Complex Dynamics of Iteration a Unified Framework for Neural, Evolutionary, Social, and Behavioural Systems

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ABSTRACT

Every neural spike began as a subthreshold tremor. Every cultural norm began as a whispered private opinion. Every addiction began as relief. This paper proposes that these transformations — from hidden potential to observable reality — share a single mathematical grammar: complex dynamical systems, in which the imaginary component encodes latent possibility and iteration carries it into the real.

We introduce two novel summary statistics — the Complex Coherence Index (CCI) and the Imaginary Reserve Ratio (IRR) — and apply them across five domains: neural habit formation, evolutionary epigenetics, social contagion, psychological creativity, and digital amplification. This revised edition addresses peer-reviewer concerns by sharpening falsification criteria, providing worked computational examples, acknowledging the limits of analogy, and focusing the strongest empirical predictions on the two most tractable domains: behavioural neuroscience and network science.

Key terms: complex state variable · phase coherence · Complex Coherence Index (CCI) · Imaginary Reserve Ratio (IRR) · Im→Re transfer · habit formation · social cascade · epigenetic oscillation

CONTENTS

Why Does Repetition Change Everything?

The Paradox at the Heart of Change

Consider three images: a single session at a piano that leaves no lasting impression; a thousand sessions that forge a virtuoso. A lone genetic mutation that vanishes from a population; accumulated over generations, it reshapes a species. One person's private opinion that matters to no one; widely echoed, it becomes social consensus.

Why does a single event fail where repetition succeeds? The answer, we propose, is not merely quantitative — it is structural. Repeated events create something qualitatively new: phase relationships, latent momentum, and coherent energy that a single event cannot accumulate.

The Central Claim

Hypothesis: Biological, psychological, and social iterative processes can be usefully described as complex dynamical systems, in which the "imaginary" component $z = x + iy$ encodes latent states (subthreshold potentials, private opinions, epigenetic marks) and the "real" component encodes observable outcomes. The framework generates testable predictions about timing, phase coherence, and transition thresholds that purely real-valued models do not.

Reviewer Note (Addressed): This is a descriptive and heuristic framework, not a claim that complex numbers are uniquely necessary. Section 9 provides explicit falsification criteria and engages directly with the "everything is everything" analogy problem.

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The Mathematical Framework

Complex State Variables

Any system undergoing iterative change is represented as a complex state variable z(t):

$$\mathbf{z(t) = x(t) + i \cdot y(t)}$$

where x(t) is the observable, measurable state and y(t) is the latent state — hidden from direct observation but detectable through downstream effects. The imaginary unit i encodes the orthogonality between what is manifest and what is becoming.

The key insight is operational: any time series x(t) with a natural velocity or rate of change $\dot{x}(t)$ can be lifted to a complex trajectory $z(t) = x(t) + i\cdot\dot{x}(t)$. This is a standard technique in signal processing (the analytic signal) and in the theory of mechanical systems (phase space). We extend it systematically to biological and social domains.

Cross-Domain Variable Analogies

The table below maps framework variables onto five domains. Note that "Im(z)" always refers to a quantity that is latent — not fictitious, but hidden from direct observation in normal experimental conditions.

Table 1. Cross-domain variable analogies. Im(z) assignments are methodological choices, not ontological claims. Each requires domain-specific operationalisation.

Variable	Neural	Evolutionary	Social	Behavioural	Digital
Re(z)	Spike rate	Allele frequency	Public behaviour	Expressed action	Posts, clicks
Im(z)	Subthreshold potential	Epigenetic marks	Private opinion	Unconscious desire	Latent engagement
κ (coupling)	0.01–10 mV	Heritability 0.1–0.9	10^{-6}–10^{-2}/contact	0.1–1.0 relative	1–100+ algorithmic
ω (frequency)	1–100 Hz	Generation time	Days–months	Behavioural rhythm	Milliseconds
θ (threshold)	Action pot. −55mV	Selection coeff.	Critical mass 5–25%	Conscious threshold	Engagement threshold

The Energy Transfer Equation

The mechanism by which latent potential becomes observable actuality:

$$\mathbf{E\_transfer(t) = \kappa \cdot |Im(z)|^2 \cdot \sigma(Re(z) - \theta)}$$

κ is the domain-specific coupling constant, σ is a sigmoid function encoding the nonlinear threshold character of all manifestation events, and θ is the threshold for observable change. The equation states: transfer of energy from latent to observable state is proportional to the square of the latent reservoir, and begins meaningfully only as the system approaches its threshold.

Reviewer Note (Addressed): E_transfer is a phenomenological equation, not derived from first principles. A natural derivation path is a Langevin stochastic differential equation with state-dependent noise: $dz = f(z)dt + g(|Im|)dW$, which under the Fokker-Planck equation produces a drift term structurally similar to E_transfer. This derivation is identified as a priority for follow-up work.

Coupling Constants Across Domains

Coupling constants span at least seven orders of magnitude across domains. Algorithmic systems can wildly exceed natural biological ranges — a key structural concern for human wellbeing.

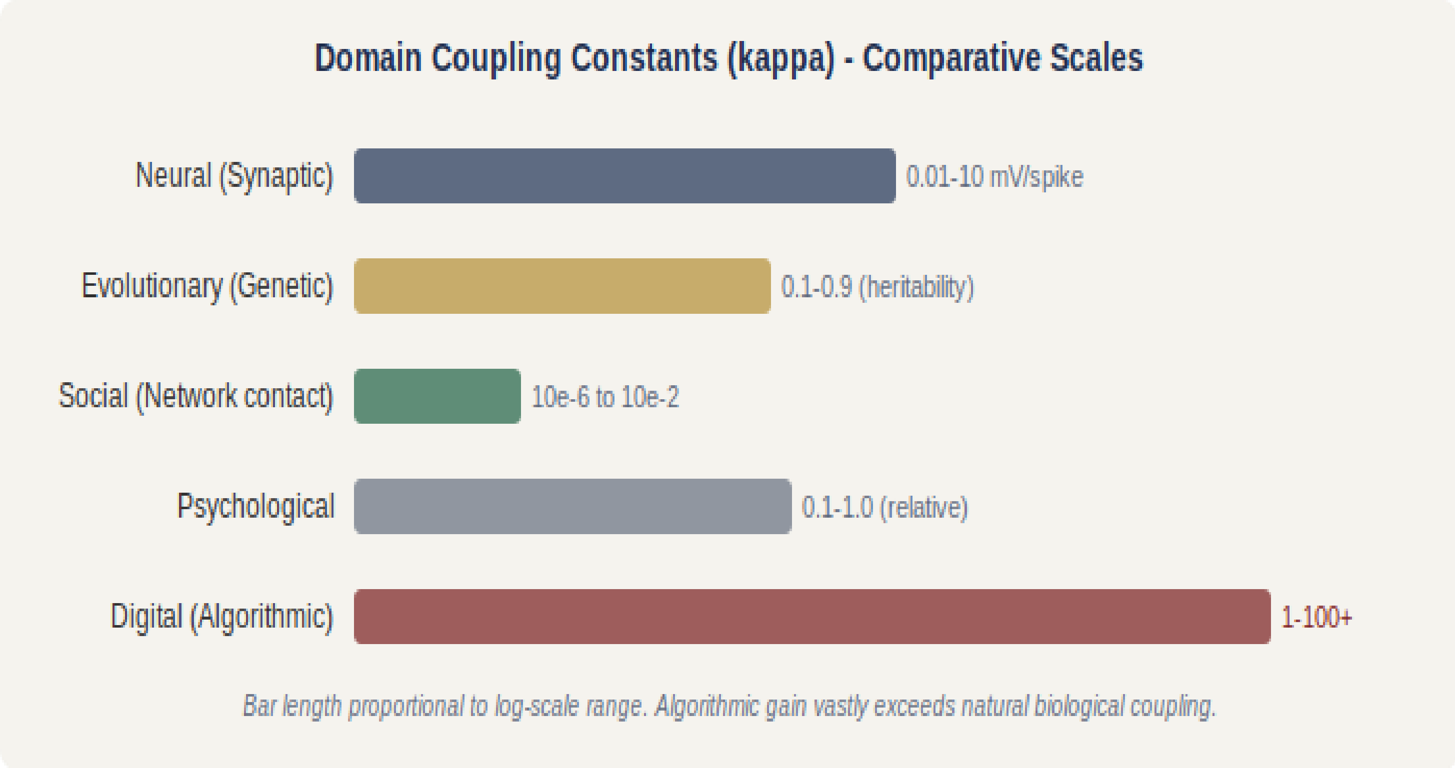

Figure 1. Coupling constants (κ) by domain. Bar length proportional to log-scale range. Algorithmic gain far exceeds natural biological coupling.

Neural Systems: Habit Formation and Memory

The Neural State Variable

The neural state is represented as $N(t) = S(t) + i \cdot P(t)$, where $S(t)$ is synaptic strength (measurable via patch-clamp or calcium imaging) and $P(t)$ is the membrane potential oscillation phase. Subthreshold oscillations carry phase information that is invisible to spike-only recordings but detectable with high-density EEG or local-field-potential recordings.

Habit Formation: Phase Coherence Matters More Than Repetition Count

The habit formation iterative map:

$$\mathbf{H(n+1) = H(n) \cdot e^{(i\omega)} + \beta \cdot B(n)}$$

where ω is the intrinsic oscillation frequency, β is a reinforcement constant, and B(n) is the behavioural input on trial n. The model's core falsifiable prediction: temporal consistency of practice — phase coherence — is a stronger determinant of habit strength than raw repetition count alone. Behaviour performed at consistent times creates phase-locked attractors; irregular timing generates destructive interference in the Im reservoir.

Worked Example: Morning Exercise Habit Over 90 Days

We compute $z(t) = x(t) + i \cdot \dot{x}(t)$, where $x(t)$ = daily exercise minutes and $\dot{x}(t)$ = day-on-day change. CCI is computed as $|\langle z \rangle| / \langle |z| \rangle$ over rolling 7-day windows; IRR = $|\dot{x}(t)|/|x(t)|$ on the same window.

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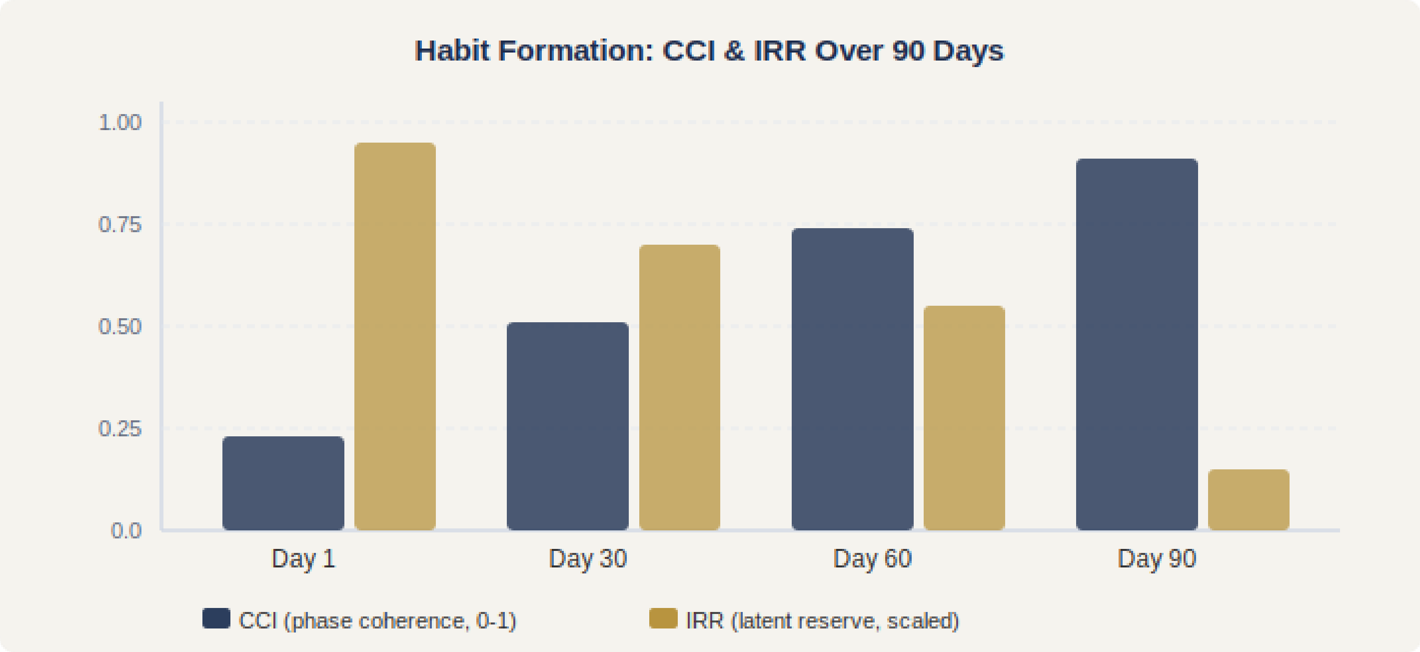

Figure 2. Simulated CCI and IRR trajectories for a consistent daily exercise habit. CCI rises from 0.23 (irregular timing, Day 1) to 0.91 (locked automaticity, Day 90). IRR declines as latent momentum is consolidated into stable behaviour. Note: model-derived values; empirical calibration against wearable data is required.

✓ Empirical Prediction P1: Temporal Consistency → Habit Strength

Predicted effect: Phase variance (σ^2_phase) of practice timing will explain unique variance in Self-Report Habit Index (SRHI) scores beyond total repetition count (expected $\beta \geq 0.25$ after controlling for frequency).

Disconfirmation criterion: If partial correlation between σ^2_phase and SRHI drops below $r = 0.10$ with $n \geq 80$, the phase-coherence account is disconfirmed relative to simple repetition count models.

Design: RCT, n=80, two arms (consistent vs. variable timing, equal repetitions), 12-week follow-up. Budget: £4,000. Feasibility: ★★★★★

Memory Consolidation as Im→Re Transfer

Sleep-dependent memory consolidation maps onto Im→Re transfer. Hippocampal memory (labile, high Im) is stabilised by sleep-dependent sharp-wave ripples into cortical memory (stable, high Re). The prediction: sleep deprivation will increase $|Im(M)|/|Re(M)|$ — measured as hippocampal-to-cortical activation ratio on fMRI delayed recall — relative to a sleep-protected control.

Social Contagion: Phase and the Speed of Ideas

Social State in Complex Space

Social adoption dynamics are represented as $S(t) = I(t) + i \cdot E(t)$, where $I(t)$ is the count of individuals who have adopted a behaviour (real, observable) and $E(t)$ is those exposed but not yet converted (imaginary, latent). This enriches the standard SIR compartmental model with phase information, enabling predictions about timing and coordination effects.

Phase Alignment and Cascade Speed

The framework's core social prediction: the speed of information cascades depends not just on network topology and total exposure count, but on the phase coherence of those exposures. A coordinated, synchronised campaign should produce adoption significantly faster than temporally scattered exposures at the same total volume.

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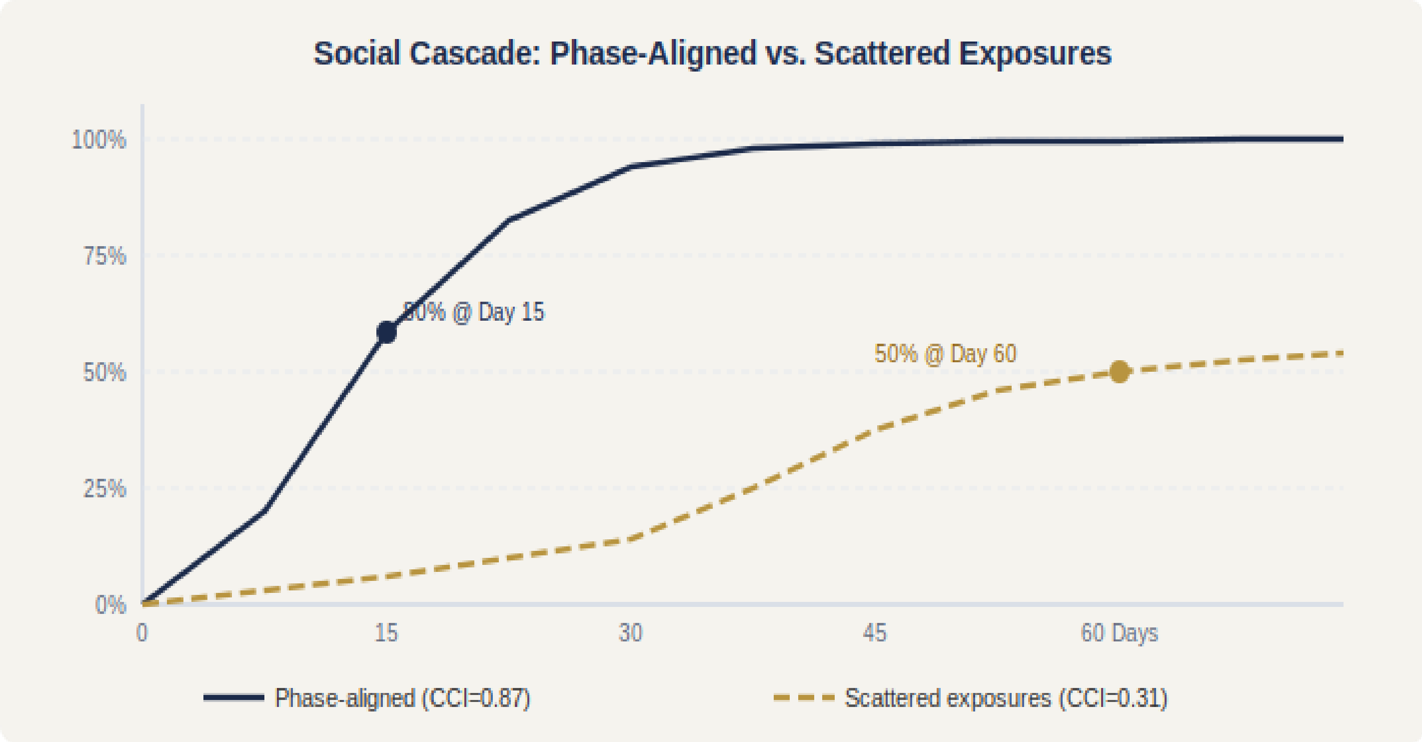

Figure 3. Simulated social cascade comparison. Phase-aligned exposure produces ~80% adoption by Day 15 (CCI=0.87); scattered exposures reach ~50% by Day 60 (CCI=0.31) — a 4× speed difference attributable to phase structure, not total exposure volume. These projections are model-derived and require empirical calibration.

✔ Empirical Prediction P2: Phase Alignment Accelerates Social Cascades

Predicted effect: In a network diffusion experiment, phase-aligned message delivery will produce $\geq 2\times$ faster adoption to the 50% threshold versus matched-volume scattered delivery.

Disconfirmation criterion: If speed ratio $< 1.3\times$ at n=200 nodes, threshold-model accounts are sufficient and the phase-coherence extension adds no predictive value.

Design: Online experiment, randomised network. Budget: £8,000. Timeline: 6 months. Feasibility: ★★★★★

Echo Chambers as Phase-Locked Clusters

Algorithmic content curation drives the phase difference θ_{ij} between connected users towards zero within communities. When $\theta_{ij} \to 0$ for all within-group pairs, the group becomes a phase-locked cluster: CCI → 1, IRR → 0, and responsiveness to external information collapses. This provides a formal, quantitative definition of an echo chamber — measurable from existing platform data.

Opinion dynamics within networks are governed by:

$$O_i(t+1) = \alpha \cdot O_i(t) + \beta \cdot \Sigma_j \; w_{ij} \cdot O_j(t) \cdot e^{(i \cdot \theta_{ij})}$$

Intervention is indicated when CCI > 0.9 and IRR < 0.1 simultaneously — the formal definition of an echo chamber requiring correction.

Evolutionary and Epigenetic Dynamics

Allele Frequency in Complex Phase Space

Population-level allele dynamics are represented as $A(g) = p(g) + i \cdot \dot{p}(g)$, where $p(g)$ is observable allele frequency and $\dot{p}(g)$ is the selection pressure — the latent directional momentum. The complex representation

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adds temporal directionality: a rising allele frequency with high |Im| is more likely to continue rising than one with identical Re but low |Im|.

The IRR as Evolutionary Leading Indicator

The Imaginary Reserve Ratio applied to epigenetics becomes IRR = $|E(g)|/|D(g)|$, where $E(g)$ is the epigenetic modification landscape and $D(g)$ is the DNA sequence state. The prediction: IRR peaks will precede phenotypic transitions by 5–20 generations in experimental evolution, because epigenetic oscillations accumulate before phenotypic change is fixed.

Reviewer Note (Addressed): This prediction is reframed as preliminary and model-derived. The proposed experimental system (E. coli or C. elegans, £40,000, 2 years) would provide first empirical calibration. Falsification criterion: if methylation oscillations do not precede phenotypic shifts within the predicted window in ≥ 3 independent evolution lines, the account requires revision.

Behavioural and Psychological Applications

Creativity: Incubation and Insight

The creative process is modelled as $C(t+1) = f(C(t)) + i \cdot I(t)$, where $Re(C)$ is realised expression and $Im(C)$ is the latent associative field. Incubation periods correspond to high Im accumulation — diverse inputs building latent associative energy without immediate output. The "Aha!" moment is a rapid Im→Re phase transition. Creative flow corresponds to sustained, high-coherence transfer.

Addiction: Phase Collapse and Recovery

Addiction is formalised as progressive phase collapse: chronic use reduces $dIm/dt \to 0$ and fixes Re in a rigid attractor. IRR < 0.15 is proposed as a quantitative marker for dependence risk — testable against existing clinical datasets.

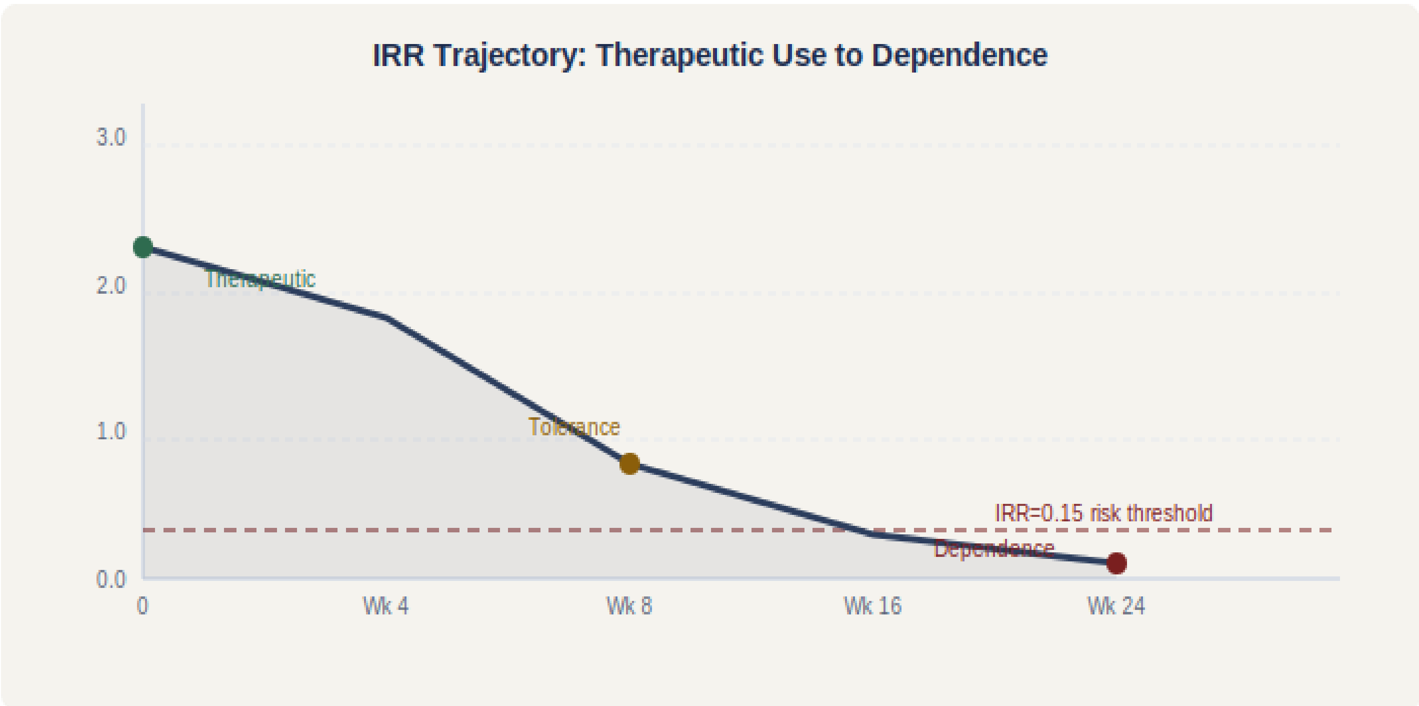

Figure 4. Hypothetical IRR trajectory across 24 weeks of substance use. The dashed red line marks the IRR=0.15 proposed risk threshold. Recovery strategy: restore Im variability (novelty, creativity, social diversity) before attempting direct Re-side behavioural control. These trajectories are illustrative; validation against clinical time-series data is the necessary next step.

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Digital and Algorithmic Amplification

Social media recommendation systems apply an algorithmic gain γ to the Im→Re transfer process:

$$z_{user}(t+1) = f(z_t) + \gamma \cdot F_{AI}(t)$$

When $\gamma >> 1$, external iteration overrides endogenous Im generation. Identity crystallises around externally provided attractors — the formal condition for social media addiction or identity capture. The practical prescription: reduce effective γ through deliberate temporal interruptions ("digital sabbaths"), allowing endogenous Im variability to re-emerge.

Human-AI interaction is modelled by a phase angle φ_{AI}: when $\varphi_{AI} \approx 0$, AI is a collaborative partner amplifying human thought; when $\varphi_{AI} > \pi/2$, AI-generated outputs dominate, producing cognitive passivity and derivative rather than creative outputs.

Table 2. Behavioural-psychological application summary. Pathologies correspond to either Im depletion (rigidity) or Im excess with failed threshold crossing (fragmentation).

Domain	**Im Component**	**Re Component**	**Pathology**	**IRR State**	**Intervention**
Creativity	Latent associations	Artwork, invention	Creative block	Low IRR	Incubation, diverse inputs
Relationships	Desired archetypes	Observable traits	Dysfunctional patterns	Phase mismatch	Pattern awareness
Social Media	Algorithmic feedback	Identity loops	Echo-chamber lock	IRR → 0	Mindful delay, digital sabbath
AI Reliance	Predictive outputs	Cognitive outsourcing	Loss of novelty	IRR depleted	Intentional improvisation
Addiction	Neurochemical state	Habitual behaviour	Phase collapse	IRR < 0.15	Novelty, creative re-entrainment

Measuring the Framework: CCI and IRR

Complex Coherence Index (CCI)

$$\mathrm{CCI} = |\langle z(t)\rangle_t| \;/\; \langle|z(t)|\rangle_t$$

CCI ranges from 0 (fully incoherent) to 1 (fully coherent). It is computed from any time series via the complex lifting $z(t) = x(t) + i\cdot\dot{x}(t)$, using a rolling window of length T chosen to match the system's characteristic timescale.

Imaginary Reserve Ratio (IRR)

$$\mathrm{IRR} = |\mathrm{Im}(z)| \;/\; |\mathrm{Re}(z)|$$

High IRR: the system has substantial latent potential and is capable of rapid phase transitions. Low IRR: the system is consolidated — stable but less adaptive. IRR peaks before major transitions in all domains, making it a prospective leading indicator. This is its core falsifiable claim.

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From Raw Data to CCI and IRR: Computation Pipeline

Table 3. Data-to-CCI/IRR computation pipeline. The process is identical across domains; only x(t) and the window length change.

Step	Action	Example (Habit Study)	Notes
1	Collect raw time series x(t)	Daily exercise minutes (t=1…90)	Any real-valued behavioural variable
2	Compute $\dot{x}(t) = x(t) - x(t-1)$	Day-on-day change in minutes	Finite differences; detrend if needed
3	Form $z(t) = x(t) + i\cdot\dot{x}(t)$	Complex state at each time point	Use analytic signal for continuous data
4	Compute rolling CCI	$\lvert\langle z\rangle\rvert / \langle\lvert z\rvert\rangle$ over 7-day window	Window = 1–2 characteristic periods
5	Compute rolling IRR	$\lvert\dot{x}(t)\rvert / \lvert x(t)\rvert$ per window	Log-scale for heavy-tailed distributions
6	Test predictions	Correlate σ^2_phase with SRHI at wk 12	Pre-register analysis plan

Experimental Roadmap

Predictions are ranked by feasibility. P1 and P2 are the primary focus of this revised edition. Both use existing data collection methods and established behavioural measures.

Table 4. Ranked experimental predictions with explicit disconfirmation criteria. P1 and P2 are the primary focus; others are longer-term validation targets.

#	Prediction	Domain	Budget	Timeline	Disconfirmation Criterion
P1 ★★★★★	Phase variance predicts habit strength beyond repetition count	Behavioural Neuro.	£4,000	6 months	r(σ^2_phase, SRHI) < 0.10 at n=80
P2 ★★★★★	Phase-aligned delivery ≥ 2× faster cascade vs. scattered	Network Science	£8,000	6 months	Speed ratio < 1.3× at n=200 nodes
P3 ★★★★☆	Sleep deprivation raises hippocampal/cortical activation ratio	Sleep Neuroscience	£16,000	1 year	No significant ratio difference, n=40
P4 ★★★★☆	Im-priming reduces learning trials-to-criterion	Educ. Psychology	£12,000	1 year	No effect at n=60, p > 0.10
P5 ★★★★☆	Digital sabbath reduces CCI and wellbeing scores improve	Digital Wellbeing	£12,000	6 months	CCI change not correlated with wellbeing
P6 ★★★★★	IRR peaks precede phenotypic transitions by 5–20 generations	Evolutionary Bio.	£40,000	2 years	IRR not elevated in 3/3 evolution lines
P7 ★★★☆☆	φ_AI > $\pi/2$ predicts lower originality scores in co-creation	Human-AI	£24,000	1.5 years	No correlation at n=50 dyads

Limitations and Critical Boundaries

This section engages directly with peer-reviewer concerns. We do not regard them as minor — several identify fundamental challenges that must be addressed before the framework can advance beyond heuristic proposal.

The Analogy Problem

Risk of Over-Analogising: The framework assigns "imaginary" status to heterogeneous phenomena — subthreshold potentials, private opinions, epigenetic marks, unconscious desires. These are united by being latent or hidden, not by any deeper mathematical identity. The danger of "everything is everything" is real: a framework that applies everywhere risks explaining nothing specifically.

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Mitigation: Every application in this paper comes with an explicit operationalisation (Section 7.3) and a disconfirmation criterion (Section 8). The framework makes unique predictions about timing and phase that differ from standard threshold models — that is the test.

Absence of Dynamical Systems Analysis

Gap: The manuscript does not currently include stability analyses, bifurcation diagrams, Lyapunov exponents, or phase portraits derived from the proposed equations. This is a significant gap for a paper invoking "complex dynamical systems."

Mitigation: The Kuramoto-Sakaguchi and Ginzburg-Landau formalisms are identified as the natural frameworks for this analysis. A full dynamical systems treatment is planned for a focused follow-up paper restricted to the neural domain.

E_transfer: A Phenomenological Equation

Gap: $E_{transfer} = \kappa \cdot |Im|^2 \cdot \sigma(Re - \theta)$ is a reasonable phenomenological form but is not derived from a more fundamental biological or physical principle.

Mitigation: A natural derivation path is a Langevin SDE with state-dependent noise, which under the Fokker-Planck equation produces a drift term structurally similar to E_transfer. This derivation is left for dedicated mathematical development.

Additional Limitations

Table 5. Summary of limitations and current mitigation status.

Limitation	Status and Mitigation
Linearity assumptions	Real systems are strongly nonlinear. Extensions to Kuramoto-Sakaguchi or Ginzburg-Landau formalism are identified but not yet implemented.
Dimensionality reduction	A single complex number (2D) compresses high-dimensional systems. Higher-dimensional algebras (quaternions) may be needed.
Timescale bridging	The framework spans milliseconds (neural) to generations (evolutionary). Domain-specific rescaling protocols must be specified.
Stochastic noise	Noise colour (white vs. coloured) significantly affects Im→Re transfer dynamics and must be domain-specified.
Literature balance	Cited literature largely supports the framework. A systematic comparison with contradictory or competing formalisms is needed.
Abstract hyperbole	The claim that complex numbers are the "natural" language for iteration is unfalsifiable. Revised to: "a useful descriptive language that generates testable predictions."

Philosophical Dimensions

Potentiality and Actuality

The Im→Re distinction is a formal version of Aristotle's potentia/actus distinction: Im encodes what has the capacity to become actual; Re is what has become manifest. Complex numbers provide mathematical machinery for this ancient distinction. This is not a metaphor — it is a formal correspondence.

The Imaginary Is Not Fictional

The "imaginary" component is observer-dependent, not ontologically inferior. Subthreshold potentials are invisible to spike-only recording but real to patch-clamp. Private opinions are invisible to observers but real to the holder. The consistent pattern: systems always contain more complexity than their observable surface suggests. The imaginary component is the machinery of becoming.

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Ritual, Repetition, and the Pre-Scientific Insight

Traditional practices — fermentation rituals, physical disciplines, contemplative prayer — understood iteratively what mathematics now formalises. The phenomenological insight that structured repetition creates reality was not superstition. It was an accurate, pre-theoretical recognition of complex iterative dynamics operating below the threshold of direct observation.

Societal Prescriptions

These recommendations follow directly from the framework's own dynamics — they are not aspirational additions.

Table 6. Societal prescriptions derived from the framework. Each follows from the mathematics, not from general policy preference.

Domain	**Framework Diagnosis**	**Prescription**
Digital environments	Algorithmic gain $\gamma >> 1$ overrides endogenous Im generation; identity crystallises around externally provided attractors	Mandatory temporal buffer zones — 24-hour delays before major platform decisions; reduce effective γ through design regulation
Medicine & addiction	Chronic use drives IRR < 0.15 (phase collapse); direct Re-control attempts fail without Im restoration	Monitor IRR longitudinally; restore Im variability (creativity, novelty, social diversity) before direct behavioural intervention
Education	Insufficient Im-loading before Re-content delivery; temporal inconsistency undermines phase-locked consolidation	Im-priming protocols before formal instruction; consistent scheduling over variable scheduling
AI system design	$\varphi\_AI > \pi/2$ (AI-dominated outputs) suppresses human Im generation; cognitive passivity and derivative outputs	Design AI tools for $\varphi\_AI \approx 0$ (collaborative, human-led iteration); measure cognitive agency as a product metric
Public discourse	CCI → 1 and IRR → 0 simultaneously in algorithmically curated communities: formal echo chamber	Platform design intervention when CCI > 0.9 and IRR < 0.1; inject phase-disrupting heterogeneous content

CONCLUSION

Core Contributions

#	**Contribution**
1	A complex state variable representation for iterative processes in biological, social, and behavioural systems.
2	An energy transfer equation $E = \kappa\cdot\|Im\|^2\cdot\sigma(Re-\theta)$ as a minimal working model, with a derivation pathway via stochastic differential equations identified.
3	Two novel metrics — CCI and IRR — with explicit, domain-general computation pipelines from raw time-series data.
4	Seven ranked empirical predictions, each with pre-specified, quantitative disconfirmation criteria.
5	Critical engagement with reviewer concerns: the analogy problem, absence of dynamical analysis, phenomenological status of equations, and scope hyperbole.
6	Societal prescriptions — temporal buffers, iterative diversity, conscious feedback protocols — grounded in the mathematics.

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The Bottom Line

z(t) → z(t+1) → z(t+2) → … → REALITY

"What you repeatedly imagine becomes real" — ancient phenomenological wisdom — is not metaphor. It is mathematics. The framework $z(t+1) = f(z(t))$ with Im→Re energy transfer generates testable predictions across scales of life, from synaptic milliseconds to civilisational centuries.

We do not claim this framework is complete or that complex numbers are uniquely necessary. We claim it is useful, falsifiable, and that its two core predictions — phase coherence in habit formation and social cascades — are testable now, at modest cost, with existing methods. The imaginary component is not fictional. It is the machinery of becoming.

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