Selective Realization of Conscious Experience:

A Methodological Framework Linking Multimodal Organization, Gravito-Inertial Estimation, and Bodily Self-Consciousness

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August 2026

Abstract

Consciousness science possesses quantitative markers of neural integration, differentiation, criticality, multisensory inference, and bodily self-consciousness, yet lacks consensus on the organizational conditions supporting unified first-person experience. Gravity is universal to ordinary physical systems; conscious experience is selective. This article develops a Selective-Realization Framework (SRF) that formally separates three claims frequently conflated in gravity-related proposals: (i) all physical systems exist within a gravitational/spacetime sector denoted Φ_G; (ii) embodied nervous systems construct an empirically measurable gravito-inertial estimate $F_G^{(N)}$ through vestibular, visual, proprioceptive, and related inference; and (iii) candidate conscious realization is associated with sufficiently organized multimodal latent states for which a preregistered organization statistic Γ exceeds a validated threshold Γ_c. A hypothetical direct fundamental gravitational coupling $F_G^{(P)}$ is retained only as an optional, currently unsupported extension.

The framework provides operational definitions of data-driven latent dimensionality, a candidate integration–differentiation statistic Γ, an operational decoder mapping latent states onto reportable self and perceptual variables, and nested-model tests requiring that $F_G^{(N)}$ demonstrate incremental predictive validity beyond established Bayesian causal-inference baselines and complexity metrics. Topology hypotheses are treated as secondary and strictly data-dependent. A staged experimental program centered on vestibular–visual conflict, body-ownership under altered orientation, and cross-state generalization of organization measures is specified, with mandatory comparison to the Perturbational Complexity Index, criticality metrics, and integration–segregation indices. The SRF constitutes a testable methodological research program for evaluating selective organizational conditions and the contribution of gravito-inertial estimation; it does not solve the hard problem of consciousness and does not claim that gravity itself is conscious.

Keywords: consciousness; bodily self-consciousness; gravity; vestibular system; multisensory integration; selective realization; organization; latent dimensionality reduction; falsifiability

1. Introduction

The empirical science of consciousness has advanced substantially. Global-neuronal-workspace models, integrated-information approaches, recurrent-processing accounts, predictive and inferential models, perturbational complexity, and network measures of integration and segregation all provide experimentally addressable descriptions of neural or computational conditions associated with conscious states. In parallel, research on bodily self-consciousness has shown that body ownership, agency, first-person perspective, and self-location depend on distributed multisensory processes involving vestibular, visual, somatosensory, proprioceptive, and interoceptive signals. These literatures constrain any proposal that attempts to connect consciousness to gravity.

The starting observation of the present work is modest yet consequential: gravity is universal to ordinary physical systems, whereas conscious experience is selective. That observation does not imply that gravity is consciousness, that gravitons are conscious particles, or that every gravitating object possesses experience. Instead, it motivates a rigorous separation between a universal physical context and the special organizational conditions present in systems such as human brains.

Proposals that link consciousness to gravity frequently conflate three distinct relations: (1) the universal participation of physical systems in spacetime and gravitation; (2) the construction, by embodied nervous systems, of neural estimates of gravito-inertial state that support spatial orientation and self-location; and (3) the special organizational conditions under which systems exhibit conscious experience. Recognizing this asymmetry is essential. Without it, the inference that every gravitating object is conscious becomes difficult to block.

The Selective-Realization Framework (SRF) developed here formalizes this separation and converts it into a set of operational, falsifiable tests. The framework begins with a three-way distinction:

1. Φ_G: the gravitational/spacetime sector in which physical systems exist;
2. F_G^(N): an empirically grounded neural estimate of gravito-inertial state that participates in bodily orientation and self-location;
3. Γ: a computable measure of multimodal organization whose relation to conscious state must be established out-of-sample.

A fourth term, F_G^(P), denotes a hypothetical direct fundamental gravitational coupling. It is explicitly optional. Setting F_G^(P) = 0 leaves the near-term framework intact. This is important because the evidence for vestibular and multisensory influences on bodily self-consciousness is substantial, whereas there is presently no comparably strong evidence that consciousness directly couples to quantum-gravitational degrees of freedom.

The primary theoretical contribution of the SRF is the selective-realization principle itself. Participation in a universal physical sector does not entail conscious realization. Any candidate contribution from gravito-inertial processing must be demonstrated through incremental predictive validity for first-person and conscious-state variables after accounting for established multisensory causal-inference models and complexity baselines. The framework therefore supplies a general methodological template for evaluating proposed special variables—whether gravitational, physiological, or computational—against the requirement of selective, out-of-sample predictive power.

The contributions of this article are correspondingly constrained and testable: (i) a formal selective-realization principle that blocks common category errors; (ii) operational definitions tied to existing multimodal and consciousness datasets, including an explicit pipeline for latent-space dimensionality reduction; (iii) an explicit candidate list of latent domains without presupposing any particular dimensionality; (iv) nested-model comparison protocols in which any gravity-tagged variable must outperform strong baselines; and (v) a near-term experimental program centered on $F_G^{(N)}$ rather than on speculative quantum gravity.

2. Scientific Status and Core Selective-Realization Principle

2.1 What the Framework Claims

Let S be a physical system. The framework begins with the uncontroversial statement that ordinary physical systems participate in spacetime and gravitation:

$$S \subset \Phi_G \tag{1}$$

Equation (1) is contextual, not psychophysical. It does not assign consciousness to S. A rock, planet, star, computer, or nervous system may all participate in Φ_G.

For embodied organisms, a second quantity is empirically meaningful. The nervous system estimates head and body motion relative to gravity and inertia using otolith and semicircular-canal signals together with vision, proprioception, and internal models. Denote the resulting neural estimate by

$$F_G^{(N)}(t) = \varepsilon[v_{vest}(t), v_{vis}(t), v_{prop}(t); \theta_E] \tag{2}$$

In Equation (2), the estimation process ε is not assumed to be localized to a single “gravity center.” It is distributed across vestibular and multisensory networks. Vestibular processing contributes to spatial reference, self-location, first-person perspective, self-motion perception, and body representation. Contemporary reviews and meta-analyses favor distributed posterior parietal, temporoparietal, insular, premotor, and related networks rather than a single cortical locus.

The framework then introduces a multimodal latent state

$$z(t) \in \mathbb{R}^k \tag{3}$$

where the dimensionality k in Equation (3) is data-derived. Neither any particular numerical value of k nor any fixed semantic decomposition is assumed at the level of the core theory.

The selective-realization hypothesis is that conscious-capable states occupy a region of this latent state space characterized by sufficient organization:

$$\Gamma_w \geq \Gamma_c \tag{4}$$

In Equation (4), Γ_w is computed over a prespecified time window w and Γ_c is frozen before external validation. This threshold relation is a candidate empirical criterion, not an ontological definition of consciousness. It must compete against established measures such as the Perturbational Complexity Index (PCI), criticality-related metrics, and integration–segregation indices.

2.2 What the Framework Does Not Claim

The following propositions are excluded from the core model:

- $\Phi_G \equiv$ consciousness;
- $F_G^{(N)} \equiv$ consciousness;
- gravitational waves carry conscious content;
- the hypothetical graviton is a “consciousness particle”;
- loss of vestibular input should abolish consciousness;
- any specific regular polyhedral or other fixed graph topology is required for conscious realization.

The last exclusions are essential. Humans remain conscious in altered gravito-inertial environments and in the presence of vestibular impairment. Therefore $F_G^{(N)}$ is treated as a contributor to embodied spatial organization, not as an on/off switch for consciousness. Topology hypotheses of any form become eligible for testing only after a stable low-dimensional latent structure has been recovered empirically and only if a gravity-tagged interface improves held-out prediction; even then they must compete against matched alternatives under strict out-of-sample criteria.

3. Empirical Anchors: Gravity, Multisensory Inference, and Bodily Self-Consciousness

3.1 Vestibular and Gravito-Inertial Processing

Otolith organs respond to gravito-inertial acceleration, not “pure gravity” in isolation. This makes the vestibular system scientifically useful but also imposes a constraint: centrifugation, tilt, parabolic flight, and orbital free fall alter sensory and inertial conditions in ways that do not isolate spacetime curvature. Any near-term experiment must therefore distinguish sensory gravito-inertial inference from a claim about fundamental gravity.

Vestibular contributions to bodily self-consciousness are well motivated. Vestibular cortical processing supplies a spatial reference for self-location and first-person perspective. Evidence links vestibular, interoceptive, and multisensory processing to body ownership, agency, and self-location. Distributed activation patterns associated with manipulated body ownership and agency involve posterior parietal and temporo-occipito-parietal regions. Interoception adds a further network-level constraint: brain–body physiological coupling influences self-related processing and argues against treating the self as a purely exteroceptive construction. Recent work on self-motion emphasizes integration of vestibular inputs, optic flow, proprioception, and motor signals over time. These findings support the empirical role assigned here to $F_G^{(N)}$ defined in Equation

(2), but they also show why it should be represented as a latent inference variable rather than a single sensory channel.

3.2 Multisensory Causal Inference as a Mandatory Baseline

Bayesian causal inference provides a strong existing framework for deciding whether signals share a common cause and how they should be reliability-weighted. This literature matters because a new state-space model must add something beyond generic “integration.” If the proposed latent architecture cannot outperform established causal-inference models on multisensory and self-location tasks, it lacks incremental value. Accordingly, the SRF treats Bayesian causal-inference models as a mandatory baseline. For any task involving visual, vestibular, proprioceptive, or interoceptive conflicts, the new model must report whether its latent organization improves held-out prediction after accounting for cue reliability and causal structure.

3.3 Existing Quantitative Markers of Conscious State

A second baseline comes from empirical complexity and network measures. The Perturbational Complexity Index (PCI) was developed to capture the joint presence of integration and differentiation in TMS-evoked EEG responses and has been independently validated in behaviorally unresponsive patients. More recent work has linked spontaneous EEG criticality to conscious state and to PCI. Dynamic fMRI measures of integration and segregation also distinguish wakefulness from propofol-induced unresponsiveness and generalize to sleep datasets. These results motivate an operational Γ statistic but also set a high bar: Γ must be computationally explicit and must demonstrate incremental predictive validity beyond existing complexity measures.

4. Operationalizing Latent Modules and the Organization Functional

4.1 Data-Derived Latent Dimensionality and Recommended Reduction Pipeline

Let $x(t) \in \mathbb{R}^p$ denote the observed multimodal feature vector (EEG/MEG time-frequency or source features, fMRI BOLD, physiological signals, behavioral reports, and task variables). A measurement model Q_ψ maps observations to a latent state

$$z(t) = Q_\psi(x(t)) \in \mathbb{R}^k \tag{3}$$

The dimensionality k must be selected exclusively by prespecified out-of-sample criteria. No value of k is presupposed by the framework. The gravity-related estimate $F_G^{(N)}$ is held outside the latent vector so that its incremental contribution can be tested rather than assumed.

Because the quality of all subsequent organization statistics and decoders depends on the latent representation, the framework adopts an explicit staged dimensionality-reduction pipeline that draws on both classical and modern techniques:

Stage 1 – Linear diagnostics and baseline. Begin with principal component analysis (PCA) or linear factor analysis. Examine the scree plot, cumulative explained variance, and results of parallel analysis to obtain an initial estimate of effective dimensionality. These linear methods are transparent, computationally efficient, and provide orthogonal (or nearly orthogonal) coordinates that can serve as a strong baseline for Q_ψ.

Stage 2 — Model comparison and nonlinear alternatives. If residual nonlinear structure is expected, parametric nonlinear models—particularly autoencoders or variational autoencoders (VAEs)—may be evaluated as alternative forms of Q_ψ. These methods must support consistent out-of-sample mapping for new time points and must demonstrate incremental held-out gain (reconstruction, likelihood, or downstream prediction of y_{self}) relative to the linear baseline. Non-parametric manifold methods such as UMAP or t-SNE are useful for exploratory visualization of the recovered latent cloud but are not recommended as the primary dynamical representation, because they do not naturally yield a stable encoder for unseen data.

Stage 3 — Selection of k. Choose k by a combination of (a) parallel analysis or information criteria applied to the linear solution, (b) cross-validated reconstruction error or held-out likelihood for both linear and nonlinear candidates, (c) stability of the resulting organization statistic Γ under bootstrap or site resampling, and (d) incremental predictive validity for self-location, body-ownership, or conscious-state variables. Automatic techniques that encourage ordered or sparse latent dimensions (nested dropout, volume penalties, effective-rank regularization) may be used provided they are locked before external testing.

Whatever method is selected for Q_ψ, the choice of reduction technique and the final value of k must be frozen in the discovery/calibration phase and never retuned on the external test set. Semantic labels from a Version-0 candidate set (Table 1) may be mapped onto the resulting factors only after factor stability and measurement invariance have been assessed; they do not determine k.

Table 1. Version-0 candidate latent domains (provisional)

Candidate domain	Example observables / manipulations	Status
Visual exteroception	Contrast, optic flow, visual reliability	Empirical
Auditory exteroception	Localization, timing, reliability	Empirical
Somatosensory / proprioceptive	Limb position, tactile conflict	Empirical
Interoception	Heartbeat/respiratory coupling, internal-state report	Empirical
Affect / salience	Valence, arousal, salience ratings	Empirical
Agency / action monitoring	Intentional binding, sensorimotor prediction error	Empirical
Body ownership / self-location	Full-body / rubber-hand manipulations	Empirical
Temporal integration	Simultaneity, temporal binding windows	Empirical
Memory / contextual access	Context reinstatement, recognition	Empirical
Global access / task coordination	Report, working-memory access	Empirical

Metacognitive / self-referential	Confidence, self-related judgment	Empirical

Note. Domains are illustrative anchors only. Dimensionality k and the form of Q_ψ must be determined by the staged reduction pipeline without presupposing any fixed number of modules.

4.2 Candidate Organization Statistic Γ

For a temporal window w containing the matrix of latent samples $Z_w \in \mathbb{R}^{(T_w \times k)}$, let W be a nonnegative coupling matrix (either prespecified from anatomy or functional connectivity, or estimated on training data only), D_W its degree matrix, and $L_W = D_W - W$ the graph Laplacian. Define the normalized integration term

$$I_w = 1 - [\mathrm{tr}(Z_w^T L_W Z_w)] / [\lambda_{max}(L_W)\, \mathrm{tr}(Z_w^T Z_w) + \varepsilon] \quad (5)$$

Equation (5) approaches 1 when activity on linked modules varies coherently relative to total energy. It is deliberately a graph statistic, not a claim that graph smoothness equals consciousness.

Differentiation is quantified by the normalized effective rank of the window covariance Σ_w. With eigenvalues $\lambda_j \geq 0$ and $p_j = \lambda_j / \Sigma_\ell \lambda_\ell$,

$$D_w = \exp(-\Sigma_j\, p_j \ln p_j) / k \quad (6)$$

Equation (6) is high when activity spans multiple independent dimensions rather than collapsing into a single synchronized mode. The effective-rank formulation is deliberately aligned with the dimensionality-reduction diagnostics of Stage 1: a latent space that has already been reduced to its intrinsic dimensionality will tend to yield higher and more stable values of D_w. A minimal candidate organization score combining integration and differentiation is

$$\Gamma_w = \sqrt{(I_w \cdot D_w)} \quad (7)$$

Equation (7) is chosen for transparency, computational simplicity, and approximate scale-invariance. It is one candidate among others. More elaborate terms—metastability, directed information, synergy, or cross-frequency coupling—may be substituted or added only if they yield preregistered out-of-sample gains. Critically, any form of Γ must be compared against established markers (PCI, spontaneous EEG criticality metrics, and dynamic integration–segregation indices) on the same datasets. Only incremental predictive validity justifies continued use of a particular form.

4.3 Separate Evaluation of the Gravito-Inertial Contribution

The contribution of $F_G^{(N)}$ is assessed independently of Γ:

$$V_{G,w} = \text{CV-}R^2(F_G^{(N)} \rightarrow y_{self}) \quad (8)$$

In Equation (8), y_{self} comprises continuous or ordinal measures of self-location, first-person perspective, body ownership, perceived vertical, or heading, and CV-R^2 denotes nested cross-validated explained variance (or an equivalent log-likelihood ratio). The decisive test is whether adding $F_G^{(N)}$ (or the residual of $F_G^{(N)}$ after regressing out pure visual and proprioceptive predictors) produces a reliable positive increment $\Delta R^2 > 0$ on held-out data relative to strong Bayesian causal-inference baselines that already incorporate cue reliability and common-cause structure. This separation prevents a circular result in which “gravity” is guaranteed to matter because it was built into the consciousness score.

4.4 Operational Decoder

Let y(t) collect measurable phenomenal/report variables such as perceived self-location, first-person perspective, body-ownership rating, heading estimate, confidence, or task report. The decoder

$$\hat{y}(t) = P_\theta [z(t), F_G^{(N)}(t)] \quad (9)$$

Equation (9) is a statistical mapping (linear, generalized linear, regularized, or state-space) whose functional form is fixed in the preregistration. Adequacy is judged solely by nested cross-validation and external replication. If P_θ does not predict perceptual/self variables better than established multisensory causal-inference baselines, it contributes no explanatory value. The decoder relation does not assert that the brain literally projects a picture outside the skull; it tests whether organized latent states can recover the structured first-person variables that characterize experienced body and world.

4.5 Threshold Estimation Without Test-Set Circularity

Γ_c must not be selected after viewing the validation labels. The protocol is:

4. Discovery set: estimate the measurement model Q_ψ (including the chosen dimensionality-reduction method and the value of k), any coupling W, and hyperparameters using only discovery participants.
5. Calibration set: choose Γ_c using a prespecified criterion (for example, the operating point optimizing balanced accuracy between benchmark conscious and unconscious conditions).
6. Lock: freeze Q_ψ, the reduction method, k, W, Γ_c, preprocessing, window length, and decision rule.
7. External test: evaluate performance once on a separate site, cohort, pharmacological, or sleep dataset.
8. Comparator analysis: test incremental performance relative to PCI, Lempel-Ziv/criticality measures, and integration–segregation metrics where available.

A threshold that fails external validation is rejected rather than retuned on the same test data.

5. Near-Term Experimental Program Centered on $F_G^{(N)}$

The strongest empirical component of the framework is the gravito-inertial/self-location channel. The first studies should therefore manipulate $F_G^{(N)}$ (Equation 2) while avoiding claims about fundamental gravity. The same locked dimensionality-reduction pipeline must be applied across all experiments.

5.1 Experiment A: Vestibular–Visual Conflict and Self-Location

A within-subject design can combine galvanic or caloric vestibular stimulation with controlled optic flow and proprioceptive cues. Primary outcomes are continuous self-location, first-person perspective, perceived vertical, heading estimate, body-ownership ratings, reaction-time, and confidence measures. Concurrent EEG or fMRI provides network features for z(t).

Predictions are deliberately modest: (i) F_G^(N) should improve out-of-sample prediction of spatial self variables beyond visual/proprioceptive inputs alone (i.e., a positive increment in the sense of Equation 8); (ii) perturbations should preferentially alter coupling among vestibular, posterior parietal, temporoparietal, insular, and body-representation features rather than abolish global conscious state; (iii) Γ may change locally or transiently but should remain above a conscious-state threshold in healthy awake participants. Failure of the first prediction would weaken the need for a distinguished gravity-tagged interface even at the neuro-gravitational level. Recommended sample size for reliable detection of medium incremental effects in within-subject designs is $N \geq 30$–40, with full preregistration of analysis plans.

5.2 Experiment B: Body-Ownership and Gravito-Inertial Orientation

Full-body or virtual-body illusions can be performed under upright, supine, tilted, and (where feasible) centrifugation-compatible conditions. The model predicts that altered gravito-inertial reliability changes the relative weighting of self-location and body-ownership cues. Bayesian causal-inference models are fitted as the mandatory baseline; SRF variables are retained only if they improve held-out prediction of ownership and self-location reports under changes in gravito-inertial reliability.

5.3 Experiment C: Conscious-State Generalization

To test Γ (Equations 5–7) rather than merely embodiment, the same preprocessing and locked statistic should be applied to datasets spanning wakefulness, non-REM sleep, propofol or xenon anesthesia, ketamine conditions with preserved experience, and disorders of consciousness. The calibration threshold is frozen before external testing. The decisive question is not whether Γ differs between groups in-sample; it is whether it generalizes across perturbations and sites and adds information beyond existing complexity metrics.

6. Falsification Criteria

The framework is weakened or rejected under any of the following preregistered outcomes (summarized in Table 2):

Table 2. Principal falsification and demotion criteria

Claim	Test	Outcome that weakens/rejects
Stable low-dimensional multimodal organization exists	Cross-validated factor/state modeling + parallel analysis	No stable latent structure across resampling/sites
A distinguished F_G^(N) adds information	Nested models for self-location/body variables	No reproducible ΔR^2 beyond visual/proprioceptive/BCI baselines
Γ indexes selective conscious realization	External validation across sleep/anesthesia/DOC	Threshold fails external generalization or adds no

		value beyond established metrics
P_θ maps latent state to report/self variables	Nested cross-validation	No predictive gain over direct baseline models
Fundamental $F_G^{(P)}$ is needed	Experiments controlling ordinary neural/inertial effects	No residual gravity-specific effect; retain $F_G^{(P)} = 0$

Note. Rejection of any particular topology or of a specific nonlinear embedding method leaves the core Φ_G – $F_G^{(N)}$ – Γ architecture intact. Failure of a generalizable organization criterion or of the incremental value of $F_G^{(N)}$ is substantially more damaging.

7. Relation to Existing Consciousness Theories

The SRF is not intended to replace established theories through relabeling. Its role is to make a narrower proposition testable. Global Neuronal Workspace theory emphasizes global availability and ignition-like access. Integrated Information Theory emphasizes intrinsic integration and differentiation. Empirical complexity approaches measure properties expected to vary with the presence of consciousness. Predictive/Bayesian approaches formalize inference under uncertainty and are particularly strong for multisensory integration. Bodily-self models explain how first-person perspective and ownership emerge from multisensory and vestibular processing.

The SRF treats these frameworks as sources of measurable variables and as mandatory comparators. Its distinct empirical question is whether a gravity-tagged embodied variable (Equation 2) and a learned multimodal organization model (Equations 5–7), obtained after a transparent dimensionality-reduction pipeline, provide reproducible incremental prediction after those baselines have been accounted for. If no incremental prediction is found, the SRF should be absorbed into existing multisensory and network descriptions rather than maintained as a separate theory.

8. Does the Framework Solve the Hard Problem?

No. The formal relations above can describe organization, decoding, self-location, and state discrimination without explaining why any such process is accompanied by subjective experience. The selective-realization threshold (Equation 4) is therefore a psychophysical hypothesis about conditions associated with conscious-capable organization, not a derivation of phenomenality from physical first principles.

This limitation is important because gravity-based proposals can easily relocate rather than solve the explanatory gap. Replacing “neural activity becomes experience” with “organized gravity-coupled activity becomes experience” does not by itself supply the missing bridge. A future theory would need either a principled identity relation, a new psychophysical law with independently testable consequences, or a successful reduction showing why the relevant organized state necessarily has phenomenal character. The SRF does not claim to provide that reduction.

9. Discussion

The Selective-Realization Framework addresses a recurring category error in proposals that link consciousness to gravity: the inference from universal physical participation in a gravitational sector (Φ_G, Equation 1) to the presence of conscious experience. By separating the contextual fact of spacetime embedding from the empirically measurable neural estimate $F_G^{(N)}$ (Equation 2) and from a preregistered organization criterion Γ (Equations 5–7), the framework prevents the claim that rocks, planets, or black holes are conscious merely because they gravitate.

The primary theoretical contribution is methodological and conceptual. Consciousness science already possesses strong accounts of global availability, intrinsic integration and differentiation, predictive multisensory inference, and the distributed vestibular-multisensory bases of bodily self-consciousness. The SRF does not replace these. Instead, it supplies an explicit testing protocol that requires any gravity-tagged variable to demonstrate reproducible incremental predictive value for self-location, body ownership, first-person perspective, and conscious-state discrimination after accounting for established baselines. The nested-model requirement (ΔR^2 or equivalent out-of-sample gain for $F_G^{(N)}$, Equation 8) and the mandatory comparison of Γ against PCI, criticality metrics, and integration–segregation indices raise the evidential bar relative to purely correlational or schematic proposals.

A further methodological contribution is the staged dimensionality-reduction pipeline for obtaining the latent state z(t). By requiring PCA or factor analysis as a transparent baseline, permitting parametric nonlinear models only when they improve held-out criteria, and treating non-parametric manifold methods as exploratory tools, the framework aligns the latent-state construction step with current best practice in high-dimensional data analysis while preserving the ability to compute organization statistics and to perform out-of-sample prediction.

Several limitations remain. First, the candidate organization statistic $\Gamma = \sqrt{I_w \cdot D_w}$ defined in Equation (7) is a minimal, computable proxy inspired by the joint requirements of integration and differentiation that appear across existing complexity measures; it is not claimed to be optimal or unique. More elaborate information-theoretic or dynamical measures may prove superior, and the framework requires that they be tested under the same protocol. Second, the Version-0 latent domains (Table 1) are provisional and must be replaced by data-driven dimensionality and factor solutions. Third, the near-term experimental program, while feasible, has not yet been executed; until vestibular–visual conflict and body-ownership studies under controlled orientation yield the predicted incremental effects, the distinguished status of $F_G^{(N)}$ remains a hypothesis. Fourth, the optional fundamental channel $F_G^{(P)}$ is currently set to zero and would require residual effects that survive all ordinary neural, inertial, and physiological controls—an extremely high bar that existing evidence does not meet.

Topology hypotheses of any form, including regular polyhedral face-adjacency graphs, are secondary. They become eligible only after a stable low-dimensional latent structure is recovered and a gravity-tagged interface improves prediction. Even then, they must compete against matched null, random-regular, small-world, and data-learned graphs under held-out criteria. Geometric attractiveness confers no scientific privilege.

More generally, the SRF offers a template that can be applied beyond gravity. Any proposed “special” physical or physiological variable can be required to satisfy the selective-realization criterion: incremental out-of-sample predictive power for conscious-state and first-person variables after strong baselines have been partialled out. This general methodological stance is the lasting contribution of the framework.

10. Conclusion

We have presented a Selective-Realization Framework that converts a common intuition about gravity and consciousness into a constrained, falsifiable research program. Physical systems universally participate in Φ_G (Equation 1). Embodied nervous systems construct $F_G^{(N)}$ (Equation 2). Multimodal states can be represented by data-derived latent variables (Equation 3) obtained via an explicit dimensionality-reduction pipeline and evaluated with preregistered organization statistics (Equations 5–7) that must outperform or add to existing complexity measures. The decisive empirical questions are whether $F_G^{(N)}$ yields reproducible incremental prediction of bodily self variables (Equation 8) and whether a locked organization threshold (Equation 4) generalizes across conscious-state transitions. Topology and any direct fundamental coupling are optional downstream hypotheses that stand or fall with data.

Future work must prioritize preregistered vestibular and multisensory experiments, cross-dataset validation of organization metrics, rigorous comparison of linear versus nonlinear latent models, and careful selection of latent dimensionality. Only after those steps succeed would more ambitious gravitational interpretations become warranted. The framework is offered as a methodological contribution to the empirical science of consciousness, not as a solution to the hard problem and not as a claim that gravity itself is conscious.

Declarations

Funding. No external funding is declared for this theoretical manuscript.

Competing interests. The author declares no competing interests.

Data and code availability. No external human dataset was analyzed in this article. The framework is offered as a methodological and theoretical contribution; empirical validation requires new or re-analyzed multimodal datasets under preregistered protocols.

Ethics. No human or animal participants were enrolled for this theoretical study.

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