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***Perspective:***

# Four development stages of collective intelligence*

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**Abstract:** The new generation of artificial intelligence (AI) research initiated by Chinese scholars conforms to the needs of a new information environment changes, and strives to advance traditional artificial intelligence (AI 1.0) to a new stage of AI 2.0. As one of the important components of AI, collective intelligence (CI 1.0), i.e., swarm intelligence, is developing to the stage of CI 2.0 (crowd intelligence). Through in-depth analysis and informative argumentation, it is found that an incompatibility exists between CI 1.0 and CI 2.0. Therefore, CI 1.5 is introduced to build a bridge between the above two stages, which is based on bio-collaborative behavioral mimicry. CI 1.5 is the transition from CI 1.0 to CI 2.0, which contributes to the compatibility of the two stages. Then, a new interpretation of the meta-synthesis of wisdom proposed by Qian Xuesen is given. The meta-synthesis of wisdom, as an improvement of crowd intelligence, is an advanced stage of bionic intelligence, i.e., CI 3.0. It is pointed out that the dual-wheel drive of large language models and big data with deep uncertainty is an evolutionary path from CI 2.0 to CI 3.0, and some elaboration is made. As a result, we propose four development stages (CI 1.0, CI 1.5, CI 2.0, and CI 3.0), which form a complete framework for the development of CI. These different stages are progressively improved and have good compatibility. Due to the dominant role of cooperation in the development stages of CI, three types of cooperation in CI are discussed: indirect regulatory cooperation in lower organisms, direct communicative cooperation in higher organisms, and shared intention based collaboration in humans. Labor division is the main form of achieving cooperation and, for this reason, this paper investigates the relationship between the complexity of behavior and types of labor division. Finally, based on the overall understanding of the four development stages of CI, the future development direction and research issues of CI are explored.

**Key words:** Collective intelligence; Meta-synthesis of wisdom; Incompatibility; Labor division; Cooperative behavior; Collective intelligence emergence; Large language model
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## 1 Presentation of the problem

The Dartmouth Conference in 1956 is generally recognized as the starting point of artificial intelligence (AI), and the Summer Research Project on Artificial Intelligence held in Dartmouth (USA) in the same year marked the birth of the emerging discipline (Nick, 2017). In the past 60 years, AI has made great progress, with some ups and downs and three low points (Pan, 2016), but in general, it has developed rapidly. At present, three major schools of AI research have been formed: symbolism (functionalism), connectionism (structuralism), and behaviorism (evolutionism). In response to the coexistence of these three schools, Zhong (2018) regarded the mechanistic AI theory as a general AI theory and tried to realize the unification of the three schools under the framework of mechanistic AI theory. Zhang B et al. (2023) proposed the concept of "third generation AI," which is a fusion of the first generation of knowledge-driven AI and the second generation of data-driven AI, and its core is to establish new interpretable and robust AI theories and methods using four elements—knowledge, data,

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algorithms, and computing power, and to develop secure, trustworthy, reliable, and scalable AI technologies.

With the emergence of a new information environment (the popularity of the Internet, the penetration of sensor networks, the emergence of big data, and the rise of information communities) and the cross-fertilization and interaction of data and information in the human society, physical space, and information space, the external environment and databases in which the development of AI today is taking place have undergone profound changes. The scientific basis and implementation vehicle of AI are facing breakthroughs and are moving to a new stage. This new generation of AI, which originates from traditional AI but is different, is called artificial intelligence 2.0 (AI 2.0) (Pan, 2016). In December 2015, the Chinese Academy of Engineering (CAE) approved the implementation of the major consulting research project, "China AI 2.0 Development Strategy Research," and took the lead in proposing and launching the "AI 2.0 Plan" (China Artificial Intelligence 2.0 Development Strategy Research Project Team, 2018). The project team completed the preparation of the "Research Report on the Planning Proposal of New Generation Artificial Intelligence" and the "Implementation Plan of Major Science and Technology Projects of New Generation Artificial Intelligence" and proposed the core concept of AI 2.0 in 2016 (Pan, 2016). In July 2017, the State Council of People's Republic of China issued the "Development Plan for New Generation Artificial Intelligence," indicating that the research on new generation AI has become the national will.

The "Development Plan of New Generation Artificial Intelligence" specifies five main directions in terms of basic theoretical systems, i.e., big data intelligence, cross-media perceptual computing, human–computer hybrid intelligence, crowd intelligence, as well as autonomous collaboration and decision-making. Among them, the research of crowd intelligence theory focuses on breaking through the theory and methods of organization, emergence, and learning of crowd intelligence, and forming a theoretical system of crowd intelligence based on the Internet.

Calling the new generation of AI 2.0 is relative to traditional AI, which implies that traditional AI is at the stage of AI 1.0. Wu F et al. (2020) is a panoramic showcase of literature on the development of AI in China. It discusses the main development directions and national level planning of AI, provides an in-depth interpretation of China's experience in industry–academia–research cooperation, provides practical application results, and depicts a blueprint of the future AI development ecosystem.

Collective intelligence (CI) can be seen as an intelligence form that is different from individual intelligence. It originated from the observation, analysis, and study of the behavior of organisms living in groups in nature, and the overall intelligence level emerging from the group in this form often exceeds the intelligence level of its constituent individuals (Xiao, 2013). CI is an important part of AI and, accordingly, CI under AI 2.0 should be rightly called CI 2.0, which has the core connotation of Internet-based CI, while traditional CI based on social insect behavioral mimicry should be called CI 1.0. In recent years, human CI has received more and more attention (Bernstein et al., 2018; Wu LF et al., 2019; Riedl et al., 2021). Environmental excitation effects provide an ex-post explanatory model for the emergence of CI phenomena. Based on the concept of environmental excitation effects, Zhang W and Mei (2020) focused on how to construct CI systems for the solution of specific problems, whereby a constructive model of CI was proposed which consists of three loops for information excitation, fusion, and feedback; individuals explore and form fragments, achieve integration, and then conduct feedback, through multiple iterations to form a solution. All these works should be classified under the category of CI 2.0.

There is currently a distinction between CI 1.0 and CI 2.0, including two different development stages. Is there an overall compatibility and correlation between CI 1.0 and CI 2.0? In the following, we provide an answer through analysis and explanation.

## 2 Incompatibility of the two stages of CI

### 2.1 Incompatibility analysis

With the evolution of science and technology and human society, CI has been given different meanings in different disciplines or fields, and its research directions are different (Xiao et al., 2022). In general, it can be divided into two major categories: one is biocentric and the other is human-centric. For example, Bonabeau et al. (1999) proposed a definition of CI in their study of natural organisms' behavior; i.e., any algorithm or distributed problem-solving strategy inspired by the social behavior mechanisms of swarming insects and other organisms is CI. They referred to this kind of biocentric CI as swarm intelligence. Li W et al. (2017) proposed a new form of CI in the era of AI 2.0, arguing that CI under AI 2.0 provides a new mode of gathering the wisdom of human groups to solve problems, which is compatible with the rapid development of the sharing economy. They called such human-centered CI as crowd intelligence, denoted as CrI in this paper. In general, CI 1.0 corresponds to swarm intelligence, while CI 2.0 corresponds to crowd intelligence.

Swarm intelligence (CI 1.0) originated from the exploration of group behavior in social organisms, such as ant colonies, bird swarms, and bee colonies. Although the behavior of a single individual is simple and limited in capability, the population as a whole could show strong self-regulation, survival ability, and the ability to accomplish complex tasks (Lin et al., 2018). Swarm intelligence has developed rapidly in the field of CI, and the research content and results are quite rich, so its concept is relatively clear. It generally refers to the simulation of CI of organisms such as plants and animals, mainly social insects, i.e., the overall intelligent behavior generated by the emergence of many individuals with simple behaviors in the process of interaction. Crowd intelligence (CI 2.0) can be understood as CI with human individuals, which is also called group intelligence or throng intelligence in Chinese, and is an emerging concept of CI. The participants of crowd intelligence are generally limited to highly intelligent bodies such as human beings, and the emphasis of crowd intelligence is on the phenomenon of intelligence emerging from the interconnected and collaborative behaviors of a large number of participants using networks and social media as channels (Li W et al., 2017). Specificallly, with the development of network technology and the popularity of mobile terminals, the development of crowd intelligence gradually shifts to the idea of integrating human intelligence with intelligent machines, so crowd intelligence will become the main research direction in the field of CI in the future (Predic and Stojanovic, 2015).

Swarm intelligence is also often referred to as group intelligence or cluster intelligence (Xiao, 2013). At the individual level, swarm intelligence emphasizes simplicity, e.g., the similar and low level of intelligence of its individuals, as well as the local perception and local interaction capabilities between individuals. At a holistic level, however, swarm intelligence exhibits emergent properties (Kennedy et al., 2001). The core idea of crowd intelligence is that a collection of human individuals can acquire knowledge and intelligence (emergence of wisdom) at a much higher level than that of a single individual at a holistic level through various types of interactions among individuals. Thus, both swarm intelligence and crowd intelligence exhibit holistic emergence, although there are significant differences in the way they are realized.

Swarm intelligence emphasizes the emulation of typical behaviors of biological prototypes (mainly swarming lower-level organisms, such as social insects) (Xiao, 2013), and the individual behaviors in the group tend to be simplified (mainly the foraging behavior of lower organisms) and follow simple rules. For example, the particle swarm optimization algorithm is an abstraction of the search and seek process of bird foraging behavior; the flock searches for food randomly in a certain area, and there is only one piece of food in this area. Birds do not know where the food is placed, but they know how far the current location is from the food. Obviously, the simplest and most effective strategy to find the food is to search the area around the bird that is currently the closest to the food, and during this search process, each bird determines its flight rate and direction based on the "vector sum" of three quantities: (1) the current rate and direction; (2) the global optimal position; (3) the optimal position experienced by the bird itself. Similar to flock foraging, the flight of a flock of birds follows simple rules. Reynolds (1987) showed that the artificial bird (Boid) follows the following rules when flying: (1) separation rule—it does not get too close to anything, including other Boids; (2) alignment rule—it tries to keep its speed in line with the speeds of other Boids around it; (3) cohesion rule—in any case, it should move towards the center of the group composed of nearby Boids.

Crowd intelligence is the imitation of crowd behavior. It has significant differences from swarm intelligence. As is the spirit of all things, the individual behaviors of people in their groups tend to be diversified, and they are generally difficult to refine into simple rules. Since crowd intelligence imitates diverse human behaviors (mainly cooperative behaviors), it is difficult to generalize and refine the typical behaviors of crowds as biological prototypes, and therefore, crowd intelligence lacks typical behaviors as a basis for biological prototypes. In other words, the diversity and complexity of crowd behaviors lead to the lack of bionic prototypes of crowd intelligence in specific situations. There are many quantitative studies on crowd intelligence. However, they are generally targeted at specific domains, e.g., opinion dynamics (Chen and Xiao, 2023), and crowd intelligence is difficult to refine into generalized rules. In contrast, swarm intelligence is based on quantitative study and generally adopts a reductionist research paradigm, which matches existing general scientific norms (i.e., the subdiscipline of research in different categories). It is more suitable for solving optimization-type allocation problems (Xiao et al., 2022) and has a strong interpretability. In contrast, the research paradigm of crowd intelligence is closer to emergentism, highlighting cross-integration. It is suitable for solving coordination-based allocation problems (Xiao et al., 2022), but is less interpretable.

Swarm intelligence is clearly at the lower hierarchy of intelligence compared with crowd intelligence, while crowd intelligence embodies a higher level of intelligence. Table 1 is a general summary of the above comparative analysis of swarm intelligence and crowd intelligence, from which it is clear that there is a difference; as two stages of CI, they need to be examined in terms of their compatibility, that is, whether they are compatible.

Even in different development stages, there should be a certain correlation relationship, that is, harmony in diversity. If they are natural promotions, they are compatible. If they are unnatural promotions, they should be analyzed for specific problems. Fig. 1 shows the compatibility analysis diagram of the two development stages of CI. In this diagram, the hollow arrow represents natural promotion, and the hollow arrow with a fork represents unnatural promotion. From Fig. 1, it can be seen that swarm intelligence is a component of traditional AI. In response to the impact of the new information environment, AI 1.0 develops to the AI 2.0 (new generation AI) stage, which is a natural promotion process. Crowd intelligence is one of the five main directions of the new generation of AI. Fig. 1 also shows that the natural promotion path directly from CI 1.0 to CI 2.0 does not exist (as shown by the hollow arrow with a fork in Fig. 1). The promotion from CI 1.0 to CI 2.0 is generated indirectly through the path of CI 1.0→AI 1.0→AI 2.0→CI 2.0 (as shown by the clockwise arrow in Fig. 1).

Since swarm intelligence to crowd intelligence is an unnatural promotion, its compatibility depends on the analysis of specific problems. As we can see from Table 1, swarm intelligence is biocentric, while crowd intelligence is human-centric. It is obvious that there is a fundamental difference between swarm intelligence and crowd intelligence, and it is difficult for them to coexist as one, so they are not compatible.

## 2.2 Resolving the incompatibility between swarm intelligence and crowd intelligence

To resolve the incompatibility between swarm intelligence and crowd intelligence, it is necessary to

**Table 1 Comparison of swarm intelligence and crowd intelligence**

| Comparison item | Swarm intelligence | Crowd intelligence |
|---|---|---|
| Bionic prototype | Relying on the typical behavior of biological prototypes | Lack of typical behavior of biological prototypes |
| Major bionic behavior | Foraging behavior of lower organisms | Diverse human behaviors dominated by cooperative acts |
| Individual behavioral characteristic | Simplification | Diversification |
| Research paradigm | Reductionism | Emergentism |
| Suitable question type | Optimal allocation problem | Coordinated allocation problem |
| Interpretability | Strong | Weak |
| Intelligence level | Low | High |

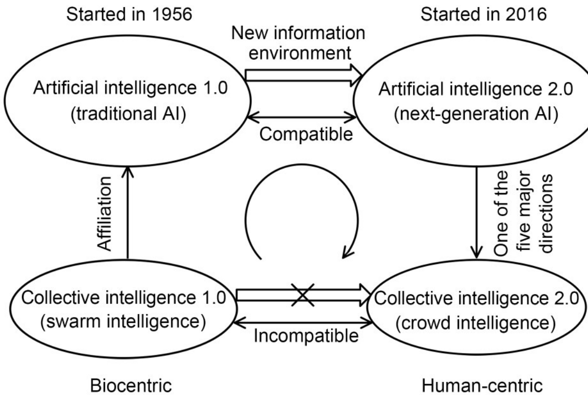


**Fig. 1 Compatibility analysis diagram**

construct a transition bridge to establish the relationship between them. This bridge is in the middle of CI 1.0 and CI 2.0, so we named it CI 1.5.

At present, swarm intelligence mentioned in the relevant domestic research has an established meaning in general and often refers specifically to swarm intelligence optimization, represented mainly by ant colony optimization and particle swarm optimization (Xiao, 2013). Swarm intelligence optimization deals mainly with the optimization-type allocation problem by mimicking the foraging behavior of swarming organisms; we are committed to advocating the development path from swarm intelligence optimization to swarm intelligence evolution, and propose the mainstream direction of the future development of swarm intelligence, namely, swarm intelligence evolution (Xiao and Chen, 2023). The basic connotation of swarm intelligence evolution refers mainly to CI 1.5 in Xiao and Chen (2023), which is a cooperative behavioral mimicry dominated by non-foraging behaviors (e.g., labor division) of swarming organisms to solve the coordination-type allocation problem. CI 1.5 is dominated by swarm intelligence evolution. CI 1.5 is biocentric and still belongs to the category of swarm intelligence. However, it abandons the traditional swarm intelligence that simulates mainly the foraging behavior of lower-level organisms and focuses on the mimicry of the cooperative behavior of swarm-dwelling organisms, which is again close to crowd intelligence.

It follows that with the help of the connecting role of CI 1.5, taking it as the transition between swarm intelligence and crowd intelligence, a natural articulation between swarm intelligence and crowd intelligence can be established, making them compatible. This is consistent with the idea of extenics when solving practical problems (Cai and Yang, 2013).

## 3 CI 1.5

### 3.1 Research significance of CI 1.5

The core concept of CI 1.5 is to solve the coordinated allocation problem employing a bionic pathway for the cooperative behaviors of swarming organisms, which covers both lower and higher organisms. By imitating the non-foraging behaviors of lower organisms and the complex behaviors of higher organisms, it seeks to build a bridge between swarm intelligence and crowd intelligence and establish an articulation between them to achieve compatibility between swarm intelligence and crowd intelligence.

Some research results on the non-foraging behaviors of lower organisms (e.g., labor division) are available. Xiao and Wang (2019) provided a corresponding review and analysis. However, existing bionic research on higher organisms focuses mainly on search-dominated merit-seeking behaviors, and the bionic research on the cooperative behaviors of higher organisms appears to be somewhat weak.

### 3.2 Research scope of CI 1.5

The following discussion of the main research components of CI 1.5 aims to illustrate which studies fall within the scope of CI 1.5 by specifying its boundaries.

#### 3.2.1 Non-foraging behavioral bionomics in lower organisms

Currently, swarm intelligence generally refers specifically to swarm intelligence optimization, which is usually embodied in the form of algorithms. These optimization algorithms are inspired mainly by the foraging behavior of lower swarming organisms, and three of the most influential swarm intelligence optimization algorithms (ant colony optimization algorithm, particle swarm optimization algorithm, and artificial bee colony algorithm) are all bionomics of the foraging behavior of lower swarming organisms; for example, the ant colony optimization algorithm is a simulation of the foraging behavior of an ant colony that finds the shortest path from its nest to a food source (Li SY et al., 2019). In addition, the bacterial foraging optimization algorithm is a bionic global stochastic search algorithm based on the theory of a biological model of bacteria *Escherichia coli* that mimics its foraging behavior (Passino, 2002); the sparrow search algorithm is a swarm intelligence optimization algorithm that simulates the foraging behavior and anti-predatory behavior of sparrows (Xue and Shen, 2020); the crow search algorithm mimics the social behavior of crow groups tracking each other to steal food (Askarzadeh, 2016); the beetle antennae search algorithm is a new swarm intelligence optimization algorithm inspired by the foraging principles of the aspen (Jiang and Li, 2018). Other such algorithms have also been proposed and are not listed in this paper.

The bionics of lower organisms in swarm intelligence focuses on foraging behavior for the following main reasons: (1) foraging behavior is relatively intuitive and rule-based, and is suitable for building optimization models and is convenient for normative research; (2) swarm intelligence optimization is performed based on search, and foraging behavior is a relatively simple search, which is in a fundamental position compared to the positions of other more complex searches (e.g., echolocation of bats).

However, the imitation of the foraging behavior of lower organisms is generally effective only in solving optimization problems. From the perspective of resource endowment, the problem to be solved in a broad sense can be essentially reduced to an allocation problem in the presence of limited resources—the resource allocation problem, as economics defines (Samuelson and Nordhaus, 2010). The resource allocation problem is usually referred to as the allocation problem (allocation problem), and solving the allocation problem usually involves pursuing optimization, which is a kind of generalized convergence, while the optimization problem is subject to the expression form of mathematical models, which is only a kind of narrow optimization. Accordingly, allocation problems are classified generally into two major types: optimal allocation problems in relatively steady state situations and coordinated allocation problems in complex dynamic situations (Xiao and Chen, 2023). In the swarm intelligence bionomics with lower organisms as the target, the imitation of foraging behavior solves the optimal allocation problem, while imitating foraging behavior is hardly effective in solving the coordinated allocation problem. What needs to be imitated is the non-foraging behavior of lower organisms, which focuses on cooperative behavior with labor division as the main focus, so swarm intelligence goes beyond the scope of CI 1.0 and takes a step toward crowd intelligence, thus becoming the group component of CI 1.5.

There have been many studies at home and abroad regarding labor division in swarm intelligence. We have undertaken systematic discussions (Xiao and Tao, 2007; Xiao, 2013) and will not repeat them here.

#### 3.2.2 Complex behavioral bionomics in higher organisms

The higher organisms referred to here are pack-like but do not include human beings. The typical representatives include wolf packs and lion packs. The behavior of higher organisms tends to be more complex (mainly cooperative behavior) than the behavior of lower organisms (mainly foraging behavior), and the imitation of the complex behavior of higher organisms is yet to solve the coordinated allocation problem.

Compared with the foraging behavior of lower organisms, the hunting behavior of higher organisms (e.g., wolf pack hunting) is much more difficult and depends on the close cooperation between higher organisms, so hunting is fundamentally a cooperative behavior.

There are also certain bionomic studies on the hunting behavior of higher organisms, such as the wolf pack algorithm (WPA), proposed to mimic the hunting behavior of wolves (Wu HS and Xiao, 2020). As a cooperative behavior, its subject behavior should be dominated by cooperation, and its search mode should be dominated by exploration (Xiao and Chen, 2023). There are obvious limitations in the proposed WPA: its subject behavior is dominated by competition, its search mode is dominated by exploitation, and it fails to deeply explore the cooperation mechanism implied by wolf hunting behavior. So, WPA still belongs to the scope of CI 1.0.

The bionic research on lion groups has a similar problem; that is, it does not pay sufficient attention to the cooperative behavior of lion groups but sticks to proposing a new optimization algorithm. The simplistic understanding of the behavior of a pride of lions inevitably leads to a situation where the blind man sees the elephant, resulting in the formation of multiple different lion pride optimization algorithms (Rajakumar, 2012; Wang B et al., 2012; Yazdani and Jolai, 2016; Liu et al., 2018) based on the local phenomenal bionomics relied upon, without correlation between them.

Compared to lower bionomics, higher bionomics is much more difficult, an important reason being the difficulty of conducting controlled experiments (e.g., binary bridge experiments for ant colonies (Bonabeau et al., 1999)) and the lack of effective means of testing and validation as in the case of lower organisms.

Research on complex behavioral bionomics (mainly cooperative behavior) in higher organisms is still rare, and it is of more importance for CI 1.5 as a high-end part of it. Therefore, it is a focus of future research attention and a frontier to be explored.

#### 3.2.3 Comparative analysis of the development stages of CI

A new CI stage, CI 1.5, is introduced above to bridge the gap from CI 1.0 to CI 2.0, making the three development stages of CI (CI 1.0, CI 1.5, and CI 2.0) into a compatible whole. Table 2 presents a comparison of the different development stages of CI, from which the following issues can be ascertained:

1. CI 1.5 is a transitional stage between CI 1.0 and CI 2.0, and has the characteristics of both CI 1.0 and CI 2.0. In terms of biological prototypes, CI 1.5 is similar to CI 1.0; in terms of major bionic behaviors and appropriate problem types, CI 1.5 is similar to CI 2.0.

2. As shown in Table 2, the imitations of (1) and (2) belong to CI 1.0, and those of (3) and (4) belong to CI 1.5, thus clearly distinguishing between CI 1.0 and CI 1.5.

3. In Table 2, (1) has been extensively studied at home and abroad, and (2) and (3) have also been studied somewhat. However, there are fewer studies on (4), which needs to be explored. It will become a major research field in the future.

#### 3.2.4 A brief summary

The main features of CI 1.5 are briefly explained here. The bionic prototype of CI 1.5 is still an organism rather than a crowd; from this point of view, it is similar to CI 1.0, and still belongs to the category of swarm intelligence. However, the bionic behavior of CI 1.5 is mainly cooperative behavior. In view of such a situation, CI 1.5 demonstrates differences from CI 1.0 but is close to CI 2.0, which imitates crowd cooperation behavior. Therefore, CI 1.5 is between CI 1.0 and CI 2.0 and constructs a bridge from swarm intelligence to crowd intelligence.

## 4 Meta-synthesis of wisdom as CI 3.0

Section 3 builds a bridge between swarm intelligence and crowd intelligence (CI 1.5) by dissolving the incompatibility between them and forming a compatible overall architecture of CI. This new architecture

**Table 2 Comparison of different development stages of collective intelligence (CI)**

| Comparison item | CI 1.0 | CI 1.5 | CI 2.0 |
|---|---|---|---|
| Bionic prototype | Dominated by lower organisms, supplemented by higher organisms | Dominated by higher organisms, supplemented by lower organisms | Human |
| Major bionic behavior | Dominated by foraging behavior<br>(1) Foraging behavior of lower organisms<br>(2) The exploitation part of the hunting behavior of higher organisms | Dominated by cooperative behavior<br>(3) Labor division behavior of lower organisms<br>(4) The exploration part of the hunting behavior of higher organisms | Cooperative behavior of crowds |
| Suitable question type | Optimal allocation problem | Coordinated allocation problem | Coordinated allocation problem |
| Intelligence level | Low | Medium | High |

distinguishes the different development stages and establishes the articulation between them so that each stage can coexist. On the other hand, when CI 2.0 was proposed, it highlighted the guiding role of Qian's academic idea of a meta-synthesis seminar hall system (China Artificial Intelligence 2.0 Development Strategy Research Project Team, 2018). The China Artificial Intelligence 2.0 Development Strategy Research Project Team (2018) wrote that the famous scientist Qian Xuesen proposed the meta-synthesis seminar hall system in the 1990s. Qian Xuesen emphasized the need for expert groups to conduct collaborative seminars in a human−computer integrated manner to work together on the challenging problems of complex giant systems. The research direction of CI proposed in the Development Plan of New Generation Artificial Intelligence is essentially the expansion and deepening of the meta-synthesis seminar hall in the new era of AI.

Based on the above discussion, this section will further explore the relationship between Qian Xuesen's academic thought on meta-synthesis and CI. First of all, we will briefly review the development history of meta-synthesis.

Qian et al. (1990) proposed the concept of open complex giant system (OCGS) and regarded it as a new field of science. They pointed out that the methodology to effectively deal with OCGS is the meta-synthesis approach, which integrates qualitative and quantitative methods. Later, Qian elevated the qualitative-quantitative integrated approach to a qualitative-to-quantitative meta-synthesis approach, which led the direction of scientific research for an era. This scientific methodology will play a more important role in the intersection and integration of the development of science (Dai, 2009).

In 1992, Qian Xuesen further proposed a meta-synthesis seminar hall system from qualitative to quantitative, which is the practical and organizational form of the application of the meta-synthesis approach (Wang WH, 2007). This heralds the advent of the new era of "human–computer combination of wisdom," and the meta-synthesis of wisdom is precisely the network wisdom formed by immersing oneself in the vast information space. The "hall" in the seminar hall system refers to the "virtual reality" technical environment composed of high-speed information networks, modern communication equipment, and computer hardware and software, which enables people to have a sense of immersion when discussing and solving problems together.

Since 2011, the primary topic of research in the meta-synthesis approach has been the renewed focus on the meta-synthesis of wisdom, and the exploration of smart Earth and the construction of smart cities have become hot topics (An et al., 2018). Integrating the meta-synthesis approach with the meta-synthesis of wisdom can realize the two-way interaction between top-down coordinated control and bottom-up wisdom emergence (Xiao and Hou, 2024). Therefore, the research on the meta-synthesis approach advances to a new stage of innovation and sublimation (An et al., 2018).

The above brief review shows that the meta-synthesis seminar hall system is supported mainly by the technical environment, which belongs to the external manifestation; the meta-synthesis of wisdom is the dominant factor of the meta-synthesis innovation sublimation, which is the internal driving force. In the final analysis, the proposal of CI 2.0 is completed under the guidance and leadership of the meta-synthesis of wisdom. Compared with CI 2.0 (crowd intelligence), the meta-synthesis of wisdom proposed by Qian Xuesen is at a higher level, leading the whole situation, and is obviously at a more advanced stage. Accordingly, it can be called CI 3.0.

Crowd intelligence originates mainly from the perception level, and its basic form is to rely on perceptual information to complete complex tasks (such as crowdsourcing), which is described figuratively as crowd paddling a big boat. Meta-synthesis of wisdom originates mainly from the cognitive level, and its basic form is the emergence of advanced intelligence driven by psychological behavior (such as idea generation), and the image of the metaphor is that many people pick up the fire. The two have distinct and significant differences, as shown in Table 3.

Both the meta-synthesis of wisdom (CI 3.0) and crowd intelligence (CI 2.0) are human intelligence bionics in the Internet era, and both highlight and emphasize the important role of the Internet and the characteristics and requirements of the Internet era, so some correlations exist between them. It is very important to clarify the correlation between CI 2.0

**Table 3 Comparison of crowd intelligence and meta-synthesis of wisdom**

| Comparison item | Collective intelligence 2.0 (crowd intelligence) | Collective intelligence 3.0 (meta-synthesis of wisdom) |
|---|---|---|
| Intelligent carrier feature | Complex task driven (such as crowdsourcing) | Psycho-behavior driven (such as raging public opinion and idea generation) |
| Type of emergence | Capacity emergence | Wisdom emergence |
| Degree of emergence of group intelligence | Emergence of general wisdom (spark of wisdom) | Emergence of advanced intelligence (burst of wisdom) |
| Collective wisdom emerging level | Perceptual level is the main focus | Cognitive level is the main focus |
| Suitable question type | General coordinated allocation problem | Social coordinated allocation problem |
| Interpretability | Weak | Very weak |
| Level of intelligence | High | Very high |
| Figurative metaphor | The crowd paddles the boat | The crowd picks up the firewood |

and CI 3.0, and then put forward an evolutionary path from CI 2.0 to CI 3.0.

The popular interpretation of the meta-synthesis of wisdom is "attaining the wisdom by great integration," which seeks to achieve a comprehensive, integrated human group intelligence. The same goal is pursued by today's emerging artificial general intelligence (AGI). Traditional AI solves mainly professional problems and specialized tasks in specific fields, while AGI can show human-like intelligence in solving complex problems and tasks in interdisciplinary fields such as reasoning and decision-making, autonomous learning, and communication (Pei et al., 2019). Complex problems and tasks in such interdisciplinary fields are often in situations of deep uncertainty (Stanton and Roelich, 2021). Not only can they not be characterized by probability, but also people do not even know what future states, factors, or situations might arise, thus exhibiting uncertainty.

The landmark achievement of AGI is called ChatGPT released by OpenAI in November 2022; it had more than 100 million active users within two months of its release. ChatGPT is implemented on the basis of a large language model (LLM) (Zhou et al., 2024). An LLM is a deep learning model that is trained by a large amount of text and has complex structures and parameters. The powerful conversation generation capability shown by ChatGPT stems from the emergence of LLMs (Wei et al., 2022), which promotes the explosive rise of generative artificial intelligence (GAI). GAI can summarize and then automatically generate new original content using deep learning techniques (Kshetri et al., 2024). ChatGPT has become a powerful demonstration of the power of GAI, which indicates the arrival of the era of "everything can be generated." In essence, the meta-synthesis of wisdom is the emergence of group intelligence, which is consistent with GAI. In fact, LLMs-based GAI is becoming an important way to implement the meta-synthesis of wisdom. Except for LLMs, the rapid development of big data breaks the limitations of the hypothesis based on the probability distribution of local samples in statistics (Hilbert and López, 2011), which makes the application scenarios of AI broader and promotes AI towards the direction of universality.

To sum up, the dual-wheel drive of LLMs and big data with deep uncertainty is an evolutionary path from swarm intelligence 2.0 (crowd intelligence) to swarm intelligence 3.0 (meta-synthesis of wisdom).

## 5 Cooperation and labor division in CI

The introduction of CI 3.0 has expanded the development of CI to four stages. In the framework of the four development stages elucidated above, the importance of cooperative behavior in the development process of group intelligence is highlighted, and the corresponding stage classification is based primarily on the development level of cooperative behavior rather than on the bionic prototype category.

The bionic prototypes of CI cover three types of social organisms: lower organisms, higher organisms (excluding humans), and humans. By investigating the cooperative behavior of the three types of bionic prototypes in depth, it can be found that each of them has its own characteristics, which are explained in the following discussion.

### 5.1 Indirect regulatory cooperation in lower organisms

Cooperation among lower organisms such as ant colonies and bee colonies (e.g., division of labor) is accomplished through the transmission of pheromones (pheromone) that interact in an indirect manner using stigmergy (Bonabeau et al., 1999; Karsai, 1999). It is an indirect mechanism of collaboration observed in natural and artificial systems and is also an information coordination mechanism for the autonomy of individual organisms in social networks. Individuals guide the behavior of others by leaving information stimuli in the environment; in the absence of central control and contact communication, the group achieves information symmetry by means of homophily. Each acts independently and adapts to the others, gradually improving the ecological environment of the group. Thus, it can be seen that cooperation among lower organisms is essentially indirectly regulated cooperation.

### 5.2 Direct communicative cooperation in higher organisms

Higher organisms, represented by wolves and lions, have richer and more direct communication and cooperation abilities. For example, lions are able to convey information through communication methods such as body posture, facial expression, voice, grooming, and scent. Specifically, roaring is the most extensive, direct, and active form of communication for lions. Lions have the largest roar of any feline and the furthest infrasound transmission. Schaller (1972) revealed that lion roars possess rich functions such as emphasizing presence, avoiding contact, strengthening group bonds, and reinforcing individual abilities. Grinnell and McComb (2001), as well as Grinnell et al. (1995), found that lions can recruit new partners and coordinate actions with them by roaring. Stander and Stander (1988) described that male lions warn and expel foreign enemies away from their territory by roaring. It is evident that higher organisms can achieve group cooperation more efficiently through direct communication by roaring.

### 5.3 Shared intention based cooperation in humans

A lot of species, from ants to killer whales, and human primate cousins, cooperate to survive in the wild. However, only human groups cooperate with a shared vision (Senge, 1990), with the ability to share intentions; i.e., humans can intuitively understand what others are thinking and work together toward a common goal. This rather powerful cognitive ability has led the human species on an extraordinary evolutionary journey, helping humans invent language and tools and realize civilization. Human cooperation requires the following conditions:

1. The existence of several individuals capable of gaining insight into each other's intentions and forming a common goal accordingly;
2. The ability of different individuals to play separate roles and eventually integrate their efforts.

These activities rely on cognitive abilities that higher organisms (e.g., chimpanzees) do not possess (Hare et al., 2001; Melis et al., 2008). Thus, the dominant form of cooperation among populations is shared-intentional cooperation.

In general, lower organisms lack cognitive abilities, and their group behavior is reflected at the level of perception. Their group behaviors are dominated by competitive behaviors and supplemented by cooperative behaviors. The higher organisms are dominated by individual perception and have limited cognitive abilities, and their group behaviors are dominated by cooperative behaviors and supplemented by competitive behaviors. Human beings, as the spirits of all things, have strong cognitive abilities. Their group behaviors are based on collective intention and dominated by shared cooperation, with competition only in a subordinate position.

CI, in essence, pursues the emergence of cooperation (Axelrod and Hamilton, 1981). Lower organisms, higher organisms, and humans show consistency in cooperative behavior; i.e., the main form of achieving cooperation is labor division, although the complexity of labor division behavior is gradually increasing. For lower organisms, competition is a universal instinct and a basic ability for survival. The cooperation behavior of lower organisms is rare, and the main form of cooperation is the simple division of labor (Xiao and Wang, 2019). Higher organisms have increased their cooperative behavior compared to lower organisms, and the main form of cooperation is the perception-driven division of roles (Wu HS and Xiao, 2021). The cooperative behavior of humans is more complex and diverse, and has developed into a perception- and cognitive-driven division of society. The evolution of the above-mentioned CI division of labor is shown in Fig. 2. Both labor division and role division belong to the category of CI 1.5, while social division of labor corresponds to the advanced stages of CI 2.0 and CI 3.0.

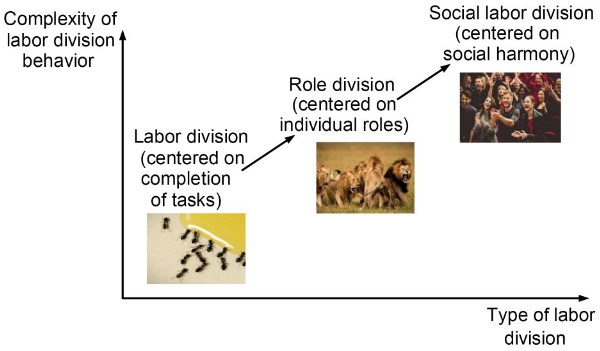


**Fig. 2 Evolutionary process of collective intelligence labor division**

## 6 Summary and prospect

### 6.1 Summary

With the popularization of the Internet and the emergence of a new information environment, traditional AI (AI 1.0) is moving into a new phase of new-generation AI (AI 2.0) (Pan, 2016). As an important component of AI, CI has also moved from CI 1.0 (swarm intelligence/swarm intelligence optimization) to CI 2.0 (crowd intelligence/Internet-based CI) stage (Li W et al., 2017). In this paper, we find the incompatibility between CI 1.0 and CI 2.0 through in-depth analysis and argumentation. To resolve this incompatibility, CI 1.5 is proposed as a transition bridge between these two stages. The bionic prototype of CI 1.5 is based on higher organisms, supplemented by lower organisms, and imitates mainly the cooperative behavior of organisms. Thus, a compatible integrated framework is formed that consists of three stages: CI 1.0, CI 1.5, and CI 2.0. CI 2.0 is proposed under the guidance of the meta-synthesis of wisdom proposed by Qian Xuesen. Compared to CI 2.0, the meta-synthesis of wisdom is at a more advanced level, i.e., CI 3.0. The above-mentioned stages form the complete structure of CI development. As shown in Fig. 3, these different stages develop progressively and with reasonable compatibility. In addition, there are differences in the coordination-based allocation problems solved by CI 2.0 and CI 3.0. CI 2.0 solves general coordination-based allocation problems (e.g., production scheduling problems). CI 3.0 addresses distribution problems mainly in terms of social systems, which are more complex and are thus called social coordinated distribution problems.

The overall architecture of the four development stages proposed in this paper has deep heuristics and can facilitate the field of CI. The framework advances the structure of CI development from two stages to four stages, and will play a corresponding leading role in CI development. The main findings and contributions of this paper are reflected in the following three respects:

1. The incompatibility of CI 1.0 and CI 2.0 is discovered, and the transition stage is further proposed, i.e., CI 1.5. With the connecting role of CI 1.5, the incompatibility between CI 1.0 and CI 2.0 is effectively dissolved.

2. Based on the analysis of the current problems of higher organism bionomics, we point out the limitations and clarify the main direction of CI 1.5. In addition, through the analysis of retrospective origin, we propose a new perspective to study the hunting behavior of higher organisms based on the cooperative behavior mimicry of higher organisms.

3. Taking the meta-synthesis of wisdom proposed by Qian Xuesen as the advanced stage of the development of crowd intelligence (CI 2.0), namely, CI 3.0, building a correlation between the meta-synthesis of wisdom and crowd intelligence is proposed. The analysis shows that the dual-wheel drive of LLMs and big data with deep uncertainty is an evolutionary path from CI 2.0 to CI 3.0.

### 6.2 Prospect

Frontier research on CI is currently emerging, showing good momentum, and becoming a popular topic for academic exploration. Based on the four development stages of CI proposed in this paper, the

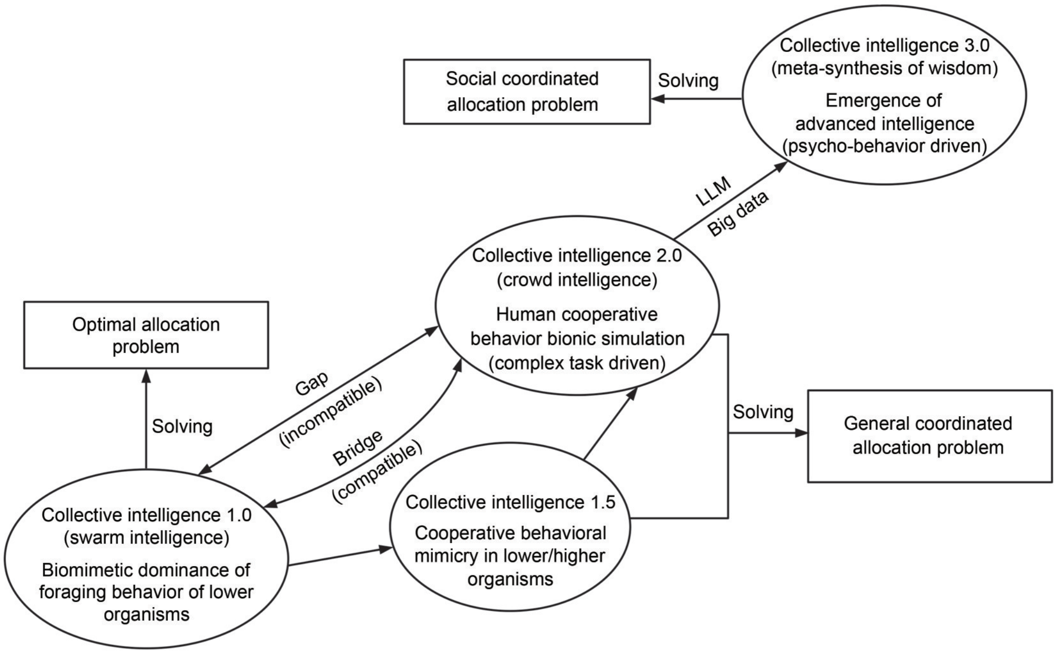


**Fig. 3 Stages of collective intelligence development**

future development directions and research issues are suggested below:

1. Many specific algorithms have been proposed for CI 1.0 (swarm intelligence optimization) (Li SY et al., 2019). Although the literature is still proliferating, it is difficult to attract special attention. The focus of future research on CI 1.0 should be on general mechanistic problems of universal significance, such as the balance between exploration and exploitation (Hills et al., 2015). At the same time, swarm intelligent algorithms for special problems (e.g., super multi-objective optimization problems (Xiao et al., 2023)) should be investigated.

2. The bionic study of cooperative behavior in higher organisms (e.g., lions and wolves) is the main part of CI 1.5. At present, the bionic study of cooperative behavior in higher organisms is still relatively rare. The proposal of CI 1.5 conforms to the development requirements of the complexity of intelligent behavior and is consistent with the idea of the theoretical conception of precision intelligence for complex dynamic objects proposed in the literature (Zheng et al., 2021). Therefore, CI 1.5 will be the focus of attention in future research on CI and is a frontier area to be explored.

3. Qian Xuesen's meta-synthesis of wisdom is a high-level academic theory, but it is also relatively abstract. The literature is generally an interpretive description of the meta-synthesis of wisdom, which lacks extensive exploration. In this paper, we consider the meta-synthesis of wisdom as an advanced stage of CI 3.0 and link it to CI 2.0. This paper advocates the deepening of the meta-synthesis of wisdom, which will inject new vitality into the study of CI.

4. As different stages of the development of CI, CI 2.0 and CI 3.0 are currently far apart. Therefore, it is important to further clarify the correlations between these two stages. We need to find the steps to realize the connectivity of the two stages, which serve as a bridge. For example, Galesic et al. (2023) proposed a conceptual framework for studying collective adaptability in complex social-cognitive systems. The framework is driven by the dynamic interaction between social integration strategies, social context, and problem structure. The exploration of collective adaptability is one of a series of stepping stones from CI 2.0 to CI 3.0 that merit in-depth study.

5. The emergence of swarm intelligence is one of the core elements of the CI theory system. The emergence mechanisms of lower organisms, higher organisms, and humans are related to each other in some way but perform differently, which needs to be studied further.

## Conflict of interest

The author declares that he has no conflict of interest.

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