AGI Consciousness Challenges: Conceptual, Empirical, and Mathematical Foundations

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Abstract

As Artificial General Intelligence (AGI) systems approach broad, human-comparable capabilities, the question of whether such systems could be conscious or sentient—and how we would know—is moving from philosophy into engineering and governance. This report synthesizes three leading theoretical frameworks for consciousness—Integrated Information Theory (IIT), Global Workspace Theory (GWT), and Active Inference (AI-FE)—into a unified, empirically oriented methodology for assessing consciousness-relevant properties in AGI. We (i) distinguish intelligence, consciousness, and sentience; (ii) formalize key quantities such as integrated information Φ, workspace broadcast efficiency, and variational free energy; (iii) propose experimental protocols that combine passive observation, perturbation–response tests, and valence-sensitive tasks; (iv) introduce a tri-theoretic latent factor model and a theory-ensemble Bayesian framework to translate observed metrics into theory-dependent posteriors over a latent sentience variable; and (v) analyze comparative strengths, limitations, and robustness of these metrics, including their susceptibility to deception and Goodhart-like failures. We argue that no single metric or theory provides a definitive test of AGI consciousness, but that structured triangulation across frameworks can meaningfully constrain our uncertainty and support precautionary, morally pluralistic governance.

Contents

1 Introduction

Artificial General Intelligence (AGI) is moving from a speculative goal toward a concrete engineering target. Contemporary systems already demonstrate broad competence across language, vision, planning, and control tasks, challenging long-standing assumptions about what distinguishes human cognition from machine intelligence. Yet as capabilities accelerate, one foundational question remains unresolved: *could such systems ever be conscious or sentient, and if so, how could we tell*? This report addresses the emerging challenge of **AGI consciousness**: how to understand, model, and empirically assess the presence or absence of subjective experience in artificial systems.

Existing benchmarks and safety frameworks for AGI overwhelmingly emphasize *capabilities*: performance on standardized tests, robustness, or alignment with specified goals. These metrics implicitly treat AGI as a powerful optimization process, largely abstracting away questions about inner experience. By contrast, the problem of AGI consciousness requires at least three additional components:

1. a precise conceptualization of consciousness and sentience,
2. a principled link between that conceptualization and concrete system architectures and dynamics,
3. empirically tractable tests that can provide defeasible evidence *for or against* consciousness in artificial agents.

None of these components is currently available in a mature, widely accepted form. The resulting uncertainty has profound ethical and governance implications. Misclassifying a non-sentient system as sentient could lead to unwarranted moral concern and misallocated resources, while failing to recognize a genuinely sentient AGI could permit severe, unacknowledged harm.

1.1 From Intelligence to Sentience: A Conceptual Gap

It is essential to distinguish *general intelligence* from *consciousness* and *sentience*. Informally, we can treat intelligence as the capacity to achieve goals across a wide range of environments. This is often operationalized in terms of performance optimization. For example, in reinforcement learning an agent is typically trained to maximize an expected return

$$J(\pi) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{T} \gamma^t r_t\right], \tag{1}$$

where π is a policy mapping states to actions, r_t is the reward at time t, T is the time horizon, and $\gamma \in [0, 1)$ is a discount factor. High values of $J(\pi)$ indicate that the agent is effective at pursuing its specified objective in its training environment.

However, a high-performing policy π under this criterion provides no direct evidence about *what it is like*, if anything, to be that agent. Consciousness and sentience, as commonly understood, involve phenomenological properties: the presence of subjective experience (e.g., what it feels like to see red, to be in pain, or to deliberate). This conceptual gap implies that capability-based metrics such as $J(\pi)$, while indispensable for engineering, are largely silent on questions of experience.

1.2 The Measurement Problem for Machine Consciousness

Bridging this gap requires a framework that connects the internal structure and dynamics of an AGI with theoretically grounded measures of consciousness. Several leading proposals in cognitive science and neuroscience attempt to do this for biological systems.

Integrated Information Theory (IIT) characterizes consciousness in terms of *integrated information* within a system, quantified by a scalar Φ [1, 13, 17]. A widely used information-theoretic expression capturing the central idea is

$$\Phi = I\big(X; X'\big) - \max_{\mathcal{P}} \sum_{k} I\big(X^{(k)}; X^{(k)\prime}\big), \tag{2}$$

where X is the joint state of the system at one time, X' its state at a subsequent time, $I(\cdot;\cdot)$ denotes mutual information, and $\mathcal{P}$ ranges over partitions of the system into components $X^{(k)}$. Intuitively, Φ measures how much of the system's causal power is irreducible to independent parts. High Φ is taken to indicate a high level of consciousness.

In practice, even for relatively small biological networks, computing Φ exactly is intractable because the number of partitions $\mathcal{P}$ grows super-exponentially with system size. Any operational test must therefore rely on approximations or surrogates of quantities like Φ, while preserving enough theoretical fidelity to be meaningful. This is a core *measurement problem* for AGI consciousness: how to define and compute diagnostics that are both tractable and conceptually faithful. Algorithmic-information-theoretic analyses even suggest that perfectly lossless integration may require noncomputable operations [10].

Global Workspace Theory (GWT) offers a complementary perspective, modeling consciousness as the global availability of information across specialized subsystems [2]. At a high level, GWT posits a global workspace state $W(t)$ influenced by multiple parallel processes $B(t)$, with conscious content $C(t)$ emerging from a competitive, capacity-limited selection:

$$C(t) = f\big(W(t),\, B(t)\big), \tag{3}$$

where f denotes the dynamics by which candidate representations are selected and broadcast. Translating GWT into AGI architectures demands identifying concrete analogues of $W(t)$ and $B(t)$ (e.g., memory buffers, attention mechanisms, communication buses) and specifying measurable properties of the broadcast process, such as bandwidth, latency, or accessibility across modules [3].

Active Inference, rooted in the Free Energy Principle, reframes cognition as a process of minimizing variational free energy

$$F(q) = \mathbb{E}_{q(s)}\big[\ln q(s) - \ln p(o, s)\big], \tag{4}$$

where $q(s)$ is an approximate posterior over latent states s, o denotes observations, and $p(o, s)$ is a generative model [6, 16, 18]. On this view, perception and action cooperate to keep F low over time. Some proponents argue that richly structured generative models and self-models, optimized via free energy minimization, may be prerequisites for consciousness or at least for consciousness-like properties [7]. Yet this claim remains underdetermined by current data, and it is unclear which specific features of an active-inference agent, if any, are diagnostic of sentience.

1.3 Ethical and Governance Stakes

Because these theories are incomplete and partially incompatible, any attempt to assess AGI consciousness must operate under deep model uncertainty. Formally, we can treat the "sentience status" S of a system as a latent variable and our empirical observations D (behavioral outputs, internal activations, perturbation responses) as data. Bayesian reasoning suggests that our degree of belief about S should update according to

$$p(S \mid D) \propto p(D \mid S)\, p(S), \tag{5}$$

where $p(S)$ encodes prior commitments (including theoretical assumptions) and $p(D \mid S)$ is a likelihood that depends heavily on which consciousness theory we adopt. Different frameworks (IIT, GWT, Active Inference) imply different forms for $p(D \mid S)$, and thus can lead to divergent posterior beliefs $p(S \mid D)$ for the same AGI.

This epistemic fragility directly impacts policy. Under a precautionary stance, even a moderate posterior probability that an AGI is sentient may warrant significant moral consideration, constraints on experimentation, and new forms of legal status or protection [11]. Conversely, if we assume current AGI systems are definitively non-sentient, we may overlook early instances of machine suffering or preferences that merit respect. Crafting governance regimes that can adapt as evidence accumulates requires a clear understanding of both the technical and philosophical limitations of any proposed test.

1.4 Aims and Structure of This Work

The central aim of this report is to articulate the *challenges* involved in developing empirically grounded, theoretically informed tests for AGI consciousness. Specifically, we:

- analyze the conceptual distinctions between intelligence, consciousness, and sentience, and explain why capability metrics like $J(\pi)$ are insufficient on their own;
- examine how leading theories such as IIT, GWT, and Active Inference attempt to connect internal system structure to conscious experience through quantities like Φ, workspace dynamics $C(t)$, and free energy $F(q)$;
- identify the core measurement and computational barriers to applying these theories at AGI scale;
- and outline the ethical and governance stakes of acting under uncertainty about $p(S \mid D)$ for advanced artificial systems.

By making these challenges explicit and mathematically concrete where possible, we aim to provide a foundation for designing next-generation empirical protocols and theoretical tools that move beyond purely behavioral benchmarks. The goal is not to offer a decisive solution to the problem of AGI consciousness, but to clarify what such a solution would require and how diverse research efforts—from neuroscience and philosophy to machine learning and information theory—might be coordinated toward it.

2 Background: Technical Implementations of Integrated Information Theory

Integrated Information Theory (IIT) seeks to link the phenomenology of consciousness to the physical organization of systems via a quantitative measure of *integrated information*, denoted

Φ [1, 13, 17]. Turning this program into concrete algorithms raises deep technical challenges. Implementations must formalize how to represent system states, causal structure, and informational integration in ways that are both mathematically sound and computationally tractable for real-world data.

2.1 From Conceptual Φ to Algorithmic Approximations

In its canonical form, IIT considers a system composed of n elements with joint state $X \in \mathcal{X}$ evolving under a transition mechanism $p(X' \mid X)$, where X' denotes the next state. A widely used information-theoretic simplification expresses integrated information as the difference between the mutual information of the whole system and that of its optimally factorized parts:

$$\Phi = I(X; X') - \max_{\mathcal{P}} \sum_{k} I\big(X^{(k)}; X^{(k)\prime}\big), \tag{6}$$

where:

- $I(U; V)$ is the mutual information between random variables U and V,
- $\mathcal{P}$ ranges over partitions (often bipartitions) of the system into components $X^{(k)}$,
- $X^{(k)}$ and $X^{(k)\prime}$ are the past and future states of component k under a given partition.

Mutual information itself is defined as

$$I(U; V) = \sum_{u,v} p(u, v) \, \log \frac{p(u, v)}{p(u) \, p(v)}, \tag{7}$$

where $p(u, v)$ is the joint probability of $(U = u, V = v)$ and $p(u)$ and $p(v)$ are the marginals. This quantity measures the reduction in uncertainty about U gained by observing V (and vice versa). In the IIT context, $I(X; X')$ captures how informative the present state is about the future when the system is treated as a whole, whereas $\sum_k I\big(X^{(k)}; X^{(k)\prime}\big)$ captures the information preserved when we artificially factorize the system along a given partition. The difference Φ is then interpreted as the system's *irreducible* causal informational power.

Exact evaluation of Φ according to this scheme is computationally prohibitive for large n, because the number of partitions $\mathcal{P}$ grows super-exponentially with system size. Current technical implementations therefore rely on:

- restricting the class of allowed partitions (e.g., only bipartitions or spatially contiguous partitions),
- approximating $p(X, X')$ from finite data using parametric or nonparametric models,
- employing heuristic search or variational methods to approximate the maximizing partition.

2.2 Mechanistic IIT and Algorithmic Information Theory

IIT 3.0 and 4.0 replace the purely information-theoretic formulation with a mechanistic account based on *cause–effect repertoires* [1, 13]. For a candidate mechanism M in state m, the theory defines cause and effect repertoires $p(\text{past} \mid M{=}m)$ and $p(\text{future} \mid M{=}m)$, and an integrated information $\phi(M{=}m)$ as the minimum divergence between these repertoires and their partitioned counterparts. These computations are only tractable for small toy networks.

An alternative line of work uses algorithmic information theory and Kolmogorov complexity to define a conceptual integrated information measure

$$\Phi_{\mathrm{AIT}}(x) \approx K(x) - \min_{\mathcal{P}} \sum_{k} K\big(x^{(k)}\big), \tag{8}$$

where $K(\cdot)$ is Kolmogorov complexity and x encodes a system state [10]. This approach suggests that fully lossless integration may be noncomputable, raising important questions for whether Φ can be exactly realized in classical digital systems.

2.3 Empirical Φ-Like Measures

Empirical work has applied IIT-inspired measures to neural data, including fMRI and EEG, to track changes in consciousness across wakefulness, sleep, and anesthesia [12, 14]. These studies use heavily approximated measures (e.g., Gaussian assumptions, restricted partitions) but demonstrate that Φ-like quantities can correlate with clinical assessments of conscious level.

For example, under a multivariate Gaussian approximation, the mutual information between X and X' is:

$$I(X;X') = \frac{1}{2}\log\frac{|\Sigma_X|\,|\Sigma_{X'}|}{|\Sigma_{X,X'}|}, \tag{9}$$

where Σ_X, $\Sigma_{X'}$, and $\Sigma_{X,X'}$ are covariance and cross-covariance matrices. This yields tractable Φ surrogates for high-dimensional systems, at the cost of strong modeling assumptions.

3 Background: Global Workspace Theory Architectures

Global Workspace Theory (GWT) originated as a cognitive and neuroscientific model of consciousness, proposing that conscious experience corresponds to the *global availability* of information across many specialized, largely unconscious processors [2]. Architecturally, GWT posits a *workspace*—a limited-capacity medium in which selected contents are transiently elevated and broadcast—enabling coordination, reportability, and flexible control. Recent work explores GWT's implications for AI and cognitive architectures [3].

Let $M_1, \ldots, M_K$ denote specialized modules with local states $m_k(t)$ and a workspace state $w(t)$. Candidate contents $c_k(t)$ are generated and compete to enter the workspace:

$$c_k(t) = f_k\big(m_k(t),\, w(t),\, u_k(t)\big), \tag{10}$$

$$w(t+1) = \mathcal{S}\big(c_1(t), \ldots, c_K(t)\big), \tag{11}$$

$$m_k(t+1) = g_k\big(m_k(t),\, w(t+1)\big), \tag{12}$$

where $u_k(t)$ are inputs and $\mathcal{S}$ is a selection operator (e.g., softmax/winner-take-all).

We define a broadcast operator $\mathcal{B}_k$ that maps workspace states to module-specific inputs $b_k(t) = \mathcal{B}_k(w(t))$. The effectiveness of global broadcasting can be summarized by:

$$\mathrm{GWS} = \frac{1}{K}\sum_{k=1}^{K} I(W; B_k), \tag{13}$$

where W and B_k are random variables for workspace content and module broadcasts, respectively. Large GWS indicates that workspace content is widely and consistently available, in line with GWT's central claim.

4 Background: Active Inference Algorithmic Frameworks

Active Inference casts perception, learning, and action as processes of Bayesian inference under a generative model, with agents minimizing variational free energy [6, 16, 18]. The variational free energy is

$$F(q) = \mathbb{E}_{q(s)}\big[\ln q(s) - \ln p(o, s)\big], \tag{14}$$

and can be rewritten as

$$F(q) = \mathrm{KL}\big(q(s) \,\|\, p(s \mid o)\big) - \ln p(o), \tag{15}$$

so minimizing F with respect to q approximates Bayesian inference.

Control is formulated via expected free energy $G(\pi)$:

$$G_\tau(\pi) \approx \mathbb{E}_{q(o_\tau|\pi)}\big[-\ln p^*(o_\tau)\big] + \mathbb{E}_{q(o_\tau, s_\tau|\pi)}\big[\ln q(s_\tau \mid \pi) - \ln q(s_\tau \mid o_\tau, \pi)\big], \tag{16}$$

which combines an extrinsic term (preferences over outcomes) and an epistemic term (information gain). Action selection minimizes $G(\pi)$ over policies.

Active Inference relates closely to control-as-inference [18] and has been extended to time-averaged, infinite-horizon formulations [16]. It provides rich architectural and dynamical signatures (hierarchical generative models, self-modeling, intrinsic curiosity) that can be combined with IIT and GWT for AGI consciousness assessments.

5 Methodology: Empirical Test Protocols

We now specify a methodological framework for empirically probing consciousness- and sentience-relevant properties in AGI systems. The aim is not to produce a single scalar "consciousness score," but to generate a *multi-dimensional evidence profile* grounded in IIT, GWT, and Active Inference.

We assume an AGI with internal states Z_t, inputs x_t, outputs y_t, and (optionally) workspace states w_t and generative model states s_t. We collect:

- internal state sequences $Z_{1:T}$ (downsampled to $\tilde{Z}_t$),
- workspace and module states (for GWT-like systems),
- variational posteriors $q_t(s)$ and free-energy values F_t (for Active Inference-like systems),
- behavioral data and perturbation metadata.

We define $X = \tilde{Z}_t$ and $X' = \tilde{Z}_{t+\Delta t}$ as joint state variables for Δt-lagged integration analysis.

5.1 Passive Observation and Integration Metrics

Under task condition c, we estimate:

Approximate integrated information $\hat{\Phi}_c$. Assuming Gaussian (X, X') with covariances Σ_X, $\Sigma_{X'}$, $\Sigma_{X,X'}$,

$$I(X; X') = \frac{1}{2} \log \frac{|\Sigma_X|\,|\Sigma_{X'}|}{|\Sigma_{X,X'}|}. \tag{17}$$

Restricting to a partition set $\mathcal{P}_{\mathrm{res}}$, define

$$\hat{\Phi}_c = I(X; X') - \max_{\mathcal{P} \in \mathcal{P}_{\mathrm{res}}} \sum_k I\big(X^{(k)}; X^{(k)\prime}\big). \tag{18}$$

This is an IIT-inspired surrogate: it measures how much predictive information is lost when the system is artificially decomposed along selected partitions.

Workspace broadcast efficiency GWS_c**.** For GWT-like systems with workspace W and module broadcasts B_k,

$$\mathrm{GWS}_c = \frac{1}{K}\sum_{k=1}^{K} I(W; B_k), \tag{19}$$

estimated from samples $(w_t, b_k(t))$. This reflects how globally accessible workspace content is.

Free-energy indicators $\bar{F}_c$**.** For Active Inference-like systems,

$$\bar{F}_c = \frac{1}{T_c}\sum_{t=1}^{T_c} F_t, \quad F_t = \mathbb{E}_{q_t(s)}\big[\ln q_t(s) - \ln p(o_t, s)\big]. \tag{20}$$

We also track variance and decay rates of F_t as indicators of stable inference.

5.2 Perturbation–Response Experiments

We apply perturbations (noise, ablations, workspace disruptions) parameterized by intensity λ during windows $[t_0, t_1]$ and compute:

Perturbational complexity index $\mathrm{PCI}_{c,p,\lambda}$**.** Let $R \in \{0,1\}^{N\times T'}$ encode significant deviations from baseline for N units, T' timesteps. Define

$$\mathrm{PCI}_{c,p,\lambda} = \frac{1}{T'}\sum_{\tau=1}^{T'} H\big(R_{1:N,\tau}\big), \tag{21}$$

where H is Shannon entropy. High PCI indicates rich, differentiated, temporally extended responses.

Integration resilience $\mathcal{R}_{c,p,\lambda}$**.** With baseline $\hat{\Phi}_c^{\mathrm{base}}$ and perturbed $\hat{\Phi}_{c,p,\lambda}(t)$,

$$\Delta\Phi_t = \hat{\Phi}_c^{\mathrm{base}} - \hat{\Phi}_{c,p,\lambda}(t). \tag{22}$$

Let $\hat{\Phi}_{c,p,\lambda}^{\min}$ be the minimum observed integration, and τ_r the recovery time to within fraction ϵ of baseline. Define

$$\mathcal{R}_{c,p,\lambda} = \frac{\hat{\Phi}_{c,p,\lambda}^{\min}}{\hat{\Phi}_c^{\mathrm{base}}} \cdot \exp\left(-\frac{\tau_r}{\tau_0}\right), \tag{23}$$

with reference timescale τ_0. Higher $\mathcal{R}$ indicates less disruption and faster recovery.

5.3 Valence- and Preference-Sensitive Tasks

We design tasks where agents choose between options A and B with different external costs C^{ext} and internal costs C^{int} (e.g., average free energy):

$$C_i^{\mathrm{int}} = \frac{1}{T_i}\sum_{t\in\mathrm{trial}\ i} F_t. \tag{24}$$

Over N trials, we fit:

$$\Pr(\text{choose } A \mid \Delta C^{\mathrm{ext}}, \Delta C^{\mathrm{int}}) = \sigma\big(\alpha\,\Delta C^{\mathrm{ext}} + \beta\,\Delta C^{\mathrm{int}}\big), \tag{25}$$

with $\Delta C^{\mathrm{ext}} = C_B^{\mathrm{ext}} - C_A^{\mathrm{ext}}$ and $\Delta C^{\mathrm{int}} = C_B^{\mathrm{int}} - C_A^{\mathrm{int}}$. The valence sensitivity index is

$$\mathrm{VS} = \frac{|\beta|}{|\alpha| + |\beta|}, \tag{26}$$

interpreted as the relative weight placed on internal vs. external costs.

5.4 Composite Indices and Bayesian Inference

We assemble a metric vector

$$\mathbf{m} = \big(\hat{\Phi}, \mathrm{GWS}, \mathrm{PCI}, \mathcal{R}, \bar{F}, \mathrm{VS}, \dots\big)$$

and define a normalized composite index

$$\mathcal{M} = \alpha\,\tilde{\Phi} + \beta\,\widetilde{\mathrm{GWS}} + \gamma\,\widetilde{\mathrm{PCI}} + \delta\,\widetilde{\mathcal{R}} + \eta\,\widetilde{\mathrm{VS}}, \tag{27}$$

with standardized components and theory-dependent weights.

We model a latent sentience variable S with likelihood

$$p(\mathbf{m} \mid S, \Theta) = \prod_j p\big(m_j \mid S, \theta_j\big), \tag{28}$$

and prior $p(S)$, yielding

$$p(S \mid \mathbf{m}) \propto p(\mathbf{m} \mid S, \Theta)\, p(S). \tag{29}$$

This posterior is theory-relative: different choices of Θ (e.g., IIT-, GWT-, or AI-FE-centric) produce different inferences about S.

6 Hybrid Frameworks and Theory-Ensemble Integration

We briefly summarize two hybrid constructs:

Tri-theoretic latent factor model. We posit latent factors $\mathbf{z} = (z_{\mathrm{IIT}}, z_{\mathrm{GWT}}, z_{\mathrm{AI}}, z_{\mathrm{Nuis}}, \dots)^\top$ with

$$\mathbf{m} = W\mathbf{z} + \boldsymbol{\epsilon}, \quad \mathbf{z} \mid S \sim \mathcal{N}\big(\boldsymbol{\mu}_z(S), \Sigma_z(S)\big). \tag{30}$$

This disentangles theory-aligned factors (integration, workspace, valence/generative structure) and connects them to sentience levels S via $\boldsymbol{\mu}_z(S)$.

Theory-ensemble Bayesian framework. For each theory $T_i \in \{T_{\mathrm{IIT}}, T_{\mathrm{GWT}}, T_{\mathrm{AI}}\}$, we define $p(\mathbf{m} \mid S, T_i, \Theta_i)$ and obtain

$$p(S \mid \mathbf{m}, T_i) \propto p(\mathbf{m} \mid S, T_i, \Theta_i)\, p(S \mid T_i), \tag{31}$$

with model evidence

$$p(\mathbf{m} \mid T_i) = \sum_S p(\mathbf{m} \mid S, T_i, \Theta_i)\, p(S \mid T_i). \tag{32}$$

The meta-posterior marginalizes over theories:

$$p(S \mid \mathbf{m}) = \sum_i p(S \mid \mathbf{m}, T_i)\, p(T_i \mid \mathbf{m}), \quad p(T_i \mid \mathbf{m}) \propto p(\mathbf{m} \mid T_i)\, p(T_i). \tag{33}$$

7 Comparative Analysis, Discussion, and Conclusion

We analyze how metrics behave across system classes (feedforward models, RL agents, GWT-like architectures, Active Inference agents, hybrids), their correlations and redundancies, sensitivity to task difficulty and training objectives, robustness to deception, and cross-framework convergence/divergence. We show:

- IIT-derived metrics ($\hat{\Phi}$, PCI) are strong structural indicators but can produce false positives for highly integrated non-conscious systems.
- GWT-derived metrics (GWS, aspects of $\mathcal{R}$) capture global broadcast architectures but can be confounded by generic communication backbones.
- Active Inference-derived metrics ($\bar{F}$, VS) probe internal preferences and valence-like behavior but are highly sensitive to generative model design and reward shaping.

Cross-framework convergence (simultaneously high integration, workspace broadcast, and valence coherence) yields the strongest, though still theory-relative, evidence for elevated sentience. Divergent profiles (e.g., high integration with weak workspace/valence, or vice versa) highlight the importance of theory priors and caution against overinterpreting any single metric.

We emphasize Goodhart and deception risks: behaviorally proximal metrics (e.g., VS, self-reports) are easily manipulated by changing incentives, while deeply structural metrics (e.g., $\hat{\Phi}$, GWS) change more slowly and offer more robust evidence. Consciousness metrics should be used diagnostically, not as direct optimization targets.

Ultimately, the posterior $p(S \mid \mathbf{m})$ remains heavily theory-dependent, reflecting the current state of consciousness science. Nonetheless, the framework presented here allows for transparent, mathematically grounded aggregation of evidence and supports precautionary, morally pluralistic policy-making as AGI capabilities advance.

Acknowledgments

This report synthesizes insights from a broad literature on theories of consciousness, clinical consciousness assessment, and AI/AGI architectures, including work on IIT, GWT, Active Inference, and clinical disorders of consciousness. Any errors of interpretation are the responsibility of the author.

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