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ALGORITHMIC COLLECTIVE: A GENERAL MODEL FOR SWARM INTELLIGENCE

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Abstract
The mechanisms underlying swarm intelligence remain largely unexplained theoretically, and existing frameworks struggle to account for both homogeneous and heterogeneous intelligent groups—this is the core problem addressed in this paper. Understanding how collective intelligence emerges from individual interactions is not only a theoretical gap in swarm intelligence research but also a critical issue in systems science, artificial intelligence, and human-machine collaboration. Based on complex adaptive systems theory and integrated with a generalized view of algorithms, this paper proposes the "algorithmic collective" model, whose theoretical innovations are threefold. First, it establishes three core ideas of the algorithmic perspective: the generalized algorithm expands the traditional scope of algorithms beyond computer programs to general rule systems; the unity of entity and rule holds that an algorithmic unit is both an objective entity and a process of rule execution, the two being dialectically unified; the hierarchy of entity and rule reveals the nested relationship between macro-rules and micro-rules, providing methodological guidance for cross-level modeling. Second, it defines the "algorithmic unit" as the basic rule-system individual constituting a group, replacing the concept of adaptive agent, with four advantages: thorough monism, wide applicability, explicit representation of heterogeneity, and higher operability. Third, it constructs a three-layer conceptual model consisting of the entity layer, rule layer, and function layer, forming a closed-loop evolutionary path of institutionalization, emergence, and embodiment. The rule layer is further decomposed into three parallel sub-rules: individual rules, communication rules, and leadership rules, decomposing the nonlinear interactions in swarm intelligence into designable, controllable, and measurable components. This study demonstrates that the algorithmic collective model provides a new ontological foundation and methodological tool for understanding the emergence process of swarm intelligence, and can effectively support computational modeling of swarm intelligence, analysis of heterogeneous groups, and interdisciplinary research on complex adaptive systems.

Keywords
Swarm Intelligence, Complex Adaptive Systems, Algorithmic Collective, Algorithmic Unit, Emergence

1 | Introduction
Against the backdrop of Industry 4.0, intelligent manufacturing and big data are driving profound transformations in human society, completely reshaping production technologies, manufacturing factors, and the production modes of labor organization (Tambare et al., 2021). Emerging technologies represented by the Internet of Things (IoT) and cyber-physical systems (CPS) have

been integrated into every aspect of human daily life (Salunkhe & Berglund, 2022). Whether it is the collaborative learning of smart home devices or the intercommunicating vehicle swarms in a fleet, these systems are essentially collectives composed of a large number of homogeneous or heterogeneous intelligent units (Wang et al., 2025). They follow a fundamental operational logic: individuals interact and cooperate under the guidance of simple rules, enabling the whole to accomplish complex tasks and giving rise to functions and intelligence that far exceed the sum of their individual parts (Tang, Liu, & Pan, 2021). This emergent, surpassing form of intelligence arising from collective collaboration is termed swarm intelligence (SI), a subfield of computational intelligence (CI) within artificial intelligence (AI) (Chakraborty & Kar, 2017), and holds substantial research promise and application value.

Today, the development of human society exhibits a novel characteristic—the "algorithmic society" (Burrell & Fourcade, 2021). As rules that drive physical devices, algorithms are now incorporating even organic human life into a vast heterogeneous intelligent agent network. Unlike traditional algorithms, modern algorithms, benefiting from the development of big data technologies, achieve self-iteration and evolution through explosively growing data streams and processing methods that transcend human understanding. They integrate into society through intelligent practices, drive social evolution, and exert profound influences on socioeconomic, political, and cultural domains (Duffy, 2020; Fortes & Amariles, 2023). Relevant studies indicate that algorithms not only monitor and make private information transparent in real time but also subtly influence human cognition, psychology, and habits by allocating social resources and tasks (Starke et al., 2022; Birhane, 2021). Consequently, human individuals, unable to remain unaffected, are inevitably destined to become a constituent element of this complex giant system. However, this does not imply the complete dissolution of human agency. Notably, it is precisely through this process that humans, as organic intelligent agents, are being incorporated—on a large scale and in a structured manner—into an algorithm-driven heterogeneous intelligent agent network, thereby greatly expanding the research boundaries of SI.

Current research in the field of SI primarily focuses on cognitive mechanisms and rule design—that is, summarizing existing instances of SI through observation, analysis, and experimentation, followed by the heuristic design of algorithms and models based on these principles (Kano, 2023). For example, Shigaki et al. developed a non-fixed experimental system specifically designed to measure and understand natural animal behaviors (Shigaki et al., 2017). The development of swarm intelligence algorithms (SIAs) over the past few decades has been extensive (Chao et al., 2025); nevertheless, there remains no unified systemic theory explaining how SI occurs, and its mechanisms are still an unclear black box. Therefore, this study attempts to construct a general model from the algorithmic perspective that can systematically articulate the mechanisms of swarm intelligence, which holds profound significance for understanding and applying SI. This paper is a foundational study on SI, and further research is needed to explore the quantitative relationships underlying the evolutionary mechanisms of SI.

2 | Research Foundation

This section introduces the research foundation of this paper. First, it reviews and summarizes the development history and characteristics of SI. Then, it presents the connotation, characteristics, and limitations of complex adaptive systems(CAS) theory, thereby leading to the research content of this study.

2.1 | Current State of Swarm Intelligence Research

Swarm intelligence is widely observed in nature and has provided a source of inspiration for designing swarm intelligence algorithms and controlling robotic swarms (Duan, Huo, & Fan, 2023). The term "swarm intelligence" was first proposed by Beni et al. in 1989 at the NATO Advanced Workshop on Robots and Biological Systems in the context of cellular robotics (Beni & Wang, 1993). In 1999, Bonabeau et al. formally introduced the concept of swarm intelligence in their monograph *Swarm Intelligence: From Natural to Artificial Systems* (Bonabeau, Dorigo, & Theraulaz, 1999), marking the beginning of this research field, although relevant studies had already been conducted for over a decade. Reynolds C. W. published his seminal paper on the Boids model in 1987 (Reynolds, 1987). Drawing on the principle of selfish herding, he designed a mechanism in which individual particles in an algorithmic swarm tend to move toward the group center to reduce their own exposure risk. This model effectively explained the dense-group survival strategy observed in nature and pioneered the development of subsequent "self-propelled particle models." Over the past several decades, the primary research approach in this field has been to identify instances of collective wisdom in nature, analyze the emergent mechanisms of swarm intelligence, and imitate the rules governing individual collaboration, thereby designing swarm intelligence algorithms and models.

In the early stage, swarm intelligence algorithms were primarily focused on mimicking animal behaviors and were widely regarded as a branch of bio-inspired algorithms (Fister Jr et al., 2013). Nowadays, there are also many examples of non-bio-inspired algorithms, such as the fireworks algorithm (Tan & Zhu, 2010) and the harmony search algorithm (Gao et al., 2015). Additionally, cellular automata, evolutionary computation, and self-organizing neural networks have also been classified under the scope of swarm intelligence (Schranz et al., 2021), indicating the fuzziness of the boundaries of SI. In fact, SI is not limited to groups in nature; any collection or system composed of interacting components falls within its scope, with general characteristics including collective decision-making, collective regulation and balance, and collective periodic patterns. SI emphasizes emergence and self-organization, while also exhibiting robustness and scalability (Jdeed et al., 2017), making it highly similar in nature to CAS which exhibit rich characteristics, including embeddedness, self-organization, non-linearity, and unpredictability (Chaffee & McNeill, 2007). The problems commonly faced by SIAs are low precision and premature convergence, which essentially result from a high exploitation ability relative to exploration ability (Wei et al., 2021). Maintaining population diversity is a common direction for improving existing algorithms. Some studies have also attempted to integrate information economics and game theory to replace the design of traditional rules (Palsule-Desai, 2012).

2.2 | Complex adaptive systems

Complex adaptive systems (CAS) is a theory of complexity science proposed by Holland on the tenth anniversary of the founding of the Santa Fe Institute. It is built upon general system theory and dialectical materialism, and its core proposition is that “adaptation builds complexity” (Holland, 2018), offering a new perspective for understanding general complex systems. The notable contribution of CAS lies in its emphasis on the role of the “agent.” In this theory, the constituent elements of a system are termed “adaptive agents.” This term consists of two parts: “agent” refers to objective matter, and “adaptive” refers to the interactions among matter. Thus, this term embodies the idea of the unity of entity and relation, effectively curbing the then-prevalent dualistic notion of separating entity from relation. CAS posits that a system’s behavior is not determined by the behavior of individual agents but by the interactions among agents;

interactions among agents and between agents and the environment are the primary drivers of system evolution. Regarding the conceptual analysis of the “adaptive agent,” the key lies in elaborating “adaptivity.” Adaptivity is a fundamental property of agents. The essence of interactions between an agent and other agents or the environment is a process in which the agent learns, memorizes, accumulates experience, and then changes its own structure and behavioral patterns (Holland, 1995)—that is, the adaptation process is also a learning process and a self-organization process.

However, CAS also have certain limitations: (1) the concept is overly broad—any entity capable of responding to external changes can be considered an adaptive agent, making the boundaries fuzzy; (2) it is difficult to explain heterogeneity—within the adaptive agent framework, heterogeneous individuals manifest differences in parameters rather than in type; (3) quantification is difficult—adaptivity is a process-oriented concept that is hard to measure in practical applications. This study, based on CAS, integrates an algorithmic perspective, proposes the concept of the “algorithmic unit,” and further advances the “algorithmic collective model” to address the limitations of CAS and enhance its applicability.

3 | Algorithmic Perspective

The algorithmic perspective is the philosophical foundation of the algorithmic collective model. It comprises three core ideas: "the generalized concept of algorithms," "the unity of entity and rule," and "the hierarchy of entity and rule."

3.1 | Generalized Algorithm

The term "algorithm" originates from the name of the 9th-century Persian mathematician Al-Khwarizmi (Mehri, 2017), referring to a finite sequence of steps for solving mathematical problems. With the development of computers, algorithms have come to be understood as specialized functional modules within computer programs. However, this paper proposes the "generalized algorithm" to refer to rule systems; that is, a rule system can be termed a generalized algorithm. For example, a sequence of mathematical formula steps constitutes a mathematical rule system; legal statutes and judicial procedures constitute a social rule system; life is composed of genetic materials such as DNA, and complex life behaviors emerge from the translation process of the "genetic code"—therefore, genetic material constitutes a natural rule system. This paper argues that an algorithm is a specific type of system. An algorithm is a whole composed of a set of interrelated and interacting imperative statements, with each statement functioning collaboratively toward a common goal. It receives external input, processes it through logical operations, and produces output. The components of an algorithm include input, processing, output, feedback, and control, a process accompanied by the flow of data. An algorithm is characterized by boundaries, goals, hierarchy, and dynamism. With the beginning and end of imperative statements serving as boundaries, an algorithm can be divided into multiple hierarchical levels.

The essence of algorithmizing an object is to abstract a complex research object into a simple algorithm to simplify the research problem. This approach has run through the entire history of human scientific development, and the underlying idea is precisely the generalized algorithm concept. The ancient Greek mathematician Pythagoras proposed that "all things are numbers," arguing that the essence of the world is mathematical relationships (Gorman, 2025). Leibniz further advanced the notion that "all things can be encoded." Turing technologically advanced the realization of this idea by proposing the universal Turing machine, laying a practical foundation for the computability of mathematical problems within a formalized model (Copeland & Sylvan, 1999).

3.2 | Unity of Entity and Rule

If both a living organism and a string of binary code can be defined as "generalized algorithms," is there some deeper connection behind these two vastly different forms of existence? Taking the particle swarm algorithm as an example, particles in a computer's virtual world operate according to preset underlying code. Their existence is simultaneously an objective entity and the result of rule execution, indicating that in the process of algorithmizing entities, entity and rule are unified. The same holds true in the real world. Behind the dynamism of a living organism lies the expression of genetic material, and the changing of the world is the effect of natural laws. Matter can be viewed either as a concrete individual or as a process of rule execution. At any given moment, the entity and all its properties are the expressed result and instantaneous manifestation of rules. An entity is explicit rules, and rules are implicit entities. The two are dialectically unified, consistent with the movement inherent in matter. The unity of entity and rule provides legitimacy for the algorithmization of entities and establishes the worldview underlying the algorithmic perspective—namely, that rules shape entities, entities execute rules, interactions generate new rules, and this process dynamically reshapes entities in an ongoing development.

This idea has discernible precedents in research on systems science. Von Neumann's self-reproducing automata theory elucidated how life phenomena can emerge from simple rules (Burks, 1969). Wolfram demonstrated through cellular automata that complex behaviors in nature can be generated from simple computational rules (Wolfram, 2018). David Marr's computational theory of vision indicated that human cognition is also a kind of information processing *system*, and the process of perceiving the external world can be simulated as an algorithmic process (Marr, 2010).

3.3 | Hierarchy of Entity and Rule

Both entities and rules exhibit hierarchy. The hierarchical nature of entity systems is common, exemplified by physiological structures such as "organ — tissue — cell — organelle." Rules also possess hierarchy: macro-rules contain micro-rules, and the two are relatively independent. For example, the rules of chemical reactions are composed of the physical rules governing the exchange of microscopic particles.

The process of human transformation of the world is replete with exploiting the hierarchy of rules. By observing intelligent phenomena in nature, identifying and extracting their local rules, and transforming them into technologies, humans have achieved various feats. For instance, bionic technology mimics specific biological functions, and SIAs mimic the mechanisms of collective behavior. However, these imitations are all local and superficial. A neuron in a deep neural network possesses only simple functions, with parameter updates relying on limited gradient algorithms (Samek et al., 2021). In contrast, a real neuron contains complex transformations of electrical and chemical signals and hosts numerous biochemical reactions, some of which remain unexplored by humans (Crowe et al., 2013).

The hierarchy of entity and rule provides methodological guidance for the algorithmic perspective. It reveals that the process by which humans utilize objective rules is gradual, progressing from the surface to the deeper interior, which aligns with the epistemological views of dialectical materialism.

4 | Algorithmic Collective Model

The algorithmic collective model is a general framework capable of explaining swarm intelligence phenomena, with strong applicability even when the research object is a group composed of heterogeneous individuals. Complex adaptive systems emphasize two components: adaptive agents and the modes of interaction. The mapping from CAS to the algorithmic collective model involves improvements to both components. First, it proceeds from the adaptive agent to the algorithmic unit. Second, it reconstructs the interaction rules of individuals. Finally, it achieves a unified explanation of emergent intelligence.

4.1 | Algorithmic Unit

The algorithmic unit is a collective term for the rule systems (individuals) that constitute a group. Its essence lies in *the algorithmization of agents*. Compared with the adaptive agent, the algorithmic unit no longer emphasizes adaptivity per se but rather emphasizes the unity of entity and rule, holding that everything about an agent—including its adaptivity—is the result of rule execution. Thus, the algorithmic unit offers both ontological and methodological advantages: (1) Thorough monism: Modeling an algorithmic unit is a transcription of its inherent internal rules; properties are products of its operation rather than independently acting factors. (2) Wide applicability: An algorithmic unit can be a piece of code, an ant, or a human employee, covering natural, social, and artificial systems. (3) Explicit representation of heterogeneity: Within the algorithmic unit framework, heterogeneity can manifest as differences in type, which can be represented more intuitively during modeling. (4) Higher operability: Algorithms are inherently decomposable, designable, and measurable, making the algorithmic unit more suitable than the adaptive agent for computational modeling and AI system design.

The algorithmic unit has several properties: (1) *Unity of entity and rule*, which is the foundational premise of the algorithmic unit—it possesses both the concreteness of an entity and the symbolic nature of expressing rule-based information. (2) As a rule system, the algorithmic unit exhibits the properties of general systems, such as purposiveness, wholeness, hierarchy, collectivity, relevance, and environmental adaptability. These are collectively referred to as the *systematicity* of the algorithmic unit.

Defining *the boundary of an algorithmic unit* is a central task in modeling a group. In specific studies, the selection of the research scope is characterized by purposiveness and subjectivity. Purposiveness means that the selection of the research object should be centered on meeting the research objectives. Subjectivity refers to the fact that, during the selection process, subjective factors may introduce certain errors into the outcome. Therefore, when defining the boundary of an algorithmic unit, the influence of subjectivity should be minimized while ensuring purposiveness. The group should neither be overly decomposed nor excessively blurred; the research value and efficiency should be balanced on scientifically sound and reasonable grounds.

4.2 | The Concept of the Collective

Various general usages exist for describing the concept of a group. For example, set theory uses "set" and "element" to describe groups and individuals (Hausdorff, 2021), while discrete mathematics uses "relationship" to describe the concept of a group, further characterizing group structure via Cartesian products (Biggs, 2002). However, both approaches neglect the characteristics of individuals. In the field of clustering, the term "cluster" is often used to describe a group, but it is limited to the spatial topological structure among individuals, completely ignoring individual attributes. In swarm intelligence, the term "swarm" emphasizes self-organization, emergent behavior, and distributed control, but it generally describes groups composed of a large number of simple, homogeneous individuals. "Collective," by contrast, is a sociological concept. It emphasizes that the connections among individuals are not merely spatial proximity but rather multidimensional complex relationships involving agency, identity, shared intentions, and social structures—aspects often overlooked in previous research (Wei et al., 2017). Compared with the scope of "swarm," "collective" views the group as a social collective, allowing individuals to be heterogeneous and possess a certain degree of cognitive capability. Collaboration may be achieved through communication, negotiation, task allocation, and role division. This offers advantages for research oriented toward AI. Furthermore, the agents used in multi-agent simulation typically possess knowledge, beliefs, goals, learning abilities, and memory mechanisms, enabling complex decision-making. Such agents have already moved beyond the traditional scope of "swarm" and are more compatible with "collective."

Definition of Algorithmic Collective: A complex system composed of a large number of algorithmic units that, under the influence of collective rules, interact and evolve to produce intelligence at the macro level.

4.3 | Conceptual Model

The algorithmic collective model is a modeling framework grounded in complex adaptive systems theory, integrated with the algorithmic perspective, and designed to describe general swarm intelligence phenomena. Its core idea is that any intelligent group can be deconstructed into algorithmized individuals. These individuals interact and act through multi-layered rules, ultimately giving rise to specific functions at the collective level.

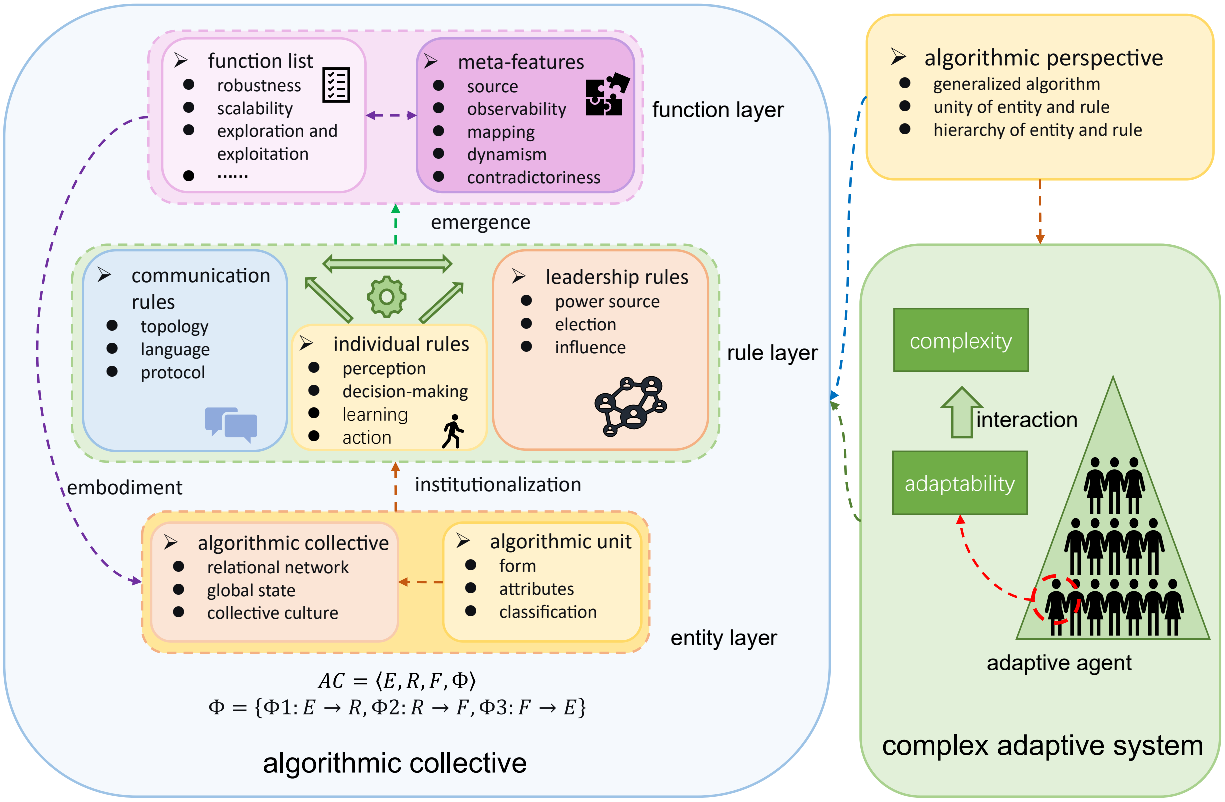
The model consists of three layers: the entity layer, the rule layer, and the function layer.

*Entity Layer***.** Located at the bottom of the model, the entity layer is the most fundamental part of the algorithmic collective. It is composed of a number of algorithmic units and their relational network, answering the question of "who constitutes the algorithmic collective." It specifies the form and connotation of algorithmic units, providing the "components" for the formation of intelligent collectives.

*Rule Layer***.** Located in the middle of the model, the rule layer serves as the bridge connecting the entity layer and the function layer. It consists of three parts: individual rules, communication rules, and leadership rules, answering the question of "how the algorithmic collective operates." It specifies the behavioral patterns of algorithmic units, the mechanisms of information exchange, and the organizational structure of the collective, serving as the "connecting wires" of the intelligent collective.

*Function Layer***.** Located at the top of the model, the function layer describes the emergent properties of the algorithmic collective at the macro level, answering the question of "what the algorithmic collective can do." It is the finished product built from the "components" through the "connecting wires."

Exhibit 1. Conceptual model of algorithmic collective .



A dynamic feedback regulation loop is formed among the three layers of the algorithmic collective architecture, which is the key pathway through which the collective generates complexity. The loop comprises three processes: institutionalization, emergence, and embodiment.

Institutionalization: Entity layer → Rule layer. Individuals at the entity layer, under the governance of rules, form a regularized collective network. The regularities provided by the rule layer can be regarded as "collective culture" that individuals adhere to.

Emergence: Rule layer → Function layer. Individuals interact according to the rules, ultimately enabling the collective to generate properties and functions that the individuals do not possess.

Embodiment: Function layer → Entity layer. The emergent functions act back upon the individuals, affecting their state or structure.

This feedback regulation loop can be summarized as "entities follow rules, rules give rise to functions, and functions reshape entities," making the algorithmic collective a dynamically evolving complex system.

The formal representation serves as the mathematical foundation for simulation based on the algorithmic collective model. Algorithmic collective can be preliminarily represented as:

$$AC = \langle E, R, F, \Phi \rangle \tag{1}$$

$$\Phi = \{\Phi_1: E \rightarrow R, \Phi_2: R \rightarrow F, \Phi_3: F \rightarrow E\} \tag{2}$$

Here AC denotes the algorithmic collective, E represents the set of entities, R represents the set of rules, F represents the set of functions, and Φ represents the set of mapping relationships among the entity layer, rule layer, and function layer.

The algorithmic collective decomposes collective rules into three parallel sub-rules, which are designable, controllable, and measurable. It emphasizes that complexity emerges from multi-layered rules, which deconstruct the nonlinear interactions within a group, clearly enumerating the interactive behaviors, and thereby providing a handle for modeling and simulation. The process by which the entity layer gives rise to the function layer through the rule layer is, under the algorithmic perspective, a mapping of "adaptation building complexity." The feedback regulation loop of the algorithmic collective is the necessary pathway through which a group adapts to its environment and self-advances.

5 | Components

This section elaborates on the components of the model to demonstrate its connotation and function. The three layers of the model are the entity layer, the rule layer, and the function layer. The rule layer, as the core layer of the model, is further divided into three sub-rules.

5.1 | Entity Layer

The entity layer is the foundational layer of the algorithmic collective, consisting of a number of algorithmic units and their relational network. The unity of entity and rule implies that an algorithmic unit is not an entity independent of rules but rather a follower and executor of rules. Therefore, an algorithmic unit should possess the basic attributes necessary to support rule execution.

This study summarizes three types of attributes: state attributes, behavioral attributes, and relational attributes. *State attributes* describe the state changes of an algorithmic unit during rule execution and determine the initial conditions for its learning, such as memory, belief, and goal (Wooldridge & Jennings, 1995). *Behavioral attributes* describe the constraints on an algorithmic unit's rule execution, such as communication radius, maximum speed, and action frequency. *Relational attributes* describe the position of an algorithmic unit within the collective and determine how it executes communication rules and leadership rules, such as identity, role division, and network neighbors (Kay et al., 2024).

According to the complexity of behavioral decision-making, algorithmic units can be roughly classified into three types: simple reflexive, goal-driven, and learning-adaptive. Simple reflexive refers to simple individuals that only respond to environmental stimuli. Goal-driven refers to individuals that make decisions based on preset goals. Learning-adaptive refers to individuals that possess advanced memory and learning capabilities, enabling self-iteration based on experience (Joyce & Maheshwari, 2025).

5.2 | Rule Layer

Through observation and summarization of numerous swarm intelligence phenomena, three major types of rules have been distilled: individual rules, communication rules, and leadership rules.

The rule layer classifies the mechanisms influencing algorithmic units within a collective into two categories: active influence and passive influence. Active influence manifests as information exchange actively initiated among algorithmic units. Its defining characteristic is optionality, and these rules are collectively termed communication rules. Passive influence manifests as constraints on algorithmic units arising from external factors such as identity differences and role division. Even without active interaction, algorithmic units are asymmetrically affected by their position within the collective (Knippenberg & Ellemers, 1990). Its defining characteristic is coerciveness, and these rules are collectively termed leadership rules. Furthermore, individual rules serve as the foundation for both, providing the basic capabilities necessary for algorithmic units to execute communication and respond to organization.

It should be emphasized that algorithmic units in actual research are not required to possess all of the mechanisms listed below.

Individual Rules. Individual rules refer to rules related to the behavior of an algorithmic unit itself. They can be divided into perception rules, decision-making rules, learning rules, and action rules (Whitehead, 1991).

Perception rules specify how an algorithmic unit obtains external information, e.g., perception radius, perception frequency, perception accuracy. Differences in perception rules affect the quality of information obtained by the algorithmic unit, thereby influencing its decision-making and action.

Decision-making rules specify the basis for an algorithmic unit's actions. Common decision-making rules include greedy algorithms, random selection, utility evaluation, and game-theoretic strategies.

Learning rules specify how an algorithmic unit updates its behavior from experience, including learning methods and memory mechanisms. Algorithmic units without learning rules exhibit more rigid behavioral patterns, and the intelligence of the collectives they form is also lower compared to those with learning rules.

Action rules specify the ways in which an algorithmic unit affects the external environment. Common mechanisms include action mode and action conditions.

Communication Rules. Communication rules describe the mechanisms of information exchange among algorithmic units. Based on the mechanisms of information exchange, they can be divided into three subcategories: communication topology, communication content, and communication protocol (Ash, 1990).

Communication topology specifies the propagation structure of information, i.e., "who can communicate with whom." Common types of communication topology include global broadcast, neighborhood broadcast, unicast, and multi-target propagation.

Communication content specifies the form and semantics of information, determining the types of knowledge that can be shared among algorithmic units. The richer the communication content, the greater the potential for collaboration among algorithmic units, but communication costs also increase.

Communication protocol specifies the standards for information interaction, ensuring that information can be effectively transmitted between senders and receivers, including information encryption and decryption. Especially in heterogeneous groups, establishing a unified communication protocol is a fundamental prerequisite for cross-type interaction.

Leadership Rules. The core questions addressed by leadership rules are "why does asymmetric influence exist in an algorithmic collective?" and "how does this influence act upon the collective?" Leadership rules include three subcategories: sources of power, leadership election, and leadership influence.

Sources of power constitute the material foundation of leadership rules and the ultimate source of differences in influence among algorithmic units. They reveal that an algorithmic unit unintentionally influences other individuals because it possesses advantages in certain dimensions, such as information advantage (Carpin & Parker, 2002), structural advantage (Chen et al., 2025), and prestige advantage (Sirait, Afrimadona, & Eriyanto, 2022).

Leadership election specifies the mechanism by which leaders are generated within a collective (Pennisi & Giallongo, 2018). Common election methods include spontaneous emergence, external appointment, and democratic election.

Leadership influence specifies how a leader affects other individuals. Sometimes this influence is passive, arising from identity differences rather than active intervention. Based on the degree of activeness, leadership influence can be divided into three subcategories: direct command (the leader issues commands directly to other individuals, who are forced to obey and execute; this approach relies on active information propagation and is suitable for hierarchical organizational structures; its advantages are clarity and high efficiency, while its disadvantage is poor flexibility), indirect guidance (the leader influences the behavior of other individuals by releasing signals without affecting their strategy selection, only their decision-making environment) (Blum, 2005), and role modeling (the leader does not actively intervene in other individuals at all but is passively imitated by them) (Manz & Sims Jr, 1981).

5.3 | Function Layer

The function layer describes the macro-level properties emergent from the algorithmic collective that individual units do not possess. Classic properties include robustness (the collective's ability to resist interference), scalability (the ability to incorporate new individuals), self-organization (individuals spontaneously forming ordered structures through interaction without central control), exploration ability (the collective's ability to find solutions in new spaces), exploitation ability (the collective's ability to find solutions in known spaces), and emergence (macro-level properties that are generally unpredictable and cannot be simply decomposed into individual-level explanations). An algorithmic collective typically possesses multiple functional properties; therefore, compiling a function list is of considerable value for studying an algorithmic collective.

The function layer exhibits systemic *meta-features*, comprising five points: (1) *Source of functions*: The function layer originates from interactions at the rule layer rather than being a direct result of properties at the entity layer. Individuals must engage with the rule layer to participate in the formation of collective functions. (2) *Observability of functions*: The function layer is observable. The observation methods and scales vary across different functions. For example, scalability is relatively straightforward to observe, whereas robustness and adaptability require indirect observation using indicators. (3) *Mapping relationship between the function layer and the rule layer*: The mapping relationship includes mapping variables and mapping conditions. The mapping variables are rules and functions, and the relationship between them is many-to-many. Mapping conditions refer to the specific conditions under which the mapping between variables holds. Revealing the mapping variables and mapping conditions is one of the goals of analyzing the function layer. (4) *Dynamism of functions*: Functions are dynamic. The dynamism of functions arises from functional feedback. Functions affect algorithmic units through embodiment, thereby promoting changes in the algorithmic collective. (5) *Contradictoriness of functions*: The function layer contains internal contradictions, meaning that multiple functions cannot be simultaneously optimized. For example, exploration and exploitation are mutually exclusive functions in organizational learning. When a collective's exploration ability is optimal, its exploitation ability is necessarily sacrificed (March, 1991). The relationship between the number of individuals and overall efficiency exhibits a U-shaped curve, revealing that a collective does not necessarily become more efficient as its size increases (Schranz et al., 2021).

6 | Applications

The value of the algorithmic collective model lies in providing a general and scientific framework to assist researchers in decomposing and analyzing swarm intelligence phenomena. Its advantages are compatibility, operability, and cross-domain generality. This section will validate the model using the particle swarm optimization (PSO) algorithm and its variants as an example, followed by an analysis of the model's limitations and future studies.

6.1 | Analysis of the PSO

The PSO is a SIAs that simulates the flight of birds. It was proposed by Kennedy and Eberhart in 1995 (Kennedy & Eberhart, 1995) and has since given rise to thousands of variants. The following provides an intuitive presentation of the analysis of PSO and a classification of the improvements made to its variants.

Exhibit 2. Analysis of PSO .

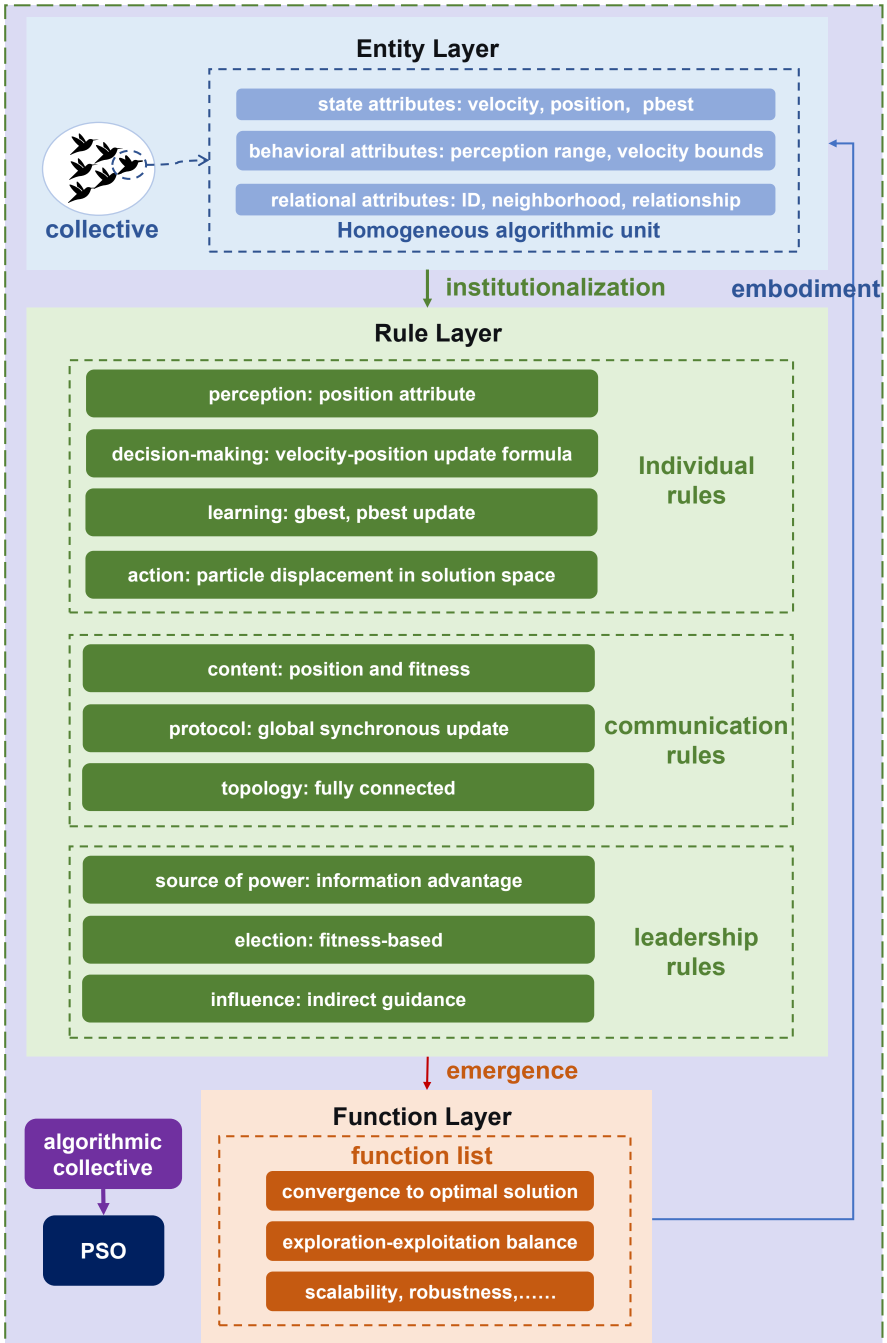


Exhibit 3. Analysis of Several Variants of PSO.

Abbreviation	Entity layer	Rule layer			Function layer
		Individual rules	Communication rules	Leadership rules	
LDPSO (Zhao, Zhou, & Zhou, 2025)	Leader-folloer heterogeneous division of labor	bidirectional search (leaders) + unidirectional search (followers)	bidirectional communication between leaders + weighted broadcast	spontaneously generated based on performance, with number dynamically decreasing	accuracy and robustness optimization
DPSO (da Costa et al., 2026)		introduce modulation term to update velocity		global best particle serves as reference center, particles are repelled away	enhance particle diversity, improve exploration ability
CLPSO (Yu & Zhang, 2014)		introduce inertia term and learning term to update velocity	independent communication of each particle attribute	no global best, each particle makes independent decisions	enhance particle diversity, improve exploration ability
ELPSO-C (Hayashida et al., 2025)		adaptively select mutation intensity based on stagnation degree		reinforce the leading particle, apply perturbation only to stagnant dimensions	control diversity dimension by dimension in high-dimensional problems to avoid premature convergence
HGCLPSO (Wang, Li, & Li, 2025)	heterogeneous subgroup GLS subgroup(exploitation) CLS subgroup (exploration)	GLS: genetic recombination to generate exemplar; CLS subgroup embeds repulsion mechanism	global topology of GLS subgroup and cross-particle learning of CLS subgroup	dual-leadership structure: GLS uses gbest for exploitation, CLS uses decentralized exploration	PEGA mechanism enhances exploitation ability; BFGS for local fine search

DPSO-MLS (Tian et al., 2024)	initial population generated by combining chaotic mapping and opposition-based learning	attract to accelerate convergence when diversity is high, repel to increase exploration when diversity is low; embed multiple local search strategies		repel gbest when diversity is low, push away converging particles	balance exploration and exploitation
DPCL-PPSO (Jiao et al., 2025)	pyramid hierarchical structure: winners in the upper layer, losers in the lower layer	loser particles learn with differentiated probability	cross-layer communication within pyramid topology	winners guide losers, losers can learn across levels	enhance diversity, improve convergence speed and accuracy

Exhibit 3 presents the improvements made by variants of PSO. Some variants improve a single layer, while others involve improvements across multiple layers. The algorithmic collective model can intuitively illustrate their work.

6.2 | Limitations and Future Studies

At present, the model remains an initial form and has several limitations: (1) Algorithmic perspective: The idea of algorithmizing objects is merely a rough epistemological shortcut. As human understanding of the world deepens, it will eventually be superseded, even though it still possesses some applicability at present. (2) Model structure: The three-layer architecture is only one perspective for deconstructing swarm intelligence, and this perspective is more aligned with the field of AI than with biosociology. (3) Model functionality: The model is closer to a descriptive framework than to a predictive theory; its realized functions are limited, and further development potential remains.

Future research can be pursued along two directions: (1) Exploring the influence mechanisms between different layers, e.g., how entity attributes constrain rule design, how rule parameters quantitatively affect functional outputs, and through which pathways functional feedback reshapes the entity layer. (2) Promoting the quantification of the model. Transforming the existing conceptual framework into a computable mathematical model to enable the application of the model in simulations and to advance research in the fields of AI and SI.

7 | Conclusion

This study provides a new theoretical perspective for explaining the emergence mechanisms of SI—the algorithmic collective model. It introduces the model's philosophical foundation, construction approach, structure, and functions. The core contribution of the model lies in deconstructing the complexity of SI into analysable and designable rule hierarchies, thereby describing the dynamic generation path of collective intelligence from micro-level interactions to macro-level performance. Finally, the PSO is used as an example for validation. The current work constitutes a fundamental theoretical construction. Future studies will focus on promoting the formalisation and quantification of the model, exploring the quantitative laws of cross-layer interactions, so as to support broader applications in CAS modelling and AI.

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