From Prebiotic Sustainability to Proto-Liveliness: A Biocomputational Framework with Structural, Energetic and Informational Metrics for Protocell Cluster Evolution

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***Abstract*- This paper presents a quantitative, operational framework for classifying protocell clusters along a continuum from passive stability to proto-biological liveliness. We define a three-dimensional Prebiotic Sustainability Space with measurable structural (S), energetic (E), and informational (I) metrics, and introduce a Life–Death Threshold ($L > L_{crit}$) that integrates these metrics into a single rule distinguishing stable, dying, and proto-living systems. Proto-liveliness is formalized as the capacity of a protocell ensemble to maintain structural connectivity, support persistent gradients, and regenerate attractor-based functional states. We further distinguish material from organizational quantities and formulate a Bridge Principle in which coupled S–E–I feedback loops render recurrent physical patterns persistence-relevant (proto-semantic) and dynamically effective (proto-pragmatic). Microfluidic protocell arrays and AI-based simulations are proposed as complementary routes for empirical classification and validation within this unified physical–informational framework.**

Keywords-Prebiotic sustainability; protocell cluster; proto-liveliness; dissipative structures; origins of life.

I. INTRODUCTION

This seventh paper concludes the series “A Constructivist Proto-Bio-Information Theory: A Physically Grounded Nano-Systems Architecture for Prebiotic Emergence, Information, Proto-Semantic Function, and Sustainability of Protocell Aggregation and Cluster Formation.”

Massoth [1] shows that Casimir–Lifshitz forces produce robust attraction and stable 5–200 nm protocell clusters, providing the structural basis for the present formulation of prebiotic sustainability.

Massoth [2] demonstrates that these clusters yield reproducible mesoscale attractors and autonomous ε-machine dynamics, supplying the informational substrate extended here into a sustainability dimension.

Massoth [3] establishes that cluster dynamics generate reproducible differences and functional meaning states, grounding the informational sustainability developed in this work, while Massoth [4] reveals that resonance zones and ε-machines generate syntactic, semantic, and pragmatic information layers, whose stabilization frames sustainability as an emergent multilayer process.

Massoth [5] identifies Matsubara-mode selection and Casimir–Polder coupling as sources of persistent proton gradients, forming the energetic core that this paper extends into energetic sustainability and connects to experimental tests, while Massoth [6] develops a physically grounded concept of prebiotic sustainability in the nanoworld.

The structure of the paper is as follows: Section II motivates the transition problem from fluctuation-stabilized protocell clustering to prebiotic information and proto-agency and defines the key retention/recovery and dissipative-structure metrics. Section III introduces the Prebiotic Sustainability Space (S, E, I) and operationalizes structural, energetic, and informational sustainability with measurable scores. Section IV formulates quantitative criteria for proto-liveliness via coupled thresholds and a Life–Death function in S–E–I space and illustrates exemplar classifications. Section V distinguishes material from organizational quantities and formalizes four levels (statistical–syntactic–semantic–pragmatic) linking dynamics to function. Section VI states the Bridge Principle and derives coupled structural, energetic, and informational feedback loops as the minimal mechanism generating proto-semantic and proto-pragmatic organization. Section VII relates the framework to autopoiesis, work-cycle theories, and information-theoretic accounts and clarifies the novel contributions. Section VIII proposes experimental and simulation probes (microfluidic arrays and AI-based models) to measure S, E, I and test the Life–Death threshold. Section IX summarizes implications, limitations, and future directions for empirical validation and design of synthetic proto-biological systems.

II. FROM PHYSICAL STABILITY TO PREBIOTIC INFORMATION AND AGENCY

Protocellular systems serve as key models of early chemical evolution [12]. They represent minimal, physically stabilized compartments capable of taking up energy, generating gradients, and producing spatial or temporal patterns. Theory and experiment show that vesicles can couple into clusters through short-range, fluctuation-induced forces [11], in particular Casimir and Casimir-like nanoscale attractions [9][10][13][14][15][16]. These interactions impose spatial order and support collective dynamics such as reinforced gradients, synchronized fluctuations, and shared energy flows.

Recent work has enabled increasingly precise characterization of the structural and energetic stability of such assemblies. Spectral descriptors of cluster geometry quantify robustness; characteristic timescales of gradient formation and decay capture energetic performance. Together, these approaches demonstrate that protocell clusters can form persistent, non-equilibrium structures maintained under continuous dissipation [19].

What remains unresolved, however, is how such *passive persistence* transitions into *functional liveliness*—that is, into a regime where a system actively reproduces and restores the conditions of its own persistence.

This motivates the central research question (RQ): *Which physical conditions mark the transition from mere stability to self-regenerative, proto-biological agency in protocell clusters?*

A. Physical Origin of Prebiotic Information in Protocell Clusters

Prebiotic information in protocell clusters arises when fluctuation-stabilized mesoscale geometries form reproducible macrostates whose future dynamics are better predicted from the macrostate than from the full microscopic configuration. Casimir–Lifshitz coupling restricts the accessible configuration space to a small set of energetically favored cluster geometries, giving rise to discrete attractors that persist despite thermal noise.

These attractor macrostates function as a physical memory substrate: past configurations bias future evolution, enabling pattern retention and recovery without polymers, genetic encoding, or biochemical control. Information, in this prebiotic sense, is not symbolic but structural and dynamical, grounded in geometry, interaction topology, and reproducible transition pathways.

B. Operational Measures of Pattern Retention and Recovery

Pattern retention is quantified by the persistence of predictive state structure in a reconstructed ε-machine, for example by the statistical complexity C_μ, which measures the memory stored in causal states, and by the excess entropy E which captures the predictable information shared between past and future observations. Pattern recovery is quantified by perturb-and-return statistics, including the regeneration time T_{regen} required to return to a dominant attractor basin after disturbance, and the return probability $P_{return}(T)$ that the system re-enters this basin within time T.

From an information-theoretic perspective, pattern retention and recovery are quantified by informational closure and attractor-based memory. Coarse-grained macrostates $Z_t=f(X_t)$ satisfy a strong reduction in conditional entropy, $H(Z_{t+1} \mid Z_t) \ll H(Z_{t+}1 \mid X_t)$, indicating that cluster geometry retains predictive information about future configurations. Recovery after perturbations follows deterministic return trajectories into the same attractor basin, expressed as

$$\|Z_{t+}1-A_i\| < \|Z_t-A_i\|.$$

Mutual information and excess entropy quantify long-range temporal correlations encoded in ε-machine causal states. Long-lived dissipative structures are identified by sustained entropy production dS/dt > 0, low normalized structural drift $D(t,\Delta t) < \delta$, high return probability $P(Z_{t+1} \in A_i \mid Z_t \in A_i) \approx 1$, and persistence of energetic patterns with $\tau_{gradient} \geq \tau_{diff}$. Together, these metrics demonstrate metastable, information-bearing dissipative protocell clusters.

In this paper, a *long-lived dissipative structure* is operationally indicated when structural cohesion (e.g., positive algebraic connectivity λ_2), energetic persistence ($\tau_{gradient} / \tau_{diff} > 1$), and informational recovery (high C_μ, short T_{regen}, and large $P_{return}(T)$) are simultaneously observed.

A related challenge is to describe functional self-organization, system identity, and the emergence of semantic and pragmatic structure within a purely physical formalism, without invoking modern cellular complexity or genetic storage.

C. From Prebiotic Information to Sustainability and Proto-Agency

Prebiotic sustainability denotes the maintenance of structural, energetic, and informational order. Prebiotic life emerges only when a sustainable system acquires autonomous capacities for self-restoration, attractor reconstruction, and functional expansion. To formalize this transition, we introduce a Prebiotic Sustainability Space, capturing structural (S), energetic (E), and informational (I) sustainability as core parameters of proto-biological persistence. Building on this, a Life–Death Threshold expressed through metric inequalities classifies cluster states along a continuum from stable to proto-liveliness.

We further distinguish material quantities—fields, forces, gradients, energy flows—from organizational ones that encode functional patterns, attractors, and proto-semantic structure. A Bridge Principle characterizes the recursive feedback loops through which physical patterns acquire functional significance and generate early forms of agency. Here, proto-agency denotes purely physical capacities for self-restoration, state reconstruction, and constraint preservation, without cognition, intention, or genetic control. A bio-computational framework demonstrates that all quantities are tractable and allow sharp classification of system states.

III. Prebiotic Sustainability Space (S, E, I)

This section defines the three-dimensional sustainability space and specifies measurable structural (S), energetic (E), and informational (I) scores for placing protocell clusters on a common quantitative scale.

A. Motivation

"Prebiotic" is used here in the origins-of-life sense (pre-genetic, pre-cellular organization). Prebiotic protocells could form higher-order units only if three fundamental domains remained jointly stable: structural integrity (S), persistence of dissipative energy flows (E), and reproduction of internal patterns and functional relations (I). These dimensions define a sustainability space in which proto-biological systems can persist, interact, and generate selectable variation. The transition from a merely stable aggregate to a functionally autonomous unit becomes intelligible only when structural, energetic, and informational conditions are considered together.

Definition: Prebiotic sustainability denotes the ability of an open protocell ensemble to maintain its structural, energetic, and informational identity while continuously dissipating energy. A system is sustainable if it preserves its mesoscale architecture, supports long-lived nonequilibrium gradients, and regenerates recurrent physical patterns despite fluctuations and molecular turnover.

B. Structural Sustainability S

Structural sustainability captures a cluster's capacity to maintain physical organization despite defects, thermal noise, or transient forces. It can be quantified using graph-theoretic measures. A key parameter is the second eigenvalue λ_2 of the Laplacian of the contact graph, which measures algebraic connectivity. For $\lambda_2 > 0$ the cluster remains connected; larger values indicate higher robustness. Structural redundancy R_{struct} measures the number of alternative load-bearing paths. Together they define $S = f(\lambda_2, R_{struct})$,

which increases with network connectivity and path diversity. S thus characterizes the physical basis for maintaining spatial organization over relevant timescales.

Operationalization of Structural Sustainability S:

Structural sustainability captures a cluster's capacity to maintain physical organization despite defects, thermal noise, and transient forces. We represent a protocell cluster as a *contact graph* G(t), where nodes are vesicles and edges indicate sustained proximity/contact (e.g., gap $L \leq L_{contact}$L for longer than a dwell time $\tau_{contact}$).

A key robustness descriptor is the *algebraic connectivity* of the graph, defined by the second eigenvalue of the (combinatorial) Laplacian $L_G(t)$:

$$\lambda_2(t) = \text{second\_smallest\_eigenvalue}\ (L_G(t))$$

For $\lambda_2(t) > 0$ the contact graph is connected; larger λ_2 indicates stronger global cohesion and lower fragmentation risk under random edge/node loss. Because λ_2 depends on the whole topology, it serves as a mesoscale stability indicator rather than a purely local measure.

We complement λ_2 by a redundancy term that captures alternative load-bearing paths. One simple operational choice is an edge-redundancy score (normalized to [0,1]):

$$R_{struct}(t) = 1 - (B(t) / E(t))$$

where B(t) is the number of bridge edges (edges whose removal disconnects the graph) and E(t) is the number of edges. High R_{struct} implies multiple alternative paths and lower single-edge failure sensitivity.

We define a dimensionless structural sustainability score S(t) by mapping the two measures into [0,1]:

$$S(t) = \sigma(\ (\lambda_2(t) - \lambda_{2,ref}) / s_\lambda\ ) \cdot \sigma(\ (R_{struct}(t) - R_{ref}) / s_R\ )$$

where $\sigma(x) = 1 / (1 + e^{(-x)})$ is a squashing function, $\lambda_{2,ref}$ and R_{ref} are reference values (e.g., medians in a calibration window), and s_λ, s_R set sensitivity.

Interpretation. S increases when clusters remain connected ($\lambda_2>0$) and structurally redundant (high R_{struct}), providing the physical substrate for persistent gradients and recurrent patterns.

C. Energetic Sustainability E

Energetic sustainability measures the ability of a cluster to generate, stabilize, and maintain gradients as dissipative flows [19]. Central is the ratio $\tau_{gradient} / \tau_{diff}$, which determines whether gradients build up faster than diffusion erodes them. The efficiency η quantifies the fraction of absorbed energy converted into structure-stabilizing dynamics. These parameters define

$$E = g(\tau_{gradient} / \tau_{diff}, \eta),$$

which attains high values when energy-driven patterns emerge reproducibly and withstand perturbations. Energetic sustainability forms the physical foundation of dissipative structure formation and early proto-metabolic feedback.

Operationalization of Energetic Sustainability E:

Energetic sustainability measures the ability of a cluster to generate, stabilize, and maintain gradients as dissipative energy flows. The core energetic object is the *electrochemical potential difference* across a relevant interface (e.g., gap vs bulk, or inside vs outside for vesicles). For protons: $\Delta\mu_{H+}(t) = k_B T\ \ln(\ c_{in}(t)\ /\ c_{out}(t)\ ) + e\ \Delta\psi(t)$

Equivalently in pH form:

$$\Delta\mu_{H+}(t) = 2.303\ k_B T \cdot \Delta pH(t) + e\ \Delta\psi(t)$$

The free energy stored in a proton gradient (over an effective number of charge carriers N_{H+}) is:

$$E_{grad}(t) = N_{H+}(t) \cdot \Delta\mu_{H+}(t).$$

In minimal protocell systems where Δψ is small or not measured, the pH term provides a conservative lower-bound proxy. A necessary persistence condition is that gradients survive diffusion. We therefore use the ratio of gradient lifetime to diffusive relaxation time:

$$\kappa(t) = \tau_{gradient}(t) / \tau_{diff}(t)$$

with $\tau_{diff}(t) \approx L_{gap}(t)^2 / D_{H+}$ in a gap of characteristic width L_{gap} and proton diffusion coefficient D_{H+}. Energetic sustainability requires $\kappa>1$, meaning dissipative processes build/maintain gradients faster than diffusion erodes them.

We further introduce an energetic allocation/efficiency term η(t) that quantifies what fraction of absorbed/available energy supports stabilization (gradients, structural cohesion, pattern retention) rather than immediate dissipation.

Operationally (experiment-compatible), η can be defined from measurable proxies:

$$\eta(t) = P_{stab}(t) / (P_{in}(t) + \varepsilon)$$

where P_{stab} is the estimated power associated with maintaining gradients/structure (e.g., gradient energy change rate plus stabilization-relevant work proxies) and P_in is the net incoming power (thermal, chemical, radiative, or imposed microfluidic work), with ε preventing division by zero. In practice, η is typically estimated comparatively across conditions rather than absolutely.

We define energetic sustainability E(t) as a bounded score:

$$E(t) = \sigma(\ (\kappa(t) - 1) / s_\kappa\ ) \cdot \sigma(\ (\eta(t) - \eta_{ref}) / s_\eta\ )$$

Threshold note (η). Values such as η>0.4 are not universal constants; they are *operational working thresholds* indicating that stabilization is not a minor side effect but a dominant energetic role. In experiments/simulations, η_{ref} and s_η should be calibrated from control recordings (e.g., isolated vesicles vs clusters).

D. Informational Sustainability I

Informational sustainability denotes a system's capacity to regenerate internal functional patterns and their causal relations. It captures organizational competence beyond structure and energetics. The number of stable attractors N_{attr} reflects functional resolution, while statistical complexity C_μ quantifies the memory required to reproduce system dynamics [18]. The regeneration time T_{regen} measures how rapidly perturbations are resolved by returning to a stable attractor. Together they define I = h(N_{attr}, C_μ, T_{regen}), whose higher values indicate systems capable of reliably reproducing their own patterns and developing proto-semantic structure.

Operationalization of informational Sustainability I:

Informational sustainability denotes a system's capacity to regenerate internal functional patterns and their causal relations—organizational competence beyond geometry and energetics. We operationalize I using three measurable ingredients: (i) the number of functionally distinct, stable macrostates (*attractors*), (ii) the memory/structure required to reproduce observed dynamics (statistical complexity), and (iii) the speed of recovery after perturbations.

Let $N_{attr}(t)$ be the number of stable attractors identified in a state-space reconstruction (e.g., clustering of trajectories, recurrence plots, or ε-machine state structure). Let $C_\mu(t)$ denote *statistical complexity*, i.e., the Shannon entropy of causal states in an ε-machine reconstruction:

$$C_\mu(t) = H[\ S\_t\ ]$$

Let T_{regen} be the characteristic regeneration time after a standardized perturbation (e.g., flow pulse, salt jump, temperature step), and T_{break} a characteristic decay/break time (e.g., mean time to fragmentation or gradient collapse under the same regime).

We define a complete, bounded informational sustainability score:

$$I(t) = (\ \ln(N_{attr}(t)) / \ln(N_{max})\ ) \cdot (\ C_\mu(t) / (C_\mu(t) + C_{\mu,ref})\ ) \cdot (\ T_{break} / (T_{break} + T_{regen})\ )$$

where N_{max} is an operational maximum used for normalization (e.g., maximum observed in a dataset), and $C_{\mu,ref}$ sets the scale at which complexity contributes substantially.

Threshold note (N_{attr} ≥ 2). The condition $N_{attr} \geq 2$ is an operational criterion for *functional resolution*: at least two distinct stable macrostates must exist for state-dependent behavior (e.g., "adsorption-favoring" vs "proton-focusing" regimes) and for meaningful regeneration to be non-trivial. This criterion is logically independent of energetic allocation η: a system may expend substantial energy on stabilization (high η) yet still collapse into a single dominant attractor (N_attr≈1). Proto-liveliness requires both energy-supported stability and non-trivial attractor structure.

E. Sustainability Space Representation

To visualize how structural, energetic, and informational sustainability jointly delimit the transition from passive persistence to proto-liveliness, we introduce a three-dimensional sustainability space in which protocell cluster states can be positioned relative to a life–death threshold (Figure 1).

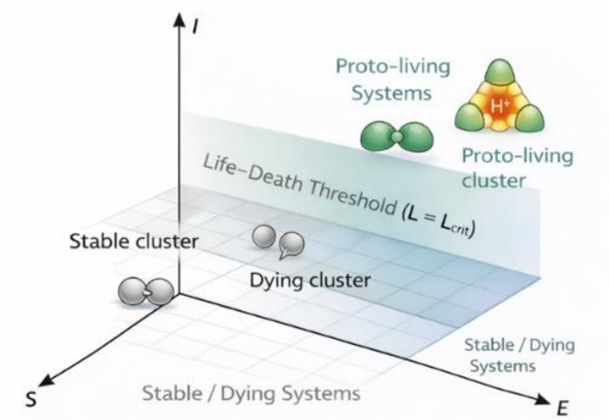

Figure 1. Prebiotic sustainability space and life–death threshold.

In Figure 1, protocell clusters are positioned within a three-dimensional sustainability space defined by structural (S), energetic (E), and informational (I) axes. A life–death threshold separates stable or dying assemblies from proto-living systems. Dimers, isolated protocells, and tetrahedral clusters illustrate how increasing coupled sustainability enables the transition to proto-liveliness.

The dimensions S, E, and I jointly span a Prebiotic Sustainability Space in which protocellular organizations can be placed. Systems with high values in all axes possess both physical robustness and functional autonomy, occupying regions of potentially proto-liveliness behavior. If any axis drops below a critical threshold, the system enters a decay zone where structural coherence, energy flows, or informational patterns cannot be sustained.

This three-dimensional space provides the conceptual basis for defining a numerical Life–Death Threshold.

The three scores define a point in a bounded sustainability space: $(S(t), E(t), I(t)) \in [0,1]^3$.

This representation enables direct comparison of protocell organizations and supports empirical phase-style classification: clusters with high S but low E exhibit cohesive structure without persistent gradients; clusters with high E but low I show sustained gradients without reliable pattern regeneration; and clusters high in all three dimensions are candidates for proto-liveliness under the criteria introduced next.

IV. From Sustainability to Proto-Liveliness: Quantitative Criteria

This section introduces a coupled threshold logic and derives a quantitative Life–Death criterion that classifies protocell clusters as stable, dying, or proto-living within S–E–I space.

A. Need for a quantitative threshold

Structural, energetic, and informational sustainability are necessary conditions for persistence, yet none alone marks the transition to proto-liveliness. The transition is best treated as a coupled threshold phenomenon in the three-dimensional S–E–I space: only when structure, gradients, and recoverable patterns mutually reinforce each other does a protocell cluster move beyond passive persistence toward autonomous self-restoration and functional renewal.

Only when all three dimensions exceed system-critical values does a state emerge in which a protocell cluster actively reproduces its own conditions of persistence. Below these thresholds, a cluster remains either merely physically stable—through mechanical cohesion or dissipative gradients—or disintegrates before functional autonomy can arise. The challenge is to formulate criteria that quantify this transition and allow experimental and theoretical testing.

Definition (Proto-liveliness). Prebiotic liveliness is defined as a sustainable protocell ensemble that autonomously regenerates functional patterns, restores dominant attractor states, and reorganizes energy flows, and thereby stabilizes its identity beyond passive physical persistence.

B. Life–Death Threshold

To operationalize this view, each sustainability dimension is assigned a minimal value above which it contributes to self-supporting organization:

$$S > S_{min},\ E > E_{min},\ I > I_{min}.$$

These conditions are necessary but not sufficient, since functional autonomy requires coordinated interplay among all three components. To capture this interdependence, a proto-liveliness function is introduced:

$$L = w_S\, S + w_E\, E + w_I\, I,$$

where w_S, w_E, and w_I are weighting factors derived from models, empirical data, or heuristic reasoning. Proto-liveliness manifests when the combined value exceeds a critical threshold: $L > L_{crit}$.

L quantifies the emergent capacity of a system to integrate structural integrity, energetic flows, and informational patterns into coherent, reciprocally coupled behavior.

Definition:

A protocell cluster is considered living when it actively maintains structural connectivity, organizes energy flows as stable gradients over diffusive timescales, and generates attractor-based functional states that can regenerate after perturbation. A dying system loses these capacities, and a dead system lacks gradients, connectivity, and attractor reconstruction.

L_{crit} marks the point at which a cluster no longer merely reacts but exhibits active self-regeneration and primitive agency.

C. Example classification

Applying these criteria enables a differentiated classification of protocellular organizations.

A *living* cluster exhibits strong structural connectivity, typically with a positive second Laplacian eigenvalue λ_2, generates stable gradients such that $\tau_{gradient} / \tau_{diff} > 1$, and allocates a significant share of energy to stabilizing processes, e.g., $\eta > 0.4$. $\eta>0.4$ is tied to energy allocation (a "substantial fraction" supporting stabilization rather than dissipation). $N_{attr} \geq 2$ is tied to functional resolution (at least two distinct stable macrostates).

It possesses multiple functional attractors ($N_{attr} \geq 2$) with substantial statistical complexity C_μ, and regenerates patterns faster than they decay ($T_{regen} < T_{break}$). Such systems robustly satisfy $L > L_{crit}$.

A *dying* cluster shows moderate structural stability, unstable or collapsing gradients, and regeneration times approaching decay intervals ($T_{regen} \approx T_{break}$), reducing both I and L below autonomy-supporting values.

A *dead* cluster is structurally fragmented ($\lambda_2 \to 0$), lacks stable attractors ($N_{attr} \to 0$), loses internal structure ($C_\mu \to 0$), and exhibits diverging regeneration times ($T_{regen} \to \infty$). These systems fall below all sustainability thresholds and remain non-living.

This classification provides the basis for quantitative tables, phase diagrams, and visualizations used later to characterize proto-liveliness transitions with precision.

Clarifying note. The thresholds (e.g., $\kappa>1$, $N_{attr} \geq 2$, $T_{regen} < T_{break}$, $\eta>\eta_{ref}$) are intended as *operational*, dataset-calibrated criteria. They define falsifiable inequalities that can be measured in microfluidic arrays or simulated ensembles and refined as empirical evidence accumulates.

V. Material vs. Organizational Quantities and the Four Levels

This section separates material from organizational variables and uses a four-level hierarchy to show where persistence-relevant meaning and function first emerge in protocell-cluster dynamics.

A. *Why distinguish these domains?*

The physical description of prebiotic systems comprises two categorically distinct classes of quantities. Material quantities refer to directly measurable parameters—forces, distances, diffusion coefficients, field strengths, energy densities—that determine the mechanical and energetic constraints under which protocell clusters exist. Organizational quantities instead capture emergent patterns and functional relations that cannot be reduced to individual molecules. They describe how a system structures states, transitions, and responses such that certain processes are preferentially produced, regenerated, or stabilized.

The distinction is essential because proto-liveliness is not determined by material parameters alone but by their embedding in self-consistent organizational forms. Material quantities define the level of physical realization; organizational quantities define functional order. Only their interplay generates the proto-liveliness phenomena analyzed in the remainder of the model.

B. *The four levels of information: statistical, syntactic, semantic, and pragmatic*

To clarify how functional organization emerges from purely material dynamics, we distinguish four hierarchical levels of system description, separated by a critical transition at which functional meaning first appears (Figure 2).

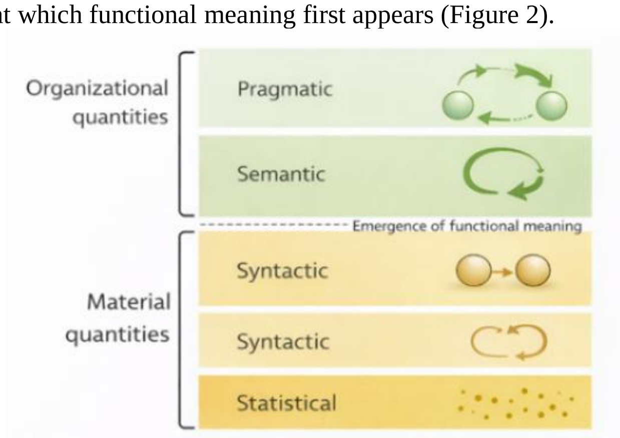

Figure 2. From material dynamics to organizational function.

In Figure 2, four hierarchical levels—statistical, syntactic, semantic, and pragmatic—organize system dynamics from material quantities to organizational structure. Functional meaning emerges at the boundary between syntactic transitions and semantic attractors, marking the shift from purely physical processes to persistence-relevant, functionally organized behavior.

(1) *Statistical level:*

At the statistical level, raw data, fluctuations, and ensemble distributions are described. Concentrations, densities, and thermal noise appear as stochastic variables. Patterns have no identity; they are deviations or aggregates without functional relevance.

(2) *Syntactic level:*

The syntactic level comprises lawful transitions between material states. It is captured by dissipative dynamics, reaction equations, and coupled differential equations. The system state $x(t)$ follows

$$x(t + \Delta t) = F(x(t)),$$

entirely determined by physical mechanisms. This level encodes chemical and mechanical rules without semantic or functional interpretation.

(3) *Semantic level:*

At the semantic level, patterns acquire meaning because they contribute to system persistence. A state x has semantic value when its reappearance after perturbation enhances survival. Meaning arises through recursive stabilization: patterns that support persistence are selectively regenerated. Formally, this is reflected in an attractor A whose maintenance maximizes survival probability. For a relevant state x:

$$P(x(t + \Delta t) \in A \mid \text{disturbance}) \rightarrow 1,$$

indicating that the system functionally orients itself toward attractor restoration.

(4) *Pragmatic level:*

The pragmatic level involves patterns that causally modulate future dynamics and act to preserve the system. Such patterns alter transition probabilities, regulate energy flows, or adjust structural couplings. The dynamics take a bidirectional form:

$$x(t + \Delta t) = F(x(t), y(t)) \text{ and } y(t + \Delta t) = G(y(t), x(t)),$$

where $y(t)$ denotes an organizational variable. At this level, an early form of system-level agency (“agency light”) emerges, enabling active influence on conditions of persistence.

C. *Core definitions*

An organizational quantity structures system dynamic at a higher level without being tied to specific physical carriers. Examples include attractor architectures, regeneration pathways, and functional coupling relations. These quantities emerge from material dynamics yet are not reducible to them, as they represent invariants over trajectories and become systemically causal.

The functional meaning of a state x is defined as its contribution to increasing a system’s probability of persistence: $P(\text{Persistence} \mid x) > P(\text{Persistence})$.

This relation quantifies meaning within a consistent physical–functional framework [8]. It links materially grounded dynamics to organizational structure and prepares the transition to the feedback mechanisms discussed in the next chapter, where semantic patterns give rise to pragmatically effective ones.

TABLE I. SUMMARY EQUATION PANEL

Level	Formal Expression	Interpretation
Statistical	$p(x)$; $\langle x^n \rangle$; $S(\omega)$	Ensemble distributions, moments, spectra, and fluctuation statistics
Syntactic	$x(t + \Delta t) = F(x(t))$	Material transition laws governing physical dynamics
Semantic	$P(x(t + \Delta t) \in A \mid \text{disturbance}) \to 1$	Persistence-relevant attractor A defines functional meaning
Pragmatic	$x(t + \Delta t) = F(x(t), y(t))$ $y(t + \Delta t) = G(y(t), x(t))$	Organizational feedback via $y(t)$ modulating future dynamics

Table I, transition from statistical description to pragmatic, function-modulating dynamics through recurrent stabilization and organizational feedback. Semantic meaning arises from persistence-oriented attractors, while pragmatic function emerges when organizational variables causally modulate future system dynamics.

VI. THE BRIDGE PRINCIPLE: FUNCTIONAL FEEDBACK LOOPS

This section states the Bridge Principle and formalizes the minimal feedback architecture by which structural, energetic, and informational loops jointly generate proto-semantic and proto-pragmatic organization.

A. *Central Claim*

The Bridge Principle describes the transition from purely physical patterns to functional organization. This transition begins when recurrent patterns modulate system dynamics and thereby maintain the conditions of their own realization. Physical patterns thus become carriers of functional meaning and seeds of proto-liveliness autonomy.

The principle shows how local structures, energy flows, and dynamic patterns become recursively coupled so that a system not only persists but actively stabilizes the conditions of its reproduction. Early forms of meaning, functionality, and autonomy arise without genetic information, enzymatic networks, or complex metabolic architectures. The Bridge Principle marks the minimal organizational threshold at which physical dynamics shift into proto-semantic and proto-pragmatic behavior, generating an operational precursor of biological agency.

The transition rests on stable feedback cycles in which recurrent patterns stabilize and regenerate the very conditions enabling them. Patterns gain semantic status when they promote persistence and pragmatic force when they causally modulate system dynamics. The shift from material to organizational quantities occurs when such patterns achieve functional stabilization. Semantic properties emerge from recurrence; pragmatic properties from causal influence. The three loops operate as coupled mechanisms of functional organization.

B. *The Three Feedback Loops: structural, energetic, and informational*

To make explicit how functional autonomy arises from recursive physical organization, we represent proto-liveliness as the mutual coupling of structural, energetic, and informational feedback loops (Figure 3).

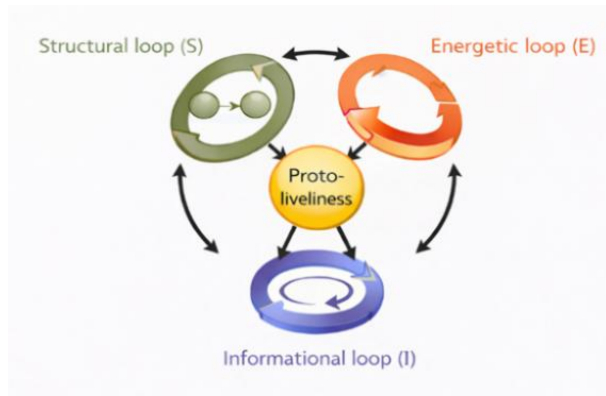

Figure 3. Coupled structural, energetic, and informational feedback loops.

In Figure 3, three mutually coupled feedback loops—structural (S), energetic (E), and informational (I)—form a recursive triad whose interaction stabilizes proto-liveliness. None of the loops is hierarchical; proto-liveliness emerges only from their continuous bidirectional coupling, which jointly sustains structure, gradients, and attractor-based functional patterns.

(1) *Structural loop:*

The structural loop captures how spatial organization increases the likelihood of stable force distributions and thereby reinforces its own persistence. Dense, redundant connectivity—mediated, for example, by Casimir-like nanoscale attractions—increases the Laplacian eigenvalue λ_2. Higher λ_2 lowers the probability of fragmentation, yielding the recursive relation: $\lambda_2 \uparrow \Rightarrow S \uparrow \Rightarrow \lambda_2$ stabilizes.

Spatial structure thus generates the conditions for its own renewal and acts as a dimensionless organizational operator at the mesoscale.

(2) *Energetic loop:*

Energetic feedback arises when energy flows stabilize gradients that in turn facilitate renewed energy uptake. The key parameter is $\tau_{gradient} / \tau_{diff}$, which determines whether dissipative patterns build faster than diffusion erodes them. For $\tau_{gradient} / \tau_{diff} > 1$ a stable gradient cycle can exist. Persistent gradients increase energetic efficiency η, allowing more of the incoming energy to support structure- and pattern-forming processes. This yields a reinforcing cycle: $(\tau_{gradient} / \tau_{diff} \uparrow)$, $\eta \uparrow \Rightarrow E \uparrow \Rightarrow$ gradients stabilized.

(3) *Informational loop:*

The informational loop appears when internal attractors generate dynamic patterns that also stabilize those attractors. An attractor with statistical complexity C_μ [18] generates robust regeneration pathways and shortens the regeneration time T_{regen}. Shorter T_{regen} increases the likelihood of returning to the same functional state after perturbation: $C_\mu \uparrow, T_{regen} \downarrow \Rightarrow I \uparrow \Rightarrow C_\mu$ stabilizes.

Here proto-semantic meaning becomes visible: a pattern is "meaningful" because its recurrence enhances system persistence, even in the absence of encoded information. All three loops interact tightly. Structure influences energy flows; energy flows stabilize patterns; patterns stabilize structure. Together they produce states with both semantic (pattern-based stability) and pragmatic (dynamic modulation) properties. The Bridge Principle therefore describes the mechanism through which physical dynamics are transformed into functional organization.

VII. Discussion and Relation to Existing Theories

This section situates the proposed metrics and thresholds within established theories of living organization and highlights what the present framework adds in terms of operational measurability and physical grounding.

A. Autopoiesis (Maturana & Varela)

The autopoietic framework characterizes living systems as networks of processes that generate the components sustaining the network itself [17]. The present theory shares this focus but provides a physically grounded, metrically defined account of prebiotic units. While Autopoiesis specifies structural closure qualitatively, the Sustainability Space enables quantitative assessment of the conditions under which protocell clusters achieve structural coherence, energetic recursion, and pattern regeneration: $S > S_{min}, \quad E > E_{min}, \quad I > I_{min}$.

Incorporating nanoscale coupling forces—especially Casimir-like interactions—adds an explicit physical mechanism for mesoscale coherence. These forces stabilize contact geometries assumed but not mechanistically explained in classical autopoietic models. The framework thus supplies a dynamically quantifiable foundation for autopoietic organization.

B. Kauffman's Work Cycles

Kauffman's notion of work cycles identifies energy flows as drivers of chemical organization [20]. This idea is formalized in $k = \tau_{gradient} / \tau_{diff} > 1$, which ensures that dissipative structures arise faster than diffusion erodes them. What is new here is the integration of structural and informational dimensions. Even strong energy input does not yield proto-liveliness organization when structural coherence is absent ($S \approx 0$) or regenerative patterns are lacking ($I \approx 0$). Only the joint action of S, E, and I determines whether work is translated into functional organization. Energetic sustainability is necessary but not sufficient.

C. Information-theoretic Proto-Liveliness Definitions

Information-theoretic proposals - such as Rosas et al. [7] -define proto-liveliness as the ability to preserve or regenerate informational patterns. This view aligns with informational sustainability, $I = h(N_{attr}, C_\mu, T_{regen})$.

N_{attr} reflects functional resolution, C_μ the memory required for dynamical reproduction, and T_{regen} the rate of recovery. Unlike abstract formulations, the present framework provides a physical implementation of these informational structures. Patterns arise from concrete couplings- geometry, osmotic gradients, Casimir-like forces, and dissipative energy networks. Information processing is not symbolic manipulation but an emergent consequence of physical dynamics enabling attractor formation and stability.

D. What is genuinely new

The key innovation is the introduction of a quantitative Life–Death Threshold within the S–E–I Sustainability Space.

The condition $L = w_S\,S + w_E\,E + w_I\,I > L_{crit}$ provides the first integrated metric for distinguishing stable, dying, and proto-living systems. The Bridge Principle further offers a physically plausible mechanism by which patterns acquire functional significance without genetic coding or enzymatic regulation. Structural, energetic, and informational feedback loops generate proto-pragmatic efficacy, enabling a system to actively stabilize the conditions that support its persistence.

This approach unites physical principles with biological and information-theoretic perspectives, offering an empirically testable account of proto-liveliness organization. Sustainability denotes passive persistence of structural, energetic, and informational order; liveliness entails active self-regeneration and functional renewal under continuous energy flow.

VIII. Outlook: Simulation and Experimental Probes

This section proposes complementary experimental and computational strategies for measuring S, E, and I and for testing the Life–Death threshold under controlled perturbations.

A. Microfluidic protocell arrays

Microfluidic platforms provide controlled environments for probing the sustainability parameters S, E, and I. Vesicle clusters can be reproducibly generated and geometrically confined. Structural sustainability S is obtained via high-resolution imaging and graph-theoretic reconstruction of contact matrices. Algebraic connectivity λ_2 and structural redundancy yield $S = f(\lambda_2, R_{struct})$.

Energetic processes are monitored through fluorescence-based pH, redox, or ion indicators that report gradient formation and lifetime, enabling measurement of

$\tau_{gradient}$ / τ_{diff} and the energetic efficiency η. Informational metrics such as T_{regen} follow from applying defined perturbations and tracking return to dominant patterns. Attractor dynamics, N_{attr}, and C_μ can be extracted from reconstructed trajectories.

Such arrays offer a direct experimental route to evaluating the Life–Death Threshold $L > L_{crit}$.

B. AI-based simulations

Simulations access parameter regimes difficult to probe experimentally. AI-driven optimization—particularly reinforcement learning—adjusts λ_2, η, and N_{attr} to maximize the life function $L = w_S\, S + w_E\, E + w_I\, I$.

This identifies organizational forms representing especially robust proto-liveliness states in the Sustainability Space. Agent-based models with large vesicle populations allow analysis of mesoscale pattern formation, emergent attractor landscapes, and functional robustness under stochastic conditions. They also reveal how the Bridge Principle operates at the population level and how structural, energetic, and informational feedback loops interact. The models generate hypotheses about required combinations of S, E, and I and highlight parameter regions most relevant for experiments.

C. Potential impact

Combining microfluidic experiments with AI-based simulations enables empirical validation of a quantitative physics of prebiotic liveliness. The quantities λ_2, $\tau_{gradient}$ / τ_{diff}, η, N_{attr}, C_μ, and T_{regen} form a coherent set of measurable indicators for functional autonomy, allowing an experimental distinction between stable, dying, and proto-living systems.

The framework also has technological relevance. It may guide the design of artificial proto-biological systems in which dissipative patterns carry functional information. Such proto-biocomputing devices would couple physical self-organization with information-processing dynamics, opening new possibilities in biotechnology, materials science, and unconventional computation. The model's criteria thus illuminate early evolutionary processes while offering an architecture for future bio-inspired technologies.

IX. CONCLUSION AND FUTURE WORK

This work establishes a quantitative framework for the emergence of proto-liveliness in Casimir-coupled protocell clusters. By defining structural (S), energetic (E), and informational (I) sustainability and integrating them into a Life–Death Threshold, we identify precise physical conditions under which a merely persistent assembly becomes functionally autonomous. The Bridge Principle reveals how recurrent physical patterns gain semantic and pragmatic roles through coupled structural, energetic, and informational feedback loops, providing a minimal mechanism for early agency.

The framework shows that proto-liveliness is not the product of any single domain but arises from the coordinated reinforcement of connectivity, dissipative gradients, and attractor-based pattern regeneration. This approach connects autopoietic, energetic, and information-theoretic theories while grounding them in measurable physical quantities.

Microfluidic protocell arrays and AI-based simulations offer concrete routes to testing the model, enabling empirical discrimination between stable, dying, and proto-living systems. As a broader implication, the theory outlines principles for designing artificial proto-biological systems in which dissipative patterns carry functional information, suggesting potential pathways toward bio-inspired materials, chemical computing, and synthetic life.

Take-home message: Life begins when matter organizes itself such that structure, energy, and information cooperatively stabilize the conditions of their own continuation.

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