in methods and analytic language. ConsciOS aliases are pedagogical—they appear in parentheses at first mention and in Appendix C for public readers.
- For each term, Appendix B contains measurement protocols and recommended instruments (e.g., HRV measurement specs, EEG coherency pipeline, policy-switch logging format).

C.1 Public notes

This appendix translates public-facing terms to canonical scholarly equivalents and points to where measures and instruments are defined. Editorial prompts used during drafting have been removed from the preprint version.

References

- [1] P. M. Senge, “The Fifth Discipline: The Art and Practice of the Learning Organization,” Revised and Updated. Doubleday/Currency, 2006.
- [2] D. H. Meadows, “Thinking in Systems: A Primer.” Chelsea Green Publishing, 2008.
- [3] S. Beer, “Brain of the Firm.” John Wiley & Sons, 1972.
- [4] P. Checkland, “Systems Thinking, Systems Practice.” John Wiley & Sons, 1981.
- [5] K. Friston, “The free-energy principle: a unified brain theory?,” *Nature Reviews Neuroscience*, vol. 11, no. 2, pp. 127–138, 2010. doi:10.1038/nrn2787.
- [6] P. Lanillos, C. Meo, C. Pezzato, et al., “Active Inference in Robotics and Artificial Agents: Survey and Challenges,” arXiv:2112.01871, 2021.
- [7] S. Pateria, B. Subagdja, A.-H. Tan, and C. Quek, “Hierarchical Reinforcement Learning: A Comprehensive Survey,” *ACM Computing Surveys*, 54(5), 1–35, 2021. doi:10.1145/3453160.
- [8] R. S. Sutton and A. G. Barto, “Reinforcement Learning: An Introduction,” 2nd ed. MIT Press, 2018.
- [9] L. F. Barrett and W. K. Simmons, “Interoceptive predictions in the brain,” *Nature Reviews Neuroscience*, vol. 16, pp. 419–429, 2015. doi:10.1038/nrn3950.
- [10] L. Ouyang, J. Wu, X. Jiang, et al., “Training language models to follow instructions with human feedback,” in *Advances in Neural Information Processing Systems (NeurIPS)*, 2022. arXiv:2203.02155.

- [11] M. Barthet, A. Khalifa, A. Liapis, and G. N. Yannakakis, “Play with Emotion: Affect-Driven Reinforcement Learning,” in 2022 10th International Conference on Affective Computing and Intelligent Interaction (ACII), 2022. doi:10.1109/ACII55700.2022.9953894.
- [12] R. S. Sutton, D. Precup, and S. Singh, “Between MDPs and semi-MDPs: A framework for temporal abstraction in reinforcement learning,” *Artificial Intelligence*, vol. 112, nos. 1–2, pp. 181–211, 1999. doi:10.1016/S0004-3702(99)00052-1.

Change Log / Versioning Notes

See `change-log-major-edits.md` for a detailed list. Summary: * v1.0 — initial public preprint; formal tone, canonical-first terms, figures linked, citations integrated, Appendix C table added, preprint assets packaged.