ChatGPT

# Executive Summary

This paper introduces **Mechanica Oceanica**, a theoretical framework for understanding how *absences* influence cognitive systems. We argue that when an anticipated event fails to occur, the resulting absence can create an **operative divergence** in a system's state of possibilities (denoted o), which then shapes subsequent processes until it is locally resolved into a coherent outcome (denoted Ω). This cycle – from conceptual openness (o) to local closure (Ω) and back – is formalized in a dynamical systems model combining philosophical insights with mathematical structure. We connect Immanuel Kant's idea of *intuition* (the conditions of givenness) and Franz Brentano–influenced concepts of *intentionality* with Al-Ghazali's epistemology of the "heart" and intention. We contrast *instinct* (inherited organization) with *impulse* (situated directional tendency) and show how their distinction leads to testable hypotheses. Formal definitions (Ψ field, Ω, o, operators $\mathscr{I}$, $\mathscr{S}$, $\mathscr{D}$, $\mathscr{N}$, transition operator T) are given, along with candidate dynamical equations (e.g. `dΩ/dt = κ o − λ Ω`). We propose experimental methods to detect and characterize operative divergences (e.g. unexpected omissions of stimuli) using behavioral and neurophysiological measures. Key predictions are formulated to discriminate this model from standard predictive-coding/working-memory accounts. A multi-stage research plan with open data and preregistration is outlined, including power analyses, divergence metrics (KL, JS, entropy), and controls. Appendices detail methods and protocols. **Mechanica Oceanica** thus yields concrete hypotheses and "risky tests" about how the unreal (non-present conditions) can causally structure cognition in ways that can be empirically validated or refuted.

# Title

**Mechanica Oceanica: A Dynamical Model of Absent Causes and Cognitive Closure**

# Abstract

Cognitive systems routinely encounter *absent* events (unfulfilled expectations, missing stimuli) that nonetheless influence thought and action. We develop **Mechanica Oceanica**, a formal framework treating absence-induced effects as dynamic constraints in a possibility field. Philosophically, we distinguish Kantian intuition (givenness) from concept, and instinct (embodied organization) from impulse (situated drive), drawing on Al-Ghazali's ethics of intent and habit. Mathematically, we represent the cognitive state as a field Ψ(x,t) decomposed into divergence (o) and coherence (Ω) components with a normalized ratio $C=\Omega/(\Omega+o)$. We define operators $\mathscr{I}$ (intuition), $\mathscr{S}$ (instinctual constraints), $\mathscr{D}$ (impulse-driving), $\mathscr{N}$ (intentional selection), and a transition map $T$ over possible actions. Candidate dynamics are proposed (e.g. $d\Omega/dt = \kappa\cdot o - \lambda\cdot\Omega$) linking divergence to eventual closure under organismic constraints. We propose empirical tests using omission paradigms: when a predicted stimulus X is unexpectedly removed, **operative divergence** $o_x$ = D[ $T_x$ || $T_0$ ] should be nonzero and measurable via behavior/EEG. Key hypotheses and competing models are tabulated. Experimental methods include EEG/fMRI omission protocols, psychophysics of action choices, and quantification of divergence (Kullback–Leibler, entropy) in choice distributions. We outline sample sizes (N≈30–50, power≥0.8) and planned analyses (ANOVA, model fitting, cross-validation). Falsifiable predictions contrast Mechanica Oceanica (persistence of an organized “non-event” effect) with standard predictive-coding (transient error only) and working-memory (short-lived trace) accounts. Results would advance understanding of how *not-yet actual* conditions shape cognition. The paper concludes with a detailed research plan, open-data commitment, and suitable publication venues.

# Keywords

Cognitive dynamical systems; absential causality; omission responses; predictive coding; Kantian intuition; Al-Ghazali ethics; impulse vs. instinct; memory and absence.

## Introduction

Cognitive neuroscience and philosophy have long wrestled with how *not* merely concrete stimuli but their **absences** or unfulfilled possibilities can influence mental processing. For example, a missing cue or an unrealized goal often continues to constrain decisions and actions. We term this phenomenon **operational divergence**: when an anticipated event fails to occur, the cognitive system’s state shifts in a measurable way, even though no new external input is present. Our goal is to formalize this shift – metaphorically, how “o” (openness) transitions into “Ω” (closure) in a **Mechanica Oceanica** of mind.

Empirical studies in omission paradigms show that anticipated but omitted stimuli elicit neural responses akin to prediction errors【7†L345-L353】【10†L193-L202】. For instance, an expected sound’s absence triggers an “auditory-like” brain response【7†L345-L353】, and unexpected tactile omissions during action evoke EEG components (oN1, oN2, oP3) paralleling those for actual stimuli【6†L53-L62】. These findings support predictive-coding theories: the brain actively generates models of expected inputs and signals errors when they fail to appear【13†L323-L332】【7†L361-L370】. However, most accounts treat the omitted event as lacking causal efficacy beyond transient error signaling.

Our approach instead models the absence as altering the *space of possibilities*. A stimulus X can disappear, but its prior occurrence has changed the organism. We view cognitive states as dynamical configurations $\Psi(x,t)$ with *divergence* $o(x,t)$ (unresolved openness) and *coherence* $\Omega(x,t)$ (resolved structure). Actualization does not nullify all o; rather it locally increases Ω at the expense of specific o. The resulting state generates new o for future resolution, in a perpetual cycle:

$$\mathbf{o \rightarrow \Omega \rightarrow o \rightarrow \ldots}$$

This conception aligns with philosophical ideas about *absence-based causality* (Deacon) and mind-in-body integration (Kant, Ghazali). It distinguishes **instinct** (an inherited organizing architecture of possible responses) from **impulse** (a context-sensitive tendency toward action), and posits **intuition** (Kantian givenness) as a mapping rather than a material force. Formalizing these distinctions yields testable hypotheses about which mathematical structures – vector fields, operators, state-spaces – best capture “intuitive givenness,” “instinctual constraint,” “impulsive drive,” and the transition to action.

# Literature Review

## Predictive Processing and Omission Paradigms

Contemporary accounts of perception and action emphasize *prediction*: higher-level areas generate anticipatory signals sent top-down to sensory areas【7†L361-L370】. Classical studies show that when a predicted sensory event fails to occur, the brain emits an error signal mirroring the expected input【13†L323-L332】【7†L345-L353】. For example, SanMiguel *et al*. (2013) found that omitted tones elicit ERP components reflecting the brain's model of the missing sound. Similarly, Dercksen *et al*. (2022) demonstrated robust EEG "omission responses" in touch: when a button press normally delivered a tactile stimulus but the touch was withheld, the EEG showed oN1/oN2/oP3 waveforms analogous to actual touch responses【6†L53-L62】. These and other auditory studies【10†L193-L202】 confirm that omission responses are a general signature of prediction error. In predictive-coding theory (e.g. Friston, 2005【7†L361-L370】), such signals update internal models when sensory input mismatches expectation. Notably, omissions modulate with context: Kimura *et al*. (2013) showed that if only "when" but not "what" of an event is predictable, no omission ERP occurs【7†L385-L394】. These data underscore that specific content predictions are needed for omission effects, and that error signals depend on both bottom-up input and top-down models【7†L385-L394】【13†L323-L332】.

## Dynamical Systems and Cognitive Organization

The cognitive state can be modeled as a trajectory in a high-dimensional phase space【25†L37-L45】. In dynamical systems theory, a system's *state variables* at time *t* determine its future evolution【25†L37-L45】. Cognitive processes (e.g. decision making, motor planning) may correspond to movement in this space toward attractors or along trajectories. For example, smooth sequences of action (ladder climbing, drawing) are seen as emergent flows rather than discrete stimulus–response chains【25†L9-L18】. Embodied-cognition perspectives suggest that cognitive processes inherit structures from sensorimotor dynamics【25†L23-L32】, making dynamical systems a natural framework for modeling mind–world interaction【25†L37-L45】. Within this view, an *absent* event can be treated as a change in the system's governing equations or constraints, creating a region of high potentiality (o) that evolves over time. Concepts like *state-space attractors* and *chaos* become relevant for how the system might settle on one possibility (Ω) or remain in ambiguity.

## Habits, Virtue, and the Heart (Kant vs. Ghazali)

Philosophical tradition distinguishes different levels of agency. Kant's transcendental framework separates sensibility (receptivity) and understanding (spontaneity)【7†L361-L370】. Intuition (Anschauung) is the condition under which any object can appear; it is not itself a force or content but the *form* of givenness. Kant warns that empirical terms like "instinct" and "impulse" belong to the world of appearances, not to the noumenal self or freedom. Still, the *feeling* of impulse reveals a gap between passive inclination and active will: we might be *inclined* but not *determined* by an impulse【7†L385-L394】. This leaves room for reason and moral self-determination. The will, for Kant, is practical reason imposing principles beyond mere inclination.

Al-Ghazali (11th c. Islamic philosopher) provides a richer psychological account that complements Kant. Ghazali distinguishes the *heart* (qalb) as the seat of ultimate orientation (toward God, virtues) from the *appetitive* (shahwa) and *irascible* (ghadab) faculties. He emphasizes *intention* (niyyah) as crucial: two identical acts may be good or bad depending on the heart's intention. An impulse (e.g. anger surging) is morally neutral until the heart consents and forms a deliberate intention. Habituation (ʿāda) gradually orders the faculties: repeated actions inculcate dispositions or "morals" in the soul. In Ghazali's terms, an absence can exercise efficacy through the *condition of the heart*: memory or fear of an absent object can shape intentions just as strongly as its presence. Thus Ghazali anticipates that non-present objects (e.g. God in prayer) can govern behavior.

Together, these traditions suggest a multi-level sequence: **intuition (object-givenness) → affection → inclination (impulse) → intention (niyyah) → action**. *Instinct* (preformed orientation) and *impulse* (situated drive) lie on the empirical side; *intuition* and *intention* involve transcendental or moral structuring. Our model will place intuition as a mapping Ψ→R (state observation), instinct as constraints $\mathscr{S}$, impulse as a tendency field $\mathscr{D}$, intention as a selection operator $\mathscr{N}$, and action as the outcome closing a possibility.

### Habits and Character

Aristotelian virtue ethics and Ghazalian ethics both stress that repeated choices shape character. Habits (Greek *êthos*, Arabic *ʿāda*) encode past resolutions in the agent's disposition. Formally, we model this as **adaptive transition structures**. If $H_t$ represents learned history, then the transition operator $T_t$ (mapping current state to possible next states) evolves: after an action $A_t$, $H_{t+1} = H_t + ΔH\_A$ changes $T_{t+1}$. Thus the distribution of future possibilities is history-dependent 【25†L37-L45】. Character is essentially the accumulation of these modifications to *T*. An agent's highest coherence state (Ω) at time *t* constrains its next divergence (o) at *t+1* via these modified transitions, embodying the "once done" into the continuing system.

## Formal Model

We represent the cognitive system as a *field configuration* Ψ(x,t), which encodes all relevant internal and external variables (cortical activity, environment, memory, etc.). This field is decomposed into two modes of organization: **coherence (Ω)** and **divergence (o)**. Intuitively, Ω(x,t) corresponds to aspects of Ψ that are locally determined or "actualized," while o(x,t) captures unresolved potentialities or structural openness. We define a normalized *coherence ratio*

$$C(x,t) = \frac{\Omega(x,t)}{\Omega(x,t) + o(x,t)}, \quad 0 \le C \le 1.$$

High *C* (≈1) indicates strong closure (dominant Ω), low *C* indicates persistent openness (dominant o). Importantly, Ω and o are not independent substances but complementary tendencies in Ψ.

We introduce formal operators for the cognitive processes:

- **Intuition ($\mathscr{I}$)**: an operator mapping the global field into a *given* representation R at a point (analogous to Kantian intuition).

$$R(x,t) = \mathcal{I}[\,\Psi(x,t)\,].$$

Crucially, 𝒥 is not a dynamic force: 𝒥[Ψ] ≠ Ω or o, it simply extracts what is intuited from the field under the subject's mode of perception.

- **Instinct (𝒮)**: an operator constraining possible actions based on embodied organization. Let ℙ(S) be the space of all possible state transitions of the system S. 𝒮 maps ℙ → ℙ_S, a subspace of transitions made accessible by the organism's innate or learned architecture. For example:

$$\mathbb{P} = \{a_1, a_2, \ldots, a_n\}, \quad \mathbb{P}_S = \mathcal{S}(\mathbb{P}) \subseteq \mathbb{P}.$$

𝒮 may depend on the current state R and history H: ℙ_S = 𝒮(R,H). This formalizes "instinct = organization of possible actions."

- **Impulse (𝒟)**: a vector field on ℙ_S representing tendency. If *I(t)* is the impulse at time t, then *I : ℙ_S → Tℙ_S* produces directional pressures among accessible transitions. For example, if the hunger impulse favors certain actions, 𝒟 will weight those transitions. Formally one may write:

$$I = \mathcal{D}(R, H, \Psi),$$

signifying how the current perceived situation R, history H, and field Ψ generate a directional bias.

- **Intention (𝒩)**: a selection operator choosing a specific action from ℙ_S. Denote by A *the selected action. Then*

$$A^* = \mathcal{N}(\, \mathbb{P}_S, I, N, K \,),$$

*where* N *encodes explicit goals or values (Ghazali's niyyah) and* K* encodes rational evaluation. Unlike simple maximization of impulse, 𝒩 allows goals or principles to override a raw impulse.

- **Action (A)**: realization of A* leading to an updated field. The chosen action induces a transition in Ψ and updates history. We write

$$\Psi_{t+1} = \Psi_t + \Delta\Psi_A, \quad H_{t+1} = H_t + \Delta H_A.$$

Collectively, the cycle is:

$$\Psi_t \xrightarrow{\mathcal{I}} R_t \xrightarrow{\mathcal{S}(H_t)} \mathbb{P}_t \xrightarrow{I_t} \xrightarrow{\mathcal{N}} A_t \xrightarrow{execution} \Psi_{t+1}, H_{t+1}.$$

In short form: **Ψ → 𝒥 → 𝒮 → 𝒟 → 𝒩 → A → Ω** (closing action), with feedback Ω→ new H→ next ℙ, etc.

We propose candidate differential equations to capture dynamics. For instance, suppose divergence o increases when constraints are lifted, and decreases under action, while coherence Ω grows when divergence is resolved. A simple phenomenological form is:

$$\frac{do}{dt} = F_{ext}(t) + R(\Omega, \Psi, H) - \kappa(\mathbb{P}, H, N, K)\, o, \quad \frac{d\Omega}{dt} = \kappa(\mathbb{P}, H, N, K)\, o - \lambda\, \Omega.$$

Here *F_{ext}(t)* represents external perturbations (e.g. stimulus changes or withdrawals), and *κ* is an *impulse-to-closure* coefficient (a function of the organism's current readiness to act), while *λ* is a decay constant for coherence (reflecting entropy or "forgetting"). At equilibrium (**closed-loop**), κ·o = λ·Ω, linking divergence and coherence. The exact forms of *F, R, κ, λ* are to be determined by empirical fitting. A more explicit form can incorporate a transition operator *T*:

$$T_t : S_t \to P(S_{t+1}), \quad o(t) = D\big[T_X(t)\,\big|\big|\,T_0(t)\big],$$

where *D* is a divergence metric (e.g. KL-divergence) between the transition probability distributions with and without the presence of X. Ω and o thus measure how current states bias future state probabilities.

**Table 1.Formal components of Mechanica Oceanica model.**

| Concept / Process | Formal Entity | Interpretation/Example |
|---|---|---|
| Cognitive Field | Ψ(x,t) | Distributed state (neural + context variables) |
| Coherence (closure) | Ω(x,t) | Structured/actualized part of Ψ |
| Divergence (openness) | o(x,t) | Unresolved possibilities in Ψ |
| Coherence Ratio | C = Ω/(Ω+o) | 0=fully open, 1=fully closed |
| Intuition | 𝒥: Ψ → R | Perceptual registration (not a causal force) |
| Instinct (constraints) | 𝒮: ℙ → ℙ_S | Subset of possible actions (e.g., affordances) |
| Impulse (drive) | 𝒟: (R,H,Ψ) → I | Vector field on ℙ_S (e.g. goal-directed urgency) |
| Intention (selection) | 𝒩: (ℙ_S,I,N,K) → A* | Selection among I-influenced options, incorporating goals |
| History/Habit | H | Memory of past actions (alters 𝒮 or 𝒮) |
| Action (outcome) | A (trajectory in Ψ) | Actualized change in Ψ; creates local increase in Ω |
| Transition Operator | T: S_t → P(S_{t+1}) | Mapping states to probability of next states |
| Divergence Metric | D (e.g. KL, JS) | Quantifies difference between two transition maps |

# Methods

## Experimental Designs

We propose several controlled paradigms to test operative divergence. Common to all is an *omission* or *absence* condition versus suitable controls. Key examples:

- **Prediction-Omission Task**: Subjects experience a repeated sequence (e.g. tone-B button-sound) so that stimulus X is reliably expected after cue Y. In **Omission** trials, X is withheld. In **Control** trials, either X was not signaled or was expected and delivered. Neural (EEG/MEG) responses are recorded time-locked to the expected onset of X, plus behavioral choices if any (e.g. forced choice of action). We expect nonzero neural and behavioral signatures of o only when omission violates a strong prediction【6†L53-L62】【7†L361-L370】.

- **Motor-Preparation Displacement**: Subjects perform reaching or saccade tasks toward a target that occasionally vanishes before movement. Condition A: target stays visible (Stimulus); B: target disappears abruptly (Omission); C: target never appears (Baseline). We measure motor-evoked potentials/EEG and kinematics. If Mechanica Oceanica holds, in B the planned movement system will show sustained activation (persistent o) after disappearance, influencing subsequent decision (e.g. search direction), even though the target is gone. By contrast, C should show no such preparatory bias.

- **Reward Omission and Action Selection**: Participants learn that action A or B normally yields reward X. On some trials, reward X is unexpectedly omitted after action A. We then examine choice probabilities on the next trial. A pure RL model would predict a brief negative prediction error. Our model predicts that the omission creates residual divergence, altering the *distribution* of chosen actions (entropy) beyond what a transient error would. Specifically, we test if $D_{\mathrm{KL}}\left(P_{\mathrm{post|omission}} \parallel P_{\mathrm{post|reward}}\right) > 0$, indicating a lasting reorganization of action probabilities.

All experiments would include counterfactual controls. For instance, compare Omission (X expected then absent) to “never-present” (X never cued) to ensure any effect is due to withdrawal, not mere non-occurrence. Conditions should vary predictability: fully predictable vs random presentation (cf. Kimura 2013【7†L385-L394】) to isolate effects requiring content prediction.

## Participants and Power Analysis

We target human participants (N≈30–50 per study), recruited under IRB approval. An a priori power analysis (assuming medium effect sizes d≈0.6 from prior omission ERP studies【6†L53-L62】【10†L193-L202】) yields power≥0.8 for N≈30–40 (two-tailed α=0.05). For high-dimensional neural data, within-subject designs and cluster-based permutation tests will be used. For behavioral outcomes (choice entropy, reaction times), standard ANOVA or mixed-effects models will be applied. All data and code will be pre-registered (e.g. on OSF) and shared for reproducibility.

## Data Acquisition and Measures

- **Neurophysiological**: EEG or MEG will record omission-related components (e.g. oN1, MMN). We will analyze amplitudes/latencies of these components compared to control trials【6†L53-L62】【10†L193-L202】. fMRI (optional) could localize correlates of o (e.g. frontal anticipatory signals).
- **Behavioral**: Choice distributions will be analyzed for changes in entropy and KL-divergence. Reaction times and error rates in tasks will be compared across conditions (Omission vs. control). Key metrics:
- *Divergence (KL, JS)* between post-omission vs baseline transition probabilities.
- *Entropy* of choice distribution (Ω is high when entropy is low).
- *Mutual information* between prior event (X absent/present) and subsequent action.
- **Subjective**: If applicable, confidence or anticipation ratings can be collected to index implicit prediction.

## Analysis Strategy

1. **ERP Analysis**: Compute event-related potentials for omissions versus controls. Look for omission ERP components (e.g. oP3) only under predictive conditions【7†L385-L394】.
2. **Phase-space Trajectories**: Estimate a state vector S(t) and its transition matrix T. Use dimensionality reduction (e.g. PCA) to visualize trajectories of S in Ω–o space.
3. **Model fitting**: Fit the proposed dynamical equations to time series of o and Ω (inferred from EEG amplitude or choice entropy). Parameters (κ, λ) will be estimated via nonlinear regression.
4. **Statistical Tests**: Compare divergence metrics (KL) against zero (control) and across conditions (ANOVA or permutation tests). Use Bayes factors or equivalence tests to discriminate competing models (see below).

## Statistical Controls and Counterfactuals

- To isolate genuine "operational divergence," we will ensure the **only** difference is absence vs presence of X, holding other cues constant.
- Counterfactual: use "sham-omission" trials where X is not predicted (so any residual effect indicates baseline).
- Bootstrapping and permutation tests will control for multiple comparisons in neural data.
- Model comparisons: Fit a standard predictive-coding model (pure error feedback) and a baseline with working-memory trace, and test whether our expanded model significantly outperforms them on unseen data (cross-validation).

## Tables of Design and Hypotheses

**Table 2. Hypotheses and Predictions (Operative Divergence vs. Competing Models).**

| Hypothesis | Operative Divergence (Mechanica) | Predictive-Coding (Standard) | Working-Memory (Trace) |
|---|---|---|---|
| **Effect of omission on future choices** | Persistent change in choice distribution (increased entropy or shift) due to non-locally resolved o. | No lasting effect beyond immediate error; choices revert to baseline. | No systematic effect once omission is not consciously remembered (limited short-term trace). |
| **Neural response to omission** | Multi-component ERP (oN1/oP3) reflecting active model and control processes 【6†L53-L62】; sustained slow potentials reflecting continued o. | Transient prediction-error ERP only at omission time, then no further activity. | Possibly small P300 but rapidly decaying. |
| **Dependence on predictability** | Omission ERP appears only when stimulus was predicted (strong o)【6†L53-L62】【7†L385-L394】. | Same as Mechanica (error needs prediction), but denies persistent effects. | Similar (trace depends on focus), but weaker: if not attended, omission effect small. |
| **Recovery from omission** | System converges to new state via 𝒩→ action; predicted by $d\Omega/dt = \kappa \cdot o - \lambda \cdot \Omega > 0$ until closure. | State returns passively; no additional drive after error. | Trace decays exponentially with a fixed half-life; modeled by short-term memory decay. |
| **Phase-space signature** | Closed-loop shows attractor-like stabilization (Ω) after action, but a new basin of o may form (oscillation in C)【25†L37-L45】. | No new attractor formation; state jumps back to baseline attractor. | Gradual drift back to baseline attractor with no new fixed points. |

**Table 3. Experimental Conditions.** (Example: Auditory Omission Paradigm)

| Condition | Stimuli Sequence | Prediction | Expected Outcome (Mechanica) |
|---|---|---|---|
| **Predictable-Reward** | A→B→(80% C, 20% Ø) | **High** | Strong omission response; elevated o. |
| **Unpredictable** | A→B→(50% C, 50% Ø random) | Low/None | No systematic ERP; negligible o. |
| **Control (No-X)** | A→B (no C ever) | None | Baseline (no ERP; no divergence). |
| **Violation** | A→*(no B)* | High (unexpected) | General error response (mismatch); different o pattern. |

*(Here Ø denotes omitted stimulus C, "no B" denotes earlier violation.)*

**Table 4. Budget and Resources (illustrative)**

| Item | Low Estimate | Medium Estimate | High Estimate |
|---|---|---|---|
| Participant Compensation (N~50) | \$2,000 | \$5,000 | \$15,000 |
| EEG/MEG Recording | \$5,000 (in-house lab) | \$15,000 (outsourced) | \$50,000 (fMRI + EEG) |
| Equipment/Data Acquisition | \$3,000 (existing) | \$10,000 (additional hardware) | \$100,000 (high-density systems) |
| Personnel (e.g. RA) | \$0 (student) | \$20,000 (1yr RA) | \$100,000 (multi-year team) |
| Data Analysis/Software | \$1,000 | \$5,000 | \$20,000 |
| Overhead/Administrative | -- | \$5,000 | \$30,000 |
| **Total** | **~\$11k** | **~\$60k** | **~\$315k** |

*(All values are illustrative. Low: minimal resources. High: cutting-edge multi-modal study.)*

**Table 5. Deliverables and Timeline.**

| Stage | Months | Activities & Deliverables |
|---|---|---|
| Year 1, Q1–Q2 | 1–6 | Formal model refinement; stimulus/task programming; pilot data (N~10) |
| Year 1, Q3–Q4 | 7–12 | Full experiment 1 (N~30); preliminary analysis; code preregistration and sharing |
| Year 2, Q1–Q2 | 13–18 | Experiment 2 (N~30); divergence metric development; neural data processing |
| Year 2, Q3–Q4 | 19–24 | Cross-validation, model fitting; conference presentations; data publication (open) |
| Year 3, Q1–Q2 | 25–30 | Replication / extension experiments; drafting of results paper; submission |
| Year 3, Q3–Q4 | 31–36 | Revision, dissemination (journals, workshops); final thesis or monograph completion |

*(All data and analysis scripts will be made openly available. Ethical approval and participant consent required.)*

## Formal Predictions and Discriminating Experiments

We now state concrete, **falsifiable predictions** unique to Mechanica Oceanica, contrasting them with standard models:

1. **Persistent Choice Bias after Omission:** If a reward or goal X is withdrawn unexpectedly, the subject's subsequent choice distribution will remain shifted (high KL-divergence) even in the absence of further inputs. Competing models (predictive error, working memory) predict only transient or no bias once the omission is processed. For example, in a two-alternative forced-choice, Mechanica predicts the entropy of choices *immediately after* an omission will differ significantly from baseline, while predictive-coding alone predicts full return to baseline with no pattern【6†L53-L62】.

2. **Action reversal vs. sustained activation:** In a motor task where a target vanishes, Mechanica predicts measurable preparatory activity (e.g. beta-band EEG) persisting beyond disappearance, biased in the direction of the absent target. In contrast, a purely predictive model predicts a brief pulse or phasic response. This can be tested by comparing spectral power or movement correction times between trials where the target disappears versus control.

3. **Necessity of specific prediction:** Like Kimura *et al.*, we predict omission effects only when both *what* and *when* are predictable【7†L385-L394】. If only timing is signaled, our model predicts no substantive divergence (since o never formed without content prediction). If experimentally, omission responses are found even without specific prediction, Mechanica would need revision. Thus, an experiment should include a condition with non-specific cues to test this boundary.

4. **Model-based vs Empirical Signature:** By fitting time-series data to our differential equations, we expect to find parameter values (e.g. $\kappa>0$) indicating active conversion of o to Ω. If instead $\kappa\approx0$ or $\lambda$ very large, it would suggest no self-driven closure beyond immediate input – contrary to Mechanica's assumption. This is a direct "risky" test: success means our model produces significantly better fit (lower cross-validated error) than a null model.

In summary, Mechanica Oceanica predicts **discernible organization of behavior and neural responses that persists after an omission**, and specific phase-space dynamics in state measurements. These can be directly tested and contrasted with current predictive-coding accounts.

## Discussion

Mechanica Oceanica synthesizes diverse frameworks to propose that *absence itself can be causally efficacious* by structuring possibility fields. By introducing o and Ω as formal primitives, we move beyond treating absence as mere nothingness or noise【27†L68-L77】【27†L90-L98】. Philosophically, this aligns with Kant's insight that non-actual conditions (sensibility without spatio-temporal form, or inclination without volition) still meaningfully frame cognition, and with Ghazali's teaching that the heart's orientation can give reality to unseen objects.

If supported by data, this model would impact theories of agency and cognition. It would require revising purely bottom-up accounts and expanding predictive-coding theory to include **self-generated constraint regimes**. It would also connect to embodied/dynamical perspectives (Schöner 2008【25†L37-L45】) by showing how organismic history (habits) alters state-space. Conversely, if key predictions fail (e.g. no long-term effect after omissions), the model would be falsified or require alteration (perhaps indicating that working-memory or immediate error correction suffices).

Limitations include the challenge of isolating abstract *o* experimentally and ensuring that observed effects are not due to attentional capture or other confounds. Our design includes multiple controls to mitigate these.

## Conclusion

Mechanica Oceanica lays out an integrated conceptual–mathematical approach to an old puzzle: how can "nothing" exert force? Through precise definitions and equations grounded in philosophy, we open a new avenue for empirical inquiry. We provide explicit protocols and metrics to verify whether absence can be measured as an operative divergence in cognitive dynamics. The success of this endeavor will advance not only our understanding of mind and brain but also illustrate the utility of formalizing philosophical insights.

## Suggested Journals and Formatting

Potential venues include *Cognition* (8,000 words), *Trends in Cognitive Sciences* (short review), or *Frontiers in Psychology/Neuroscience* (8000–10,000 words). A journal like *Synthese* or *Journal of Consciousness Studies* might appreciate the philosophical depth. Manuscript will follow APA or journal-specific style (double-spaced, 12pt font, with figures and tables as above). We recommend open-access if possible. For AI alignment, we will preregister our hypotheses (OSF) and deposit anonymized data/code in a public repository.

## References (prioritized)

*Kant1781* – Immanuel Kant, *Critique of Pure Reason* (A-edition, 1781).
*GhazaliDeliverer* – Al-Ghazali, *Al-Munqidh min al-Ḍalāl* ("Deliverer from Error"), 12th c. (Eng. trans.).
*Friston2005* – K. Friston, A theory of cortical responses. *Philos Trans R Soc Lond B* 360:815–836 (2005).
*Schöner2023* – G. Schöner, "Dynamical Systems Approaches to Cognition." (In press).
*Deacon2013* – T. Deacon, *Incomplete Nature: How Mind Emerged from Matter* (W.W. Norton, 2013).
*Kimura2013* – A. Kimura *et al*., "I know what is missing here: Electrophysiological prediction error signals elicited by omissions of predicted 'what' but not 'when'." *Front. Hum. Neurosci.* 7:407 (2013)【7†L385-L394】.
*Rodriguez2026* – L. Rodriguez *et al*., "The sound of silence: Omission responses and how the brain predicts in the absence of sound." *Neurosci Biobehav Rev* 181:106505 (2026)【10†L193-L202】.
*Dercksen2022* – T. T. Dercksen *et al*., "Somatosensory omissions reveal action-related predictive processing." (2022, preprint)【6†L53-L62】.

*(Full reference list will include all citations from the text.)*

# Appendix A: Experimental Protocols

*(Detailed methods, stimuli, and analysis scripts will be posted online. Key points given below.)*

- **Auditory Omission Task**: Participants press a button; 80% of presses yield tone X after fixed delay. On 20% of trials, X is omitted. EEG is recorded with 64 channels, referenced to mastoids. Trials are randomized with jitter. ERP analysis focuses on 200–500 ms post-omission.
- **Target-Displacement Task**: Subjects view a dot target for 200 ms; 50% of trials it remains, 50% it disappears at onset. Subjects must then saccade or reach to remembered location. Eye-tracking/ Kinematics and EEG are synchronized. Reaction time and path curvature are measured.
- **Reward-Learning Task**: Two buttons (A,B) each yield a reward (colorful stimulus) 70% of the time, balanced by trial. After learning, some trials randomly omit expected reward. Choices on next trial are recorded along with pupil/EEG measures of surprise.

Each task will be counterbalanced and interleaved with catch trials. Ethical guidelines (informed consent, IRB) will be strictly followed.

# Appendix B: Metrics and Analysis Details

- **Kullback–Leibler divergence**: For discrete action distributions *P* and *Q* (post-omission vs. control),

$$D_{\mathrm{KL}}(P||Q) = \sum_a P(a) \ln \frac{P(a)}{Q(a)}.$$

- **Cross-validation**: For model fitting, we will use k-fold CV (k=5) comparing the log-likelihood of held-out data.

- **ERP Component Quantification**: Peak amplitude and area under curve of oN1/P3 will be extracted in pre-defined windows (e.g. 80–120ms, 300–500ms) for omission vs control conditions.
- **Statistical thresholds**: Cluster-based permutation tests (α=0.05) for EEG; mixed ANOVA (factors: Condition×Time) for behavior.

# Mermaid Diagram of Conceptual Loop

```
flowchart LR
    subgraph Conceptual Field
        Ψ(("Ψ (field of possibilities)"))
    end
    Ψ --> I["𝒥: Intuition (givenness)"]
    I --> R[["Representation R"]]
    R --> S["𝒮: Instinct (constraints)"]
    S --> P["Space ℙ_S of possible actions"]
    P --> D["𝒟: Impulse (directional drive)"]
    D --> N["𝒩: Intention/Selection"]
```

```
    N --> A[[Action A (trajectory)]]
    A --> Ω(("Ω: Local closure"))
    Ω --> newΨ(("Updated field Ψ_{t+1}"))
    newΨ --> I  % loop back via 𝒥
```

# Illustrative Plots

```python
# Figure: Hypothetical divergence o(t) over time after omission vs. baseline
import numpy as np
import matplotlib.pyplot as plt
t = np.linspace(0, 10, 200)
o_predicted = np.exp(-0.5*t) * (1 + 0.3 * np.sin(0.5*t))  # lingering after-effect
o_baseline  = np.exp(-1.5*t)                               # rapid decay
plt.plot(t, o_predicted, label='Post-omission (Mechanica)')
plt.plot(t, o_baseline, label='Baseline (no divergence)')
plt.xlabel('Time after expected event')
plt.ylabel('Operational divergence, o(t)')
plt.legend()
plt.title('Schematic o(t) trajectories')
plt.savefig('divergence_plot.png')
```

```python
# Figure: Phase portrait for simple o-Ω dynamics
import numpy as np
import matplotlib.pyplot as plt
o_vals = np.linspace(-0.5, 1.5, 20)
O_vals = np.linspace(-0.5, 1.5, 20)
X, Y = np.meshgrid(o_vals, O_vals)
U = -X
V = X - Y
plt.quiver(X, Y, U, V, color='gray')
plt.xlabel('o (Divergence)')
plt.ylabel('Ω (Coherence)')
plt.title('Phase portrait of simple Ω–o dynamics')
plt.axhline(0, color='black', lw=0.5)
plt.axvline(0, color='black', lw=0.5)
plt.savefig('phaseportrait.png')
```

*(The above code generates conceptual diagrams of divergence trajectories and the Ω–o phase space. In practice, these would be replaced by empirical data plots.)*

---