Collaborative Decision-Making Processes Analysis of Service Ecosystem: A Case Study of Academic Ecosystem Involution

Xiangpei Yan[1], Xiao Xue[1](✉), Chao Peng[1], Donghua Liu[2], Zhiyong Feng[1], and Wang Xiao[3]

[1] School of Computer Software, College of Intelligence and Computing, Tianjin University, Tianjin, China
`jzxuexiao@tju.edu.cn`
[2] China Waterborne Transport Research Institute, Tianjin, China
[3] State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing, China

Abstract. With the collaboration of several intelligent services, a crowd intelligence service network has been formed, and a service ecosystem has gradually emerged. As a novel service organization model, the Service Ecosystem (SE) can provide more sophisticated, precise, and thorough services and has attracted widespread attention. However, it also brings negative effects such as involution, and information cocoon room. Thus, how to analyze the collaborative decision-making mechanism between the SE regulation algorithm and the crowd intelligence group, exploring the reasons behind the negative effects, and finding effective intervention strategies have become problems in this field. To solve the challenges, we propose a Computational Experiments-based method Decision-making processes Analysis model in SE, namely CEDA. The proposed CEDA model consists of three modules: the autonomous evolution mechanism module, the learning evolution mechanism module, and the collaborative decision-making analysis module. Among them, the computational experiments can provide a customized test environment for the analysis of collaborative decision-making processes and find out the appropriate intervention strategy. Finally, the validity of the CEDA model is verified through the case of academic ecosystem involution. The results show that computational experiments can provide new ideas and paths for collaborative decision-making processes analysis.

Keywords: Collaborative Decision-making Processes · Case Studies of Collaborative Application · Performance Evaluation · Service Ecosystem · Interaction Mechanism · Computational Experiments

1 Introduction

With the era of the intelligent interconnection of all things, new technologies and products such as big data, cloud computing, and artificial intelligence continue to pour into the modern service industry, which can be combined and integrated to meet complex

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application scenarios [1, 2]. "Data + computing power + AI algorithm = intelligent service" is forming a new type of social infrastructure. In this technical architecture, "Everything as a Service", the service gradually endows everything in society with a unified logic, including applications, platforms, data, algorithms, and resources, and the entire social landscape is redefined under the service logic [3]. By focusing on the structure of the process and neglecting the exchange of data and resources between collaborators traditional service systems gradually turn into Service Ecosystems (SE) where many agents (people, companies, governments, intelligent machines, etc.) work together and operate together [1], as shown in Fig. 1.

As a complex service system that is influenced by many factors, the efficient operation of the service ecosystem requires collaboration between the supply and demand sides. The supply side constantly pursues high efficiency (Efficiency = output/time), while the demand side continuously provides valuable output (Effectiveness = valuable output/time). This collaboration is crucial to prevent the whole system from falling into a loop of ineffective output. In this context, intelligent regulation algorithms play an increasingly important role in helping individuals, businesses, and governments make decisions and deal with everyday matters. These algorithms provide a more granular, precise, and thorough model of service operation in a more intelligent way than traditional service. For example, recommendation algorithms can influence the speed of enhancing people's access to information [2] and service platform algorithms can perform route planning [4]. Intelligent regulation algorithms are playing an increasingly important role in the collaborative decision-making and processing of everyday affairs, enabling significant changes in how services are organized and operated. They are also having a growing impact on shaping the processes of human interaction with politics, economics, and society [3]. However, the complexity, opacity, and lack of interpretability of intelligent moderation algorithms themselves [3]. Have led to a rise in the risks associated with their use. For example, algorithms for ranking scientific results have led the academic ecosystem into a state of involution with diminishing marginal effects [5]. In addition, problems such as complex network wind [4], and "information cocoon room" [6]. Caused by intelligent regulation algorithms pose new challenges to the service efficiency of the public intelligence service system. To ensure the effective and efficient operation of the service ecosystem, it is crucial to address the risks and challenges associated with the use of intelligent regulation algorithms.

Therefore, exploring the reasons for the negative effects and interaction processes between the regulation algorithm and the crowd intelligence group becomes the key to research. For example, Shi et al. used a simulation system to simulate the real world and effectively assess the impact of the interaction between algorithms and people [8, 9]. Kang et al. use quantitative methods to analyze interaction data and conclude that algorithm-human interaction exacerbates algorithm discrimination [2, 10]. However, the inherent complexity, opacity, and lack of interpretability of intelligent regulation algorithms have increased the risks of SE. Existing analysis methods ignore the complexity and dynamics of the interaction between algorithms and agents, making it difficult to reveal the underlying mechanisms of system evolution and to give effective regulation strategies. In this context, this paper investigates the mechanism of interaction between the regulation algorithm and the intelligent behavior of the crowd intelligence group in SE and explores the reasons for the negative effects of the interaction between the regulation algorithm and the crowd intelligence group.

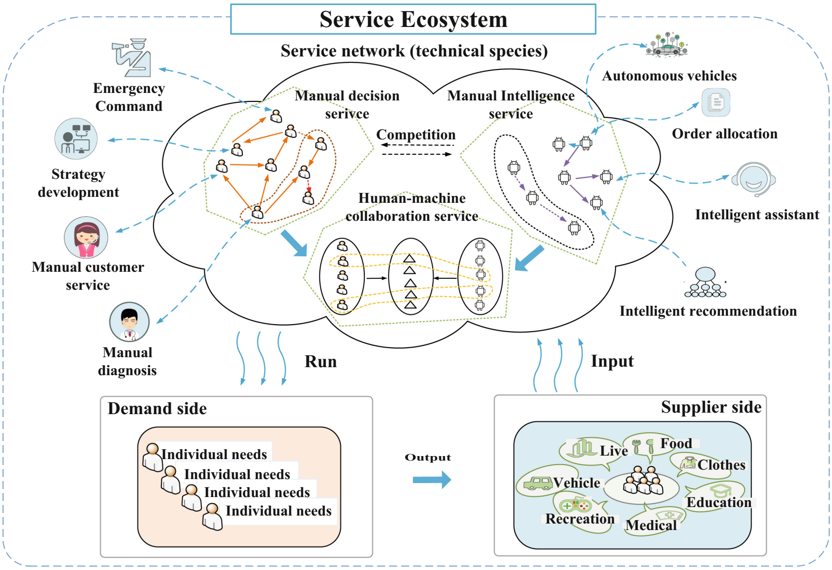

Fig. 1. The SE consists of several agents such as people, enterprises, intelligent machines, and regulation algorithms, which are self-learning and capable of self-evolution, as well as interacting with other agents to accelerate their evolution and facilitate the evolution of SE.

Computational experiments are based on the underlying agents to simulate real-world microscopic behavior and have the advantage of being accurate, controllable, and repeatable. This paper combines the characteristics of computational experiments to connect the micro and macro and proposes a Computational Experiments-based Decision-making processes Analysis model in SE, referred to as the CEBA model. The CEBA model describes the cyclic mechanism of positive and negative feedback between the intelligent regulation algorithm and the crowd intelligence group in SE from a macroscopic perspective and analyses the state properties, behavior changes, and correlations between the two from a microscopic perspective. Finally, the case of scientific academic ecosystem involution using the CEBA model is analyzed to explore the internal mechanism of the creation, exacerbation, and mitigation of scientific academic ecosystem involution.

2 Background and Motivation

The SE is a complex service system that facilitates the service effectiveness of the service system under limited resources through the centralized provision of infrastructure and public services. The operation logic of the SE consists of three parts: crowd intelligence group, service network, and value network [11, 12].

In recent years, the SE has become the most important organizational form of the service system [13, 14]. In a SE, agents autonomously adjust their behaviors and decisions according to their value output to improve their effectiveness, while the regulation algorithm regulates the behavior and habits of the intelligence to improve the service effectiveness of the whole service system. With the increasing complexity of the coupling between intelligent regulation algorithms and crowd intelligence group, it is becoming more important to analyze the interaction processes between the two [14]. A review of the literature reveals that current research approaches to algorithm-human interaction fall into three main categories.

The first category is to evaluate the impact of the interaction between algorithms and humans based on real systems or simulated systems using A/B tests or combinations of multiple variables. Miikkulainen et al. [5] proposed to use of an evolutionary algorithm to select the A/B test feature space; Shi et al. [8] proposed to use reinforcement learning to establish a virtual Taobao for A/B testing; Koster et al. [10] proposed a virtual environment to explore the influence of people on algorithm-making policy.

The second category is qualitative analysis from psychology, causality, and influencing factors. Bucher et al. [15] investigated the emotional dimension and perception of algorithms and people; Alvarado et al. [16] proposed an algorithmic experience (analytical framework for analyzing the experience of algorithm-human interaction; Shin et al. [17] proposed the models to influence users' perceptions of algorithmic systems in the context of algorithmic ecology.

The third category is to collect interactive data based on questionnaires, interviews, and web crawlers for quantitative analysis. Li et al. [19] proposed a psychological perspective on the positive impact of anthropomorphism in the interaction of AI assistants; Kang et al. [2] investigated the impact of AI features embedded in core aspects of social media; Vlasceanu et al. [9] verified that non-human factors induce lasting social influence outside the group environment.

Currently, all existing methods of interaction analyses have certain limitations. For online systems, too much analysis can put pressure on the system and degrade the user experience. Simulation systems focus on top-down modeling, and the simulation process requires human participation, which does not allow for large-scale, long-term simulation. Qualitative analysis methods cannot quantify the interactions between factors, and can only provide a rough analysis from a macro perspective, which is insufficient to explain the decision-making and interaction processes. Quantitative analysis methods cannot effectively analyze the decision-making and interaction processes since a large number of assumptions and a large amount of data are required when building the model.

To solve the problems in the interaction analysis methods for the SE regulation algorithm and crowd intelligence groups, this paper proposes a Computational Experiments-based Decision-making processes Analysis model in SE. The model separates the crowd intelligence group and the regulation algorithm in the hybrid system and then abstracts them into an artificial society agent and the SE regulation algorithm respectively. It can simulate the interaction processes between the SE regulation algorithm and the artificial society agent, and analyze the circular feedback logic and inner mechanism of the interaction between the SE regulation algorithm and the artificial society agent. Finally, the proposed model is validated by setting up different types of intervention strategies and different types of artificial society agents to analyze the generation, exacerbation, and mitigation of the phenomenon of involution in the academic ecology.

3 Computational Experiments-Based on Collaborative Decision-Making Processes Model in SE

This section first introduces the proposed CEBA model, followed by a detailed description of the autonomous evolution mechanism of the regulation algorithm and the learning evolution mechanism of the artificial society agent model, and then describes the cyclical mechanism and dynamic evolution process between the two. Finally, individual effectiveness, system effectiveness, and other analysis indicators are given.

3.1 Computational Experimental Analysis Model of SE

The CEBA model uses computational experiments to model the whole process of interaction between the SE regulation algorithm and the artificial society agent, focusing on the analysis of the changes in the artificial society agent. Additionally, exploring the internal mechanism of the interaction between the SE regulation algorithm and the artificial society agent can help to mitigate the negative effect of the regulation algorithm on the artificial society. As shown in Fig. 2, the first is to introduce the SE regulation algorithm, and the agents perceive and make corresponding feedback. Secondly, the introduction of the SE regulation algorithm will accelerate the evolution process of artificial society learning, thus affecting the interaction between the SE regulation algorithm and the artificial society agent. Finally, after a period of operation, the artificial society produces certain negative phenomena of the algorithm. To mitigate or avoid the negative phenomenon of the SE regulation algorithm, the SE regulation algorithm will be modified or replaced. Therefore, the CEDA model will analyze the collaborative decision-making and interaction processes between the SE regulation algorithm and artificial society from the following three aspects, and explain the internal mechanism of the generation, exacerbation, and mitigation of social phenomena caused by the interaction between the two.

(1) **The changes in the artificial society agent before and after the regulation**

The SE regulation algorithm has changed the organizational norms and management measures of the service system, which makes the evaluation, allocation, and recommendation more rational, automatic, and standardized. However, agents need to learn the best strategy to improve competitiveness and rewards in the process of interaction between the regulation algorithm and other agents, due to the limitation of resources and the pursuit of reward maximization. The agent strategy is gradually homogenized and biased, forming a negative effect, with a certain social phenomenon emerging, such as ①, ②, ③, ④, ⑤, ⑥ processes in Fig. 2. Therefore, we set up an artificial society agent experiment after regulation, and analyze the performance differences of the crowd intelligence group after the regulation algorithm is applied, meanwhile explore the impact of the regulation algorithm on the effectiveness and negative effects of SE.

(2) Artificial society agent changes, while the regulation algorithm remains unchanged

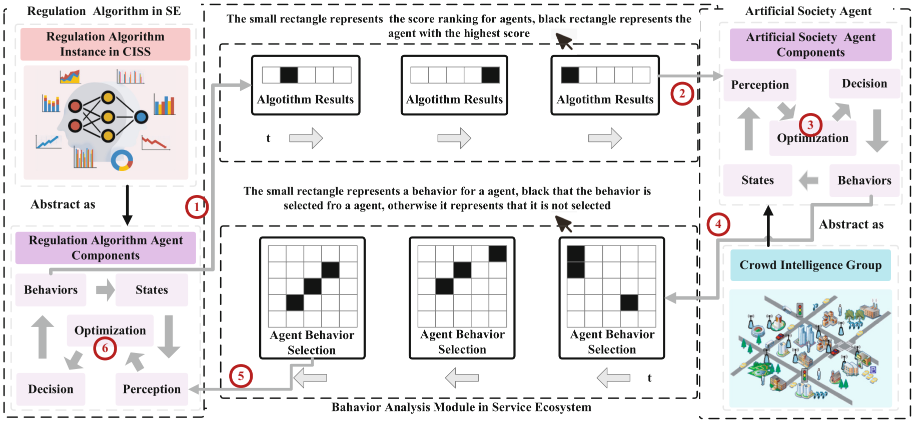

Fig. 2. The framework of the proposed CEDA model, consists of three modules: the SE regulation algorithm module, the collaborative decision-making processes analysis module, and the artificial society agent module. The left side represents the SE regulation algorithm module abstracted from different SE regulation algorithm instances, the right side represents the artificial society agent abstracted from different crow intelligence group instances modules, and the middle represents the abstracted collaborative decision-making processes analyses module.

From the interaction processes in Fig. 2 ③, ④, ⑤, ⑥, ①, ②, we can see that: Many factors affect SE regulation algorithms, different artificial society agents have different influences on the SE regulation algorithm, such as the organizational structure of the agent, the intelligence degree of the agent, and individual differences. We need to determine and analyze the factors, so we set different values for the influencing factors of different artificial society agents and then design a group of controlled experiments to analyze the performance differences between the same regulation algorithm and the crowd intelligence groups with different settings. Besides, we can explore how the influence factors of the artificial society agent shape the behavior mode and evolution of the agent process and also evaluate the impact of negative effects on the regulation algorithm.

(3) The regulation algorithm changes, but the artificial society agent remains unchanged

The original intention of introducing the management and regulation algorithm into the SE is further improving service efficiency through refined management. However, the regulation algorithm affects the job evaluation and income distribution of the agent, so there could be a negative impact on the direction and speed of the artificial society learning evolution. It is necessary to update the regulation algorithm, migrate or avoid the negative impact as much as possible meanwhile ensuring the goal of the regulation algorithm, as shown in the process of ⑥, ①, ②, ③, ④, ⑤ in Fig. 2. Therefore, we set up controlled experiments to analyze the attributes and state changes of the agent under the regulation algorithm of different intervention strategies and explore the mitigation effect of the regulation algorithm on the negative impact of the algorithm under different intervention strategies.

3.2 Autonomous Evolution Mechanism of the SE Regulation Algorithm

Control and induction are two ways to regulate SE. However, effective regulation cannot be achieved due to the complexity of the system. Therefore, induction is usually used for regulation. As a general algorithm module, the regulation algorithm can be replaced by other regulation algorithms. The regulation algorithms generally consist of three parts: input, output, and self-learning capabilities. Self-learning is using a large amount of data generated by the interaction between regulatory algorithms and artificial society to carry out self-training and evolution to form a "rule set". The formulation of the regulation algorithm is as follows:

$$RA_{out,t} = RA_t \odot RA_{in,t} \quad t \geq 0 \tag{1}$$

where RA_t represents the regulation algorithm at time t, which can reflect the learning ability of the regulation algorithm at time t. $RA_{in,t}$ denotes the input of the regulation algorithm at time t, and its input is the comprehensive output of factors such as the state of the regulation algorithm and the emergence of social phenomena from artificial society agents. $RA_{out,t}$ represents the output of the regulation algorithm at time t after evolution. $\odot$ represents the update of the regulation algorithm RA_t based on the comprehensive output of the artificial society at time t.

The characteristic index space $\{q_{j,t}\}$ of the SE regulation algorithm RA_t is defined as follows:

$$\{q_{j,t}\} = \left\{q_{j,t}^1, q_{j,t}^2, q_{j,t}^3 \ldots, q_{j,t}^N\right\} \tag{2}$$

where $\{q_{j,t}\}$ is the set of all agent index j feature values, and N is the number of all agents in the artificial society agent model. The average reward index of the agent is defined as:

$$\text{Income}_{agent_T} = \frac{\sum_{i=0}^{i=N}\sum_{t=0}^{t=T} Reward_{t,i}}{N} \quad t \geq 1 \tag{3}$$

where $Reward_{t,i}$ indicates the income of the agent i from $t-1$ to t and Income_{agent_T} indicates the average income of the agent in the artificial society at time T.

The input of the regulation algorithm $RA_{in,t}$, that is, the index system $Qos(i, t)$ value of agent i at time t is defined as follows:

$$Qos(i, t) = \sum_{j=0}^{j=M} w_{j,t} q_{j,t}^i \tag{4}$$

where M represents the number of characteristic indicators of the SE regulation algorithm RA, $q_{j,t}^x$ represents the feature value of the index j of the agent x at time t, and w_j represents the preference weight of the index system at time t.

The index discrimination degree $D_{j,t}$ of SE regulation algorithm RA_t is defined as follows:

$$D_{j,t} = \frac{H_{j,t} - L_{j,t}}{Max_{j,t}} \quad t \geq 0 \tag{5}$$

Here, the discrimination calculation method adopts the two-end grouping method: first, the values of $\{q_{j,t}\}$ at time t are arranged in descending order, and the first $\alpha\%$ entities are listed as high-scoring entities, and the latter $\alpha\%$ entities are listed as low-scoring entities group, then the discrimination degree of index j is $D_{j,t}$. Among them, $H_{j,t}$ is the average score of the high group in index j, $L_{j,t}$ is the average score of the low group in index j, $Max_{j,t}$ is the highest score value of index j.

The index system discrimination degree D_t of SE regulation algorithm RA_t is defined as follows:

$$D_t = max\big(D_{0,t}, \ldots D_{j,t}, D_{m,t}\big)\ t \geq 0 \tag{6}$$

where D_t represents the maximum value of discrimination in all index systems. m represents the number of indicators under the indicator system.

The fitness function of the SE regulation algorithm RA at time t is as follows:

$$Fit_{RA,t} = \alpha * \text{Income}_{agent_t} + (1-\alpha) * D_t \quad 0 \leq \alpha \leq 1 \tag{7}$$

where $Fit_{RA,t}$ represents the fitness function of the regulation algorithm at time t, which is not only related to the interaction of the artificial society but also affected by the regulation algorithm itself. α is a proportional coefficient, which is used to indicate the average income of an artificial society occupies the size of the fitness function value. When α is larger, it means that the average income of the artificial society occupies a larger fitness function value and vice versa.

3.3 The Learning Evolution Mechanism of the Artificial Society Agent Model

The artificial society agent is a complex system composed of a large number of agents that follow certain rules, interact with each other, and have certain autonomous capabilities, which can simulate the structure, function, and evolution mechanism of SE. The artificial society agent is regarded as an alternative version of the crowd intelligence group to study various phenomena in reality. Artificial society is divided into three parts: input, output, and self-learning ability. The learning evolution process of the artificial society agent model can be modeled using the SLE framework [19]. SLE is a customized evolution model that includes three evolution modules: individuals, organizations, and society. The evolution of the three models can be specifically expressed as:

(1) **Individual evolution mechanism**

An individual refers to a single agent in different types of artificial societies, a genetic component. The agent has the characteristics of autonomy, responsiveness, initiative, and sociality, and it perceives, makes decisions, acts, and optimizes through the propagation of information flows, forming an evolutionary mechanism with the following behavioral rules expressed as follows:

$$\forall v_t \in V_t, \varepsilon(\alpha, v_t, E_t, Y_t) \Rightarrow \langle S, D_t, N, \max(Value_{t+1})\rangle \tag{8}$$

$\varepsilon(\alpha, v_t, E_t, Y_t)$ represents the evaluation of the result of the agent α completing the behavior v_t in the environment E_t and the decision Y_t, $\Rightarrow$ means “satisfied”, N represents the constraints on the agent, S represents static attributes, D_t represents dynamic attributes at time t, $\max(Value_{t+1})$ indicates the task standard.

In an artificial society, the agent is not unconscious or does not lack initiative, and its learning process is an important dynamic mechanism for system evolution. During this operation, the agent updates its rule by interacting with the environment, which can affect its decision-making mechanism. Generally speaking, the agent will adopt the feedback learning principle of "increasing rewards" to gradually optimize its decision-making mechanism, so that it can take actions that are closer to the accomplishment of the goal. The formula is expressed as follows:

$$Y_{t+1} = Y_t \oplus Fit_{AS,t}(E_t) \quad t \geq 0 \tag{9}$$

$Fit_{AS,t}(.)$ represents the fitness function at time t, which is used to describe the survivability of the agent and can be regarded as the mapping relationship between strategy and fitness. $\oplus$ indicates that the decision mechanism Y_t is based on the update of the environment state E_t.

(2) **Organizational learning evolution mechanism**

In the real world, the agent can adapt to the external environment through individual learning, and it also learns to evolve by observing and imitating the corresponding organization where the organization is composed of agents with the same activity scope and behavior set.

Organizational learning is to transform different small organizations formed in the process of neighbor learning into smaller and higher-level organizations. In the same learning organization, there is not only competition but also a certain degree of collaboration among agents within the organization due to the principle of knowledge sharing within the learning organization. Different organizations will compete with each other to obtain favorable positions based on the organization as a unit, and the competitiveness is reflected in the income and vision of the leaders within the organization. The competitiveness of agents can be improved continuously by learning from excellent partners. Whether the agent wants to learn from the organization depends on the following formula:

$$O\left(org_j, v_{i,t}, v_{org_j,t}\right) > 1?Evo(yes) : Evo(no) \tag{10}$$

$$O\left(org_j, v_{i,t}, v_{org_j,t}\right) = \frac{\left|\text{Income}_{(org_j, v_{org_j,t})} - \text{Income}_{v_{i,t}}\right|}{Distance}$$

where $\text{Income}_{(org_j, v_{org_j,t})}$ represents the income of the agent i in the organization j at the time t of behavior $v_{org_j,t}$, $\text{Income}_{v_{i,t}}$ represents the reward of agent i making behavior $v_{i,t}$ at time t, and *Distance* represents the cost of learning organization j for agent i. If $O\left(org_j, v_{i,t}, v_{org_j,t}\right)$ is greater than 1, the agent i will learn the excellent strategy of the organization to improve its ability. Otherwise, the agent will continue to take action according to its original strategy.

(3) **Social learning evolution mechanism**

According to the principle of survival of the fittest, the artificial society selects the most adaptive agent as the elite, and its excellent knowledge will be passed on to the top.

It builds a culture through knowledge accumulation and also spreads the culture to other agents for learning. The specific policy rules of the social learning layer are as follows:

1) **The policy of probability principle:** the agents can choose different rewards to achieve strategy selection. For example, some agents will pursue the maximum income so that they will learn from low-income individuals with a small probability.
2) **The principle of income comparison:** an agent with a small income will imitate the behavior and strategy of an agent with a large income, while the agent with a larger income maintains its original behavior and strategy.

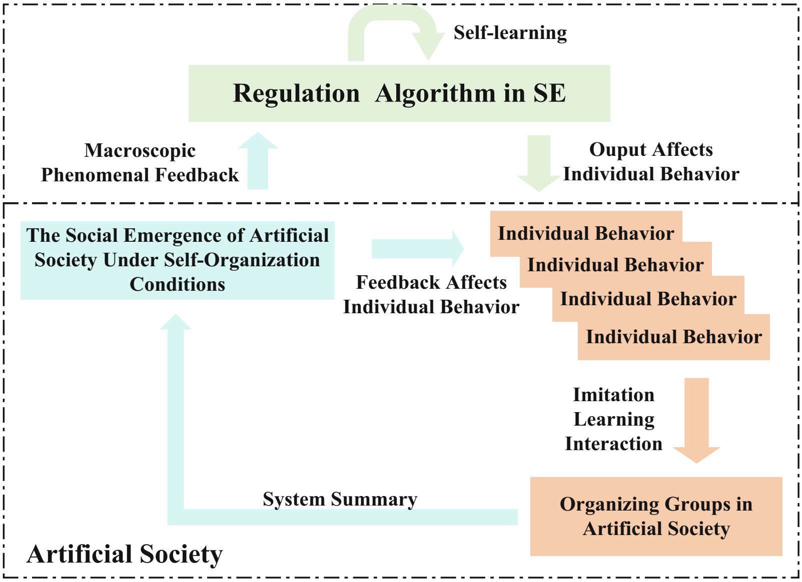

Fig. 3. The cyclic mechanism and dynamic evolution process, the output of the SE regulation algorithm acts on artificial society agents, and the artificial society agents learn, imitate and interact with themselves to form a certain organizational group in the artificial society. After a period of learning and the evolution of different organizational groups, a macroscopic social phenomenon will emerge. The macro-phenomenon influences the direction of the regulation algorithm's learning evolution. The organizational groups and the output of the regulation algorithm in turn change the cognition of the artificial society agents, resulting in different agents behaving differently, thus forming a circular process of action.

3.4 The Cyclic Mechanism and Dynamic Evolution Process Between Regulation Algorithm and Artificial Society

The learning evolution of the SE regulation algorithm and artificial society is the process of interaction between artificial society and the SE regulation algorithm, as shown in Fig. 3.

The SE regulation algorithm acting on the artificial society is expressed as follows:

$$Fit_{AS,t+1} = Fit_{AS,t} \otimes R_t \quad t \geq 1 \tag{11}$$

$$R_t = \left\{Reward_{t,0}, Reward_{t,1} \ldots Reward_{t,N}\right\}$$

where R_t represents the set of gains for all agents from $t-1$ to time t, and N is the number of all agents in the artificial society. $\otimes$ represents the update of the fitness function $Fit_{AS,t+1}$ of the artificial society agent at time $t+1$ based on the fitness function $Fit_{AS,t}$ of the artificial society agent at time t and R_t.

The expression of the emerging social phenomena $AS_{phenomenal,t}$ in the artificial society acting on the SE regulation algorithm RA_t at time t is as follows:

$$W_{t+1} = RA_t \circledcirc AS_{phenomenal,t} \quad t \geq 0 \tag{12}$$

$$W_{t+1} = \left\{w_{0,t+1}, w_{1,t+1} \ldots, w_{M,t+1}\right\}$$

where $AS_{phenomenal,t}$ indicates the social phenomenon that emerges in the artificial society time t. W_{t+1} represents the preference weight of the index system at time $t+1$, and M represents the number of characteristic indicators of the regulation algorithm. $\circledcirc$ represents the updating of the index system weights of the regulation algorithm according to the emerging social phenomena at time t.

3.5 Individual Effectiveness, System Effectiveness, and Other Analysis Indicators

The service efficiency of the SE is affected by many factors, and any failure or problem in any link may lead to negative effects on the entire service system. For the healthy and orderly development of the crowd intelligent service system, this paper proposes an Individual Effectiveness *IE* to evaluate the performance of agents in the service system. In particular, the *IE* is a concave function, which is increasing the agent's income and linearly decreasing in the cost. The Individual Effectiveness $IE_{T,i}$ is a function of the change in reward $\sum_{t=0}^{t=T} Reward_{t,i}$ and cost $\sum_{t=0}^{t=T} Cost_{t,i}$ for agent i from time 0 to T, the formula looks like this:

$$IE_{T,i} = crra\left(\sum_{t=0}^{t=T} Reward_{t,i}\right) - \sum_{t=0}^{t=T} Cost_{t,i} \tag{13}$$

$$\mathrm{C}ost_{agent_T} = \frac{\sum_{i=0}^{i=N} \sum_{t=0}^{t=T} Cost_{t,i}}{N} t \geq 0$$

$$crra(z) = \frac{z^{1-\eta} - 1}{1-\eta} \eta > 0$$

where $Cost_{t,i}$ denotes the cost of agent i from time $t-1$ to t and Cost_{agent_T} denotes the average cost of all agents in the artificial society at moment T. The *crra* function is marginal in effect, and its magnitude may decrease as the reward increases. The parameter η controls the degree of non-linearity: higher η indicates more non-linear behavior.

To balance the healthy development of the SE and the number of output results, the system effectiveness of the SE is defined below. A new indicator for judging the healthy development of the SE, namely the System Effectiveness SE_T at time T, is synthesized here and defined as follows:

$$SE_T = \frac{\sum_{i=0}^{i=N}\sum_{t=0}^{t=T} IE_{t,i}}{N} * \frac{\sum_{i=0}^{i=N}\sum_{t=0}^{t=T} Task_{t,i}}{N} \tag{14}$$

where $\frac{\sum_{i=0}^{i=N}\sum_{t=0}^{t=T} IE_{t,i}}{N}$ is the average of the individual effectiveness of all agents at time T. When this value is less than or equal to 0, it indicates that there is involution in the SE at this time. $Task_{t,i}$ denotes the number of tasks completed by agent i from time $t-1$ to t, $\frac{\sum_{i=0}^{i=N}\sum_{t=0}^{t=T} Task_{t,i}}{N}$ denotes the average number of tasks completed by all agents at time T.

Here are some other analytical metrics that use the number of agents that occurs across space to reflect the state of competition within a disciplinary area, with the following formula:

$$Cross_T = \sum_{i=0}^{i=P}\sum_{t=0}^{t=T} Cross_{field_{i,t}} \quad t \geq 0 \tag{15}$$

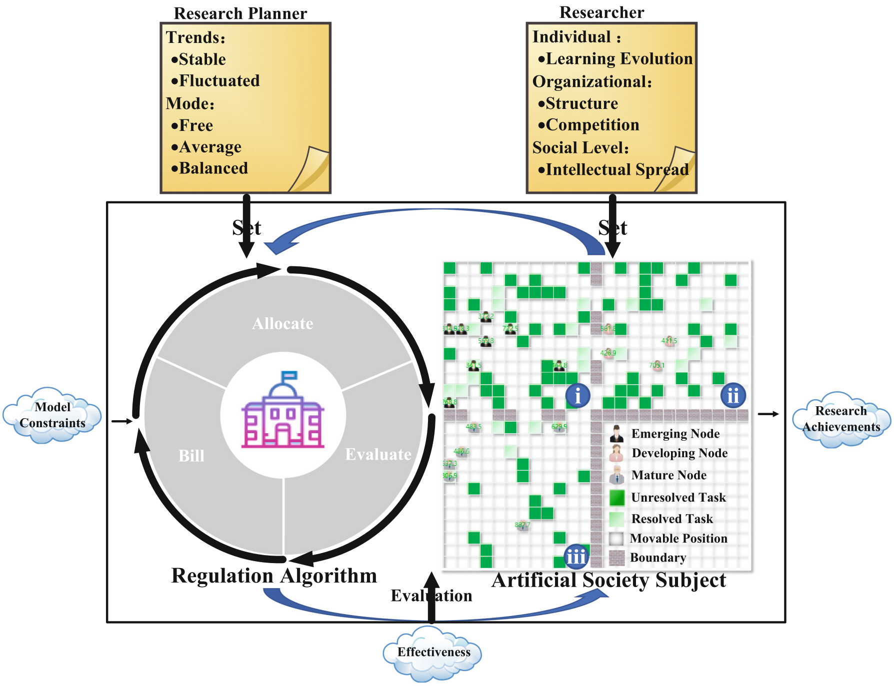

Fig. 4. Design of Computational Experiment System.

where $Cross_{field_{i,t}}$ denotes the number of domains crossed by field i from time $t-1$ to t, and P represents the number of fields.

4 A Case Study of the Academic Ecosystem

To verify the validity of the model, this paper uses the CEBA model to simulate and analyze the involution of the academic ecosystem. The involution of the academic ecosystem is mainly due to the shortcomings of the research regulation algorithm itself. For example, ignoring the correlation between the difficulty of a research project and the amount of funding support for the project leads to more difficult projects and less support funding for unpopular fields of research. Many researchers in unpopular fields will turn to research in popular fields, leading to a dramatic increase in the number of researchers in popular fields. Researchers in popular fields who engage in some low-value research need to maintain their competitive edge by guaranteeing their number of research outputs, which leads to involution. At the same time, the formation process of involution is influenced by a variety of factors, but the current research on the mechanism of the trend of involution mainly adopts a qualitative analysis method, and it is difficult to fully and dynamically reflect the inner operating mechanism of the involution of the academic ecosystem. Therefore, this paper constructs an experimental system of academic ecology based on the proposed CEBA model for analysis.

Table 1. Parameter settings of experiments

System variable	Experiment setting
Initial Number of Researchers	Area 1: Area 2: Area 3 = 6: 6: 6
Fund for a Tick	$Revenue_t = 20$
Running Time	1000
Vision Range	Bounded random within the range of [1, 4]
Distance Cost	Y = k * x (x > 0, x indicates distance moved. k = 1)
Processing Cost	Bounded random within the range of [1, 3]
Cross-Domain Cost	Bounded random within the range of [9, 14]
Solve Payment	$Y = \frac{km^k}{x^{k+1}}$, * 3(x is random within [0,1000], k = 4, m = 18)
Task Complexity	Bounded random within the range of [1, 3]
Researcher Ability	The ability obeys standard normal distribution
Task Type	Bounded random within the range of [1, 3]
Task Regeneration probability	0.1
Tolerance	Bounded random within the range of [1, 4]
Degree of Nonlinearity	$\eta = 0.23$

(*continued*)

Table 1. (*continued*)

System variable	Experiment setting
Task Generation Rules	$Y = N + M * \sin(T)$. N represents the task and M represents the fluctuation range. Area 1, $N = 40$, $M = 5$ Area 2, $N = 30$, $M = 3$ Area 3, $N = 20$, $M = 2$
Distribution of Task	Tasks are distributed randomly in three areas with centers of (6, 6) (Area 1), (18, 6) (Area 2), and (6, 18) (Area 3) respectively

This section first proposes the general framework of the experimental system, then introduces how to design and construct an academic ecology computing experimental system based on the CEBA model, and finally presents a statistical analysis of the obtained experimental results.

4.1 The Framework of the Experimental System

The experimental system has two roles: the researcher and the research planner. Disciplinary tasks are assigned to various disciplinary areas according to certain rules. Researchers take the initiative to explore and tackle disciplinary tasks, generating some cost. New disciplinary tasks are automatically generated when they are tackled. The research planner evaluates the work of the researchers and distributes the incomes according to a regulation algorithm.

The framework of the CEBA model-based academic ecosystem shown in Fig. 4 is constructed, where the entire academic ecosystem is divided into four regions.

Different numbers of disciplinary tasks and researchers are scattered across the three disciplinary regions: i, ii, and iii (emerging, developing, and mature disciplinary nodes). And various experimentation scenarios can be customized by setting different SE moderation algorithms and parameters of the academic ecosystem. In addition, the involution pattern of the academic ecosystem is analyzed by observing the evolutionary phenomena in the experimental system.

4.2 Experimental System Design

The CEBA model proposed in this paper focuses on three aspects of the interaction processes between the regulation algorithm and the academic ecosystem: before and after the regulation, changes in the artificial society agent, and changes in the regulation algorithm. Specifically, this paper sets up two sets of controlled experiments using the same initialization conditions and a fixed total amount of money for the researcher and disciplinary tasks, as well as different learning mechanisms and regulation algorithms for different artificial society agents.

Experiment 1 used the free model regulation algorithm, with funding allocated according to the ratio of the number of disciplinary tasks tackled by the researcher to the number of all disciplinary tasks tackled in the system. Then we can reveal the process of involution generation and exacerbation by exploring the impact of the academic ecosystem with different learning mechanisms (individual, organizational, and social learning) on the individual effectiveness of the system. The different learning mechanisms represent different capabilities of information dissemination.

Experiment 2 is carried out based on the social learning used in Experiment 1. The impact of regulation algorithms on system effectiveness is explored by setting up the regulation algorithm with different intervention strategies (free mode, average mode, and balanced mode), which in turn enables the mitigation of involution in the academic ecosystem through adjusting the intervention strategies. The income of researchers under different intervention strategies is as follows.

$$\begin{gathered} Reward_{t,i} = \frac{\beta * Revenue_t}{N} + \\ (1-\beta) * Revenue_t * Proportion_{t,i} \end{gathered} \tag{16}$$

where $Proportion_{t,i}$ represents the number of disciplinary tasks that researcher i has tackled in time $t-1$ to t as a proportion of the number of all disciplinary tasks in the system. N is the number of all agents in the academic ecosystem. $Revenue_t$ indicates the total amount of allocated funds in a cycle. Three different intervention models were set up based on the ratio of basic income to performance incentives: Free mode parameter: $\beta = 0$ (Liberal Distribution); Average mode parameter: (Strict Egalitarian Redistribution); Balanced mode parameter: $\beta = 0.5$ (Liberal Egalitarian Redistribution).

The length of the experimental environment is 25 cells and the width is 25 cells, with different types of nodes randomly distributed in their respective areas. The experimental parameters are mainly set at the same scale scaled according to the global scientific community surveyed in Nature [20]. The experimental parameters are set as shown in Table 1. In this paper, the average income to researchers, average cost consumed, the average number of disciplinary tasks tackled, individual effectiveness, and system effectiveness are used to assess the impact of different models of the SE regulation algorithms and different learning capabilities of the academic ecosystem on the generation, exacerbation and mitigation of academic ecosystem involution.

4.3 Experimental System Analysis

a) **Experiment 1:** Classified academic ecosystems into three categories based on the speed of information dissemination: those with different learning mechanisms. It helps us explore the impact of academic ecosystems with different learning mechanisms on individual effectiveness.

Figure 5 compares and analyses the changes in the average income, the average cost of consumption, the average number of disciplinary tasks tackled, and the mean individual effectiveness of researchers during the evolution of learning in the academic ecosystem under three different learning mechanisms. The results of the experiment are as follows.

(1) By analyzing the income and individual effectiveness under the three types of learning in Fig. 5(a)–(c), it is concluded that: 1) With individual learning, the gap in income between researchers is larger, but those with individual effectiveness greater

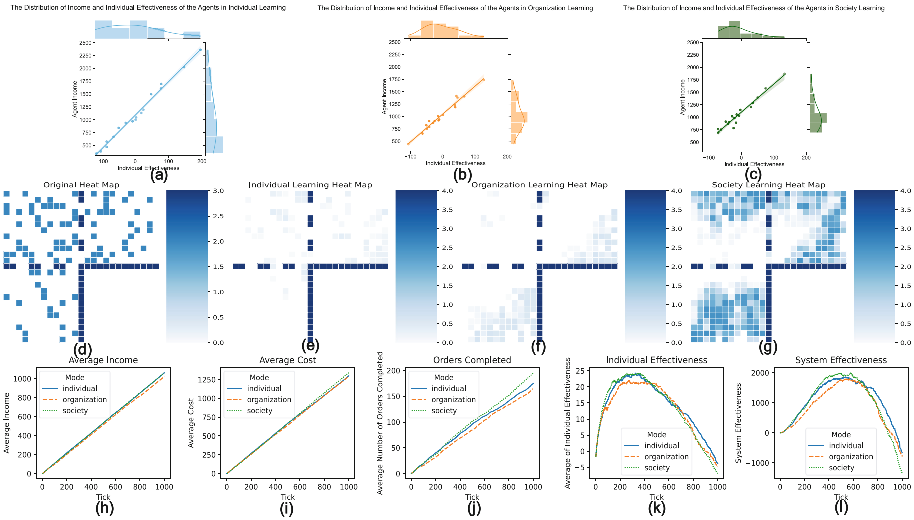

Fig. 5. Comparative analysis of the characteristic index of academic ecosystems under three different learning mechanisms

than zero occupy the majority, and the degree of involution is not serious. 2) With organizational learning, researchers' incomes are normally distributed, and the gap in the overall average level of incomes narrows; those with individual effectiveness less than zero occupy the majority, and involution deepens. 3) With social learning, the returns increase, and the gap between the researchers' incomes is further reduced; the majority of those with individual effectiveness less than zero are more severely involuted.

(2) By analyzing the heat maps of the initialized disciplinary task distribution under the three learning mechanisms in Fig. 5(d)–(g) and the heat maps of the researchers' trajectory run, it can be summarized that 1) the heat maps of the researchers' trajectories under individual learning are lighter in except for a few darker squares, which indicates a certain randomness of movement focusing on free exploration and no aggregation effect. 2) under organizational learning and social learning, the aggregation effect is obvious in the heat map of the researcher's trajectory, with social learning being the most evident. This suggests that the researchers learn through interaction and follow those with higher gains to explore less randomly. Moreover, the movement trajectories can appear highly overlapping.

(3) By analyzing the average income, the average cost of consumption, the average number of disciplinary tasks tackled, the average individual effectiveness, and the system effectiveness of the researchers under the three learning mechanisms shown in Fig. 5 (h)–(l), it can be obtained that 1) for the average income and cost of consumption, social learning $>$ organizational learning $>$ individual learning; for the number of tasks tackled, social learning $>$ organizational learning $>$ individual learning; indicating that the researcher's learning ability and the ability to disseminate information

is stronger, meanwhile all indicators increase. For the individual effectiveness indicator, all three learning mechanisms showed involution (the increase in average consumption costs exceeded the increase in average incomes); for system effectiveness, individual learning > organizational learning > social learning. 2) Social learning can quickly disseminate information, strong inter-individual imitation, and greatest involution; organizational learning improves the speed of information dissemination, where although its output increase is not obvious, its cost is not increased much and it maintains high performance for the longest time; individual learning has the slowest information dissemination and the lowest cost with the middle number of tasks and the best system effectiveness.

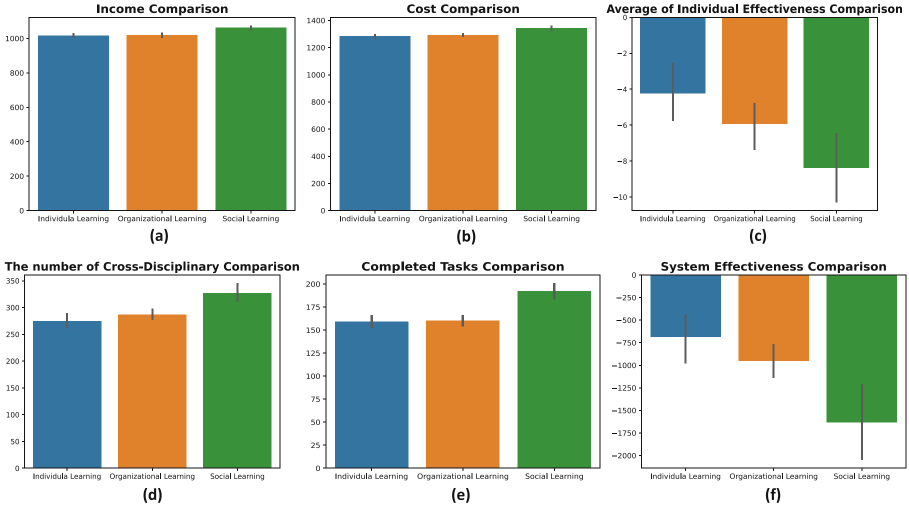

Fig. 6. The average value is calculated in the case of 10 groups of random numbers, and the comparison chart of each index.

The results of a single run in Fig. 5 show that the distribution of incomes according to the number of tasks completed in the discipline creates an involution as the system is run. Since individual mechanisms, organizational mechanisms, and social learning mechanisms are more utilized, the ability of the academic ecosystem to learn and evolve (the ability to disseminate information) increases, accelerating the rate of learning and evolution of the academic ecosystem and deepening the degree of involution.

To further verify the validity of the model and also avoid the possible randomness in a single experiment, 10 random groups are randomly selected for the experiment and results are averaged to obtain the following experimental results, as shown in Fig. 6(a)–(f). The analysis shows that individual learning, organizational learning, and social learning lead to increasing information dissemination among researchers, decreasing mean individual effectiveness, accelerating the rate of evolution of the academic ecosystem, and deepening the degree of involution.

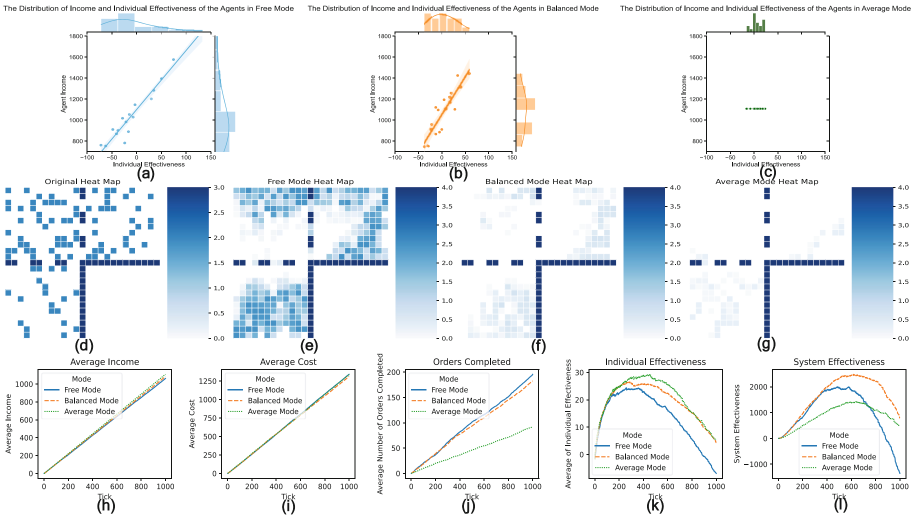

Fig. 7. Comparative analysis of the characteristic index of academic ecosystems under three different learning mechanisms.

b) **Experiment 2:** Improving or updating the regulation algorithm through three different intervention strategies to observe the mitigation effect of different intervention strategies of the regulation algorithm on the involution of the academic ecosystems.

Figure 7 compares and analyses the different characteristic indicators of the learning evolution of the academic ecosystem under the three different intervention modes.

(1) Figure 7 (a)–(c) shows the distribution of researchers' incomes and individual effectiveness under the free, balanced, and average modes, yielding that: 1) under the free mode, the majority of effectiveness values are less than 0 and the degree of involution is severe; there is a large gap in researchers' incomes; 2) under the balanced mode, the proportion of effectiveness values greater than 0 increases and the degree of involution decreases; the gap in researchers' incomes decreases; 3) under the average mode, most of the effectiveness values are greater than 0 with the mean value of effectiveness greater than that of the balanced mode; the incomes of different researchers are equal, and there is no gap in researchers' incomes.
(2) Figure 7 (d)–(g) represents the heat map of the disciplinary task distribution and the heat map of the researcher's trajectory for the three intervention modes, yielding: 1) the aggregation effect and the overlap between the researcher's trajectory and the disciplinary task are both highest in the free mode; 2) the aggregation effect occurs in the balanced mode and there is a degree of overlap between the researcher's trajectory and the location of the disciplinary task distribution; 3) the colors are lighter in the average mode, and the researcher's movement is somewhat exploratory and random, meanwhile, there is no overlap in the movement trajectory.
(3) By analyzing the average income, the average cost of consumption, the average number of disciplinary tasks tackled, the average individual effectiveness, and system effectiveness for the researchers in the three intervention modes in Fig. 7 (h)–(l), it

can be concluded that: 1) For the average income, the average mode > the balanced mode > the free mode. For the average cost of consumption, the three are close to each other. For the number of tasks, the free mode > the balanced mode, and the balanced mode is > the average mode. 2) For mitigating involution, the average mode is > the balanced mode, and the balanced mode > the free mode; however, the number of tasks completed by the average mode is severely reduced, making the academic ecosystem develop slowly. 3) For system effectiveness, the balanced mode performs best and it can ensure the continued rapid development of the academic ecosystem while mitigating involution.

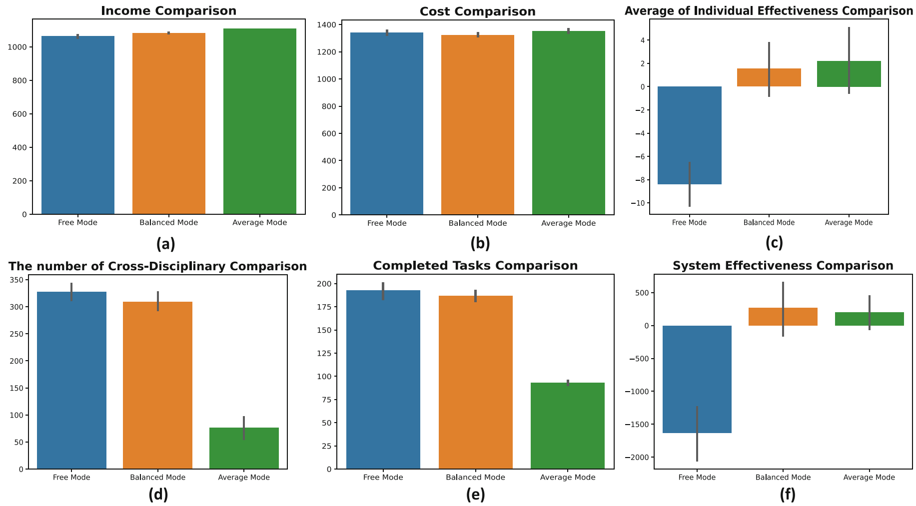

Fig. 8. The average value is calculated in the case of 10 groups of random numbers, and the comparison chart of each.

Figure 7 analyzes the results of a single run of the experiment and shows that the degree of involution is continually mitigated as the proportion of the researcher's basic income to the total income of the researchers rises, but the total number of disciplinary tasks tackled in the whole academic ecosystem is constantly decreasing. Considering the specificity of involution and disciplinary areas in the academic ecosystem, we chose a balanced mode. We cannot choose the average mode that is most effective in mitigating involution, nor the free mode that is most effective in accelerating the development of the discipline of studying ecosystems. The advantage of the balanced mode is that it reduces involution while rapidly developing each disciplinary area.

To verify the validity of the results of a single experiment, 10 random sets of random numbers are randomly selected for the experiment, and the results are averaged as shown in Fig. 8 (a)–(f). The analysis shows that: 1) in the average mode, there is randomness in the researcher's behavior to get more disciplinary tasks; 2) in the free mode, the academic ecosystem has the most serious involution, which is mitigated in the balanced model and the average mode; 3) the balanced mode can mitigate involution based on ensuring rapid disciplinary development of the academic ecosystem and the highest system effectiveness.

5 Conclusion

To better analyze the decision-making processes between the regulation algorithm and the crowd intelligence group in the SE, the CEBA model is proposed in this paper. The above work can provide new research ideas and tools for decision-making processes analysis of SE. For example, in the delivery industry, the delivery time of takeaway riders is getting shorter and shorter under the intelligent regulation algorithm, while more and more effort cannot produce any increase in income, showing an overall state of decreasing marginal effect of involution, etc.

In future work, the CEBA will be further refined and the research will focus on two aspects: 1) comparing artificial society agents with real crowd intelligence groups; 2) replacing the algorithms in the analysis model with the current widely used recommendation algorithms, etc.

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