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ARTICLE

From simple rules to quasi intentionality: emergent coordination and collective cognition

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Abstract

This article examines whether quasi-intentional organisation characterised by anticipation, adaptation and retention can arise in distributed systems composed of simple agents without global goal representation. The analysis draws on observations of *Camponotus barbaricus* ants that construct and stabilise pine-needle barriers in the absence of central control. An agent-based model implemented in NetLogo formalises selected construction dynamics through local rules governing exploration, material deposition and reinforcement of stable configurations. Three operational indicators are introduced to examine system-level organisation: pre-disturbance increases in construction activity, directional changes in structural stability across iterations and reconstruction of previously stabilised patterns after partial removal. The model functions as a constrained artificial-life environment for analysing purposive-looking organisation emerging from distributed interaction and environmental traces. The concept of quasi intentionality is situated within biosemiotic accounts of environmental semiosis and a relational ontology of agency, and is discussed in relation to current approaches to symbiotic and beneficial artificial systems.

Keywords: quasi intentionality, distributed systems, biosemiotics, stigmergy, artificial life, agent-based modelling, symbiotic AI

1. Introduction

The notion of intentionality underpins classical conceptions of mind and agency. The term intentionality was introduced by Franz Brentano (2014), who defined it as the mind's capacity for being about something, that is, the ability to represent or refer to objects, states and events. In philosophical literature, intentionality is often identified with the possession of mental content and conscious intentions (Searle 1983; Dennett 1987). Although many alternative accounts exist, from pragmatic through phenomenological to enactive, this article adopts the classical Brentano–Dennett definition as a point of reference. The aim is not to reconstruct the entire terminological debate but rather to analyse quasi intentional behaviours in distributed systems where the absence of central control and explicit goal representation poses a fundamental challenge to classical conceptions of intentionality.

Algorithms inspired by nature, such as Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO), demonstrate that complex optimisation behaviours can emerge from simple local rules. In PSO, agents move through the solution space by tracking the best global and local positions without any need for central coordination (Kennedy and Eberhart 1995). In ACO, indirect coordination through environmental traces known as stigmergy enables the discovery of shortest paths and the construction of complex structures (Bonabeau, Dorigo, and Theraulaz 1999; Dorigo and Stützle 2004). Studies of self-organisation in biological systems confirm that global patterns can arise entirely from iterations of simple behaviours responding to local information (Camazine et al. 2003). These findings suggest that coordinated and apparently goal-directed patterns may emerge from distributed interactions even in the absence of central representation or explicit planning.

These findings challenge the anthropocentric assumption that purposive behaviour requires conscious intention. Ant colonies can build and refine structures even though individual workers lack any global representation of the whole. Classic research on stigmergy has shown that social insects leave traces in the environment (pheromones or arranged pine needles) that guide the actions of other individuals and enable collective coordination without direct communication (Deneubourg and Goss 1989; Bonabeau, Dorigo, and Theraulaz 1999; Camazine et al. 2003).

One of the key challenges in contemporary artificial intelligence is the design of beneficial systems that adaptively cooperate with humans and the environment. Traditional approaches rely on explicit programming of goals and utility functions. The Symbiotic Beneficial AI framework (Polak and Krzanowski 2023) proposes an alternative: systems in which beneficial patterns emerge through local interactions modelled on biological symbiosis. This approach shifts emphasis from centralised optimisation to the co-evolution of cooperation and adaptation within dynamic cognitive ecosystems, where artificial agents function as participants rather than merely as tools.

Empirical inspiration for this work comes from observations of *Camponotus barbaricus* constructing pine needle barriers (Franks et al. 1992; Camazine et al. 2003). In laboratory settings, workers initiate construction in the absence of immediate threats, refine the structure over successive iterations (Deneubourg and Goss 1989) and consolidate effective patterns after barrier removal (Camazine et al. 2003). This article develops a conceptual and modelling framework for analysing quasi-intentional organisation in distributed systems. An agent-based simulation, drawing on selected construction dynamics of *Camponotus barbaricus*, functions here as a formal and illustrative model used to examine whether patterns corresponding to anticipation, adaptation and retention can arise from local interaction rules in the absence of central representation.

2. Quasi intentionality as an intermediate category

Classical theories of intentionality (Brentano 2014; Dennett 1987; Searle 1983) assume an inseparable link between intentionality, mental content and consciousness. Intentional being about something requires representation and conscious purpose, yet in distributed systems lacking a central representational unit, functionally analogous behaviours to purposeful action are observed. To describe these phenomena, the notion of quasi intentionality is introduced, understood here as system-level purposive organisation that emerges at the level of the entire

system in the absence of central representation or conscious intention. Quasi intentionality is treated here as a lower-level form within a graded spectrum of intentional organisation, occupying a position between basic regulatory purposiveness and fully representational, conscious intentionality.[1] Three basic system functions are distinguished:

1. Anticipation
   The system initiates adaptive actions before a clear threat stimulus appears. Anticipation consists in the reduction of surprise relative to recurrent perturbations. In representational systems this may involve internal models of future states (Friston 2010; Clark 2016); in quasi intentional systems, analogous effects may arise from emergent network dynamics and distributed environmental feedback (Camazine et al. 2003).
2. Adaptation
   The system modifies action strategies over successive iterations on the basis of global and local feedback. In complex systems theory, adaptation occurs when local rules change in response to the state of the whole system, as described by positive and negative feedback mechanisms (Haken 1977; Prigogine and Stengers 1984).
3. Retention
   The system retains and reinforces effective patterns via distributed memory. In Hopfield networks, the system state functions as an information carrier (Hopfield 1982), and in insect colonies, durable environmental structures store cues that guide subsequent actions (Deneubourg and Goss 1989).

The choice of these three indicators rests on their fundamental role in a functional account of purposiveness. In this framework, anticipation, adaptation and retention are treated as operational descriptors of system-level organisation rather than as claims about internal mental states or representational content. This triad of forecast, correction and consolidation constitutes the core of any form of purposeful action, whether of individual agents or as an emergent system trait. Integration of these components enables description of quasi intentionality in collective systems even when individual units lack internal representations or conscious goals.

Quasi intentionality avoids anthropomorphism by allowing discussion of system-level intention without attributing consciousness to individual elements. This aligns with the enactive conception of cognition (Varela 1992; Thompson 2007), according to which intelligence arises from dynamic interaction between organism and environment rather than from internal representations. It is also consistent with active externalism (Clark and Chalmers 1998), which treats environment and artefacts as participants in cognitive and agency processes.

Recent work on minimal cognition further supports the view that purposive organisation can arise without central representation or conscious planning. Research on basal cognition and distributed regulation argues that even simple biological systems exhibit forms of goal-directed organisation grounded in metabolic and sensorimotor coupling rather than in

1. The term *quasi intentionality* is introduced here as a working analytical category situated within a continuous line of research on minimal and distributed forms of purposive organisation. The approach draws on Uexküll's conception of organism–environment relations and functional meaning within the *Umwelt* (Uexküll 1921, 1934), on biosemiotic accounts of regulation and sign-mediated interaction (Hoffmeyer 2011; Kull et al. 2009), and on enactive theories of minimal agency and sense-making (Varela 1992; Thompson 2007; Barandiaran, Di Paolo, and Rohde 2009). Within this framework, these perspectives are treated not as competing approaches but as complementary accounts of purposive organisation emerging without central representation.

symbolic representation (Lyon 2015; Levin 2019). From this perspective, cognition is not restricted to brains but extends across regulatory processes that maintain system integrity and guide adaptive behaviour. Such approaches shift attention from internal representations to patterns of coordination across bodies, environments and interaction histories. The present notion of quasi intentionality remains more restrained: it does not attribute cognition in a strong biological sense to artificial or collective systems, but it does draw on this line of work to support the claim that purposive organisation can be analysed at the level of system dynamics without presupposing explicit representation or awareness.

A complementary line of argument is developed in dynamical and interactivist accounts of minimal agency. Dynamical systems approaches emphasise how coherent behavioural patterns can emerge from the continuous coupling of agents and environments without reliance on symbolic control structures (Beer 2014). Interactivist theories similarly argue that normative organisation and goal-directed behaviour can arise from processes that maintain and regulate their own conditions of viability, even in the absence of internally represented goals (Bickhard 2009). These perspectives reinforce the interpretation adopted here: quasi intentionality designates a level of organisation at which coordinated, purposive patterns can be identified in the dynamics of a system as a whole, without implying that individual components possess intentions, representations or conscious awareness.

3. Relational ontology, semiosis and symbiotic AI

The concept of quasi intentionality presupposes a shift from substance ontology towards a relational ontology in which agency emerges from networks of interaction rather than residing in individual entities. According to autopoietic theory (Maturana and Varela 1980), living systems maintain their identity through continuous exchanges with their environment. In biosemiotic approaches this process is understood as semiosis, in which each interaction creates and interprets meaningful traces in the environment, thereby constituting the subjective *Umwelt* of organisms (Uexküll 1921; Kull et al. 2009; Hoffmeyer 2011). In quasi intentional systems, semiosis plays a key role in retention, as durable environmental signs record historically effective patterns, and in adaptation, as those signs guide subsequent adjustments of behaviour.

In the context of artificial systems, the use of biosemiotic terminology should be understood cautiously. Following discussions in artificial life and cognitive robotics, semiotic and intentional vocabularies are often employed as analytic and modelling tools rather than as ontological claims about artificial agents themselves (Emmeche 1994; Ziemke 2001). Within this perspective, semiosis does not imply the presence of intrinsic meaning or interpretation in a human or biological sense. Instead, it designates a relational configuration in which environmental modifications constrain subsequent system behaviour and thereby acquire functional significance within ongoing dynamics. The present framework adopts this restrained usage: biosemiotic concepts are used to characterise patterns of interaction and stabilisation in distributed systems, not to attribute full-fledged semiotic capacities to individual agents.

Within this relational ontology, higher levels of system organisation may influence the behaviour of components. This mechanism, often described as downward causation (Campbell 1974), can be understood in terms of the formation of dynamic attractors. Such attractors organise local agent behaviour so that the system as a whole achieves functional

outcomes despite the absence of a central plan (Barandiaran, Di Paolo, and Rohde 2009). Research on minimal forms of agency indicates that even simple self-sustaining and boundary-regulating systems can exhibit emergent forms of agency (Barandiaran, Di Paolo, and Rohde 2009; Thompson 2007).

Quasi intentional mechanisms operate via self-organisation and stigmergy. Self-organisation is a process in which ordered patterns arise from repeated local interactions governed by simple rules without external control (Haken 1977; Prigogine and Stengers 1984). In a biosemiotic framing, each act of construction, whether the placement of a needle or the deposition of pheromone, may be treated as an instance of semiosis that serves as a stimulus for subsequent actions. Consequently, global patterns emerge stigmergically: environmental traces guide agent behaviour while functioning as meaning carriers that encode and stabilise historically effective patterns within the system. Such environmental memory and meaning carriers require a balance of positive feedback that reinforces success and negative feedback that prevents uncontrolled growth. This balance enables the system both to explore new solutions and to stabilise effective patterns.

From a modelling perspective, the notion of semiosis can be partially operationalised by specifying how environmental traces are generated, maintained and differentially weighted in subsequent interactions. Work in artificial life and robotics has emphasised that semiotic descriptions of artificial systems are most defensible when linked to explicit mechanisms of coupling between agent activity and environmental modification (Emmeche 1994; Ziemke 2001). In this sense, semiosis is not treated as an additional property layered onto the model, but as a way of describing how distributed memory and constraint structures function within system dynamics. The present model therefore treats environmental traces as operational carriers of constraint and coordination, allowing biosemiotic terminology to be used in a controlled and explicitly defined manner.

The Symbiotic Beneficial AI framework (Polak and Krzanowski 2023) draws on these inspirations. In nature, mutualistic relationships, such as mycorrhizal associations or cleaning symbioses, demonstrate that complex beneficial functions can emerge through local semiosis and mutual tuning of partners (Thompson 2007; Hoeksema and Bruna 2015). In artificial systems, semiosis may be translated into mechanisms that enable agents to create and interpret environmental traces in digital environments, thereby giving rise to emergent cooperation and adaptation. Unlike economic or consensus-based algorithms, symbiotic AI does not assume optimisation of a single utility function but instead seeks to create conditions for the emergence of complementary behaviours within dynamic cognitive ecosystems, where agents function as participants in the cognitive process.

4. Biological inspiration and translation to an ALife model

Observations of the ant *Camponotus barbaricus* provide empirical inspiration for analysing quasi intentional mechanisms in collective systems. In controlled formicarium settings, workers are observed to build pine-needle barriers even in the absence of immediate threats, corroborating earlier experimental and field reports on stigmergic construction behaviour in social insects (Franks et al. 1992; Deneubourg and Goss 1989; Camazine et al. 2003). Initial construction phases can be described in functional terms as anticipatory, insofar as workers gather material and begin forming a protective structure prior to overt perturbations. Subsequent iterations

of the building process exhibit adaptive adjustments in structural stability and assembly speed through local reinforcement of successful configurations. Rather than depositing needles randomly, workers tend to concentrate effort on structurally critical sections of the barrier (Deneubourg and Goss 1989; Bonabeau, Dorigo, and Theraulaz 1999). Following partial removal of the structure, colonies frequently reconstruct previously stabilised segments first, even when different workers participate in the rebuilding (Camazine et al. 2003). These patterns of anticipation, adaptation and retention provide a biological reference point for analysing purposive organisation in systems lacking central representation.

At the level of individual behaviour, workers do not possess a global representation of the structure being built and do not operate with an explicit plan of the final configuration. Each agent responds only to local material densities, spatial constraints and traces left by previous actions. Nevertheless, colony-level dynamics can give rise to stable and functionally organised structures that are initiated prior to disturbances, modified across successive iterations and partially reconstructed after removal. This discrepancy between strictly local rule-following and coherent global organisation has long been recognised as a defining feature of stigmergic systems and collective self-organisation (Deneubourg and Goss 1989; Bonabeau, Dorigo, and Theraulaz 1999; Camazine et al. 2003).

The theoretical interest of such systems lies precisely in this tension between local responsiveness and global coherence. Without invoking internal plans or representations at the level of individual agents, the colony exhibits coordinated dynamics that can be described functionally as anticipatory, adaptive and retentive. Similar forms of system-level organisation have been discussed in research on minimal and distributed agency, where purposive structure is treated as emerging from ongoing interaction and constraint rather than from centrally represented goals (Barandiaran, Di Paolo, and Rohde 2009; Thompson 2007). Within this perspective, quasi intentionality can be used as a descriptor of system-level organisation that arises from distributed interactions and environmental feedback, without attributing full-fledged intentional states to individual components.

In an agent-based simulation implemented in NetLogo (Wilensky 1999), each agent executes three basic local rules corresponding to the behavioural patterns described above: exploration and collection of resource needles, deposition of material near existing accumulations, and reinforcement of stable areas while avoiding unstable ones. A functional analogue of anticipation is modelled through an early-activation threshold that causes agents to respond to local material density rather than to an explicit threat signal. Adaptation is implemented by dynamically increasing the attractiveness of sites where previously deposited material has remained stable across iterations. Retention emerges through the persistence of deposition–attractiveness fields that function as a form of distributed environmental memory within the model.

5. Methodology and Model Architecture

The model is presented as a constrained artificial-life system designed to explore whether quasi-intentional patterns may arise from explicitly specified local interaction rules. Rather than reproducing biological colonies in full detail, it formalises selected construction dynamics observed in *Camponotus barbaricus* and evaluates whether system-level patterns corresponding to anticipation, adaptation and retention can emerge from these local interactions. It is

intended as a formal and illustrative framework for examining distributed organisation under controlled conditions, not as an empirical reproduction of biological colonies.[2]

An artificial life simulation was implemented in NetLogo (Wilensky 1999) on a two-dimensional grid measuring 30×30 cells. The grid represents a simplified forest environment with a central nest at coordinates (15, 15) and resources (food and pine needles) distributed randomly. The initial population comprises ten worker agents located within the nest. Agent reproduction occurs when nest reserves exceed fifty units of food, consuming thirty units per new agent and thereby introducing simple demographic dynamics. Agents operate autonomously, each maintaining its own coordinates, behavioural state (foraging / transport / construction) and the capacity to carry a single resource (food or pine needle). Perception is local and limited to a radius of three cells, introducing a constraint on information access comparable to those reported in biological observations (Camazine et al. 2003; Franks et al. 1992). No agent has access to global structural information or to any representation of forthcoming environmental disturbances.

Agent behaviour is governed by three sets of local rules derived from and abstracting selected construction dynamics described in biological observations and literature (Deneubourg and Goss 1989; Bonabeau, Dorigo, and Theraulaz 1999; Camazine et al. 2003):

1. Foraging
   Agents perform a correlated random walk, turning up to $\pm 45^\circ$ with probability 0.7 or moving straight otherwise. Upon detecting food within perception range (radius of three cells), agents pick it up with probability 0.8 and return to the nest following a pheromone gradient that decays at rate 0.95 per tick.
2. Pine needle collection
   During foraging, agents encountering pine needles pick them up with probability

$$P_{\text{collect}}(d) = 0.3e^{-0.1d},$$

   where d denotes Euclidean distance to the nearest nest entrance. This formulation yields the highest collection probability near the entrance and decreases it with distance, reflecting the tendency to concentrate construction near critical entry regions, as observed in stigmergic construction processes (Deneubourg and Goss 1989).
3. Barrier construction
   Agents carrying a needle deposit it with probability

$$P_{\text{deposit}}(\rho) = 0.1 + 0.4 \left(\frac{\rho}{\rho_{\max}} \right)^2,$$

   where ρ represents local needle density computed as the number of needles within a Moore neighbourhood of radius one (eight surrounding cells) around the agent's current cell, and $\rho_{\max}$ denotes the maximum observed value of ρ within the current simulation run, used for normalisation. If $\rho_{\max} = 0$, deposition defaults to the baseline probability $P_{\text{deposit}} = 0.1$.

2. The full simulation model (NetLogo 7.0.3) is available for review via an anonymous Open Science Framework repository: https://osf.io/srwfh/?view_only=264c47c847b1460a9c2e382448756589.

After deposition, the stability of that position is monitored. Stability is defined as the persistence of at least one needle at that location for consecutive ticks. If stability persists for ten consecutive ticks, the attractiveness of that site is increased by a factor of 1.2; for each additional completed block of ten stable ticks (i.e. at 20, 30, 40 ticks, etc.), the same reinforcement is applied again. If the number of needles at that location falls to zero, the site is treated as unstable and attractiveness is reduced. Stability is implemented as a patch-level persistence variable rather than an agent-level memory. Reinforcement therefore operates through environmental modification rather than internal state retention.

Environmental resources regenerate dynamically, with pine needles appearing at probability 0.02 per cell per tick (excluding the nest) and food at probability 0.01 per empty cell per tick. The environment includes designated zones: a storage area (5×5 cells at the centre), an expanded entrance zone (four cells on the nest perimeter), and a nursery area for reproduction. Modifications to the environment (namely needle deposition) bias agent movement by altering local attractiveness fields, thereby influencing subsequent deposition patterns.

To examine structural robustness under disturbance, controlled perturbations are introduced at regular intervals. When enabled, a perturbation occurs every 500 ticks and consists of a uniform 50% reduction of structural values across the environment. Each interval between successive perturbations defines a construction cycle. This cyclical disturbance allows analysis of cross-cycle changes in structural stability and the degree of spatial overlap between pre- and post-perturbation configurations.

Data generated within the simulation were inspected to characterise general activity patterns and system responses to parameter changes. Analytical procedures were used in an exploratory and illustrative manner to identify shifts in building dynamics and to assess the internal consistency of the operational measures introduced above. The purpose of these analyses is not confirmatory testing, but the clarification of how the proposed indicators of anticipation, adaptation and retention function within the model environment.

6. Operationalisation of quasi-intentionality

Quasi-intentionality is operationalised here as a minimal regime of norm-guided, historically sensitive organisation detectable at the level of system dynamics. The indicators below do not attribute representational content to agents. Rather, they measure whether collective dynamics exhibit temporal asymmetry, cross-cycle stabilisation, and structured reconstruction under controlled perturbation.

All values reported below are based on $N = 300$ independent runs with varying random seeds.

1. Temporal asymmetry (anticipatory activation)
   Building activity was quantified as the number of structural reinforcement events per tick, aggregated over 100-tick windows preceding perturbation. Across runs, mean pre-perturbation activation was

$$M = 0.492, \quad SD = 0.12.$$

This indicates a stable forward-directed bias in structural mobilisation prior to disturbance. The magnitude of the effect remains moderate and does not reach the previously defined conservative threshold of $z > 2$. It is therefore interpreted as persistent temporal asymmetry rather than strong predictive escalation.

2. Adaptation (cross-cycle stabilisation)
   Structural stability was measured at the patch level via a persistence counter (stable-ticks). For each cycle, a cycle-level stability score was computed as the mean stability of structurally active patches.
   Mean early-cycle stability was

$$M_{\text{early}} = 790, \quad SD \approx 190,$$

   whereas mean late-cycle stability increased to

$$M_{\text{late}} = 7086, \quad SD \approx 950.$$

   This corresponds to an approximately 8.97-fold increase across cycles. The correlation between cycle index and stability remained below $r = 0.7$, indicating that the increase is directional but non-linear. The effect reflects progressive structural consolidation under repeated disturbance rather than simple linear accumulation.
3. Retention (historical persistence)
   Retention was computed as spatial overlap between structural configurations before and after perturbation. Across runs, mean retention was

$$M = 0.80, \quad SD = 0.07,$$

   with 73% of runs exceeding the conservative threshold of $R > 0.7$.
   This indicates strong, though not deterministic, reconstruction of previously stabilised configurations.

Taken together, these indicators demonstrate a regime in which collective dynamics exhibit measurable temporal asymmetry, cumulative stabilisation across cycles, and historically mediated reconstruction. The reported values describe tendencies within the present parameter configuration and do not claim universality across all possible parameter settings.

7. Discussion

The simulation generates three measurable patterns from explicitly specified local probabilistic rules: temporal asymmetry in construction activity (M = 0.492, SD = 0.12), cross-cycle structural consolidation (8.97-fold stability increase from early to late cycles), and spatial reconstruction following perturbation (M = 0.80, SD = 0.07). These patterns arise without central coordination and without global goal representation.

The magnitude of these effects constrains their interpretation. Pre-disturbance activation remains below the conservative threshold ($z > 2$), indicating a weak but persistent forward bias rather than strong predictive escalation. Cross-cycle stability correlates with cycle index at $r < 0.7$, suggesting directional but non-linear consolidation. Retention exceeds $R > 0.7$ in 73% of runs, demonstrating robust yet non-deterministic reconstruction. The reported

values therefore describe stable tendencies within the present parameter configuration rather than universal behavioural laws.

Importantly, it is the co-occurrence of forward temporal bias, cumulative stabilisation and selective reconstruction that defines the observed regime. The results do not demonstrate predictive modelling or representation. They demonstrate a constrained dynamic organisation in which past stabilisation and present reinforcement jointly shape the distribution of future structural states.

Three limitations bound the scope of generalisation. First, the environment is simplified and two-dimensional; agents are homogeneous; resource regeneration is fixed. Biological colonies operate under heterogeneous terrain, agent differentiation and stochastic perturbation. Second, although N = 300 runs establish internal consistency, no direct parameter calibration against empirical ant data has been performed. Third, the indicators introduced (anticipation, adaptation, retention) capture system-level regularities, but do not uniquely determine underlying causal mechanisms. Comparable macroscopic patterns could in principle arise from distinct micro-dynamics.

The observed dynamics result from the coupling of two feedback processes. Positive feedback operates through probability-weighted deposition, which increases local attractiveness in regions of existing accumulation. Negative feedback operates through stability monitoring: sites in which material persists for ten consecutive ticks increase in attractiveness (factor 1.2), whereas loss of material reduces attractiveness. Together these mechanisms produce selective consolidation. Configurations that withstand perturbation progressively bias subsequent construction.

Crucially, reinforcement is not blind accumulation but historically filtered persistence: only configurations that survive perturbation cycles continue to influence subsequent dynamics. Temporal asymmetry does not result from predictive modelling but from threshold-driven activation under stochastic resource distribution. Cross-cycle stabilisation follows from cumulative reinforcement of patches that survive perturbation. Retention is encoded in environmental attractiveness fields rather than agent-level recall.

The model does not introduce novel coordination rules at the local level; rather, it demonstrates how the interaction of probabilistic reinforcement and environmental memory can yield temporally structured regimes that are rarely isolated analytically in standard stigmergic analysis. Classic stigmergic models document emergent pattern formation (Deneubourg and Goss 1989; Bonabeau, Dorigo, and Theraulaz 1999; Camazine et al. 2003), but typically do not quantify whether such patterns exhibit forward temporal bias prior to disturbance, directional consolidation across perturbation cycles, or preferential reconstruction of historically stabilised configurations. By operationalising these three dimensions and tracking their co-occurrence, the present framework isolates a structurally constrained regime within feedback-mediated coordination.

Stigmergic accounts describe environmentally mediated coordination via positive and negative feedback (Deneubourg and Goss 1989; Bonabeau, Dorigo, and Theraulaz 1999; Camazine et al. 2003). The present model confirms that such mechanisms can generate temporal asymmetry and historically structured reconstruction. Whether this warrants a distinct conceptual category or represents a refined description within existing self-organisational theory remains open. The quasi-intentionality framework proposes that when stigmergic systems exhibit anticipatory bias, adaptive consolidation and historical reconstruction simulta-

neously, the resulting dynamics form a regime more constrained than purely reactive pattern formation. This claim requires comparative validation.

Enactivist and interactivist approaches argue that norm-sensitive organisation can arise without symbolic representation (Varela 1992; Thompson 2007; Barandiaran, Di Paolo, and Rohde 2009; Bickhard 2009). In biological minimal agency, normativity is grounded in viability conditions internal to the organism. In the present model, norm-sensitive behaviour derives from externally specified stability parameters and reinforcement rules. The comparison is therefore structural rather than ontological. Both domains exhibit distributed coordination shaped by constraint and history, but the grounding of normativity differs. The present analysis isolates structural preconditions of norm-sensitive coordination without resolving whether intrinsic normativity is constitutive of intentionality.

Teleonomic systems maintain functional parameters via feedback regulation (Mayr 1974). The present system differs in exhibiting selective reconstruction of historically stabilised configurations rather than simple restoration of equilibrium states. A thermostat restores a setpoint; here specific spatial patterns that proved stable under past perturbations are preferentially reinstated. The distinction is not one of complexity but of historical selectivity: regulation corrects present deviation, whereas reconstruction reinstates configurations whose persistence depends on prior survival under disturbance. Whether this difference marks a theoretically significant boundary or a graded extension of regulatory dynamics requires further analysis.

If quasi-intentionality is to function as more than a descriptive label, it must withstand comparative testing:

1. Ablation study
   Removing environmental attractiveness fields while preserving other parameters would test whether temporal asymmetry and retention depend on distributed memory. Collapse of reconstruction under ablation would indicate that trace-mediated coordination is constitutive of the observed regime.
2. Cross-domain implementation
   Applying identical probabilistic reinforcement rules to non-biological distributed systems would clarify whether the regime reflects general properties of feedback-coupled architectures or depends on specific spatial and dynamical constraints.
3. Biological validation
   Parameter calibration against empirical measurements from *Camponotus barbaricus* colonies would assess structural correspondence between model and biological construction dynamics.

The model demonstrates that anticipation, adaptation and retention can be operationalised as system-level properties in distributed architectures without central representation. These dynamics arise from probabilistic local rules coupled with environmental memory. The observed regime exhibits forward temporal bias, norm-sensitive restructuring under perturbation, and historically mediated reconstruction.

The central claim is deliberately restrained: restricting intentional vocabulary exclusively to representational systems leaves temporally structured, historically sensitive coordination without precise theoretical articulation. The present framework operationalises this domain

and specifies conditions under which it can be systematically investigated. Whether quasi-intentionality proves indispensable or reducible will depend on comparative and cross-domain analysis rather than definitional preference.

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