FRAMEWORK FOR A GENERAL SYSTEM THEORY

John A Challoner
BSc(Eng), CEng, MICE (Retired)

Abstract
This paper presents a comprehensive framework for understanding systems across all domains of complexity: physical, biological, cognitive, and social. The framework builds upon, unifies, and extends classical systems science by grounding systemic behaviour in open system thermodynamics, energy landscapes, systems causality, and recursive emergence. At its core lies the concept of information at source: a measure of internal recursively structured order, and its dynamic relationship with energy and entropy.

Systems are defined by the emergence of properties absent from their components, and their operation depends on the balance between energy available for maintaining internal structure and that required for exercising function. The framework explains how systems form, persist, collapse, or evolve by stabilising in attractor basins within energy landscapes, scaling recursively through fractal architecture.

Sets of formal definitions and propositions, whose provenance is given, underpin the theory, offering a structured, logically coherent, and cross-disciplinary model. The framework unifies foundational work by von Bertalanffy, Ashby, Beer, Bateson, Prigogine, Rosen, and others. It also incorporates more recent developments by Bhaskar, Cronin and Walker, Parisi, and the author.

Keywords
General System Theory, Emergence, Free Energy, Recursive Structure, Energy Landscape.

1 | Introduction
The search for a General System Theory (GST) has been a defining theme in systems science for over seventy years. First articulated in Ludwig von Bertalanffy's early work during the 1940s and later formalised in his 1968 book, the idea was to uncover universal principles of organisation that apply across the natural and social sciences. Despite rich theoretical advances by many pioneers, systems theory has often remained fragmented, i.e., split between physical systems, biological models, cybernetics, social structures, and cognitive frameworks.

What has been lacking is a unified framework that explains not only the structure and function of systems, but also their emergence, scaling, and life-cycle, doing so in a way that applies across domains without sacrificing coherence or explanatory power. This paper proposes such a framework. It brings together thermodynamic insights, recursive organisation, systems causality and a formal structure of definitions and propositions to offer a potential GST that is general in both scope and logic.

This framework rests on a foundational shift from thinking of systems as static aggregates or input–output machines to viewing them as energy-bound, structure-dependent entities that emerge recursively. Central to the framework is the concept of information at source. That is, a physically grounded, recursive measure of order that underpins emergent function. Systems emerge when a structured configuration stabilises within an attractor in an energy landscape. They persist and evolve through a balance between internal maintenance and functional output; a trade-off that can be formally expressed in a modified free energy equation.

The framework explains how systems scale via nesting, evolve through ratcheting in a fractal energy landscape, and collapse when complexity of structure outgrows its function. It treats theories, organisations, belief systems, and even personal roles as systems subject to the same principles as stars, cells, or ecosystems. And crucially, it recognises the ability to assemble, manipulate, and recombine abstract conceptual structures, as the cognitive engine that enables the recursive evolution of systems of thought. Symbolic reasoning, which employs a modified form of set theory, can formalise and facilitate the latter (Challoner, 2023).

In doing so, this framework also integrates the major insights of foundational systemists, e.g., Ashby's variety (1956), Bertalanffy's hierarchy (1968), Beer's viability (1972), Bateson's information (1972), Prigogine's dissipative structures (1977), Rosen's anticipatory systems (1985), and others, into a coherent whole. These contributions, once seen as distinct "stations" in the intellectual landscape of systems theory, are here reinterpreted as surface expressions of deeper organising principles visible through this framework, like the network of tunnels beneath a subway system.

The following sections introduce the framework step by step: first by defining its core concepts, then by developing a sequence of formal propositions. The provenance of each definition and proposition is also provided.

2 | Foundational Definitions

To develop a theory that can apply across domains and explain systemic behaviour consistently, it is necessary to clearly define its foundational terms. These definitions provide the semantic and conceptual infrastructure of the framework. Many of them extend traditional systems terminology.

2.1 Subcritical Structure

A subcritical structure is also known as a pre-critical assembly or a precursor state. It is a stable configuration of interacting components that does not yet give rise to emergent properties. While internally organised, such a structure lacks holistic behaviour that cannot be reduced to the sum of its parts. It may persist in time, but it does not yet function as a true system. Subcritical structures are often precursors to systems, awaiting a reconfiguration that will allow emergence to occur.

The concept underlying "subcritical structure" draws primarily from early systems thinking, particularly the distinction between mere aggregates of components and true emergent systems. Ludwig von Bertalanffy (1968) emphasised that a system must exhibit properties that are not reducible to those of its parts alone, marking the threshold of emergence. Herbert Simon (1962) also described "nearly decomposable systems," where tightly interacting subsystems could exist without yet producing novel emergent behaviours. More recently, complexity theorists such as Stuart Kauffman (1993) and Peter Corning (2002) have stressed that mere organisation without emergent properties does not constitute a system in the full sense.

2.2 Emergent Property

Emergent properties are sometimes also known as phase transitions or symmetry breaking. (Anderson, 1972). An emergent property is a novel behaviour, capacity, or relationship that arises from the internal organisation of a system and is not evident in any component part. Emergent properties are indicators that a structure has crossed a critical threshold and become a system. They may manifest as cognitive function, adaptive behaviour, resilience, reproduction, self-regulation, or other holistic abilities.

Building directly on the systems tradition discussed in the previous section**,** including the work of Bertalanffy (1968), Simon (1962), Kauffman (1993), and Corning (2002)**,** this framework defines emergent properties as indicators of transition from subcritical structure to true systemic function. These properties may include cognition, adaptation, resilience, reproduction, or self-regulation, and mark the onset of causal capabilities not reducible to the system's individual elements.

2.3 System

A system is defined as a configuration of components that interact in such a way that one or more emergent properties arise. These emergent properties are not attributable to any component in isolation, but arise from the organisation and interactions of the whole. A system is thus characterised not merely by stability, but by functional novelty and relational integration. It also exists within and interacts with an environment.

This definition follows the foundational systems literature, including Bertalanffy's (1968) emphasis on irreducible complexity, Simon's (1962) insights on hierarchical organisation, Bateson's (1972) focus on relational structure, and Capra's (1996) view of environmental embeddedness. These perspectives, introduced in earlier sections, collectively support the view of a system as an emergent, dynamic, and environmentally coupled whole.

2.4 Recursive Emergence

Recursive or hierarchical emergence is the process by which emergent systems themselves become components in higher-order systems, producing new layers of organisation. Each layer exhibits its own emergent properties, boundaries, and internal structure.

The concept of recursive emergence has deep roots in systems theory and complexity science. Ludwig von Bertalanffy (1968) introduced the idea of hierarchical organisation, where systems exist at multiple levels, each with their own emergent properties. Herbert Simon (1962) described "nearly decomposable systems," highlighting how hierarchical structures facilitate complexity by enabling stability and adaptation across layers. Stuart Kauffman (1993) further developed the idea in biological contexts, showing how self-organisation and emergence recur across scales, from molecules to organisms to ecosystems.

More recently, Assembly Theory, developed by Cronin and Walker (2021), provides a quantitative basis for recursive emergence by measuring how complex objects are built from simpler components through stepwise assembly. The assembly index reflects the historical depth of construction, showing that higher-order systems carry embedded records of their compositional lineage, a principle fully aligned with the idea that emergent systems are recursively assembled from prior systems.

2.5 Closed System

For the purposes of this framework, a closed system is defined as a system that neither exchanges matter nor energy with its environment. Its total internal energy and matter content remain effectively constant, and its evolution is driven solely by internal dynamics toward thermodynamic equilibrium.

This definition of a closed system is grounded in classical thermodynamics, particularly the work of Rudolf Clausius (1865) and Lord Kelvin (William Thomson). Clausius formulated the second law of thermodynamics, showing that in an isolated system, entropy must increase over time, eventually leading to equilibrium. While modern terminology distinguishes between *closed* systems (no matter exchange) and *isolated* systems (no matter or energy exchange), early thermodynamic models often treated closed systems as if they were fully isolated for simplicity.

Ludwig von Bertalanffy (1968) later highlighted the contrast between closed and living systems, stressing that life depends on continuous exchanges of energy and matter. For the purposes of this framework, a closed system is defined strictly, effectively treated as isolated, to clearly separate systems governed by internal-only dynamics from those sustained by external inputs.

2.6 Entropy

Entropy is a measure of the number of microscopic configurations (or microstates) available to a system consistent with its macroscopic properties. It quantifies the system's degree of disorder or randomness. Entropy is denoted by S, and increases as the components of a system become more disordered or unconstrained. In statistical mechanics, entropy is given by Boltzmann's formula:

$$S = k_B \ln \Omega \tag{1}$$

where Ω is the number of accessible microstates and k_B is Boltzmann's constant.

Maximum entropy S_{max} represents the highest possible disorder a system can attain under its constraints, typically occurring when energy is fully dispersed and structure is absent. The precise value of S_{max} depends on the system's configuration space and constraints, and is generally not analytically known. However, thermodynamic principles ensure that:

$$S_{max} \leq E/T \tag{2}$$

where E is the internal energy of the system (in Joules, J) and T is its absolute temperature (in degrees Kelvin, K). This inequality guarantees that free energy remains non-negative and physically meaningful. It defines a thermodynamic limit: no system can possess more entropy than E/T without violating the second law of thermodynamics.

The modern understanding of entropy originates in the foundational work of Ludwig Boltzmann (1877) in statistical mechanics. Boltzmann introduced the celebrated entropy formula (1), linking entropy to the number of microstates accessible to a system. Rudolf Clausius (1865) earlier introduced the general thermodynamic concept of entropy as a tendency toward energy dispersion and increased disorder, formulating the second law of thermodynamics. The statistical interpretation provided by Boltzmann and later refined by J. Willard Gibbs (1902) firmly established entropy as a bridge between microscopic dynamics and macroscopic thermodynamic behaviour.

2.7 Free Energy

Free energy is the portion of a system's internal energy that is available to do useful work. The Helmholtz free energy F is defined as:

$$F = E - TS \tag{3}$$

where:

- E is the total internal energy of the system (J),
- T is the absolute temperature (K),
- S is the entropy (J/K).

This equation applies to both open and closed systems. In closed systems, where E is constant, not all energy is usable. As entropy increases, more of the system's energy becomes "locked in" by disorder, distributed across microstates. The more disordered or entropic a system, the less free energy there is to do work. Free energy therefore measures the system's potential to function or transform, after accounting for the energetic cost of disorder. In equilibrium thermodynamics, free energy always satisfies:

$$F \leq E \tag{4}$$

because entropy cannot be negative, and increasing disorder always reduces the usable portion of internal energy.

This balance between structure, energy, and entropy in a system determines its position and stability within its energy landscape.

The concept of free energy was formalised in classical thermodynamics by Hermann von Helmholtz (1882). Helmholtz introduced free energy to describe the portion of a system's internal energy available to perform useful work at constant temperature and volume. Ludwig Boltzmann (1877) and J. Willard Gibbs (1902) later integrated free energy concepts into statistical mechanics, linking them to microscopic states and entropy. Gibbs generalised free energy formulations, particularly in systems where multiple thermodynamic potentials (e.g., Gibbs free energy for constant pressure) were important. In modern complex systems science, free energy is understood not only as a thermodynamic quantity but also as a measure of a system's capacity for organised transformation, adaptability, and systemic function.

2.8 Information at Source

Information at source, a term coined by the author, is the structured, recursive organisation within a system and its subsystems that enables emergent function. It is conceptually equivalent to negentropy, a measure of internal order that reflects the system's departure from thermodynamic equilibrium. Note, however, that negentropy is not literally "negative entropy" rather it is the reduction in a system's maximum entropy brought about by structure.

Information at source can be quantitatively defined as:

$$I = (F - E + TS_{max})/T \tag{5}$$

Where:

- I = Information at source (in entropy units, J/K),
- F = Free energy (energy available to do work) (J),
- E = Internal energy of the system (J),
- T = Absolute temperature (K),
- S_{max} = Maximum possible entropy of a system (J/K).

This formulation is derived by rearranging the classical thermodynamic identity $F = E - TS$ (3), where S is entropy and $I = S_{max} - S$.

The concept of "information at source" as structured, recursive organisation enabling emergent function builds upon earlier notions of negentropy and information in physical and biological systems. Erwin Schrödinger (1944) first introduced the idea that life maintains itself by feeding on "negative entropy," though he acknowledged that "negentropy" was a conceptual rather than a strictly mathematical term. Claude Shannon (1948) formalised information theory by quantifying information as a reduction in uncertainty, mathematically linking it to entropy, but did not directly associate it with physical structure. Leon Brillouin (1956) attempted to unify thermodynamics and information theory, proposing that acquiring information requires physical energy expenditure, reinforcing the connection between order, information, and energetic cost. More recently, Howard Pattee (1969) and later researchers in complex systems science have developed models connecting internal organisation, information processing, and systemic function. In this paper, the author refines these traditions by introducing "information at source" as a specific, measurable quantity reflecting the internal organisation of a system relative to its maximum entropy, and deriving a formal expression linking free energy, entropy, and internal structure. This approach frames information at source not merely as a metaphorical negentropy, but as a real, thermodynamically meaningful structural property of systems.

2.9 Energy Landscape

An energy landscape is a conceptual and mathematical model used to describe the internal energy, either total or free depending on context, of a complex system across all its possible configurations. Each point in the landscape represents a complete arrangement of the system's components, and the "elevation" at that point corresponds to the energy associated with that specific configuration. In formal terms, the landscape is defined by:

- A high-dimensional configuration vector: $\vec{x} = (x_1, x_2, x_3, ..., x_n)$ where each x_i represents a degree of freedom or state variable in the system, e.g., the orientation of a spin, the state of a node, or a component's behaviour.
- A corresponding energy value: $z = E(\vec{x}) = E(x_1, x_2, ..., x_n)$ where z or "height" in the landscape is the internal energy of the configuration.

In systems with many components, this energy landscape can have thousands or millions of dimensions, making direct visualisation impossible. However, important features can still be inferred or illustrated by reducing dimensionality.

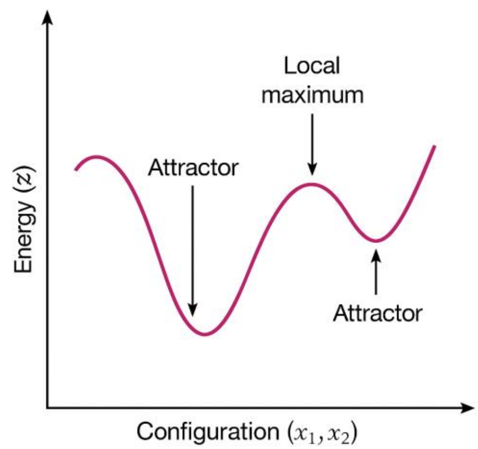
To make energy landscapes accessible for conceptual and visual exploration, we can hold some variables constant, effectively slicing through the full high-dimensional space. This produces a simplified landscape showing local and global energy minima (troughs), maxima (peaks), and the transitions between them. In this framework:

- Troughs represent stable configurations where systems "settle" into stability and properties can emerge.
- Peaks represent unstable, disordered, or unsustainable arrangements.

The concept of an energy landscape originated in physical chemistry and statistical mechanics as a way to model the potential energy of molecular systems across different configurations. It was formalised in the study of reaction dynamics, notably through the work of Michael Polanyi (1935) and later in chemical kinetics by Eyring and others. In statistical physics, the idea matured through the study of disordered systems, particularly in spin glasses, where Giorgio Parisi (1980s) demonstrated that the free energy landscape of such systems exhibits a complex, fractal structure of nested local minima. In biology, energy landscapes have also been used to model protein folding (Bryngelson & Wolynes, 1987), showing how biological systems navigate rugged landscapes toward stable functional states. In complexity science more broadly, energy landscapes have been adapted as metaphors and formal models for system stability, adaptation, and emergence. In this paper, the author formalises the energy landscape concept to encompass both total and free energy as dimensions of system state, linking landscape topology to systemic stability, emergence, and information at source across multiple levels of complexity.

2.10 Attractor

An attractor, also known as a stable state, trough or basin of attraction, is a stable configuration within a system's energy landscape toward which the system tends to evolve. Once a system has settled into an attractor, it resists small perturbations and may exhibit resilience. In the case of systems, attractors may be optimal, sub-optimal, or super-optimal, depending on the balance between structure and function.



The concept of an attractor originated in the study of dynamical systems and nonlinear mathematics. Henri Poincaré (1890s) introduced the idea of trajectories tending toward certain states in phase space. In the 20th century, Stephen Smale (1960s) formalised mathematical structures like strange attractors in chaos theory, expanding the concept beyond simple equilibrium points to complex, stable, recurring patterns. In systems theory, Ludwig von Bertalanffy (1968) described steady states in open systems, implicitly invoking attractor-like behaviour in systemic regulation. Stuart Kauffman (1993) extended the attractor concept into biology, particularly genetic networks, where different gene expression patterns represent different basins of attraction. In statistical physics, Giorgio Parisi's work on energy landscapes in spin glasses also formalised attractor basins in rugged, fractal energy topographies.

2.11 Fractal Pattern
A recursive or fractal pattern can emerge when a generator, that is, a consistent set of rules or laws, is applied to a substrate.

The concept of fractal patterns was first formalised by Benoît Mandelbrot (1982) in his foundational work *The Fractal Geometry of Nature*. Mandelbrot demonstrated that fractal structures could be generated mathematically by applying iterative generators to continuous spaces, with the Mandelbrot Set becoming a canonical example. This example arises when a mathematical generator is applied to the field of complex numbers. In physical systems, fractal structures have been observed in diverse domains such as turbulence, geology, and biological growth. In complexity science, the concept of fractal organisation, i.e., self-similar patterns appearing across different levels, has also been explored by Benoît Mandelbrot (1982), especially in the context of natural and social systems.

Recursive emergence is also fractal in nature: each new layer of emergent structure arises from the interaction of previously formed systems, creating a nested, self-similar hierarchy that spans from the material to the symbolic.

Finally, Giorgio Parisi (1980s) discovered a fractal pattern in the realm of disordered physical systems, particularly spin glasses, demonstrating that their free energy landscapes exhibited hierarchical, nested basins reflecting a form of structural self-similarity. Parisi's groundbreaking work, for which he later received the Nobel Prize in Physics, showed that fractal geometries could emerge in complex, multi-scale stability structures.

2.12 Open System
Open systems are also known as a dissipative structures. Strictly, an open system exchanges both energy and matter with its environment. However, in this framework, the term refers to a system composed only

of the components that at some time form or contribute to the formation of the emergent whole. As such, there is no exchange of matter with the environment, only energy. This modelling assumption preserves a constant set of internal components, allowing the system's energy landscape to retain a stable structure of attractors while still permitting dynamic internal transformations.

This selective closure is not a physical absolute but a deliberate abstraction that enables the configuration space and attractor topology to remain identifiable over relevant timescales, even as energy flows in and out. Continuous energy inflows sustain far-from-equilibrium states and enable the maintenance and evolution of internal structure.

Inflows of free energy are assumed to be approximately constant over short timescales, permitting a quasi-static analysis of system ratcheting and emergence. Formally, the relationship between internal energy E, information at source I, free energy F, and maximum entropy S_{max} is given by:

$$E+TI = F+TS_{max} \quad (6)$$

where T is the system's temperature.

If F, T, and S_{max} are held constant, it follows directly from this equation that as I increases, E decreases, and vice versa. This reciprocal dynamic shapes the system's energy landscape. However, if F varies, the entire energy landscape and the system's energy position shift vertically together, preserving the system's relative location within the attractor structure. This dynamic ensures that, while absolute energy levels may change, the structural form of the landscape and the system's progression within it remain consistent. This partial openness thus strikes a balance between realism and analytical tractability, and is consistent with approaches in fields such as ecology, thermodynamics, and systems biology, where systems persist far from equilibrium through continuous energy exchange.

The concept of an open system, one that exchanges energy (and sometimes matter) with its environment, emerged as a central theme in thermodynamics and systems theory during the 20th century. Ludwig von Bertalanffy (1968) distinguished open systems from closed systems, emphasising that living organisms maintain themselves far from thermodynamic equilibrium through continuous energy and matter exchanges. Ilya Prigogine and Isabelle Stengers (1984) further developed this idea through the concept of dissipative structures, demonstrating that open systems could self-organise and increase internal complexity by exporting entropy to the environment. More recent treatments, such as those by Fritjof Capra (1996), stressed the embeddedness of open systems within larger dynamic networks. In this paper, the author sharpens the classical definition by focusing specifically on systems that exchange energy but not matter, thereby preserving a constant internal component structure. This approach allows the internal energy landscape to remain stable for modelling purposes, while still capturing the dynamic far-from-equilibrium behaviour characteristic of open systems.

2.13 Ratcheting

Ratcheting, also known as path dependent evolution, describes the historical process by which open systems transition from less to more structure or information at source over time. Once a higher-order structure emerges and stabilises, it becomes increasingly difficult to reverse. This is not due to physical impossibility, but to the probability of disruptive events and the fractal configuration of energy landscapes.

The idea that systems undergo path-dependent, largely irreversible structural evolution has roots across evolutionary biology, thermodynamics, and systems theory. Stephen Jay Gould (1989) famously emphasised the historical contingency and irreversibility of evolutionary paths in biology, noting that complexity tends to accumulate because reversal requires improbable coordinated changes. In thermodynamics, Ilya Prigogine (1977) highlighted that open systems evolving far from equilibrium tend to stabilise emergent structures that resist simple reversion to earlier states. Stuart Kauffman (1993) showed that biological systems often move toward more complex attractors within rugged landscapes, making backward transitions increasingly unlikely. Giorgio Parisi's (2021) work on fractal energy landscapes further demonstrated that structural "deepening" in complex systems increases energy barriers to change. In this paper, the author synthesises these insights into a unified framework of "ratcheting", describing how the emergence of higher-order systemic structure makes reversal not physically impossible, but increasingly improbable due to the nested and rugged configuration of systemic energy landscapes.

2.14 Systemic Optimality

Systemic optimality refers to the state in which a system balances the internal free energy required to maintain structure (F_m) with that required for functional output (F_o). If structure becomes too complex or costly, the system becomes super-optimal and function declines. Conversely, sub-optimal systems lack sufficient structure to function effectively. The balance point represents peak functional effectiveness.

Systemic Optimality is defined as:

$$\Omega = O_I / O_{Imax} \tag{7}$$

Where:

- Ω = Systemic optimality (dimensionless. Maximum = 1. Minimum = 0.),
- O_I= Information at source in the system's outputs ($JK^{-1}s^{-1}$),
- O_{Imax} = Potential maximum information at source in the system's ouputs ($JK^{-1}s^{-1}$).

The concept of systemic optimality, i.e., the balance between structural complexity and functional output, draws on foundational ideas from systems theory, thermodynamics, and cybernetics. W. Ross Ashby (1956) formulated the Law of Requisite Variety, proposing that system effectiveness depends on matching internal complexity to environmental challenges. Ludwig von Bertalanffy (1968) emphasised that open systems must maintain internal order while remaining adaptable, implying an optimal balance between structure and energy use. In biological evolution, Stuart Kauffman (1993) demonstrated that complex systems tend to evolve toward a critical point between order and chaos, achieving maximal adaptive capacity. In statistical mechanics, models of self-organised criticality (Bak, Tang, & Wiesenfeld, 1987) similarly show systems evolving toward optimal states without external fine-tuning. In this paper, the author provides a quantitative basis for evaluating systemic performance at all levels of emergence.

2.15 Super-Optimal System

A super-optimal system, also known as an overcomplex or rigid system, is one that has accumulated more internal structure than is needed for its function, consuming most of its energy in self-maintenance thereby losing productive and adaptive capacity. Super-optimal systems may remain stable for some time but become vulnerable to further decline or collapse when environmental conditions change, and internal rigidity suppresses adaptation. Examples include over-bureaucratised institutions and ageing biological systems.

The concept of a super-optimal system builds upon foundational ideas in systems theory, evolutionary theory, and sociology. Ludwig von Bertalanffy (1968) noted that increasing systemic complexity can, beyond a certain point, reduce functional flexibility and increase vulnerability. Stuart Kauffman (1993) similarly argued that biological systems can move from adaptive complexity to rigidity, becoming trapped in suboptimal attractors within rugged fitness landscapes. Joseph Tainter (1988) developed this idea in his study of societal collapse, suggesting that increasing complexity imposes rising costs of maintenance, eventually exceeding the adaptive benefits. In organisational theory, the phenomenon of bureaucratic overgrowth, explored by Max Weber (1922/1978), describes how institutions may accumulate rigid structures that inhibit flexibility and innovation.

Manfred Max-Neef (1995) extended this principle into economic and human development, showing that while GDP growth initially improves human well-being, it eventually reaches a peak and then declines, a pattern known as the threshold hypothesis. This reflects super-optimality at the societal scale: increasing structural and economic throughput leads to diminishing and eventually negative returns in quality of life, as resources are absorbed by system maintenance rather than meaningful function.

2.16 Critical Realism

This concept and the one that follows are highly relevant to the idea that processed information and models can also be regarded as systems. Critical realism is a philosophical perspective asserting that reality exists independently of our perception, but our knowledge of it is mediated through structured, emergent cognitive systems. In this framework, cognition, belief systems, and theories are treated as real entities with causal power, not just representations, but systems within reality. This allows for a unified treatment of physical, biological, and conceptual systems under a General System Theory.

Critical realism was first developed by Roy Bhaskar (1975) in *A Realist Theory of Science*. Bhaskar argued that reality exists independently of human perception, but that our understanding of it is always mediated through fallible, socially and cognitively structured mechanisms. In later works, including *The Possibility of Naturalism* (1979) and *Scientific Realism and Human Emancipation* (1986), Bhaskar expanded critical realism to include social structures, emphasising that beliefs, theories, and institutions possess causal powers in their own right. Margaret Archer (1995) built on Bhaskar's foundations to develop the morphogenetic approach, treating cognitive and social systems as emergent realities operating with their own internal dynamics. In this paper, the author extends critical realism into the domain of General System Theory by treating cognitive constructs, including beliefs, theories, and symbolic systems, as real systemic entities, subject to the same principles of structure, causality, and emergence that govern physical and biological systems.

2.17 Processed Information

Processed information is information at source that has been recognised, translated, stored, transmitted, and/or received. The ability to process information in this way emerged with life. The processing of information is also known as semiotic processing and the discipline is sometimes referred to as biosemiotics.

The concept of processed information integrates foundational insights from information theory, systems biology, and the study of the origin of life. Claude Shannon (1948) formalised the mathematical theory of communication, defining information transmission and noise in purely probabilistic terms. Warren Weaver (1949) extended Shannon's model to emphasise meaning and recognition in communication processes. In systems biology, Howard Pattee (1969) argued that the capacity to process information symbolically, i.e., linking informational and physical domains, emerged with life, particularly with the evolution of genetic coding systems. More recently, Sara Walker (2014) has proposed that life should be understood fundamentally as information processing across self-sustaining networks. In this paper, the author builds upon these traditions by defining processed information explicitly as the operational transformation of "information at source," recognising its emergence with life as a critical threshold in the evolution of complex, adaptive systems.

2.18 Complex Adaptive System (CAS)

The processing of information underpins the behaviour of complex adaptive systems. A complex adaptive system is a dynamic system composed of many interacting components (agents) that:

- Adapt to internal and external changes,
- Exhibit emergent behaviour that is not predictable from the properties of individual parts,
- Operate far from equilibrium, requiring a continuous flow of energy or information, and

- Evolve over time through learning, feedback, or selection mechanisms.

All living organisms are CAS, but the concept also includes larger organised entities such as ecosystems, societies, institutions, and some technological artifacts, provided they exhibit the core features of complexity and adaptivity. In contrast, physical systems such as atoms, simple molecules, or stars are not complex adaptive systems, as they lack the capacity for adaptation and learning.

The concept of a Complex Adaptive System (CAS) evolved from foundational work in cybernetics, systems theory, and complex systems science. Early insights came from Norbert Wiener (1948), who introduced the study of feedback and control in cybernetic systems. Ludwig von Bertalanffy (1968) extended systems theory to living organisms, highlighting dynamic, far-from-equilibrium processes. John Holland (1992) at the Santa Fe Institute formalised the term "complex adaptive system," describing systems that adapt through learning, feedback, and selection across distributed networks of agents. Stuart Kauffman (1993) further developed the biological and evolutionary dimensions of CAS, demonstrating how emergent properties arise from decentralised interactions. In this paper, the author formalises the definition of CAS to include not only living organisms but also higher-order organised entities such as ecosystems, institutions, and some technological systems, provided they meet the criteria of adaptivity, emergence, far-from-equilibrium operation, and evolutionary capacity, distinguishing them from simpler physical systems lacking adaptive feedback.

2.19 Renewal and Reintegration

Renewal and reintegration describes the process by which a super-optimal open system regains functional capacity by simplifying internal structure. This requires an input of free energy often greater than that for ratcheting. So, renewal is often initiated by an open super-system that is ratcheting towards optimality. Reintegration often follows the recognition of dysfunction in the former by the latter and requires sufficient energy to restructure toward a new attractor. This is a key transition in the system lifecycle, enabling recovery, transformation, or re-embedding within a higher-order system. Examples include institutional reform following systemic crisis; cognitive reorganisation after burnout or breakdown; and the emergence of new political paradigms post-disruption.

The concepts of renewal and reintegration build upon foundational ideas from systems theory, sociology, and evolutionary biology. Ludwig von Bertalanffy (1968) discussed the adaptive cycles of living systems, noting that survival often requires simplification and reorganisation under environmental stress. Margaret Archer (1995) introduced the morphogenetic cycle, describing how social systems restructure themselves over time through interplay between structure and agency, particularly following crises or dysfunctions. In evolutionary theory, Stephen Jay Gould and Niles Eldredge (1972) proposed the theory of punctuated equilibrium, where periods of rapid structural change and reorganisation interrupt long periods of stability. Joseph Tainter (1988) similarly described societal collapses and renewals in terms of complexity reduction and systemic reformation.

2.20 Universal Disciplines

Universal disciplines are those whose laws apply at all levels of emergence. They include not only systems theory but also natural language, mathematics, logic, and causality. Other disciplines are domain specific and limited to a range of organisation between levels of emergence. (Challoner, 2025)

The idea that certain disciplines or principles apply universally across different levels of organisation has deep roots in the philosophy of science and systems theory. Ludwig von Bertalanffy (1968) argued that general systems principles, such as organisation, feedback, and hierarchy, apply across biological, social, and technological systems, regardless of specific material composition. Alfred North Whitehead (1929) similarly posited that mathematics, logic, and processual causality are universal aspects of reality, underpinning structures at all scales. Gregory Bateson (1972) emphasised that natural language, as a pattern-recognising and relational system, reflects universal cognitive principles that operate across levels of complexity. More recently, Edgar Morin (2008) highlighted that systems thinking itself must embrace universal transdisciplinary principles if it is to understand the complexity of real-world phenomena.

2.21 Systems Causality

Systems causality is a generalisation of conventional causality that accounts for the dynamics of systems. (Challoner, 2025). It distinguishes between two complementary elements:

- Processes (P) — internal operations within a system that transform or condition its internal state and produce outputs, and
- Transfers (T) — flows of matter, energy, or information into, out of, or between systems.

Unlike traditional causality, systems causality recognises that causation involves the interplay between internal processes and external exchanges. The outcome of a causal relationship depends not just on external inputs but on how they are processed internally by the receiving system. The rules of systems causality follow those of conventional cause and effect, e.g., temporal order, consistency, necessity/sufficiency, enablement/inhibition, but apply them to interconnected, dynamic, and recursively structured systems.

When causal relationships recur, they represent laws and emergent properties.

The concept of systems causality builds upon classical philosophical treatments of causality, as found in the works of Aristotle (causa materialis, causa formalis, causa efficiens, and causa finalis), but adapts them for dynamic, internally organised systems. In modern science, David Hume (1748) formalised causality as regular succession, emphasising temporal precedence and necessary connection. Systems theorists such as Norbert Wiener (1948) and Ludwig von Bertalanffy (1968) recognised that in complex, organised systems, causality could not be understood solely as external stimulus-response chains; rather, internal structure, feedback, and transformation processes crucially shape causal outcomes. Herbert Simon (1962) further elaborated on how internal modularity and nearly decomposable subsystems mediate external influences. More recently, Judea Pearl (2000) introduced formal causal models in complex networks, emphasising the need to distinguish direct intervention from internal systemic processing.

2.22 Organising Principles

Systems causality and fractal patterns underpin the concept of organising principles (OPRs). These principles define the architecture of causality within and between systems, thus enabling the emergence of stable behaviour and higher-level function. OPRs represent the organising logic that shapes emergence at each recursive level of system development.

The idea of organising principles, i.e., rules or causal architectures that give rise to systemic behaviour, has its roots in early systems theory and cybernetics. Ludwig von Bertalanffy (1968) proposed that systems are characterised not just by their components but by the organisational rules that govern interactions and stability. Herbert Simon (1962) also emphasised hierarchical organisation and modular structuring as principles guiding system complexity and resilience. Later, Gregory Bateson (1972) articulated that "the pattern that connects" underlies the organisation of systems at every level, reinforcing that emergence depends on relational logic rather than material properties alone.

2.23 Theoretical Optimality

Systems based solely on information, such as theories, perspectives and worldviews, are systems like any other, and so, their optimality can also be assessed. Theoretical optimality is therefore the efficiency with which a theory transforms cognitive effort into structured, action-relevant understanding. Theoretical optimality is defined as:

$$\Omega_T = A_I / A_{Imax} \quad (8)$$

Where:

- Ω_T = theoretical optimality (dimensionless. Maximum = 1. Minimum = 0.),
- A_I = action-relevant information in the theory's output (dimensions: variable),
- A_{Imax} = maximum potential action-relevant information in the theory's output (dimensions: variable).

The concept of theoretical optimality, i.e., the efficiency with which a theory transforms cognitive effort into structured, action-relevant understanding, builds upon developments in epistemology, information theory, and systems thinking. Karl Popper (1959) argued that scientific theories should be judged by their falsifiability and explanatory power, implicitly suggesting a measure of functional efficiency. Gregory Bateson (1972) introduced the idea that information is "the difference that makes a difference," emphasising that cognitive and conceptual structures should be assessed by their capacity to produce meaningful action. More formally, Claude Shannon's (1948) information theory established a foundation for measuring the efficiency of information transmission, which has been adapted to conceptual systems in later work on knowledge systems and epistemic utility. In this paper, the author extends these traditions by explicitly defining theoretical optimality (Ω_T), framing theories as cognitive systems subject to the same systemic principles of structure, energy, and optimality that govern physical and biological systems.

2.24 Symbolic Reasoning

Symbolic Reasoning is a form of symbolic logic developed by the author (Challoner, 2023). It unifies the various branches of conventional logic by providing a common, intuitive symbolism and common axioms. It is based on an enhanced form of set theory and is highly compatible with systems theory. It is capable, therefore, of representing and manipulating expressions and combinations of expressions in all universal disciplines. Thus, Symbolic Reasoning is a bridge across universal disciplines, offering a common structure in which systems theory, natural language, mathematics, logic, and causality may be coherently integrated.

3 | Core Propositions

The theory presented in this paper comprises a series of interconnected propositions that articulate the emergence, structure, function, and evolution of systems. This structure has been deliberately chosen to demonstrate the assertion that theories, including this one, are systems like any other and thus are composed of sub-systems, that is, propositions.

3.1 From Chaos to Emergence

Proposition P1: Every system is assembled from components that are previously assembled systems.

This proposition is inspired by the work of Sara Imari Walker and Lee Cronin, whose *Assembly Theory* proposes that complex objects, particularly in biological and prebiotic chemistry, are formed through the recursive assembly of simpler molecular units. In their framework, the *assembly index* quantifies how many steps are required to construct a molecule from fundamental building blocks, providing a measurable indicator of the object's historical complexity. Their work focuses on demonstrating that objects with high assembly indices are likely to be the products of evolutionary or informational processes, rather than random occurrence. While their research is grounded in molecular and chemical systems, this framework extends the principle more generally: that all systems are composed of previously assembled systems. Such an extension is conceptually reasonable and supported by examples from multiple domains (e.g., cells from organelles, institutions from roles, technologies from components), but it is not yet universally accepted. Nevertheless, it provides a powerful unifying assumption for a General System Theory, embedding historical contingency, compositional recursion, and traceable emergence into the foundations of system formation.

The idea that systems are assembled from subsystems is a foundational principle of systems theory, biology, and complexity science. Ludwig von Bertalanffy (1968) emphasised hierarchical organisation, where each system level is composed of interacting subsystems. Herbert Simon (1962) developed the concept of "nearly decomposable systems," showing how complex structures evolve by recombining simpler, relatively independent modules. In evolutionary biology, Helen Cronin (1991) highlighted how complex biological and social behaviours emerge from successive layers of structural assembly. Sara Walker (2014) further extended this principle into physics and information theory, proposing that life and complexity emerge through the assembly and processing of information across multiple scales. Stuart Kauffman (1993) demonstrated similar principles in biological evolution, showing how autonomous agents assemble into higher-order adaptive structures.

Proposition P2: Every mutually contiguous set of systems has its own energy landscape.
This proposition states that every group of systems that are close enough in space and time to interact causally have their own unique shared energy landscape. This landscape reflects the possible ways the systems could be configured whether in an organised manner or not. Because causal relationships require space-time contiguity, only mutually contiguous systems can influence one another to form new structures.

The idea that systems and subsystems are embedded in structured "landscapes" that govern their dynamics derives from foundational work in physics, biology, and complexity theory. In thermodynamics, energy landscapes were used to describe the multiple potential states of molecules and chemical systems, especially in reaction kinetics (Eyring, 1935). In theoretical biology, energy landscapes were adapted to model protein folding and the dynamics of complex biological systems (Frauenfelder et al., 1991). Giorgio Parisi (2021) extended the concept to disordered systems (e.g., spin glasses), demonstrating that complex systems possess rugged, fractal energy landscapes with many local minima. These landscapes describe how component interactions create stable and metastable configurations across multiple scales.

Proposition P4: Stability in closed systems corresponds to low free energy, and in open systems to high information at source.
The concept that stability in closed systems corresponds to minimising free energy is a core principle of classical thermodynamics and statistical mechanics. Rudolf Clausius (1865) and later Josiah Willard Gibbs (1876) formalised the tendency of isolated or closed systems to evolve toward states of maximum entropy and minimum free energy. In open systems, however, Ilya Prigogine (1977) demonstrated that sustained organisation can emerge far from equilibrium through continuous flows of energy, leading to the formation of dissipative structures. The idea that such open system stability is linked not simply to energy, but to the maintenance and enhancement of internal order (negentropy or "information at source"), was articulated by Erwin Schrödinger (1944) and later expanded in systems theory by thinkers such as Gregory Bateson (1972). In this paper, the author unifies these perspectives by proposing that in closed systems, stability equates to minimal free energy, while in open systems, it corresponds to maximising structured, low-entropy configurations, formally captured as "information at source."

Proposition P3: In an open system, if free energy is held constant, the landscape of total energy for any given collection of components is fractal in nature.
In closed systems, total internal energy (E) is constant. According to the Helmholtz free energy equation, $F=E-TS$, any decrease in free energy (F) corresponds directly to an increase in entropy (S). Stability in such systems arises as internal structure decays and entropy increases and they move toward low free

energy states or “troughs” in the energy landscape. Entropy carries an energy cost not because it is consumed, but because it is constrained by the system’s internal configuration.

In open systems, by contrast, stability corresponds not to the maximisation of entropy but to the maximisation of internal organisation or information at source (I). These ordered states resist spontaneous change because disrupting their structure to increase entropy requires energy. This creates basins of attraction in the energy landscape, i.e., regions of stability that the system tends to settle into.

Crucially, in open systems, energy is not “locked” into entropy as it is in closed systems. Instead, the system can export it, often as heat, in compliance with the second law of thermodynamics. This process, sometimes described as the “export of entropy” (Prigogine, 1977), allows open systems to maintain or increase internal complexity while remaining energetically balanced.

As a result, attractors in open system landscapes correspond not to lower free energy, but to lower total internal energy (E) and higher information at source (I). This is thermodynamically impossible in closed systems, where E is fixed. In open systems, if we assume F, T, and S_{max} constant, the following relationship holds:

$$E+TI = F+TS_{max} \tag{9}$$

which simplifies to:

$$E+TI = \text{constant} \tag{10}$$

Thus, as internal information (I) increases, internal energy (E) must decrease and vice versa. This inverse relationship defines the topology of the open system’s energy landscape.

Giorgio Parisi’s Nobel Prize-winning work on spin glasses showed that, under near-closed conditions, free energy landscapes in disordered systems exhibit a fractal, hierarchical structure, i.e., a nested pattern of peaks and troughs across scales. In such closed systems, troughs represent high-entropy, disordered states.

In open systems, however, the logic inverts. Troughs correspond to more ordered, information-rich states, and peaks to disordered, high-entropy ones. Importantly, fractal structure is preserved under this inversion, since fractality depends not on absolute height but on scale-invariant roughness, the self-similar nesting of attractors. Therefore, the concept of fractal landscapes extends naturally from closed to open systems, with the interpretation of stability reversed.

Returning to the equation $E+TI=F+TS_{max}$, we can see that variations in free energy F due to environmental fluctuations shift the entire landscape vertically. However, the system’s relative position within the landscape remains unchanged. This means the topological structure of the landscape and the system’s trajectory toward attractors is preserved, even as absolute energy levels vary.

Parisi’s work (1980, 2021) laid the foundation for this understanding, but later researchers such as Stuart Kauffman (1993) and Per Bak (1996) showed that similar rugged, fractal-like landscapes underlie the behaviour of open, self-organising systems. In this framework, attractors in an open system’s total energy landscape correspond to configurations with greater internal organisation (I), while peaks represent more disordered, higher-entropy states.

This interpretation echoes von Bertalanffy’s (1968) principles of equifinality and multifinality. Different paths may lead to the same stable outcome, while similar starting conditions can diverge toward different attractors, depending on environmental influences.

Proposition P5. Systems form when a collection of components that have previously emerged ratchet into successively lower attractors in the collection's energy landscape, thereby developing increasing structure or information at source until new properties emerge.
A contiguous collection of systems can move from a chaotic configuration to a subcritical structure. From there, it may transition into a true system, marked by the appearance of novel, system-level functions.

However, emergence is not spontaneous. It is driven by energy flows from the environment. External inputs, such as heat, environmental perturbations, or informational shocks, deliver random packets of energy that alter the system's configuration. These energy packets can either strengthen internal organisation or disrupt it.

The directional tendency from subcritical structure to emergent system is rooted in the probabilistic nature of energy fluctuations in open systems. Most energy packets are small, statistically speaking, and thus more likely to cause minor shifts in the system's energy state. These shifts tend to push the system deeper into its existing attractor basin, reinforcing structure, or slightly out of it, reducing structure.

Occasionally, a larger energy packet may push the system to a higher-energy, unstable state, i.e., a "peak" in the energy landscape. However, the statistical nature of energy packets means that this peak is more likely to be a lower one than a higher one. At this elevated position, the system becomes susceptible to multiple nearby attractors. Due to the fractal structure of the landscape, this local region is often densely packed with attractor basins. Some of these attractors lie deeper than the system's previous configuration, offering greater internal organisation and higher information at source.

When this happens, the system may not return to its original attractor basin but instead fall into a deeper one, a process described here as ratcheting. This dynamic produces a directional but non-deterministic drift toward greater internal order and stability.

Thus, energy flow enables systems to cross organisational thresholds and stabilise in new configurations. In a fractal energy landscape, as described by Parisi (1980, 2021), these small, probabilistic energy-driven shifts allow systems to ratchet forward, incrementally evolving toward more complex and stable forms.

This mechanism builds upon several traditions in thermodynamics, complexity theory, and evolutionary biology. The foundational insight that energy fluctuations in open systems can drive self-organisation was developed by Ilya Prigogine (1977) through his theory of dissipative structures, showing how systems far from equilibrium can generate new, stable forms of order. Stuart Kauffman (1993) introduced the concept of adaptive landscapes in biological evolution, suggesting that random perturbations can cause systems to shift between local minima, sometimes ratcheting toward new functional configurations. Giorgio Parisi's (1980, 2021) discovery of fractal free energy landscapes in disordered systems provided a mathematical basis for understanding how densely packed attractor basins allow such probabilistic transitions.

Proposition P6: The likelihood of a group of systems ratcheting from chaotic to structured diminishes as the internal complexity of the constituent systems increases.
Random collections of systems often continuously wander their energy landscape without becoming subcritical structures. The same is true of subcritical structures which do not necessarily become systems. Although energy landscapes make system formation possible, the probability that a group of contiguous systems will transition into a coherent structure is strongly influenced by their internal complexity. Complex systems require more free energy to maintain their internal structure. The availability of free energy is often limited and so less is available for structural reorganisation. Emergence becomes less likely not because it is impossible, but because stabilising higher-order organisation requires conditions that are increasingly rare and energetically demanding.

Additionally, as systems become more internally complex, the likelihood that they will encounter other compatible systems in space and time, a necessary condition for causal interaction, tends to decrease. Simpler systems are more numerous, and often more mobile, increasing the chance that they will become mutually contiguous and form new structures. In contrast, complex systems are typically more specialised, less abundant, and less likely to overlap by chance. This further reduces the probability that they will spontaneously ratchet into higher-order configurations, at least until mechanisms such as reproduction or guided assembly evolve to overcome this limitation.

Empirical evidence for such constraints can be found in multiple domains. In evolutionary biology, the leap from single cells to multicellular organisms required highly specific environmental conditions and internal regulatory mechanisms. In software systems, growing internal complexity leads to fragile architectures that resist integration or expansion unless carefully modularised. In social systems, highly diverse or decentralised groups often fail to organise unless bounded by shared norms or institutions.

This proposition highlights an important caveat in the theory of emergence. While energy flow and attractor landscapes make emergence possible, increasing internal complexity reduces the likelihood that it will occur spontaneously or stably. It explains why simpler systems more readily combine into higher-order systems, and why the emergence of complex, adaptive structures is rare.

The principle that increasing internal complexity can inhibit further systemic reorganisation draws from both thermodynamic theory and complex systems science. In thermodynamics, highly ordered systems require precise, energetically costly maintenance, making spontaneous reorganisation less probable as structure increases (Prigogine, 1977). In complexity theory, Herbert Simon (1962) noted that as systems become more deeply hierarchically structured, their capacity for flexible reassembly diminishes because internal dependencies constrain reconfiguration. Stuart Kauffman (1993) similarly showed that in biological evolution, highly complex systems tend to become "locked-in" to local fitness peaks, making major adaptive shifts increasingly rare. In network theory, Barabási (2002) demonstrated that as networks become denser and more interconnected, their dynamics often slow and reorganisational flexibility decreases.

3.2 From Simple to Complex Systems

Proposition P7: Systems at each level of emergence are assembled according to organising principles determined by the levels below.
These organising principles can be categorised as follows:

OPR0 comprises the foundational, acausal organising principles that emerged with the Big Bang. They act as generators that collectively structure the basic fabric of reality. While not causal themselves, they constrain and channel all subsequent causal processes. OPR0 includes (but is not limited to):

- **Space-time:** the medium in which those things described below exist.
- **Energy.** Energy cannot be created or destroyed. It merely exists and can only be transformed.
- **Spin:** a form of angular momentum in particles that can be quantified and that distinguishes fermions from bosons.
- **Electric charge:** a property of quarks, leptons, and bosons that distinguishes them from one another and determines how they interact with the electromagnetic force.
- **Colour charge:** a property unique to quarks and gluons. It determines how the strong nuclear force can bind Quarks together to form other non-fundamental particles.

- **Generations.** Quarks and leptons are grouped together into a hierarchy of three families or generations of increasing mass and instability. The more massive, less stable ones can decay into less massive, more stable ones.
- **Interaction with Forces:** a characteristic that determines whether a particle of a particular type can or cannot interact with the strong or weak nuclear force, or with the electromagnetic force.

OPR2 describes the plural set of causal rules or generators that operate at each level of emergence. These principles govern how systems interact, combine, and stabilise giving rise to the next level of emergence : OPR2 describes plural sets of generators at each level of emergence which when sufficient in organisation and number lead to the next level of emergence. At each level:

- Each generator defines a type of causal transfer (of matter, energy, or information) between systems. The transfer comprises systems that were formed by organising principles at a lower level of emergence.
- Transfers, and thus the number of generators, are constrained by the requirement that what is transferred must originate within the source system.
- Generators operate globally as a plural set but may act locally in subsets. When one dominates, it may yield a recognisable fractal pattern.
- OPR2 is structurally recursive. The same principles apply at each level, but what is transferred becomes progressively more complex. This means that the overall OPR framework is fractal in nature and governed by a meta-rule.

OPR1 describes a situation in which only one generator dominates locally. Here the term "locally" is used in the conceptual rather than physical sense. When this occurs, it can lead to recursive, fractal patterns in the structure of matter, energy, or information. Such patterns are not however guaranteed and their generator may vary.

Fractal patterns have been observed in multiple domains: coastlines and tree branching, blood vessels and bronchial networks, river systems, predator-prey dynamics, and even the distribution of galaxies in the universe. Giorgio Parisi's discovery of a fractal structure in the energy landscape of spin glasses provides a particularly striking and relevant example.

The idea that higher levels of systemic organisation are constrained and shaped by the organising principles of lower levels originates in hierarchical and relational models of system development. Ludwig von Bertalanffy (1968) introduced the idea of hierarchical organisation in systems, where each level emerges from, but remains dependent on, the structures and laws operating at lower levels. Mario Bunge (1979) emphasised that emergence is lawful: higher-order properties are determined by the relational patterns among lower-level components, not by their individual properties alone. In theoretical biology, Stuart Kauffman (1993) showed that biological complexity arises through combinatorial interactions governed by simpler genetic and biochemical rules at foundational levels. Similarly, in the philosophy of science, Roy Bhaskar's critical realism (1975) proposed that reality is stratified, with emergent levels depending causally on lower-level structures and mechanisms.

Proposition P8: Information at source accumulates over time.

As systems form and combine into higher-order systems, internal organisation or information at source accumulates. Over time, this process leads to the layered build-up of structure across scales. From the emergence of atomic matter to life, cognition, and human society, this trajectory reflects a non-deterministic but directional increase in systemic complexity. This concept is foundational in information theory, thermodynamics, evolutionary biology, and systems science. In Big History and complexity science, scholars like David Christian (2011) and Eric Chaisson (2001) argued that cosmic, biological, and social systems show an overall trend toward greater energy flow density and internal information processing over time.

Big History provides the narrative framework for this unfolding, not as a predictive model, but as a descriptive record of how information at source has accumulated across cosmic, biological, cognitive, and social domains. Each stage adds new layers of organisation without erasing those before it, creating a fractal structure of nested systems that persists and evolves over time.

Proposition P9: The ability to replicate has emerged in complex systems increasing their proliferation.
As systems become more internally complex, the spontaneous emergence of higher-order organisation becomes increasingly unlikely due to the vast configuration space, energy costs, and low probability of contiguous, compatible systems. However, the evolution of replication has provided a powerful counteracting mechanism. Once a system develops the ability to copy its structure and function, it no longer relies on rare chance encounters to persist or combine. Replication allows successful configurations to propagate, increasing their presence in the environment and creating the preconditions for further emergence.

The emergence of replication is widely believed to have originated from autocatalysis, a process in which a molecule facilitates its own formation. This concept was extended by Stuart Kauffman, who proposed the idea of autocatalytic sets: networks of molecules that catalyse each other's formation, creating a self-sustaining, collectively reproducing system. These sets are considered plausible precursors to the origin of life, and they offer a model of how replication may have emerged gradually from simpler chemical networks without requiring a fully-formed genome.

The ability to replicate transformed the landscape of emergence. It allowed systems not only to persist and multiply, but also to evolve, adapt, and form more complex, information-rich configurations. Replication thus created a new dynamic: selection acting on structured information, enabling the accumulation of complexity far beyond what random assembly could achieve on its own.

The emergence of replication as a key evolutionary milestone is fundamental to biology, complexity science, and systems theory. Erwin Schrödinger (1944) speculated that the secret to life lay in a stable, heritable structure, what he called an "aperiodic crystal", foreshadowing the discovery of DNA as the molecular basis of replication. John von Neumann (1966) formally modelled self-replicating automata, demonstrating that replication could arise from sufficiently complex informational structures. Stuart Kauffman (1993) showed how autocatalytic networks, collections of mutually reinforcing chemical reactions, can give rise to replication-like behaviour before the emergence of modern genetic mechanisms. In Big History frameworks, scholars like David Christian (2011) highlight replication as a fundamental innovation driving biological and social proliferation, from genes to memes.

Proposition P10: The ability to protect against environmental damage has emerged in complex systems increasing their proliferation.
As systems increase in complexity, they often develop internal mechanisms to regulate their interaction with the environment. This selectively controls what enters and exits, and defends against potentially destabilising inputs. This capacity has been described most prominently in the concept of autopoiesis, developed by Maturana and Varela, which characterises living systems as self-producing and self-maintaining through the continuous regeneration of their components and boundaries. In systemic terms, this boundary regulation acts as a form of structural resilience: it reduces the likelihood of environmental disturbances disrupting internal organisation, thereby extending the lifespan of the system. Importantly, this increases the probability that the system will remain mutually contiguous others long enough for further coordination, integration, and emergence. This principle applies across domains, from biological

cells with semi-permeable membranes, to social institutions with legal boundaries, to cognitive systems with filtering mechanisms for attention and relevance. The emergence of this protective function marks a significant shift in a system's autonomy and evolutionary potential, enabling greater stability, increased functional continuity, and a higher likelihood of participation in larger-scale systemic structures.

Protective mechanisms as a strategy for increasing systemic stability and survival have long been recognised across biology, ecology, and systems science. In biological evolution, natural selection favours structures that enhance resilience against environmental perturbations, from cell membranes that protect internal chemical gradients (Deamer, 1985) to immune systems that defend against pathogenic invasion (Medzhitov & Janeway, 1997). Stuart Kauffman (1993) noted that as autocatalytic networks became more complex, the emergence of compartmentalisation and boundary structures allowed them to resist environmental degradation and sustain internal order. In cybernetics, Norbert Wiener (1948) identified feedback mechanisms as crucial to maintaining system stability in the face of external disturbances. Similarly, Big History perspectives (Christian, 2011) highlight that increasing organisational complexity has been accompanied by the evolution of adaptive strategies for buffering against environmental volatility.

Proposition 11: The Processing of information emerged with life.
The ability to process information, that is, to recognise information at source, translate, store, transmit, receive, and respond to it, emerges with life. While non-living systems may carry low-entropy patterns (e.g., in crystals or planetary motion), they do not interpret or functionally act on such patterns. By contrast, even the simplest living systems use internal structure to guide interaction with their environment. This transforms information from a passive state into an active, causal force.

This view originates in several major theoretical traditions. The theory of autopoiesis (Maturana & Varela, 1980) defines life as a self-producing, self-maintaining system that regulates itself through ongoing interaction with its environment. In biosemiotics, thinkers such as Hoffmeyer (1996) and Barbieri (2008) argue that life is fundamentally semiotic, i.e., capable of interpreting and responding to signs. Systems biology, including work by Noble (2006) and Kitano (2002), shows that organisms act as integrated information-processing networks, dynamically regulating gene expression, biochemical reactions, and external responses.

These traditions build on foundations laid by cybernetics and information theory. Norbert Wiener (1948), Claude Shannon (1948), and W. Ross Ashby (1956) characterised functional systems in terms of feedback, regulation, and control, laying the groundwork for understanding life as information-driven.

Once life emerges, information processing scales recursively. Empirical examples abound. Prokaryotes exhibit chemotaxis, i.e., moving in response to environmental gradients. For example, *E. coli* adjusts its movement based on nutrient concentration. Eukaryotic cells engage in complex signal transduction to coordinate internal function. Multicellular organisms develop specialised systems, neural, hormonal, or immune, that process information. In humans, information processing, using language, logic, and mathematics to manipulate symbolic information, enables abstract thought, theory formation, and the simulation of future scenarios. At higher levels still, societies and institutions process distributed information via communication, norms, and collective decision-making.

In summary, the processing of information, the causal use of internal structure to interpret and respond to the environment, first emerges with life and scales upward through increasingly complex adaptive systems. This capacity distinguishes living systems from passive physical ones and underpins the development of all higher-order cognition and coordination.
As Schrödinger (1944) observed, life maintains order by exporting entropy, implicitly linking thermodynamic stability to informational function. Shannon (1948) formalised information as reduction

in uncertainty, enabling researchers to analyse biological signalling and replication. Pattee (1969) proposed that life arises when symbolic and dynamic processes separate, a fundamental shift enabling information control. Kauffman (1993) showed that autocatalytic networks process environmental signals, forming the basis of biological function. More recently, Walker (2014) argued that information processing is the defining signature of life, marking a systemic threshold beyond which adaptive, evolving behaviour becomes possible.

3.3 System Lifecycle

Proposition 12: Systemic optimality occurs when the balance between internal structure and available free energy maximises functional output.
Every system has limited access to free energy (F), which must be allocated between:

- F_m: Energy used to maintain internal structure and organisation (information at source, I), and

- F_o: Energy available for operational functions (output generation).

This creates the trade-off:

$$F = F_m + F_o \tag{11}$$

where $F_m = f(I)$ and $df(I)/dI > 0$. That is, F_m is a function of I and as internal complexity (I) increases, maintenance demands (F_m) rise.

Systemic optimality is achieved when a system balances its internal structure with the free energy available for function, resulting in maximum functional output. This relationship is non-linear, forming an inverted-U curve; as structure increases functional output increases to a maximum and then decreases.

This System Functionality Curve comprises three regions:

- Sub-optimal region (low I): Insufficient internal organisation causes instability or incoherence; the system lacks the structure needed to efficiently produce outputs.

- Optimal region (moderate I): The system has enough structure to produce outputs at maximum efficiency.

- Super-optimal region (high I): Too much structure diverts too much energy from production to system maintenance, thereby reducing operational efficiency.

- Colllapse: Further increases in structure can ultimately lead to insufficient free energy for even maintenance and adaptability. An inability to adapt to environmental change or excessive shocks from the environment can lead to system collapse.

Systems perform best when complexity and energy are balanced: enough structure to maintain coherence, but not so much that it overwhelms functional capacity. This principle applies across biological, technological, cognitive, and social systems, providing a robust framework for analysing design, evolution, and systemic collapse. For example, a small startup company may operate efficiently with minimal overhead, but as it scales up, excessive bureaucracy can reduce output and responsiveness.

The relationship between structure, free energy, and functional efficiency is a central theme in thermodynamics, biology, and systems theory. The Helmholtz free energy equation ($F = E – TS$) formalises the trade-off between internal energy and entropy, establishing that only a portion of a system's energy is available for performing work (Gibbs, 1876). In biological systems, Ilya Prigogine (1977) demonstrated that open systems achieve and maintain complex structure through a delicate balance between internal organisation and energy flow, far from equilibrium. Stuart Kauffman (1993) proposed that biological systems achieve optimal function when poised at the "edge of chaos", where enough structure exists to maintain coherence, but enough flexibility remains for adaptation. In cybernetic terms, Norbert Wiener (1948) stressed that optimal system function depends on a balance between stability (structure) and adaptability (energy responsiveness).

Proposition 13: A system's lifecycle, i.e., its birth development and decline, is a non-teleological evolutionary process driven by ratcheting in the system's energy landscape.
Ratcheting occurs in a system's energy landscape with no regard for the system's efficiency in producing outputs. Thus, a system can progress from a sub-critical structure, with no emergent outputs, to a sub-optimal structure with emergent outputs, to an optimal structure, a super-optimal one and ultimately to collapse. This is known as the system's lifecycle; a process evident in physical, biological and social systems. Thus, in the absence of mechanisms for adaptation or simplification, systems often evolve toward increasing complexity, stagnation and collapse.

The idea that systems undergo lifecycles without an inherent teleological goal is deeply rooted in thermodynamics, complexity science, and evolutionary theory. Thermodynamically, the second law implies that systems naturally evolve toward states of greater entropy or dispersion unless sustained by external energy flows (Clausius, 1865; Prigogine, 1977). Stuart Kauffman (1993) proposed that biological and complex adaptive systems evolve through explorations of rugged fitness landscapes, with ratcheting dynamics leading to the emergence of increasingly structured but also increasingly vulnerable configurations. In systems ecology, Howard Odum (1983) modelled ecosystems as energy-processing structures that undergo succession from youthful growth phases to mature, slower-adapting climax states and eventual senescence.

Proposition 14: Super-optimal systems are only renewed by the action of complex adaptive parent systems.
Super-optimal systems, those with excessive internal complexity that inhibits function, can only be renewed through the intervention of complex adaptive parent systems. Renewal requires a simplification of internal structure and a reorientation toward a more functional attractor. However, this process is constrained by the parent system's own energetic and structural capacity. If the parent system is also super-optimal, or lacks surplus free energy, renewal may be delayed, misdirected, or entirely blocked, increasing the risk of cascading dysfunction.

The renewal process typically demands more energy than the initial ratcheting into complexity and is usually triggered when the parent system, still within or near optimal range, recognises dysfunction in its component. Reintegration restores the subsystem's functionality, enabling recovery or transformation.

Examples include institutional reform after systemic crises, e.g., post-war reconstruction, cognitive recovery from burnout (through therapy or supportive environments), and ecological restoration initiated by policy or climate stabilisation. Where renewal is not possible, collapse may serve as a reset mechanism, simplifying the system and re-opening pathways toward future emergence.

The principle that super-optimal systems require intervention from higher-order adaptive structures for renewal builds on insights from evolutionary theory, sociology, and systems science. In biological evolution, Peter Medawar (1952) proposed that individual organisms and systems accumulate internal "wear" over time, and that external evolutionary forces, e.g., reproduction, replacement, are necessary for renewal. In sociology, Margaret Archer's (1995) morphogenetic approach argued that social structures become resistant to change unless disrupted by reflexive agency operating within broader social contexts.

In complex adaptive systems theory, John Holland (1992) and Stuart Kauffman (1993) showed that complex systems often require external perturbations or higher-order reorganisation to escape sub-optimal local states. In cybernetic thinking, Stafford Beer (1972) proposed that viable systems survive environmental complexity by recursively embedding adaptive structures or meta-systems capable of reorganising lower levels.

3.4 Theories as Systems

Proposition 15: A Proposition is a cognitive construct that, either correctly or incorrectly, reflects some relationship observed in the real world.
A proposition is a cognitive construct that reflects a perceived relationship within the real world, either accurately or inaccurately. Rooted in the philosophy of critical realism, this view treats human cognition not as a passive mirror of reality, but as an active, structured system embedded within reality itself.

Propositions are the building blocks of theories, models, beliefs, and explanations. They encode perceived patterns of causality, structure, or correlation in symbolic form.

While propositions aim to represent aspects of reality, they are shaped by internal cognitive structures, social context, and historical learning. As such, they are subject to distortion, omission, or error. Nevertheless, even flawed propositions can be causally efficacious: beliefs based on them can influence behaviour, and behaviour in turn alters the world. Conversely, changes in the world, through experience, observation, or contradiction, act causally upon cognition, leading to the revision, reinforcement, or rejection of propositions.

This bidirectional causality explains why propositions matter: they form the cognitive substrate through which humans understand, navigate, and act upon the world. For example:

- The proposition "The Earth is flat" once guided navigational decisions and cultural beliefs, despite being false.
- The proposition "Vaccines reduce disease transmission" leads to public health policies and individual choices that shape collective outcomes.
- In economics, the proposition "Markets are self-correcting" affects regulatory decisions and investment strategies, whether or not the assumption holds in practice.

Thus, propositions are simultaneously representational and functional. They reflect our models of reality, and they shape the systems in which we live.

This framing of propositions has deep roots in philosophy, epistemology, and cognitive science. Aristotle's (c. 350 BCE) work on logic introduced propositions as declarative sentences that assert something about reality, capable of being true or false. In modern philosophy, Ludwig Wittgenstein (1922) in his *Tractatus Logico-Philosophicus* proposed that propositions are logical pictures of facts, reflecting possible states of affairs in the world. Critical realism, especially through the work of Roy Bhaskar (1975, 1979), advanced the view that while reality exists independently of human perception, human knowledge of it, including propositions, is always mediated by cognitive structures that may more or less accurately represent reality. Cognitive science further supports this view, recognising that human perception and reasoning generate mental representations (Johnson-Laird, 1983) which aim to capture real-world relationships but are subject to error, bias, and limitation.

Proposition 16: Due to limitations on human perception and cognition, cognitive information about a system normally comprises only the information at its level of emergence and the level below.
Human understanding of systems is typically constrained to two adjacent levels of emergence: the system as a whole in its context (the holistic perspective), and its immediate internal structure (the reductionist perspective). Cognitively, we grasp systems by relating them to their environment, identifying their

boundaries, roles, and systemic interactions, while simultaneously decomposing them into their most accessible components. These two perspectives are normally integrated in our mental models. For example, a dog is understood both as a companion (holistic perspective), and as an organism composed of head, body, legs, and tail (reductionist perspective). Rarely do we perceive or process information about the deeper microstructures, e.g., cellular or molecular composition, nor do we easily grasp the broader emergent structures beyond the system, e.g., species-level ecological patterns, unless specialised tools or frameworks are introduced.

This concept has deep roots in cognitive science, psychology, and systems theory. Herbert Simon (1957) introduced the concept of "bounded rationality," emphasising that human decision-making is limited by available information, cognitive capacity, and time constraints. Jean Piaget (1954) demonstrated that cognitive development proceeds through hierarchical stages, each capable of handling increasingly complex structures, but generally limited to grasping phenomena one level above and below current developmental capacity. In systems theory, Kenneth Boulding (1956) proposed that perception of system complexity is inherently layered and stratified, with individuals often confined to understanding interactions near their immediate level of engagement. In critical realism, Roy Bhaskar (1975) argued that human knowledge is mediated through emergent structures that constrain what can be known or accessed directly. In this paper, the author formalises these insights, proposing that human cognitive models of systems typically reflect information at the level of emergence directly observable and at the next lower level where internal components are structured, rarely penetrating deeper without abstraction, instrumentation, or theory.

Proposition 17: A theory is a system composed of interacting propositions that exhibit emergent explanatory power.
Theories, including paradigms, hypotheses, beliefs, worldviews, perspectives, etc., are systems like any other and composed of interrelated and interacting propositions that, when organised coherently, generate emergent explanatory and functional outcomes. Like other complex adaptive systems, theories exhibit properties not found in their individual components, including predictive power, coherence, and the ability to guide action. These emergent qualities arise from the structure of interacting propositions within the theory, which are shaped by internal logic and refined through interaction with their environment, e.g., empirical observation, conceptual critique, or social utility.

This concept has strong roots in the philosophy of science, systems theory, and epistemology. Karl Popper (1959) described scientific theories as structured sets of falsifiable propositions that together explain patterns in the natural world. Thomas Kuhn (1962) emphasised that theories form paradigms, i.e., coherent networks of interrelated concepts, whose explanatory power emerges from their internal organisation, not from isolated claims. Ludwig von Bertalanffy (1968) framed knowledge itself as systemic, noting that understanding arises through the integration of interdependent ideas rather than the accumulation of isolated facts. Mario Bunge (1974) similarly formalised theories as systems composed of concepts, propositions, and models, with structure and logical coherence essential for explanatory emergence.

Proposition 18a: Propositions Within a Theory Interact Causally
A theory is a system of interrelated propositions. These propositions do not exist in isolation but interact dynamically, producing emergent explanatory power. Their interaction is not purely logical or semantic, but causal in a systemic sense. That is, some propositions enable, constrain, or condition the meaning or applicability of others.

This internal structure can be understood using the principles of **systems causality**, which distinguishes between:

- **Processes** or transformations within a system (e.g., reasoning or inference), and

- **Transfers** or flows of energy, matter, or information between systems (e.g., meaning activation across propositions).

For example, in physics, the proposition *"Force equals mass times acceleration"* enables others that describe motion or energy. In medicine, *"Pathogen X causes disease Y"* activates further propositions such as *"Administer treatment Z."* These relationships are not merely logical; they are causal dependencies within the theoretical system.

This view is supported across disciplines:

- In logic, propositions function as premises that cause conclusions to follow (Aristotle, 350 BCE/1984).
- In cognitive science, propositions are connected in semantic networks or Bayesian models where meaning spreads causally through directional links.
- In explanation-based learning, AI systems refine propositions based on their causal relevance to observed outcomes.

Systems theory (Bertalanffy, 1968) treats knowledge structures as dynamic systems where internal interactions shape systemic behaviour. Critical realism (Bhaskar, 1975) affirms that even conceptual structures have real causal powers when they operate within systems of thought or action. In this framework, propositions function like components of a living system. Their interactions produce the higher-order function of the theory, i.e., explanation and prediction.

Proposition 18b: Theories Interact Causally with the Physical World

Theories are not only systems with internal causal relationships. They also interact causally with the world. Theories respond to real-world phenomena (as effects) and guide decisions, actions, and interventions (as causes). In this sense, a theory does not just describe the world. It participates in shaping it.

This view is central to critical realism (Bhaskar, 1975), which holds that models, beliefs, and theories have causal efficacy. When a person or group adopts a theory, it influences behaviour, changes systems, and sets feedback loops in motion. For instance, economic theories shape policy; medical theories guide treatment; scientific models alter technologies and environments. The resulting outcomes, in turn, reshape the theory.

This dynamic reflects how theories evolve, fragment, stabilise, or collapse, just like physical or social systems. Theories receive feedback from the systems they affect and are revised accordingly. This positions theories not only as tools for analysis, but as real systems subject to the same organising principles, such as feedback, resilience, attractor dynamics, and energy constraints, that they are used to model.

The causal role of theories has deep roots:

- Hempel and Oppenheim (1948) described scientific explanation as a system of propositions that causally entails observed phenomena.
- Bhaskar (1975) argued that theories must reflect real mechanisms, not just regular patterns.
- Bertalanffy (1968) viewed knowledge itself as a dynamic system.
- In modern systems science, this understanding allows us to analyse the life cycle of theories as we would any complex adaptive system.

In this view, theories are not passive descriptions but active participants in the unfolding of reality. They both influence and are influenced: a hallmark of all open, living systems.

Proposition 19: Theories evolve via the recombination and assembly of propositions, much like biological systems evolve through variation and selection.
Theories and models evolve analogously to physical systems under assembly theory, progressively reusing, recombining, and selecting conceptual components over time. This occurs under selective pressures that favour coherence, explanatory power, and functional utility. This dynamic process produces increasingly structured configurations of meaning. Theories can thus be understood, analysed, and optimised as systems in their own right, subject to the same principles of emergence, structure-function balance, and lifecycle dynamics as biological, cognitive, and social systems. Thus, they can be subcritical structures, sub-optimal, optimal super-optimal or collapse due to overcomplexity.

This view has strong roots in epistemology, evolutionary theory, and the philosophy of science. Donald T. Campbell (1960) proposed the concept of "blind variation and selective retention" as a general model for the evolution of knowledge, suggesting that scientific theories, ideas, and cultural innovations evolve much like biological traits. Karl Popper (1963) also framed scientific knowledge as evolving through a process of conjectures (variation) and refutations (selection), closely paralleling Darwinian mechanisms. Stuart Kauffman (1993) extended these ideas into the domain of complex adaptive systems, showing how new configurations, including conceptual systems, emerge from the recombination of existing elements. In theoretical biology, researchers such as Gerald Edelman (1987) in his theory of "Neural Darwinism" applied evolutionary selection principles directly to cognitive structures, reinforcing the analogy.

Proposition 20: Symbolic Reasoning can unify the universal disciplines of systems, causality, logic, and natural language into a manipulable symbolic structure.
Symbolic Reasoning, developed by the author (Challoner, 2023), is a formal framework that treats abstract propositions as symbolic units capable of recursive recombination. It provides a common representational language in which logical operations, causal relationships, systemic structures, and natural language expressions can all be encoded and manipulated. This unified symbolic framework enables the construction of complex theoretical structures through consistent, rule-based assembly. By linking systems theory with other universal disciplines, Symbolic Reasoning serves as a cognitive and formal bridge, allowing abstract concepts to be structured, evaluated, and evolved within a single integrated system.

The idea that symbolic reasoning underpins the unification of diverse universal disciplines, such as logic, language, causality, and systems theory, has deep roots in philosophy, cognitive science, and cybernetics. Gottfried Wilhelm Leibniz (1703/1951) envisioned a "universal calculus" where reasoning could be conducted symbolically to unify all knowledge through logical manipulation. In the 20th century, Alan Turing (1936) formalised the manipulation of symbols as the basis of computation, showing that symbolic operations could model any process of logical inference. Noam Chomsky (1957) demonstrated that natural language itself has a symbolic, rule-based generative structure, supporting the idea that symbolic systems underpin cognitive and communicative capacities. In systems theory, Norbert Wiener (1948) and Ludwig von Bertalanffy (1968) treated systems and causality as symbolic models capturing patterns of organisation and interaction.

4 | Summary of the framework

- Systems comprise matter, energy, and/or information, where information is structured matter or energy. Some systems, such as human cognition and theories (including this one), may comprise information alone.
- Systems have inputs, internal processes, and outputs. Each system is assembled from previously assembled systems, forming a nested structure of subsystems and super-systems.

- Systems emerge when structural organisation gives rise to new properties not found in their parts. Collections that do not exhibit emergent behaviour are termed subcritical structures.
- Assembly theory shows that complexity grows historically as systems are built from prior components. The internal structure of a system reflects its “negentropy” or “information at source.”
- Causality is universal and operates through the transfer of lesser systems from one system to another. Systems causality distinguishes between internal processes and external transfers, and applies equally to physical and conceptual domains.
- In open systems, energy landscapes are fractal and inverted relative to closed systems: troughs represent high information at source and low internal energy. This structure supports ratcheting, i.e., a directional but non-deterministic drift into deeper attractors that preserve and increase organisation.
- As systems age, they may progress from subcritical structure to functioning systems, reach optimal balance, and eventually become super-optimal, overly structured, energetically inefficient, and prone to collapse.
- Systemic optimality is achieved when internal complexity and free energy are balanced, maximising functional output. Beyond this, energy is diverted to maintenance rather than function.
- Super-optimal systems can only be renewed or reintegrated through intervention by higher-order adaptive systems that restore structural simplicity and functionality.
- Big History from atoms to life, mind, and culture reflects the progressive accumulation of structure and information at source across time.
- In cognitive systems, the recombination and evolution of propositions allows theories and beliefs to emerge and adapt. These systems exhibit theoretical optimality, the efficiency with which internal structure produces action-relevant understanding.
- Symbolic reasoning provides a unified framework for representing and manipulating the structures of logic, causality, systems theory, and natural language, enabling coherent theoretical evolution across universal disciplines.

5 | Extending the Framework to Social Systems

5.1 Potential for Extension

The general system framework developed thus far applies across physical, biological, and cognitive domains. However, its structure is equally capable of extension into the social sciences. Social systems, including societies, institutions, and cultural structures, are themselves complex adaptive systems, governed by systemic causality, feedback, information dynamics, and energy flows. The same underlying principles of structure, emergence, optimality, and lifecycle behaviour remain operative, but their expressions become more elaborate due to the presence of reflexive agents: human beings capable of conscious interpretation, communication, and purposive action.

Extending the framework into the social domain therefore does not require abandoning its foundations, but rather adapting and enriching them to capture emergent social phenomena. Theories, institutions, worldviews, and symbolic systems can all be modelled as dynamic systems composed of interacting propositions, needs, satisfiers, and reflexive agents.

5.2 Challenges

Extending General Systems Theory into the social sciences presents both conceptual and practical challenges. Notably, the language used to describe systemic behaviour must shift to accommodate higher levels of emergence. Where in physical systems we describe inputs as "transfers" and processes as "functions," in social systems we must recognise enabling inputs as "satisfiers" and internal processes as "needs" or "motivational structures."

To cite another example, in social and cognitive systems, energy corresponds not to physical energy alone but also to available cognitive, emotional, social, and material resources. Time, attention, creativity, political will, and economic capital all serve as forms of usable "energy" that sustain systemic structures and enable adaptive change. Just as biological systems require metabolic free energy to maintain structure and function, social systems require continual inputs of human and material resources to maintain institutions, evolve symbolic systems, and drive renewal. When these resources become overly committed to maintaining existing structures, systems drift toward super-optimality and reduced adaptive capacity.

Moreover, the presence of reflexivity, the capacity of individuals to interpret, evaluate, and modify their own internal models in light of external feedback, introduces a recursive layer of complexity not found in simpler systems. Human social systems are not merely adaptive; they are self-interpreting and self-transforming.

These shifts demand careful elaboration of definitions and propositions to preserve coherence while acknowledging the unique properties of social organisation.

5.3 Illustration: The Modified Morphogenetic Cycle

An illustrative example of this extension is provided by the Modified Morphogenetic Cycle. Building on the work of Roy Bhaskar and Margaret Archer, this model describes how social systems evolve through cycles of:

- Environmental and social conditioning: External environmental pressures and existing social structures influence individuals,
- Motivational reflexivity: Individuals internally reflect on their needs, satisfiers, and roles in social structures,
- Strategic action: Individuals act, either reinforcing or transforming social structures,
- Social elaboration: Society changes in response, leading to new cycles of conditioning and adaptation,
- Environmental feedback: Society itself alters the natural environment, introducing new constraints and opportunities.

This dynamic captures the recursive feedback between individuals, society, and environment, illustrating how systemic evolution operates even at the highest emergent levels. Concepts such as satisfiers, contra-satisfiers, needs, and reflexive processes can all be modelled within the general systems framework, albeit using a modified terminology appropriate to the social domain.

5.4 Next Steps

While this paper focuses on establishing the general foundations of systems theory, the structured extension into the social sciences remains an important avenue for future research. Developing this extension will involve systematically defining social-specific constructs (e.g., needs, satisfiers, belief systems, cultural attractors) and deriving new propositions based on their interactions.
The aim is to produce a unified General System Theory capable of describing and explaining the full arc of systemic emergence, from physical processes through biological evolution to human cognition and social organisation. Work toward this extension is ongoing and will be the subject of future elaboration.

6 | Discussion

The fragmentation of knowledge across disciplines has long impeded the development of an integrated understanding of systems in nature, society, and cognition. Despite significant advances in specialised domains such as thermodynamics, information theory, cybernetics, biology, and the social sciences, a fully general system theory that spans these domains has remained elusive. The purpose of this paper has been to contribute toward such a theory by identifying universal principles that govern the emergence, organisation, optimisation, and collapse of complex systems.

Building on and extending the insights of thinkers such as Lotka, Shannon, Wiener, Bateson, Prigogine, Rosen, Bhaskar, Archer, Parisi, and Cronin & Walker, this paper proposes a coherent, recursive framework that unites the physical, biological, cognitive, social, and symbolic levels of reality. This framework integrates thermodynamics, energy landscapes, symbolic reasoning, systems causality, and recursive emergence into a single structure.

The theory treats systems as dynamic assemblies of matter, energy, and information, governed by principles of structure, function, and transformation. Systems emerge, stabilise, and evolve through trade-offs between free energy, internal organisation, and functional output. Attractors within fractal energy landscapes guide these transitions, while systemic optimality determines periods of peak functional capacity.

Critical realism provides the ontological foundation for this approach. It recognises that cognition, theories, and symbolic systems are not mere representations but real, causally efficacious systems. Within this framework, symbolic reasoning, developed by the author, can function as a unifying mechanism, integrating systems causality, logic, and natural language into a manipulable conceptual architecture. This enables the recursive construction and evolution of complex theoretical systems.

An important open research area concerns the form of the maintenance cost function, f(I), where I is internal information at source. While conceptually clear, the exact functional form of this relationship, e.g., linear, superlinear, or threshold-dependent, remains an empirical question. Clarifying f(I) could sharpen our ability to model systemic optimality, predict collapse thresholds, and design more resilient structures.

The fractal nature of systemic energy landscapes, originally observed by Giorgio Parisi in closed spin-glass systems, is here extended to open systems where free energy is held approximately constant. In such systems, attractors correspond to states of higher internal information, rather than simply states of lower free energy. Although open systems continuously exchange energy with their environments, the rugged, hierarchical landscape structure remains, shaping pathways of evolution across biological, cognitive, and social domains.

Finally, recognising that symbolic systems, such as theories, ideologies, laws, and roles, follow the same dynamics as physical systems opens new possibilities. These structures can be analysed using the same principles of systemic emergence, ratcheting, optimality, and renewal. In free societies, such symbolic systems enable adaptive self-organisation, but are equally susceptible to super-optimal drift, becoming rigid and inefficient over time. Sustained adaptability therefore depends on the conscious simplification and renewal of these symbolic systems.

In sum, this framework lays the foundation for a unified General System Theory. It invites future work in formal modelling, empirical testing, cross-disciplinary integration, and practical application, from system design to resilience planning and knowledge management.

7 | Conclusions

The propositions developed in this paper collectively establish a foundation for a General System Theory. Systems at all levels are shown to emerge through the assembly of components from prior systems, to organise around information at source, and to optimise functional capacity through a trade-off between structure and available free energy. The evolution of systems is described as a recursive, fractal process constrained by thermodynamic principles and punctuated by phases of growth, optimality, super-optimality, collapse, and renewal.

Cognition and cultural systems are understood as extensions of these dynamics into the symbolic domain, where propositions, theories, laws, and institutions emerge, propagate, and evolve according to systemic principles. Free societies demonstrate how symbolic systems can stabilise adaptive structures, although they too are subject to the risks of overcomplexity and systemic rigidity.

In unifying insights from the natural sciences, cognitive science, and social theory, this framework provides a coherent and practical lens for understanding the structure and lifecycle of complex systems. It offers tools for diagnosing systemic health, predicting critical transitions, and designing more resilient structures at every scale of organisation. Further empirical development and refinement will be necessary, but the foundations laid here provide a promising starting point for a truly integrated General System Theory.

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