

Coherence time in neural oscillator assemblies sets the speed of thought

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Abstract

Neuroscience has established that cognitive processing depends on coherent oscillations across neural assemblies: working memory maintenance requires sustained theta-gamma coupling [1], attention modulates inter-areal synchronization [2], and perceptual binding emerges from transient phase alignment [3]. Yet the physical principles determining how fast these assemblies can synchronize—and thus how fast we can think—remain incompletely formalized. We derive a quantitative framework showing that coherence time in coupled oscillator networks scales exponentially with coordination depth. For M semi-independent modules requiring phase alignment within tolerance ε at Kuramoto coherence r and phase-exploration rate $\Delta\omega$:

$$\tau_{\text{coh}} = \frac{1}{\Delta\omega} \left(\frac{2\pi}{\varepsilon} \right)^{\alpha(1-r)(M-1)}$$

where circular variance $(1-r)$ governs phase dispersion and α reflects the effective coordination regime. This produces a fundamental speed-flexibility trade-off: increasing

coordination depth M expands combinatorial flexibility but slows commits exponentially; tighter coherence (higher r) speeds synchronization but restricts dynamics to low-dimensional attractors. Combining coherence time with quantum, noise, and power limits yields a unified temporal resolution bound explaining millisecond-scale perceptual windows, arousal-driven time dilation, alpha frequency correlates of temporal acuity, and metabolic scaling across species. While neural oscillators provide the most empirically accessible measurements, the framework applies to any biological oscillator system—molecular motors, genetic oscillators, circadian networks. We provide parameter estimation protocols from electrophysiological recordings and testable predictions including alpha entrainment linearity and dual-loop dissociations under arousal.

Keywords: neural oscillations, coherence time, dimensional coordination, temporal resolution, working memory, coupled oscillators

1 Introduction

1.1 Neural oscillations determine processing speed

A fundamental insight from systems neuroscience is that cognition emerges from coherent oscillations across neural assemblies, not merely from individual spike rates. Working memory maintenance requires sustained theta-gamma phase-amplitude coupling [1, 4]. Attention selectively enhances inter-areal synchronization in gamma band [2, 5]. Perceptual binding depends on transient phase alignment across sensory cortices [3, 6]. Long-range communication occurs preferentially during coherent states [7]. The “communication through coherence” framework [8] has become central to understanding neural computation.

Yet despite extensive empirical characterization, the physical principles governing *how fast* distributed assemblies can achieve coherence—and thus how quickly cognitive operations can proceed—remain incompletely formalized. Why does perceptual binding require 30–50 ms rather than 3 ms or 300 ms? Why do larger assemblies integrating more information

process more slowly? What determines the relationship between oscillation frequency (e.g., α at 10 Hz) and temporal acuity?

1.2 The missing quantitative framework

We propose that neural processing speed is fundamentally limited by *coherence time*: the time required for distributed oscillators to achieve sufficient phase alignment for a collective computation to register. This coherence time exhibits three critical properties:

1. Exponential scaling with coordination depth. Larger numbers of semi-independent modules requiring phase alignment synchronize exponentially more slowly. For typical parameters ($r = 0.6$, $\varepsilon = \pi$, $\alpha = 0.9$), increasing M from 5 to 15 slows coherence time by a factor of $\sim 2^4 \approx 16$, while increasing from 10 to 30 yields a $\sim 10^3$ -fold slowdown.

2. Modulation by coupling strength. Stronger coupling (higher Kuramoto coherence r , lower circular variance $1 - r$) dramatically speeds synchronization by reducing phase dispersion, but at the cost of restricting dynamics to low-dimensional synchronized attractors. This creates a fundamental speed-flexibility trade-off.

3. Universality across biological oscillators. While neural oscillators are the most accessible experimentally, the same principles govern any coupled biological oscillator system: molecular motors requiring conformational alignment, genetic regulatory networks, circadian pacemakers. The physics is general; neuroscience simply provides the richest empirical testbed.

1.3 Empirical puzzles and predictions

Three phenomena motivate and test our framework:

Scale-dependent temporal resolution. Proteins explore conformational space on picosecond timescales yet catalytic turnover occurs at microseconds-to-milliseconds. Neural populations fire at kilohertz rates yet perceptual binding requires tens of milliseconds. Circadian oscillators maintain 24-hour periods. We demonstrate these span different physical

regimes of a unified bound.

Subjective time dilation without motor slowing. Under acute stress (tachypsychia), subjective time slows while reaction times remain constant [12]. We show this dissociation reveals dual commit pathways: high-dimensional cortical coherence (perception) versus low-dimensional cerebellar primitives (motor execution), each with different coherence times.

Metabolic scaling of temporal acuity. Critical flicker fusion frequency correlates with mass-specific metabolic rate across three orders of magnitude in body size [13]. Flies perceive at 240 Hz, humans at 60 Hz, turtles at 15 Hz. We derive this relationship from power-limited coherence time.

The framework generates specific, testable predictions: alpha frequency entrainment should linearly shift perceptual windows; arousal should dissociate perceptual and motor timing; consciousness should correlate more strongly with field coherence measures than spike counts.

1.4 Structure of this work

We first derive the coherence time formula from principles of phase synchronization in coupled oscillator networks (§2.1), then embed it in a unified temporal resolution bound combining quantum, noise, and power constraints (§2.2). Section 3 applies the framework to neural systems, demonstrating quantitative agreement with perceptual binding windows, tachypsychia dissociations, and metabolic scaling. Section 4 discusses the speed-flexibility trade-off, provides testable predictions, and notes scope boundaries. While we emphasize neural applications given their empirical accessibility, we highlight throughout that coherence time is a general principle governing any biological oscillator assembly.

Previous work established sub-Landauer biological computation [14] and timing inaccessibility in high-dimensional systems [15]. Here we complete the framework by quantifying how assembly size and coupling strength determine processing speed.

1.5 Historical context: Biological time and Igamberdiev’s framework

The concept that biological systems exhibit temporal organization distinct from physical time has deep roots. Vernadsky [16] proposed that living systems possess a non-Euclidean “biological space-time” geometry fundamentally different from the Newtonian absolute time of physics. Building on this foundation, Igamberdiev [17] formalized the notion of *biological time*—a logarithmic function of physical time that reflects the rate-dependent nature of biological processes. He demonstrated that temporal resolution in living systems is:

- **Process-dependent:** Different biological operations (molecular conformational changes, developmental morphogenesis, neural processing) occur on timescales determined by their internal dynamics, not external clocks
- **Logarithmically scaled:** Early ontogenetic stages exhibit faster temporal resolution than later stages, suggesting exponential slowdown with system complexity
- **Governed by non-holonomic constraints:** The direction of temporal development is determined by path-dependent irreversibilities in the system’s state space
- **Analogous to quantum measurement:** Biological transformations resemble the reduction of the wavefunction in quantum mechanics—distributed states collapse to definite outcomes at characteristic timescales

Igamberdiev’s framework remained largely phenomenological, lacking a quantitative mechanistic basis. Our coherence time formula (Eq. 3) provides this missing link: the exponential scaling with coordination depth M is precisely the mathematical realization of biological time’s logarithmic relationship to physical time. When M modules must achieve phase alignment, coherence time grows as $\tau_{\text{coh}} \propto \exp[\alpha(1-r)(M-1)\ln(2\pi/\varepsilon)]$, making biological time $t_{\text{bio}} \sim \ln(\tau_{\text{coh}}) \propto M$, linear in system complexity.

The non-holonomic constraints Igamberdiev identified correspond to our coordination depth M : the set of modules that must jointly synchronize determines which trajectories in phase space can reach the commit threshold, making temporal development path-dependent and irreversible. The quantum measurement analogy becomes concrete: wavefunction collapse maps to the order parameter $r(t)$ crossing the coherence threshold, projecting the high-dimensional oscillator state onto a low-dimensional synchronized manifold.

Igamberdiev later extended this framework to quantum mechanical properties of biosystems [18], arguing that living systems perform internal “quantum non-demolition measurements” with low energy dissipation via slow conformational relaxation. This corresponds precisely to our collision-free dynamics in high-dimensional phase space (see [14]): biological oscillator networks maintain coherent dynamics without discrete enumeration costs, collapsing dimensionality only at commit boundaries. The present work completes a 40-year theoretical arc from Vernadsky’s intuition through Igamberdiev’s formalization to a quantitative, testable formula grounded in coupled oscillator physics.

2 Theory and Methods

2.1 The unified temporal resolution bound

We model biological temporal processing as a sequence of *commits*—thermodynamically irreversible events that register high-dimensional internal state as low-dimensional output. A commit requires: (1) dimensional collapse from distributed state (D_{eff} dimensions) to registered outcome (few dimensions), (2) dissipation of at least $k_B T \ln 2$ per bit (Landauer bound), and (3) creation of a persistent measurement influencing future dynamics.

The minimum time between commits is bounded by four physical constraints:

$$\boxed{\tau_{\text{eff}} = \max[\tau_{\text{QSL}}, \tau_{\text{SNR}}, \tau_{\text{coh}}, \tau_{\text{power}}]} \quad (1)$$

where the **max** operation reflects that the slowest mechanism dominates. The four terms are:

Quantum speed limits (τ_{QSL}). The Mandelstam-Tamm and Margolus-Levitin bounds [19, 20] establish

$$\tau_{\text{QSL}} = \max \left[\frac{\hbar}{2\Delta E}, \frac{\pi\hbar}{2\langle E \rangle} \right]$$

For biological temperatures ($\Delta E \sim k_{\text{B}}T$), $\tau_{\text{QSL}} \sim 10^{-13}$ s, relevant only for ultrafast molecular dynamics.

Signal-to-noise limit (τ_{SNR}). Matched-filter detection in additive white Gaussian noise (two-sided power spectral density N_0 , units: power/Hz) over bandwidth B achieves $\text{SNR}(T) = 2P_s T / N_0$ where P_s is signal power and T is integration time [21]. Reaching detection threshold $\rho_{\text{min}} \sim 5$ –10 requires

$$\tau_{\text{SNR}} = \frac{\rho_{\text{min}} N_0}{2P_s}$$

For neural LFP signals, N_0 is estimated from background noise variance and sampling bandwidth (see ESM 1 for conversion protocols).

Power limit (τ_{power}). Dimensional collapse by $\Delta\mathcal{D}$ at dimensional chemical potential $\lambda_{\mathcal{D}} \sim k_{\text{B}}T_{\text{eff}}$ costs energy $\sim \lambda_{\mathcal{D}}\Delta\mathcal{D}$ (derivation in ESM 2). At sustained power P , commit rate is bounded by

$$\tau_{\text{power}} = \frac{\lambda_{\mathcal{D}}\Delta\mathcal{D}}{P}$$

Coherence time (τ_{coh}). We model commits as threshold crossings of the order parameter across M semi-independent modules. (By “commit” we mean an irreversible registration of distributed state into a low-dimensional outcome that constrains subsequent dynamics—not necessarily a single spike or discrete behavioral choice.) Let r be the mean resultant length (Kuramoto order parameter), and $\kappa(r)$ the von Mises concentration with $r = I_1(\kappa)/I_0(\kappa)$ [26].

For small phase window ε per module, the per-module alignment probability is

$$p_{\text{align}}(\varepsilon, \kappa) \approx \frac{\varepsilon}{2\pi} \frac{e^\kappa}{I_0(\kappa)} \approx \frac{\varepsilon}{2\pi} \sqrt{2\pi\kappa} \quad (\kappa \gg 1).$$

Assuming independence across modules on the commit timescale, the mean waiting time for all M modules to align is

$$\tau_{\text{coh}} \approx \frac{1}{\Delta\omega} \left[p_{\text{align}}(\varepsilon, \kappa(r)) \right]^{-(M-1)}. \quad (2)$$

A practical surrogate consistent with Kuramoto synchronization theory [24, 25] is

$$\tau_{\text{coh}} \approx \frac{1}{\Delta\omega} \left(\frac{2\pi}{\varepsilon} \right)^{\alpha(1-r)(M-1)}, \quad \alpha \in [0.6, 1.0], \quad (3)$$

where α reflects the effective coordination regime (empirical validation in ESM 3: modular networks yield $\hat{\alpha} \approx 0.65$; fully-connected and sparse networks show weak or absent scaling).

Physical interpretation: M is the **coordination depth**—the number of semi-independent modules (locally coherent clusters) whose order parameters must jointly exceed a threshold for a commit to register. $\Delta\omega$ is the **phase-exploration rate**: the characteristic frequency at which phases mix, combining natural frequency spread and phase diffusion from noise [27, 28]. Circular variance $1 - r$ quantifies residual phase dispersion [26]. Note: $M \leq D_{\text{eff}}$ where D_{eff} is the full manifold dimensionality; M counts only commit-relevant modules.

Key assumptions:

1. **Module independence:** Semi-independent dynamics across modules on the commit timescale (weak inter-module coupling compared to intra-module).
2. **Moderate coupling regime:** Near synchronization onset where topology parameter α is approximately constant; breakdown in deep-synchronization or fully-incoherent limits.

3. **Stationary noise:** Phase diffusion rate $\Delta\omega$ remains approximately constant during the alignment window τ_{coh} .
4. **Modular topology:** The theory applies when modules are internally coherent but not globally phase-locked. Fully synchronized (all-to-all) or highly fragmented (sparse) regimes fall outside its scope (see ESM 3).

2.2 The speed-flexibility trade-off

The coherence time reveals opposing constraints on commit rate:

Proposition 1 (Speed-Flexibility Frontier). *At fixed power P , systems face a Pareto frontier in (M, r) space:*

- **Increasing M :** *Expands combinatorial flexibility (number of modules whose phases can vary independently) but slows commits via $\tau_{\text{coh}} \propto (\text{const})^M$*
- **Increasing r :** *Speeds commits via reduced circular variance $(1 - r)$ but restricts exploration to low-dimensional synchronized manifold*

Proof: Taking logarithmic derivatives of Eq. 3:

$$\frac{\partial \ln \tau_{\text{coh}}}{\partial M} = \alpha(1 - r) \ln \frac{2\pi}{\varepsilon} > 0 \quad (4)$$

$$\frac{\partial \ln \tau_{\text{coh}}}{\partial r} = -\alpha(M - 1) \ln \frac{2\pi}{\varepsilon} < 0 \quad (5)$$

State-space volume accessible in time τ scales as $\sim \exp(D_{\text{eff}})$ where $D_{\text{eff}} \geq M$. Thus increasing coordination depth M expands the dimensionality of commit-registered outcomes but requires exponentially longer alignment time. Increasing coherence r speeds commits but forces trajectories onto low-dimensional attractors, reducing the set of accessible commit outcomes. \square

2.3 Parameter estimation protocols

Effective dimensionality (D_{eff}). From neural population recordings (spike trains from N neurons), compute $N \times N$ covariance matrix $C_{ij} = \langle (x_i - \langle x_i \rangle)(x_j - \langle x_j \rangle) \rangle$. Eigendecomposition yields eigenvalues $\{\lambda_1, \dots, \lambda_N\}$. Define participation ratio:

$$D_{\text{eff}} = \frac{(\sum_i \lambda_i)^2}{\sum_i \lambda_i^2}$$

Alternatively, count principal components capturing 90% variance. Typical values: visual cortex $D_{\text{eff}} \sim 10\text{--}50$ from ~ 100 neurons [30, 31, 32].

Coordination depth (M). M is the count of semi-independent modules (locally coherent clusters) whose order parameters must jointly exceed a threshold to register a commit.

Operational estimation:

1. Cluster channels/units by band-limited coherence (e.g., via phase-locking value $>$ threshold) or Granger causality/transfer entropy into modules.
2. Identify the minimal set of modules whose joint activity predicts behavioral commits (e.g., via logistic regression on module order parameters).
3. Typical values: occipital visual tasks yield $M \sim 6\text{--}10$; cross-modal binding $M \sim 10\text{--}15$; default-mode wandering $M \sim 15\text{--}20$.

Critical distinction: D_{eff} measures full manifold geometry (participation ratio); $M \leq D_{\text{eff}}$ counts only commit-relevant modules requiring coordination. For single-area local processing, M may be small ($\sim 5\text{--}10$) even when $D_{\text{eff}} \sim 30\text{--}50$.

Kuramoto coherence (r). Extract instantaneous phase $\theta_j(t)$ from bandpass-filtered LFP/EEG via Hilbert transform. Compute

$$r(t) = \left| \frac{1}{N} \sum_{j=1}^N e^{i\theta_j(t)} \right|$$

Average over task epochs: $\langle r \rangle$. **Caveat:** Hilbert transform assumes narrowband signals; for multi-frequency or transient dynamics, consider wavelet-based phase extraction [37] or analytic signal methods. Typical values: spontaneous cortex ~ 0.2 – 0.4 ; attention ~ 0.5 – 0.7 ; circadian networks ~ 0.7 – 0.9 [2].

Phase alignment window (ε). From spike train or LFP cross-correlograms, measure half-width at half-maximum (HWHM, units: seconds). The **full** phase window is $\varepsilon = 2\omega_0$ HWHM (radians), where $\omega_0 = 2\pi f_0$ is the angular frequency. Example: gamma-band ($f_0 = 40$ Hz), HWHM ~ 6 ms $\rightarrow \varepsilon = 2 \times 2\pi \times 40 \times 0.006 \sim 3$ rad $\approx \pi$. We use the full window throughout. For cross-modal binding with looser temporal windows, ε can approach 2π .

Phase-exploration rate ($\Delta\omega$). Estimate from instantaneous frequency spread or phase diffusion, *not* the carrier frequency. Practically: the standard deviation of the band-limited instantaneous frequency (from Hilbert or wavelet transform), or the diffusion coefficient fitted to phase increments $\Delta\theta(t)$. Typical values: $\Delta\omega \sim 2\pi \times (5\text{--}20)$ rad/s for cortical gamma/alpha bands.

Dimensional chemical potential ($\lambda_{\mathcal{D}}$). Near equilibrium: $\lambda_{\mathcal{D}} \approx k_{\text{B}}T \sim 4.1 \times 10^{-21}$ J. Far from equilibrium (neural systems): $\lambda_{\mathcal{D}} \sim (5\text{--}20)k_{\text{B}}T$. From metabolic measurements: $\lambda_{\mathcal{D}} \sim P/(r_{\text{commit}}\Delta\mathcal{D})$.

3 Results

3.1 Visual perceptual binding windows

Human visual perception exhibits temporal integration windows of 30–50 ms (flicker fusion at 20–30 Hz). We apply Eq. 1 with neural parameters.

Visual binding window (recomputed). Take $M = 8$ occipital modules (V1, V4, posterior parietal sub-regions), $r = 0.7$ (attention [2]), full tolerance $\varepsilon = \pi$ rad ($\pm 90^\circ$ across modules), and phase-exploration rate $\Delta\omega = 2\pi \times 20$ rad/s (alpha–beta spread/phase diffusion). Using Eq. 3 with $\alpha = 0.9$ (strongly coupled cortical regime):

$$\tau_{\text{coh}} \approx \frac{1}{125.66} \left(\frac{2\pi}{\pi} \right)^{0.9(1-0.7)(7)} = \frac{1}{125.66} 2^{1.89} \approx \frac{3.7}{125.66} \approx 30 \text{ ms}.$$

Computing all terms in Eq. 1:

$$\tau_{\text{QSL}} \sim 10^{-14} \text{ s} \quad (\text{negligible}) \tag{6}$$

$$\tau_{\text{SNR}} \sim 5\text{--}10 \text{ ms} \quad (\text{task-dependent; see ESM 1}) \tag{7}$$

$$\tau_{\text{power}} \ll 1 \text{ ms} \quad (\text{per commit, local assembly power}) \tag{8}$$

$$\tau_{\text{coh}} \approx 30 \text{ ms} \tag{9}$$

The effective commit time is $\tau_{\text{eff}} = \max[10^{-14}, 5\text{--}10, < 1, 30] \approx 30\text{--}50$ ms, matching human binding windows. **Coherence time dominates.**

Modest parameter variations produce order-of-magnitude shifts: $r = 0.8$ (stronger attention) yields $\tau_{\text{coh}} \sim 10$ ms; $r = 0.6$ (relaxed coupling) yields $\tau_{\text{coh}} \sim 80$ ms; $M = 12$ (cross-modal audio-visual) yields $\tau_{\text{coh}} \sim 150$ ms, matching cross-modal binding latencies [10].

3.2 Tachypsychia: dual-loop dissociation

During acute stress or falls, subjects report subjective time slowing while objective reaction times remain unchanged [12]. This provides exclusion-based evidence about conscious experience:

Exclusion logic:

- Conscious time perception \neq motor commit rate (time dilation without reaction time change)
- Conscious time perception \neq post-commit memory encoding (would also predict reaction time change)
- **Inference:** Phenomenal temporal experience may correlate with continuous pre-commit coherent dynamics rather than discrete commit events

This resonates with Integrated Information Theory’s emphasis on integrated states [38] and Global Workspace Theory’s requirement for sustained coherent broadcasting [39]. Both frameworks predict consciousness should correlate with field-level dynamics (high coherence, broad integration) rather than sparse spiking events.

Mechanistic explanation: We propose dual commit pathways:

Perceptual loop (cortical): High- M (~ 10 – 15 modules) coherent field dynamics across sensory and associative areas. Commits sparse (5–20 Hz), expensive ($\lambda_{\mathcal{D}}\Delta\mathcal{D} \sim 10^6 k_{\text{B}}T$). Arousal increases coherence r and thus information rate $\mathcal{I}(t)$ via enhanced synchronization and gain modulation. Subjective duration scales as

$$T_{\text{subjective}} \propto \int_0^{\Delta t} \mathcal{I}(t) dt$$

Richer $\mathcal{I}(t)$ per inter-commit interval produces time dilation experience.

Motor loop (cerebellar/basal ganglia): Low- M (~ 3 – 5 modules) primitives executing learned policies. Commits faster (50–150 ms), cheaper. Arousal modulates decision thresh-

old/drift rate, preserving reaction time:

$$\text{RT} = T_{\text{nondec}} + \frac{a}{v}$$

where lowered threshold a and increased drift v approximately offset.

This dual-loop architecture explains the dissociation: perceptual commits (high M , modulated by arousal) proceed independently of motor commits (low M , threshold-compensated).

3.3 Alpha oscillations and temporal acuity

Alpha oscillations (8–12 Hz) in visual cortex correlate with temporal acuity: individuals with faster alpha perceive time faster [33, 34]. We interpret alpha as reflecting commit frequency:

$$r_{\text{commit}} \sim f_{\alpha}.$$

Prediction: Manipulating alpha via transcranial alternating current stimulation (tACS) should proportionally shift perceptual windows. Increasing f_{α} from 10 Hz to 12 Hz (20% increase) predicts 20% reduction in flicker fusion threshold (50 ms \rightarrow 42 ms).

3.4 Metabolic scaling across species

Equation 1 predicts different regimes. When coordination time is slow ($\tau_{\text{coh}} \gg \tau_{\text{power}}$), coherence dominates (as in human perception). When power is limiting ($\tau_{\text{power}} \gg \tau_{\text{coh}}$), we obtain $\tau_{\text{eff}} \sim 1/P$.

Derivation of metabolic scaling: For animals with similar neural architecture ($M \sim 5\text{--}10$, $r \sim 0.5\text{--}0.7$, $\varepsilon \sim \pi$), coordination time is roughly constant: $\tau_{\text{coh}} \sim 10\text{--}100$ ms. However, power available for neural computation scales with mass-specific metabolic rate P_{meta} (mL $\text{O}_2/\text{g}/\text{hr}$). Converting to neural power via ATP yield: $P \propto P_{\text{meta}}$. From Eq. 1, when $\tau_{\text{power}} = \lambda_{\mathcal{D}}\Delta\mathcal{D}/P$ dominates (small animals with high metabolic rates), critical flicker fusion frequency is

$$f_{\text{CFF}} \sim \frac{1}{\tau_{\text{power}}} \sim \frac{P}{\lambda_{\mathcal{D}}\Delta\mathcal{D}} \propto P_{\text{meta}}$$

With allometric scaling $P_{\text{meta}} \propto M^{-1/4}$ (Kleiber’s law), this predicts $f_{\text{CFF}} \propto M^{-1/4}$.

Healy et al. [13] measured critical flicker fusion frequency across diverse taxa:

- Flies: ~ 240 Hz (metabolic rate ~ 10 mL $\text{O}_2/\text{g/hr}$, mass ~ 10 mg)
- Humans: ~ 60 Hz (~ 0.25 mL $\text{O}_2/\text{g/hr}$, mass ~ 70 kg)
- Leatherback turtles: ~ 15 Hz (~ 0.02 mL $\text{O}_2/\text{g/hr}$, mass ~ 500 kg)

Log-log regression shows $R^2 \approx 0.6$ across three orders of magnitude in body mass, with $f_{\text{CFF}} \propto P_{\text{meta}}^{0.6}$ (Figure 2 in Ref. [13]). The near-linear relationship validates the power-limited regime for small, high-metabolism animals.

3.5 Parameter sensitivity enables dynamic range

The exponential scaling in Eq. 3 produces extreme parameter sensitivity (Figure 3):

- $M : 5 \rightarrow 15$ shifts τ by $\sim 2^{10\alpha(1-r)} \sim 10^2\text{--}10^3$ (fixed $r = 0.6$, $\varepsilon = \pi$, $\alpha = 0.9$)
- $r : 0.5 \rightarrow 0.7$ shifts τ by $\sim 2^{2(M-1)\alpha} \sim 10^2$ (fixed $M = 8$)
- $\varepsilon : \pi \rightarrow \pi/3$ shifts τ by $\sim 3^{\alpha(1-r)(M-1)} \sim 10^1\text{--}10^2$

This is *not a flaw* but the mechanism enabling massive dynamic range. Arousal, attention, and training modulate r and task-recruit different M by factors of 2, producing order-of-magnitude temporal changes without proportional metabolic costs. Linear scaling would require $100\times$ power for $100\times$ faster perception—energetically prohibitive.

4 Discussion

4.1 Biological examples of the speed-flexibility trade-off

Mind-wandering and creative insight (high M , low r). Default-mode network activity exhibits low inter-regional coherence ($r \sim 0.3$) and high coordination depth ($M \sim 12\text{--}20$)

distributed modules). Commits are rare ($\sim 0.1\text{--}1$ Hz), producing subjective “slow thinking” but enabling novel cross-network associations unavailable to high-coherence focused states.

Focused attention (moderate M , moderate r). Attention increases coherence ($r : 0.3 \rightarrow 0.6$) and narrows coordination to task-relevant modules ($M : 15 \rightarrow 8$) by suppressing task-irrelevant networks [2]. This produces faster commits (10–30 Hz) in a restricted “spot-light” subspace—the classic attention speed-accuracy trade-off recast as speed-flexibility.

Automaticity and skill learning (low M , high r). Overlearned motor sequences compress to low-dimensional cerebellar/basal ganglia primitives ($M \sim 3\text{--}5$ coordinating modules) with tight forward-model coherence ($r \sim 0.8$). Commits are rapid (50–150 ms motor latencies) but inflexible. Perturbations requiring cortical intervention feel “jarring” because the system must switch regimes (low- M /high- $r \rightarrow$ high- M /low- r).

4.2 Testable predictions

Alpha entrainment. tACS at alpha frequency should shift perceptual binding windows linearly with frequency change. Effect strongest in occipital cortex during visual tasks. 20% frequency increase \rightarrow 20% threshold reduction. Deviations from linearity indicate subharmonic/burst mechanisms.

Arousal effects on dual-loop dissociation. During simultaneous simple reaction time + temporal-order judgment under acute stress (or noradrenergic agonism):

- Temporal-order discrimination threshold changes
- Simple reaction time unchanged or slightly faster
- Statistical independence between measures (evidence of separate pathways)

Immediate versus delayed duration judgments. Pre-commit framework predicts arousal expands *both* immediate and retrospective duration reports. Pure memory-encoding accounts predict only retrospective effects. Test via immediate temporal-order judgments during arousal.

Coherence measures and consciousness. If phenomenal experience reflects pre-commit coherent dynamics (as suggested by the tachypsychia dissociation), conscious states should correlate more strongly with phase-locking index, theta-gamma coupling, and beta-band coherence than with spike count or mean firing rate. Testable: during automaticity, high cerebellar/basal ganglia spiking combined with low cortical coherence should predict unconscious execution [38, 39].

Psychedelic dose-dependence. Psychedelics produce dose-dependent time distortions. Framework prediction: time perception direction depends on **band-specific** coherence changes that shift τ_{coh} via modulation of r and M . Low doses may sharpen task-relevant coherence (increase r in gamma/beta, narrow M) \rightarrow faster commits, subjectively accelerated time. High doses disrupt long-range coordination (suppress alpha, increase LZ-complexity, fragment M) \rightarrow exponentially rare commits, subjectively frozen or dilated time. Empirical tests should correlate time distortion *direction* with band-resolved Δr in task-active frequencies, not global coherence metrics.

4.3 Relationship to existing frameworks

Integrated Information Theory [38]: We provide thermodynamic/temporal foundations. Integration costs energy ($\sim \lambda_{\mathcal{D}} \Delta \mathcal{D}$) and takes time (exponentially with D_{eff}).

Free Energy Principle [40]: We add temporal structure. Prediction updates occur at commit events with rate limited by Eq. 1. Hierarchy of commit depths maps onto prediction error hierarchies.

Neural criticality [41]: Near synchronization transition ($r \rightarrow r_c$), critical slowing predicts commit rate suppression. Benefits: sub-commit integration enables weak-signal sensitivity. Costs: altered time perception as commits become rare.

4.4 Scope boundaries

The framework applies most directly to oscillatory systems with coupled dynamics where Kuramoto r is well-defined. Non-oscillatory systems (bacterial chemotaxis, plant circadian clocks without neural oscillators) may require alternative coherence measures.

Circadian example (demonstrating scope): Circadian gene networks exhibit $M \sim 3\text{--}5$ core feedback loops, $r \sim 0.8$ (tight coupling), and $\varepsilon \sim 0.5$ rad (loose phase tolerance). These parameters yield $f \approx 1\text{--}10$ via Eq. 3, implying coordination is *not* the bottleneck. The 24-hour period arises instead from molecular lags (transcription, translation, protein accumulation timescales). The framework correctly identifies the dominant regime: circadian clocks are *biochemical-delay-limited*, not coordination-limited.

Extending to hierarchical, modular architectures with nested commits remains an empirical challenge. Quantum coherence effects (photosynthesis, magnetoreception) could extend the framework to regimes where quantum and dimensional coordination compete.

4.5 Fundamental versus biological principles

While we emphasize neural applications, the relationships between time, energy, dimensionality, and measurement are fundamental. Equation 1 applies to any system performing irreversible measurements: molecular catalysis (microsecond turnover from nanosecond fluctuations), chemical reaction networks (multi-protein assembly), quantum measurement (high-dimensional Hilbert space decoherence).

Biology provides empirically rich examples spanning 15 orders of magnitude, with consciousness offering direct phenomenological access to pre-commit dynamics unavailable for molecular or quantum systems. The tachypsychia dissociation constrains *where* in physi-

cal dynamics experience resides—potentially informing measurement theory beyond neuroscience.

5 Conclusion

We have established that coherence time sets the speed of thought. The bound

$$\tau_{\text{eff}} = \max[\tau_{\text{QSL}}, \tau_{\text{SNR}}, \tau_{\text{coh}}, \tau_{\text{power}}]$$

with coherence time

$$\tau_{\text{coh}} = \frac{1}{\Delta\omega} \left(\frac{2\pi}{\varepsilon} \right)^{\alpha(1-r)(M-1)}$$

unifies quantum, noise, and coordination limits to explain temporal resolution in physical measurement systems. Here M is coordination depth (number of semi-independent modules requiring alignment), $(1-r)$ is circular variance (phase dispersion), and α reflects the effective coordination regime (topology \times coupling), not topology alone.

Key findings:

1. **Speed-flexibility trade-off:** Increasing M exponentially slows commits but expands combinatorial flexibility. Increasing r speeds commits but restricts dynamics to low-dimensional synchronized manifolds. Biology operates on a Pareto frontier in (M, r) space.
2. **Dual-loop architecture:** Separate perceptual (high- M cortical) and motor (low- M cerebellar) pathways explain tachypsychia dissociation. The dissociation suggests phenomenal temporal experience may correlate with pre-commit coherent dynamics rather than discrete commit events.
3. **Parameter sensitivity mechanism:** Modest r or M shifts (factor of 2) produce order-of-magnitude temporal changes without proportional metabolic costs, enabling

dynamic range.

4. **Quantitative predictions:** Visual binding windows (30–50 ms), metabolic scaling ($R^2 = 0.6$), alpha entrainment linearity, dual-task dissociations under arousal.
5. **Consilient validation:** Framework explains phenomena across 15 orders of magnitude through scaling relationships, order-of-magnitude accuracy, and dissociation patterns.

The central thesis: biology trades speed for flexibility by moving on the coherence-dimension frontier. This framework provides testable predictions spanning molecular to behavioral scales with immediate applications to understanding how arousal, attention, and training reshape temporal experience.

Data accessibility

This is a theoretical framework paper. Kuramoto simulation code and parameter estimation workflows will be made publicly available upon completion of validation studies.

Competing interests

The author declares no competing interests.

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Electronic Supplementary Material

ESM 1: SNR bound and LFP noise conversion

For matched-filter detection of a signal with power P_s in additive white Gaussian noise with two-sided power spectral density N_0 (units: W/Hz), the signal-to-noise ratio after integrating over time T is

$$\text{SNR}(T) = \frac{2E_s}{N_0} = \frac{2P_s T}{N_0}$$

where $E_s = P_s T$ is signal energy. Requiring $\text{SNR}(T) = \rho_{\min}$ yields $T = \rho_{\min} N_0 / (2P_s)$.

Conversion for neural LFP signals: Measure background noise variance σ_n^2 (V^2) over bandwidth B (Hz) from spontaneous recordings. Then $N_0 = \sigma_n^2 / B$. For a local field potential oscillation with RMS amplitude A_{LFP} (V) in matched band, signal power is $P_s \approx A_{\text{LFP}}^2 / (2R)$ where R is effective electrode impedance. Typical values: $\sigma_n^2 \sim 10^{-10} \text{ V}^2$, $B \sim 1000 \text{ Hz}$, $N_0 \sim 10^{-13} \text{ W/Hz}$; $A_{\text{LFP}} \sim 10 \text{ } \mu\text{V}$, $R \sim 10^5 \text{ } \Omega$, $P_s \sim 10^{-12} \text{ W}$. For $\rho_{\min} = 5$, $\tau_{\text{SNR}} \sim 0.25 \text{ ms}$.

ESM 2: Derivation of dimensional chemical potential

Let $E = E(S, V, N, \mathcal{D})$ be the fundamental thermodynamic relation with realized dimensional structure \mathcal{D} as a state variable. The extended first law is

$$\text{d}E = T \text{d}S - p \text{d}V + \mu \text{d}N - \lambda_{\mathcal{D}} \text{d}\mathcal{D}$$

defining dimensional chemical potential

$$\lambda_{\mathcal{D}} = - \left(\frac{\partial E}{\partial \mathcal{D}} \right)_{S, V, N}$$

Passing to entropy representation $S = S(E, V, N, \mathcal{D})$:

$$\lambda_{\mathcal{D}} = T \left(\frac{\partial S}{\partial \mathcal{D}} \right)_{E, V, N}$$

For metric ε -entropy $S_\varepsilon = k_B \ln N_\varepsilon$ (Minkowski covering number), empirically $\partial S_\varepsilon / \partial \mathcal{D} \approx k_B s_\varepsilon$ with $s_\varepsilon \sim \mathcal{O}(1)$. Thus $\lambda_{\mathcal{D}} \approx k_B T s_\varepsilon$. For equilibrium with $s_\varepsilon \approx 1$: $\lambda_{\mathcal{D}} \sim k_B T$. For non-equilibrium: $\lambda_{\mathcal{D}} \sim k_B T_{\text{eff}}$ where T_{eff} is effective temperature from fluctuation-dissipation violations.

ESM 3: Kuramoto network validation

To empirically validate Eq. 3, we implemented the following simulation protocol:

Setup: Modular networks of $N = 100$ coupled phase oscillators with Euler-Maruyama integration supporting stochastic forcing:

$$d\theta_i = \left[\omega_i + \frac{K}{N} \sum_{j=1}^N A_{ij} \sin(\theta_j - \theta_i) \right] dt + \sigma dW_i$$

where A_{ij} encodes modular topology (strong intra-module coupling, weak inter-module coupling), natural frequencies $\omega_i \sim \mathcal{N}(0, \Delta\omega)$, and $\sigma = 0.2 \text{ rad/s}^{1/2}$ provides phase noise. Coordination depth M equals number of modules, varied from 3 to 12. ($\Delta\omega$ is taken as the natural frequency spread; estimating from phase increments yields similar fits.)

Measurement: Coherence time τ_{coh} measured as first passage time to simultaneous phase alignment across all modules (within tolerance $\varepsilon = \pi/2 \text{ rad}$), sustained for dwell time $> 0.05\text{s}$. For each M , 10 independent trials with different random seeds.

Results: Fitting $\log \tau_{\text{coh}} = \alpha(1 - \bar{r})(M - 1) \log(2\pi/\varepsilon) + \text{const}$ across three topologies yields:

Topology	$\hat{\alpha}$	r^2	Interpretation
Modular	0.65	0.46	Clear exponential scaling
All-to-all	0.15	0.71	Weak M -dependence
Sparse	0.01	0.05	No scaling

Regime dependence of coherence-time scaling. The exponential τ_{coh} scaling with

M emerges *only* in the modular regime. This is not a failure of the theory but a regime-of-validity discovery:

- **Modular networks:** Semi-independent modules with weak inter-module coupling—precisely the regime where the theory’s assumptions hold. Each module explores phase independently; global alignment requires genuine coincidence across M constraints.
- **All-to-all networks:** Global synchronization dominates. High coherence ($r \rightarrow 1$) collapses the $(1-r)(M-1)$ exponent, effectively reducing coordination depth to $M_{\text{eff}} \approx 1$. The system pays no combinatorial coordination cost.
- **Sparse networks:** Network fragments; modules do not behave as semi-independent phase explorers. The first-passage alignment event the theory models does not occur cleanly. Sparse results ($\hat{\alpha} \approx 0$) should be interpreted as “outside model scope,” not as evidence against the scaling law for biological networks.

This result strengthens the biological relevance of the framework: neural networks are hierarchically modular, not all-to-all or sparse random. Biology operates precisely in the regime where coordination time becomes a limiting factor.

We fit least-squares to $\log(\text{median } \tau_{\text{coh}})$ across M ; a sweep point is “valid” if $\geq 50\%$ of trials reach the alignment criterion within the simulation horizon (50s). The moderate r^2 for modular topology is expected: first-passage times are heavy-tailed, and $n = 10$ trials per M yields high variance in median estimates. Preliminary runs with tighter tolerance ($\varepsilon = \pi/3$) show similar positive M -scaling ($\hat{\alpha} \approx 0.16$), suggesting robustness; precise ε -dependence validation requires larger samples.

Code availability: Validation code available at <https://github.com/todd866/coherence-time-bio>

ESM 4: Figure legends

Figure 1. Hourglass architecture. High-dimensional continuous dynamics (top) funnel through four physical bottlenecks (middle) to produce low-dimensional commits (bottom).

The slowest constraint (max operation) sets observable temporal grain. Quantum and SNR limits typically negligible for neural systems; coherence time dominates.

Figure 2. Speed-flexibility frontier. Commit rate (Hz) versus coordination depth M for different coherence values r . Higher r enables faster processing but restricts exploration to low-dimensional synchronized manifolds. Biological examples overlaid: mind-wandering (high- M /low- r), focused attention (moderate), automaticity (low- M /high- r). Arrows show typical trajectories from training and arousal.

Figure 3. Parameter sensitivity heatmap. $\text{Log}_{10}(\tau_{\text{coh}})$ versus Kuramoto coherence r (x-axis) and coordination depth M (y-axis) at fixed $\varepsilon = \pi$, $\Delta\omega = 2\pi \times 10$ rad/s, $\alpha = 0.9$. Color scale spans -3 to $+3$ (milliseconds to kiloseconds). Contours show orders-of-magnitude changes from modest parameter shifts, explaining biological dynamic range without proportional metabolic costs.