

A Multi-Agent Simulation Study of the “Involution” Mechanism in Competition Among University Student Populations: Postprint

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Abstract

[Purpose/Significance] Currently, the popularity of “involution” has become a cultural phenomenon, and the social reality issues it reflects merit greater attention. Elucidating the concept and characteristics of “involution” and quantitatively measuring it can facilitate analysis of its formation mechanism and the exploration of solutions. [Method/Process] First, we review the evolution of the “involution” concept; second, propose a quantitative measurement of “involution” based on competitive scenarios among university student populations; third, explore the impact of different strategies on the degree of “involution” in simulation systems from three perspectives: network topology, competition strategy, and value evaluation; finally, based on the aforementioned experimental results, propose corresponding recommendations at both individual and group levels. [Results/Conclusions] As randomness in network topology decreases, the degree of “involution” competition in the system becomes increasingly severe. Cooperative strategies can enhance total system output, whereas competitive strategies yield high total input but low total output. Regarding value evaluation, the global mode exhibits pronounced characteristics of high input, low return, and diminishing marginal utility, indicating severe “involution” .

Full Text

Preamble

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Research on the “Involution” Mechanism of College Student Group Competition Based on Multi-Agent Simulation

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Abstract

[Purpose/Significance] Currently, the popularity of “involution” has become a cultural phenomenon, and the social reality it reflects deserves greater attention. Clarifying the concept and characteristics of “involution” and measuring it from a quantitative perspective can help analyze its formation mechanism and identify potential solutions. **[Method/Process]** First, we trace the evolution of the “involution” concept. Second, we propose quantitative measures for “involution” in the context of college student competition. Third, we explore how different strategies—network topology, competition-cooperation strategies, and value evaluation—affect the degree of “involution” in the simulation system. Finally, based on these experimental results, we offer recommendations at both individual and group levels. **[Results/Conclusion]** As the randomness in network topology decreases, the system’s “involution” competition intensifies. Cooperative strategies can enhance total system output, while competitive strategies result in high total input but relatively low total output. Regarding value evaluation, the global mode particularly exhibits characteristics of high input, low return, and diminishing marginal utility, indicating severe “involution.”

Keywords: involution; multi-agent simulation; knowledge flow; group learning competition

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Introduction

In recent years, “involution” has become a popular internet buzzword. It was listed among the “Top Ten Buzzwords of 2020” by *Yaowen Jiaozi*, defined as “a phenomenon within a certain field where, as more people enter and the field’s inherent limitations become apparent, everyone must exert greater effort to obtain the same benefits as before,” also known as “effort inflation” [1]. In reality, college students are undoubtedly part of the “involution army.” Under the influence of university enrollment expansion and economic slowdown, college students face increasing employment pressure from the moment they enter school. They consciously or unconsciously compete with others, intensifying over time and developing toward an “involution” trend. “Involution” is not only a form of self-mockery among college students but also a true reflection of their state under various pressures such as academic and employment stress. Whether for individuals or society, involution represents a negative state. Wang Junxiu [2] points out that involution involves low-level imitation and replication, resulting in growth only in “quantity” without “quality” improvement—merely formal transformation without substantive breakthroughs. For individuals, college stu-

dents in a state of “involution” endure tremendous pressure, which can lead to mental health issues. For society, “involution” creates tension in interpersonal relationships among college students, insufficient information exchange, and a “prisoner’ s dilemma” situation.

“Involution” is not a new term. As early as the 18th century, Kant proposed the concept of “involution” [3]. However, the current popular meaning of “involution” has undergone significant evolution. Existing theoretical research on “involution” primarily focuses on its traditional meaning, while a theoretical framework for the internet-popularized “involution” has yet to be established. Moreover, current studies on internet-popularized “involution” mostly adopt qualitative perspectives to examine its phenomena, causes, harms, and solutions, lacking quantitative analysis of measurement indicators and influencing factors. This makes it difficult to establish clear standards for exploring “involution.” Examining the “involution” phenomenon among college student groups from a combined qualitative and quantitative perspective and uncovering its influencing mechanisms can help comprehensively understand and systematically address the current intense “involution” phenomenon among college students and society at large.

To this end, this paper first reviews relevant literature on “involution,” discusses the evolution of the “involution” concept, and proposes the definition and characteristics of “involution” for this study. It then reviews research on “involution” in college student group competition contexts, summarizes manifestations of college student “involution” at individual and group levels, and constructs evaluation indicators for “involution” from both absolute and relative dimensions. Next, it builds a simulation model and conducts simulation experiments from three aspects—network topology, competition-cooperation strategies, and value evaluation—to explore how different strategies affect the degree of “involution” in college student group competition. Finally, based on experimental results, it provides recommendations for both college students and administrators to properly address “involution.”

Literature Review and Theoretical Framework

2.1 Concept and Evolution of “Involution”

As early as the 18th century, Kant [3] introduced the concept of “involution,” viewing it as a phenomenon where things become internally complex without affecting the external world. Goldenweiser [4] supplemented this concept, describing it as a process where systems undergo continuous internal refinement and complexity when external expansion is constrained. In the 1960s, Geertz [5] applied the concept of “involution” to study rice agriculture in Java, proposing the concept of “agricultural involution.” In the 1980s, the concept was introduced into Chinese academic circles. Huang Zongzhi [6] employed it to study smallholder economy issues, defining “involution” through diminishing marginal labor productivity or diminishing marginal returns. Subsequently, “involution”

was applied to various fields including social systems [7], market economies [8], and social welfare [9].

Compared with academic terminology, the internet buzzword “involution” differs in meaning. Since the second half of 2020, “involution” has become wildly popular online, with terms like “educational involution” and “worker involution” quickly becoming hot topics. However, behind this popularity lies conceptual ambiguity. Zhang Shunyue [10] argues that discussions about “involution” show signs of misuse and abuse, as many peculiar forms of “involution” could be described with more plain and appropriate concepts. Xu Yingjin [11] believes the current concept of “involution” represents a misinterpretation and overgeneralization, where people simplistically equate “excessive competition” with “involution.”

The classical concept of “involution” has five key characteristics: (1) growth without development in group key elements; (2) diminishing marginal utility in group key element growth; (3) continuous refinement and complexity within the group; (4) lack of sufficient competition within the group; and (5) lack of change in group behavioral logic. The internet buzzword “involution” adds new characteristics while blurring some existing ones, though the core feature of diminishing marginal utility remains unchanged. At the individual level, typical characteristics include “effort inflation” and a “racing self” that pursues comprehensive, rapid competition [12]. At the group level, characteristics (1) and (2) from classical involution are inherited, characteristic (3) is downplayed, characteristic (4) shifts from insufficient competition to excessive competition, and characteristic (5) shifts from repeating the past to constantly seeking new breakthroughs. summarizes the characteristics of both concepts.

** Comparison of Characteristics Between Two “Involution” Concepts**

Classical “Involution”	Internet Buzzword “Involution”
Growth without development	Growth without development
Diminishing marginal utility	Diminishing marginal utility
Continuous refinement and complexity	Seeking breakthroughs, continuous innovation
Lack of sufficient competition	Effort inflation
Lack of change in behavioral logic	Racing self

Based on the above review of the evolution of the “involution” concept, we can see that its scope has continuously expanded while its connotation has been updated. With college student groups as our research object, this study focuses on the internet-popularized meaning of “involution” : a state of intense competition within a system where all individuals must exert more effort than before to obtain the same benefits as previously, resulting in diminishing marginal returns on investment. This “involution” manifests as increasingly fierce competition

among system members, leading to greater overall system input but decreasing returns.

2.2 Relevant Theories and Research

(1) Tournament Theory. The main content of tournament theory is that when absolute performance is uncertain, corporate principals establish performance-based compensation systems linking agents' rewards to their performance rankings to ensure agents meet their expected benefits while improving corporate efficiency [19]. Tournament systems have three characteristics: (1) fixed prizes; (2) prize allocation based on performance ranking; and (3) larger prize gaps create stronger motivation for participants. Similarly, current college student group competition exhibits obvious tournament characteristics. Despite societal calls for diversified evaluation systems, tournament systems remain widely used in college student competition due to their measurability, operability, and strong incentives. Tournament theory is applicable for explaining “involution” in selection-oriented contexts such as graduate school admissions and job assessments.

(2) Zero-Sum Game Theory. Zero-sum game theory refers to a situation in strict competition where one party's gain means another party's loss, with the total gains and losses always summing to “zero” [20]. In zero-sum games, no cooperation is possible between parties—one's gain is another's loss, and overall social interests remain unchanged. Zero-sum game phenomena also exist in college student award and honor selection based on tournament systems. Under ranking-based evaluation, one person's success in award competitions often means another's failure. Graduate school admissions and employment “involution” phenomena also represent zero-sum games, as selections are made proportionally through ranking, and the situation of “many participants but few admissions” directly leads to zero-sum competition among groups.

(3) Self-Efficacy Theory. Proposed by Bandura in 1982, self-efficacy theory suggests that human behavior is influenced not only by outcome expectations but more importantly by self-efficacy expectations [21]. When facing a task, individuals first conduct subjective assessments of task difficulty before taking corresponding actions. If individuals evaluate the task as challenging, it generates positive incentive effects. When evaluated as an obstacle, incentive effects decrease and may even produce anxiety.

2.3 College Student Group Competition

College student group “involution” has attracted significant attention from academia and society [13-14]. Yuan Jinshan [15] explores the pseudo-learning logic of college student “involution” participants from three aspects: evaluation distortion, competition disqualification, and individual loss of independence, pointing out three reasons for students' involvement in “involution”: environmental orientation deviation, group coercion, and poor individual physical and

mental health. Lu Xiaowen [16] views “involution” as a self-locking state under excessive competition. Lin Yangqian [17] discusses manifestations, harms, and countermeasures for college student “involution,” including establishing “involution” early warning mechanisms, emphasizing psychological counseling, and improving resource allocation. Zhao Xianghui [18] studies “involution” in doctoral student publication systems, arguing that goal substitution, path dependence, resource competition, and functional lock-in cause “involution.” Current research on college student “involution” primarily uses theoretical perspectives to qualitatively discuss its causes and solutions.

College student group competition “involution” is one of the most serious and concerning “involution” phenomena in contemporary society. Understanding and addressing this issue is crucial for healthy student development and social harmony. Currently, the scope of internet-popularized “involution” continues to expand while its connotation becomes more refined. Based on the characteristics and evolution of the “involution” concept, this study defines college student group competition “involution” as: within college student groups, a state of intense competition where individuals must exert more effort than before to obtain the same benefits, with diminishing marginal effects of input on returns. This phenomenon involves numerous individuals with complex social networks, cognitive foundations, and nonlinear dynamic competitive-cooperative behaviors that cannot be computed or reproduced through reductionist decomposition methods [22-23].

Simulation Model Design

3.1 Simulation Scenario and Assumptions

3.1.1 Simulation Scenario A typical scenario of contemporary college student “involution” is competition for graduate school recommendation quotas. Against the backdrop of increasingly severe employment prospects, many college students have chosen the path of graduate education. According to statistics, in 2021, China enrolled 1.0507 million master’s students, with 3.37 million applicants, while 2022 saw a record-high 4.57 million applicants. To avoid the fiercely competitive graduate entrance exam and direct employment, students have turned their attention to the graduate recommendation track. According to Ministry of Education regulations, ordinary universities with graduate schools typically allocate recommendation quotas at approximately 15%, varying by institution. This means that in qualified universities, only the top 15% of students can secure recommendation spots, while the remaining 85% will fail regardless of their performance. The scarcity of recommendation quotas and the large number of participants have created “involution” in graduate school competition. When students’ hard work not only fails to yield expected benefits but actually produces negative returns, an “involution trap” emerges. In graduate recommendation calculations, course grades account for approximately 90% of the weight, serving as a hard indicator. Therefore, this simulation focuses on the knowledge learning and application process of college student groups aiming

for graduate school recommendation.

According to M. H. Boisot' s theory [24], group knowledge learning and application can be summarized into four stages: knowledge diffusion (spreading one' s own knowledge), knowledge absorption (absorbing others' knowledge), knowledge scanning (creating new knowledge based on absorbed and existing knowledge), and problem-solving. Correspondingly, in the context of college student knowledge learning and group competition, the knowledge flow process includes four sub-processes: knowledge diffusion, knowledge absorption, knowledge integration, and knowledge application. Knowledge diffusion includes passive spillover and active diffusion; knowledge absorption depends on individual capacity and willingness; knowledge integration manifests as the absorber' s innovation on absorbed knowledge; and knowledge application involves individuals using their knowledge to create value.

3.1.2 Simulation Assumptions Based on the above scenario and existing theories, this study makes appropriate simplifications to the simulation model and proposes the following basic assumptions:

- (1) According to tournament theory, the sole purpose of college students learning knowledge and skills is to achieve good grades in knowledge application and obtain better rankings for selection.
- (2) College students form social networks with acquaintances that evolve dynamically, and individuals only exchange knowledge through network connections.
- (3) Each student' s knowledge background is represented by a vector, where different dimensions represent different knowledge skills, and the numerical value indicates individual knowledge stock in that dimension.

3.2 Agent and Interaction Rule Design

3.2.1 Agent and Agent Attribute Design In the context of mobile internet, big data, and artificial intelligence, higher education forms and scenarios have become more diversified. Beyond traditional classroom teaching and independent reading, online knowledge communities and courses provide contemporary college students with more knowledge acquisition channels [25]. Therefore, the simulation model includes two types of agents: student agents and knowledge source agents, where knowledge sources include teachers, books, online platforms, and other external knowledge acquisition sources. Correspondingly, the model designs student agents' knowledge background as comprehensive knowledge and specialized knowledge. Comprehensive knowledge initially follows a normal distribution, representing the student' s initial knowledge level; specialized knowledge is absorbed from knowledge sources, initially set to zero. During knowledge diffusion and absorption, individuals exchange knowledge with neighbor nodes through social networks. Due to competitive relationships, not all individuals are willing to share knowledge, leading to competitive and cooperative

strategies. The model uses the attribute `compete_{will}` to represent student agents' competition-cooperation strategies. If individual i adopts a competitive strategy toward individual j (`compete_{will}i[j] = 1`), i does not share knowledge skills with j ; if i adopts a cooperative strategy (`compete_{will}i[j] = 0`), i shares knowledge skills with j . In the knowledge application stage, student agents achieve knowledge output based on knowledge background and executive power (the product of knowledge background and executive power). Each dimension's value in the output vector represents the individual's grade in the corresponding knowledge dimension.

The model designs two ranking attributes for student agents based on tournament theory and relevant literature [26]: (1) local ranking `rank_{regional}` (ranking among network neighbors); and (2) overall ranking `rank_{whole}` (ranking among all student agents). Individuals know their local ranking among neighbors but not their overall ranking. Based on self-efficacy theory, the degree of self-efficacy fulfillment is an important incentive mechanism determining whether students can maintain effort. Based on ranking changes, the model designs a reward attribute `reward` to capture the degree of self-efficacy fulfillment from learning, where larger ranking improvements yield greater self-fulfillment. Cumulative reward across rounds is `reward_{total}`. Table 2 summarizes agent attributes in the simulation model.

** Model Agents and Their Attributes**

Agent	Attribute	Description
Student	knowledge	Knowledge vector representing the student's knowledge background
	<code>compete_{will}</code>	Vector of dimension <code>nstudents</code> representing the agent's competition-cooperation willingness. <code>compete_{will}i[j] = 1</code> means agent i is competitive toward agent $*j$; <code>compete_{will}i[j] = 0</code> means cooperative
	<code>executive_{power}</code>	Agent's execution ability, representing knowledge application capacity
	<code>rank_{local}</code>	Agent's local ranking among connected neighbors
	<code>rank_{global}</code>	Agent's overall ranking among all student agents
	input	Agent's instantaneous input

Agent	Attribute	Description
	input_{all}	Agent' s cumulative input
	output	Agent' s instantaneous output
	output_{all}	Agent' s cumulative output
	reward	Agent' s instantaneous reward
	reward_{all}	Agent' s cumulative reward
KnowledgeSource	knowledge	Knowledge vector

3.2.2 Agent Interaction Rule Design Student agents interact according to the following rules:

- (1) **Vector Representation of Knowledge Structure.** Following Ba Zhichao et al. [24], each individual' s knowledge base can be represented by a D -dimensional knowledge vector, where the first M dimensions represent specialized knowledge and dimensions $M+1$ to D represent comprehensive knowledge. At time t , individual i ' s knowledge vector is:

$$K_i(t) = [K_i(t)_1, K_i(t)_2, \dots, K_i(t)_M, K_i(t)_{M+1}, \dots, K_i(t)_D] \quad \text{Formula (1)}$$

- (2) **Knowledge Flow.** College students absorb knowledge from knowledge sources and peers. For individuals i and j , if j adopts a cooperative strategy toward i and j ' s knowledge in dimension d exceeds i ' s, then i can receive knowledge from j :

$$\text{if } Compete_willi[j] = 0 \text{ and } K_j(t)_d > K_i(t)_d, \text{ then } \Delta K_i(t)_d = \beta_{ij} \cdot (K_j(t)_d - K_i(t)_d) \quad \text{Formula (2)}$$

where $K_j(t)_d - K_i(t)_d$ represents knowledge inherited by i from j , and β_{ij} is i ' s knowledge absorption capacity ($0 < \beta_{ij} < 1$). β_{ij} is influenced by i and j ' s knowledge levels in that dimension and their connection strength $L_0(i, j)$ [27]:

$$\beta_{ij} = f(K_i(t)_d, K_j(t)_d, L_0(i, j)) \quad \text{Formula (3)}$$

$\Delta K_i(t)_d$ represents innovative knowledge created by i on the basis of received knowledge, manifesting as subjective innovative growth throughout the evolution process [28]:

$$\Delta K_i(t)_d = K_i(t)_d \cdot (\lambda_i) \quad \text{Formula (4)}$$

where $0 < \lambda_i < 1$ represents individual i ' s innovation capability.

- (3) **New Connections.** Over time, according to triadic closure theory [29], individuals tend to establish new social relationships among second-order neighbors and, with small probability, connect with unconnected individuals. The model designs that after every given time period T , individual i forms a connection with second-order neighbor $j1$ with probability $Link_prob_1$, and with unconnected individual $j2$ with probability $Link_prob_2$.
- (4) **Input Update.** An agent's input includes time and energy costs. Agent i 's input is:

$$input_i(t) = execute_i(t) \quad \text{Formula (5)}$$

$$input_alli(t) = \sum_{a=0}^t input_i(a) \quad \text{Formula (6)}$$

- (5) **Output Update.** Student agents achieve knowledge output based on knowledge background and executive power. Agent i 's output update formula is:

$$output_i(t)_d = Knowledge_i(t)_d \cdot executive_power_i(t) \quad \text{Formula (7)}$$

$$output_alli(t) = \sum_{a=0}^t output_i(a) \quad \text{Formula (8)}$$

- (6) **Ranking Update.** Students' rankings include local and overall rankings. Individuals know their local ranking among neighbors but not their overall ranking. The system conducts overall ranking every given time period T :

$$rank_locali(t) = Rank'(|output_i(t)|) \quad \text{Formula (9)}$$

$$rank_globali(t) = Rank(|output_i(t)|) \quad \text{Formula (10)}$$

where $|output_i(t)|$ represents the vector magnitude of $output_i(t)$, $Rank(|output_i(t)|)$ represents the ranking of $|output_i(t)|$ in the set $\{|output_i(t)|, 0 \leq i < nstudents\}$, and $Order'(|output_i(t)|)$ represents the ranking of $|output_j(t)|$ in the set $\{|output_j(t)|, j \in neighbor(i)\}$.

- (7) **Competition-Cooperation Willingness Update.** Following the announcement of periodic global rankings, individuals adjust their competition-cooperation willingness toward those ranked ahead of them [30]. The model designs different update rules for agents in different ranking intervals. Let N be the number of selective spots. The model

sets that individuals ranked in interval $1 \leq r < 0.5N$ adjust their willingness toward others to cooperative; individuals ranked in interval $0.5N \leq r < 1.5N$ (on the edge of selection) adopt competitive strategies toward others in the same interval and cooperative strategies toward those in other intervals; individuals ranked in interval $1.5N < r \leq nstudents$ adopt cooperative strategies due to ranking disadvantage.

- (8) **Reward Update.** College students focus on their rankings and view ranking changes as rewards for learning effort. Considering the ranking mechanism is a zero-sum game—one person's rise means another's fall—and combining self-efficacy theory, an individual's subjective reward is affected by both ranking changes and initial ranking. Moving from 100th to 99th place yields far less subjective reward than moving from 2nd to 1st place. Therefore, this study adopts the NDCG metric from information retrieval [31]:

$$reward_i(t) = \frac{1}{\log_2(rank_globali(t) + 1)} - \frac{1}{\log_2(rank_globali(t-1) + 1)} \quad \text{Formula (11)}$$

$$reward_alli(t) = \sum_{a=0}^t reward_i(a) \quad \text{Formula (12)}$$

- (9) **Executive Power Update.** According to self-efficacy theory, agent i 's current reward affects its executive power in the next stage. Positive rewards provide positive feedback, increasing executive power; negative rewards provide negative feedback, decreasing executive power. Accordingly, the update rule for agent i 's executive power is:

$$execute_i(t) = \begin{cases} execute_i(t-1) + 0.05, & \text{if } reward_i(t) > 0 \\ execute_i(t-1) - 0.05, & \text{if } reward_i(t) < 0 \end{cases} \quad \text{Formula (13)}$$

Simulation parameters and their descriptions are shown in Table 3. Simulation diagrams are shown in Figure 1 [Figure 1: see original paper] and Figure 2 [Figure 2: see original paper].

** Simulation Parameters and Initialization Settings**

Parameter	Description	Initialization
nstudents	Number of college students	200
D	Knowledge vector dimension	10

Parameter	Description	Initialization
λ_i	Innovation capability of agent i	$\lambda_i \sim DiscreteU[0, 1]$
$L_0(i, j)$	Connection strength between agents i and j	Random value in (0,1)
$compete_willingness[i][j]$	Initial competition-cooperation willingness of agent i toward j	Random 0 or 1
$Link_prob$	Probability of forming new connections	0.1

[Figure 1: see original paper] Simulation Diagram at Time T1

[Figure 2: see original paper] Simulation Diagram at Time T2

3.3 “Involution” Metrics

College student group competition “involution” exhibits four characteristics: high input, low return, diminishing marginal utility, and intense competition. These manifest in both the stability of relative rankings and the convergence of absolute performance. Under intense competition, each individual invests significant effort with minimal gaps between them, yet cannot change relative rankings.

The high-input characteristic of “involution” is measured by cumulative instantaneous input (Formula 14). “Involution” measures a group state, so its indicators should consider the group level. Combining the “high input” characteristic, the model sums all agents’ instantaneous input as system input and observes its trend:

$$Input_system(t) = \sum_{i=1}^{ns} input_i(t) \quad \text{Formula (14)}$$

The low-return characteristic is measured by cumulative instantaneous reward (Formula 15). The model sums all agents’ instantaneous rewards as system reward and observes its trend:

$$Reward_system(t) = \sum_{i=1}^{ns} reward_i(t) \quad \text{Formula (15)}$$

The diminishing marginal utility characteristic is measured by the input-output ratio from economics (Formula 16). Referencing the input-output ratio, the system’ s ROI is calculated as:

$$ROI(t) = \frac{Reward_system(t)}{Input_system(t)} = \frac{\sum_{i=1}^{ns} reward_i(t)}{\sum_{i=1}^{ns} input_i(t)} \quad \text{Formula (16)}$$

The intense competition characteristic is measured by the coefficient of variation (Formulas 17-20). For system instantaneous input, the coefficient of variation $Input_system_CV(t)$ is:

$$Input_system_CV(t) = \frac{\sigma_{input}(t)}{\mu_{input}(t)} \quad \text{Formula (17)}$$

For cumulative system input, $Input_all_system_CV(t)$:

$$Input_all_system_CV(t) = \frac{\sigma_{input_all}(t)}{\mu_{input_all}(t)} \quad \text{Formula (18)}$$

For system instantaneous output, $Output_system_CV(t)$:

$$Output_system_CV(t) = \frac{\sigma_{output}(t)}{\mu_{output}(t)} \quad \text{Formula (19)}$$

For cumulative system output, $Output_all_system_CV(t)$:

$$Output_all_system_CV(t) = \frac{\sigma_{output_all}(t)}{\mu_{output_all}(t)} \quad \text{Formula (20)}$$

Table 4 summarizes “involution” characteristics and corresponding measurement indicators.

** “Involution” Characteristics and Corresponding Measurement Indicators**

Characteristic	Indicator	Description
High input	Input_{system}	System instantaneous total input
Low return	Reward_{system}	System instantaneous total reward
Diminishing marginal utility	ROI	System instantaneous input-output ratio
Intense competition	Input_{system} CV	Coefficient of variation of system instantaneous total input
	Input_{all} CV	Coefficient of variation of system cumulative total input

Characteristic	Indicator	Description
	$Output_{\{\{\{system\}\}\} - C_{\{G\}}(t)$	Coefficient of variation of system instantaneous total output
	$Output_{\{\{\{all\}\}\}\{system\} - C_{\{G\}}(t)$	Coefficient of variation of system cumulative total output

This study implements the complex simulation model with numerous agents and their interactions using Netlogo, which offers simple syntax, powerful functionality, extensive model libraries, and good visualization. The simulation process is shown in Figure 3 [Figure 3: see original paper]. The specific steps are:

- (1) **Initialization:** Initialize the scale-free network; set model parameters according to Table 3; initialize student agents' knowledge background vectors, executive power, and innovation capability according to Section 3.2; initialize agent rewards to 0.
- (2) **Knowledge Application:** Calculate agents' instantaneous input, cumulative input, instantaneous output, and cumulative output using Formulas (5)-(8).
- (3) **Ranking and Reward Calculation:** Calculate agents' local and global rankings using Formula (9); calculate instantaneous and cumulative rewards using Formulas (10) and (11).
- (4) **Adjust Competition-Cooperation Attitudes:** Adjust agents' competition-cooperation attitudes according to Interaction Rule 7.
- (5) **Knowledge Flow:** Update agents' knowledge vectors using Formula (2).
- (6) **Update Executive Power:** Update agents' executive power using Formula (12).
- (7) **Form New Connections:** Agents expand social relationships and form new connections according to Interaction Rule 3.
- (8) **Calculate "Involution" Metrics:** Calculate "involution" indicators using Formulas (13)-(19) based on Section 3.3.
- (9) **$t = t + 1$:** Increase simulation time by 1.
- (10) **Check $t < 200$:** Determine if simulation time has reached 200; if yes, end simulation; otherwise, return to step (2) for the next cycle.

[Figure 3: see original paper] **Simulation Flowchart**

Experiments and Results Analysis

To explore the formation mechanism of “involution” and identify potential solutions, this section first analyzes results under default parameters, then examines how network topology, competition-cooperation strategies, and value evaluation affect “involution” in college student group competition.

4.1 Default Parameter Results Analysis

This subsection conducts simulation experiments and analysis using the default parameters designed in Table 3, examining system “involution” from executive power, input-output, and their coefficients of variation.

Figure 4 [Figure 4: see original paper] shows the evolution of total system executive power. Over time, the group’s overall effort level increases, stabilizing after simulation time $t = 70$. Figures 4(a) and 4(b) show the standard deviation and coefficient of variation of total system executive power, both decreasing after a brief increase to reach stable states. This indicates that over time, college students exert greater effort with decreasing gaps, making competition increasingly intense.

Addressing “involution” characteristics of high input, low return, and diminishing marginal utility, Figure 5 [Figure 5: see original paper] plots system input-reward evolution based on Formulas (13)-(15). Over time, total group input increases while total reward decreases, with corresponding ROI showing a downward trend. The system reward and ROI plots show obvious periodic bumps because reward calculations at $t = \text{multiples of } 25$ use agents’ overall rankings. Simulation results align with the “involution” characteristics described earlier.

Regarding coefficients of variation, Figure 6 [Figure 6: see original paper] shows system input-output coefficient of variation evolution. Whether considering input or output, instantaneous or cumulative measures, all CV trends decline. This indicates that college students’ input and output continuously increase while gaps narrow, making competition increasingly intense.

In summary, simulation results validate the model design. In the simulation system, agents’ executive power and input increase over time. However, due to system “involution,” agents’ efforts do not yield corresponding rewards—total system reward decreases, marginal utility diminishes, and competition among agents intensifies.

[Figure 4: see original paper] Evolution of Total System Executive Power

[Figure 5: see original paper] System Input-Reward Evolution

[Figure 6: see original paper] Evolution of System Input-Output Coefficient of Variation

4.2 Network Topology Effects on “Involution”

This subsection selects four classic network topologies—regular network, small-world network, random network, and scale-free (BA) network [32-33]—to analyze their impact on system “involution.” The experiments keep other parameters constant to verify model stability. Simulation parameters are shown in Table 5, where K represents the initial network’s average node degree and p represents the small-world network’s rewiring probability. This section analyzes total input, total output, total reward, system ROI, cumulative total input coefficient of variation, and cumulative total output coefficient of variation across different networks.

Figures 7 [Figure 7: see original paper] through 12 [Figure 12: see original paper] show that simulation results are roughly consistent across network topologies. In Figure 7, before reaching equilibrium, the small-world network with rewiring probability 0.2 shows the highest total system input, while the BA network shows the lowest. However, after reaching equilibrium, different networks converge at similar times and values. Figures 8 [Figure 8: see original paper] through 10 [Figure 10: see original paper] show that total system output, total reward, and system ROI are largely similar across networks. Figures 7, 9 [Figure 9: see original paper], and 10 indicate that for “involution” characteristics of high input, low return, and diminishing marginal utility, different network topologies have minimal impact. However, for the intense competition characteristic, system coefficient of variation indicators differ significantly across network topologies, showing clear patterns. In Figures 11 [Figure 11: see original paper] and 12 [Figure 12: see original paper], random networks show the largest coefficient of variation, followed by small-world networks, then regular networks, and finally BA networks.

** Network Topology and Simulation Parameter Settings**

Network Type	Parameters
Regular Network	$K = 4$
Small-World Network	$K = 4, p = 0.2$
Small-World Network	$K = 4, p = 0.8$
Random Network	$K = 4$
BA Network	-

[Figure 7: see original paper] **Total System Input Across Different Networks**

[Figure 8: see original paper] **Total System Output Across Different Networks**

[Figure 9: see original paper] **Total System Reward Across Different Networks**

[Figure 10: see original paper] **System ROI Across Different Networks**

[Figure 11: see original paper] **Cumulative Total Input Coefficient of Variation Across Different Networks**

[Figure 12: see original paper] **Cumulative Total Output Coefficient of Variation Across Different Networks**

Therefore, network topology primarily affects the intense competition characteristic of group “involution.” As randomness in network topology decreases, group “involution” competition intensifies. Against the backdrop of slowing economic growth and expanding talent pools, competition within industries intensifies, and corporate talent selection standards rise sharply, forcing more students into the graduate school track and deeper “involution” 困境. To increase randomness in group networks, individuals should reasonably assess their capabilities and choose development directions that better leverage their advantages rather than blindly following the trend into graduate school competition. For groups, more information about diverse employment and education options should be provided to clarify future prospects across different development paths and encourage members to pursue diversified development.

4.3 Competition-Cooperation Strategy Effects on “Involution”

Competition is an important driver of group “involution.” Reasonable competition can promote group vitality, but excessive competition can easily lead to “involution.” This subsection sets up three competition strategies—competitive, co-opetitive, and cooperative—to explore their impact on “involution.” Strategy settings are shown in Table 6 . This section analyzes total input, total output, total reward, system ROI, cumulative total input coefficient of variation, and cumulative total output coefficient of variation under different strategies.

** Competition Strategies and Simulation Parameter Settings**

Strategy	Description
Competitive Strategy	Throughout simulation, agent i ' s competition willingness toward agent j remains competitive: $compete_{will}i[j] = 1$
Co-opetitive Strategy	See Formulas (3)-(12) for dynamic adjustment
Cooperative Strategy	Throughout simulation, agent i ' s competition willingness toward agent j remains cooperative: $compete_{will}i[j] = 0$

Figure 13 [Figure 13: see original paper] shows total system input evolution under different strategies. Total input trends differ significantly across strategy

types. The competitive strategy yields higher total system input than the other two strategies. Figure 14 [Figure 14: see original paper] shows total system output evolution. The competitive strategy's output stabilizes after a brief increase, while co-opetitive and cooperative strategies show no clear stabilization trends within simulation time. Thus, among the three strategies, competitive strategy produces the highest total input but lowest total output.

Figures 15 [Figure 15: see original paper] and 16 [Figure 16: see original paper] show total reward and system ROI evolution under different strategies. Different strategies have similar impacts on total reward and system ROI, both showing downward trends that reflect “involution” characteristics of low return and diminishing marginal utility.

Figures 17 [Figure 17: see original paper] and 18 [Figure 18: see original paper] reflect system “involution” competition intensity under different strategies. Before $t = 50$, cooperative strategy shows the largest coefficient of variation, followed by competitive strategy, with co-opetitive strategy the smallest. Over time, competitive strategy's coefficient of variation surpasses that of cooperative strategy. In competitive strategy simulations, the initial stage features intense competition as agents chase each other closely. Over time, competitive strategies hinder knowledge flow, widening gaps between agents and increasing system coefficient of variation, while cooperative strategies show the opposite pattern. Both competitive and cooperative strategies' coefficients of variation exceed that of co-opetitive strategy.

[Figure 13: see original paper] Total System Input Under Different Competition Strategies

[Figure 14: see original paper] Total System Output Under Different Competition Strategies

[Figure 15: see original paper] Total System Reward Under Different Competition Strategies

[Figure 16: see original paper] System ROI Under Different Competition Strategies

[Figure 17: see original paper] Coefficient of Variation of Total System Input Under Different Competition Strategies

[Figure 18: see original paper] Coefficient of Variation of Total System Output Under Different Competition Strategies

In summary, competition-cooperation strategies primarily affect the high-input and intense competition characteristics of “involution.” Cooperative strategies can enhance total system output, while competitive strategies yield high total input but low total output. Therefore, groups should monitor members' competitive states, advocate value orientations focusing on actual improvement, encourage healthy competition-cooperation relationships, promote total output improvement, and effectively raise overall group member levels. Individuals

should reasonably view competition-cooperation relationships with group members, abandon the mindset of always being first, and seek win-win cooperation.

4.4 Value Evaluation Effects on “Involution”

Ranking-based selection mechanisms are important factors causing group “involution,” reflecting group value evaluation systems. This subsection explores how different ranking mechanisms within the system affect “involution” formation. Specifically, the simulation experiments set up three different ranking announcement mechanisms: (1) Global mode—announcing agents’ global ranking at every simulation iteration; (2) Normal mode—announcing global ranking every 25 time units (current default); and (3) Local mode—not announcing agents’ global ranking. Simulation settings are shown in Table 7. This section analyzes total input, total output, total reward, system ROI, cumulative total input coefficient of variation, and cumulative total output coefficient of variation under different value evaluation systems.

** Ranking Announcement Mechanisms and Simulation Parameter Settings**

Mode	Description	Interval T
Global Mode	Announce global ranking every iteration	T = 1
Normal Mode	Announce global ranking every 25 time units	T = 25
Local Mode	Do not announce global ranking	T = $+\infty$

Figures 19 [Figure 19: see original paper] through 22 [Figure 22: see original paper] show that in terms of total input and output, global mode yields the highest total input and output but the lowest total reward and system ROI, with earlier inflection points, indicating more severe “involution” than the other two value evaluation systems.

[Figure 19: see original paper] Total System Input Under Different Value Evaluation Modes

[Figure 20: see original paper] Total System Output Under Different Value Evaluation Modes

[Figure 21: see original paper] Total System Reward Under Different Value Evaluation Modes

[Figure 22: see original paper] System ROI Under Different Value Evaluation Modes

Figures 23 [Figure 23: see original paper] and 24 [Figure 24: see original paper] show that in early simulation stages, global mode has the largest coefficients of variation for cumulative total input and output, with normal mode the smallest. In middle stages, local mode shows the largest coefficient of variation, while normal mode remains the smallest.

[Figure 23: see original paper] Coefficient of Variation of Cumulative Total Input Under Different Value Evaluation Modes

[Figure 24: see original paper] Coefficient of Variation of Cumulative Total Output Under Different Value Evaluation Modes

In summary, value evaluation affects all four “involution” characteristics: high input, low return, diminishing marginal utility, and intense competition. Global mode value evaluation particularly exhibits high input, low return, and diminishing marginal utility, indicating severe “involution,” while showing less intense competition. A possible explanation is that frequent global ranking announcements enable individuals to comprehensively understand competitors’ strengths, allowing targeted competition that achieves severe “involution” without an intensely competitive atmosphere. Therefore, administrators should choose appropriate timing and frequency for ranking announcements, such as publishing rankings once before graduate school evaluation to help potentially recommended students prepare while allowing lower-ranked students to adjust strategies. Individuals should reasonably view graduate school rankings, focus on actual growth, and adopt multidimensional perspectives on their development and achievements.

Conclusion and Outlook

Currently, “involution” has become a hot topic, and the social reality it reflects deserves attention. On one hand, the popularity of the term has led to some evolution of the concept, causing ambiguity. On the other hand, existing research mostly qualitatively describes its manifestations, causes, harms, and countermeasures, with few quantitative measurements and mechanism analyses. This study addresses these gaps by focusing on college student group competition scenarios, systematically summarizing “involution” manifestations at individual and group levels, and proposing comprehensive quantitative measures from four dimensions: input statistics, output statistics, input-output utility, and coefficient of variation. Using multi-agent simulation, the study explores how network topology, competition-cooperation strategies, and value evaluation affect “involution” degree. Results show that network topology primarily affects the intense competition characteristic—as randomness decreases, “involution” competition intensifies. Competition-cooperation strategies mainly affect high input and intense competition characteristics; cooperative strategies enhance total output, while competitive strategies yield high input but low output. Value evaluation affects all characteristics; global mode value evaluation particularly shows high input, low return, and diminishing marginal utility, indicating severe “involution.”

The simulation modeling approach used for the typical graduate school recommendation scenario also applies to other selection-based competition contexts such as employment, graduate school admissions, civil service exams, and studying abroad. The conclusions can inform responses to “involution” for both

college students and administrators. For students: expand social networks, develop comprehensive cognition, and view “involution” from multiple dimensions; maintain appropriate competitive willingness to enhance group output while avoiding all-out competition; focus on actual growth rather than ranking fluctuations. For administrators: facilitate adequate information exchange, monitor members’ competitive states, advocate value orientations focusing on actual improvement, and avoid evaluating success solely by outcomes.

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Author Contributions

He Chaocheng: Research design, experiment implementation, paper writing; Wu Jiang: Research design, paper revision; Huang Qian: Experiment implementation, paper writing; Zuo Renxian: Experiment implementation, paper writing; Tang Zhenhua: Experiment implementation, paper writing.

Note: Figure translations are in progress. See original paper for figures.

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