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Evolutionary Game Analysis of New Farmers in e-Commerce Chains

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Abstract: This study presents a rural e-commerce ecosystem model that underscores the synergistic efforts of multiple stakeholders in cultivating new farmers, a key driver in China's agricultural and rural modernization. We integrate a neural network into the evolutionary game framework and employ particle swarm optimization (PSO) to train it, simulating the learning and behavior of new farmers. The study applies this model to analyze the repeated Prisoner's Dilemma, revealing the PSO-trained neural network's efficacy in modeling the learning and strategy adjustment of bounded rational new farmers. Key findings include the significant influence of initial cooperative thresholds, investment costs, and collaborative surplus profits on strategic decisions for co-cultivating new farmers. The research contributes to rural revitalization strategies by highlighting the importance of cooperative mechanisms in fostering sustainable rural e-commerce development. The integration of PSO with neural networks to analyze evolutionary games represents a novel approach, offering a strategic roadmap for enhancing rural economic growth through new farmer cultivation.

Keywords: cooperative dynamics; e-commerce industry chain; evolutionary game algorithm; new farmers; rural economic development

1 INTRODUCTION

The advent of the digital era has catalyzed significant changes in China's agricultural sector, particularly in rural areas. The synergy between e-Commerce Enterprises and Logistics Companies has revitalized rural economies, with the cultivation of "new farmers" emerging as a strategic pathway to economic self-sufficiency and sustainable growth [1, 2]. "New farmers" refer to individuals with modern agricultural knowledge and skills, adept at leveraging technology for innovation and efficient agricultural management [3]. Major e-Commerce platforms like Pinduoduo, Alibaba, and China Post have developed models to nurture new farmers, while smaller enterprises such as Huitongda and Lexiang Tianshui are also refining their approaches.

Evolutionary game theory, a subset of game theory, is often used to analyze the co-evolutionary dynamics among entities with both competitive and cooperative interactions. Studies on the rural e-commerce industry chain have concentrated on the evolutionary game behaviors between government and enterprises [2, 4], buyers and sellers [5], platforms and enterprises [6], and among enterprises [7]. These investigations have primarily focused on regulatory, reward, and punishment mechanisms, as well as interest distribution and relationship governance to foster a healthy e-commerce ecosystem. However, there is a dearth of research on the shared social responsibility mechanisms between e-commerce platforms and logistics companies, particularly regarding their joint efforts in cultivating new rural talents [8].

This paper posits that the development of new farmers is pivotal not only for agricultural progress but also for the economic and social infrastructure of rural communities. The rise of rural e-commerce offers a critical opportunity to explore the complex collaboration dynamics between e-commerce businesses and logistics corporations, which are key stakeholders in this transformation [9, 10]. The strategic interplay between these entities, operating within their respective spheres, involves navigating cooperation and competition to achieve mutual benefits and sustainability. The co-evolutionary game dynamics between these sectors are thus of significant interest, requiring a detailed understanding of their strategic interactions and the factors influencing their collaborative efforts [11, 12].

To address this, we develop an evolutionary game framework to model and evaluate the strategic decisions and stable evolutionary outcomes for e-Commerce Enterprises and logistics firms as they engage in new farmer development. The model incorporates factors influencing decision-making, such as initial cooperation willingness, investment costs, cost-sharing coefficients, surplus benefit distribution, and moral hazard considerations.

Using MATLAB R2023b for simulation experiments, this study aims to provide empirical evidence and theoretical insights into the conditions that foster active collaboration. The findings enrich the academic discourse on strategic governance and cooperative innovation, particularly in rural development and e-commerce logistics. This paper offers practical guidance for policymakers, industry leaders, and agricultural stakeholders. By examining the evolution mechanism of the e-commerce industry chain to new farmers under the evolutionary game model, this study clarifies the mechanisms for promoting cooperation and the stability of collaborative efforts. The research aims to inform strategies that encourage new farmers to cultivate, contributing to rural revitalization and economic prosperity.

In the following sections, this paper will conduct a literature review, and then systematically present the methodology, results, and conclusions derived from the evolutionary game analysis, providing a comprehensive perspective on the dynamics of cooperation between e-Commerce Enterprises and Logistics Companies in cultivating new farmers.

2 EVOLUTIONARY GAME MODEL

2.1 The Game-Theoretic of e-Commerce Industry

In the decision-making regarding cooperation in cultivating new farmers, e-Commerce Enterprises and logistics companies form a complex game relationship. The game objectives mainly focus on maximizing cost-effectiveness, market expansion, risk sharing, and establishing long-term cooperative relationships [13]. The game objectives of e-Commerce Enterprises may include ensuring efficient delivery of agricultural products, improving consumer satisfaction, enhancing supply chain stability, and obtaining more market data and user insights through cooperation [14]. Logistics companies may seek to expand their business scope, improve delivery efficiency, reduce operational costs, and obtain a stable source of orders through cooperation [15].

Factors affecting the game include market demand, cost control, service quality, technological capabilities, policy environment, and the reputation of both parties [16]. E-commerce Enterprises will consider the logistics company's service network coverage, delivery speed, and cost-effectiveness when choosing a partner. Logistics companies need to assess the e-Commerce industry's order volume, market potential, and payment ability [17].

In addition, both parties need to consider the long-term sustainability of cooperation, including investment in rural infrastructure, support for training new farmers, and consideration of environmental and social impacts [18]. Successful cooperation requires both parties to communicate and coordinate effectively based on a clear common goal, achieving resource sharing and complementary advantages [19, 20].

Based on the aforementioned analysis, we will delve into the analysis of the evolution mechanism of new farmers in the rural e-commerce industry chain from two aspects. On one hand, we utilize evolutionary game analysis to explore the evolutionary game issues between e-commerce platforms and logistics enterprises in nurturing new farmers. On the other hand, we investigate the strategic choices of new farmers through training with the Particle Swarm Optimization (PSO) algorithm and neural networks [21]. The combined use of these two methods, which differs from previous related literature, can more comprehensively assist us in understanding the evolution mechanism of new farmers within the rural e-commerce industry chain.

2.2 Model Postulates

In analyzing the dynamic between logistics companies and e-Commerce Enterprises in the development of new farmers, the following assumptions are made for the construction and study of an evolutionary game model:

Assumption 1: Considering the shared benefits of joint cultivation, it is assumed that both parties are motivated to collaborate. However, influenced by a competitive environment and information constraints, they may choose between "active" and "passive" cooperation, with the latter potentially leading to independent development or disengagement.

Assumption 2: The probabilities of choosing "active" cooperation for e-Commerce Enterprises and Logistics Companies are x and y, respectively (both ranging from 0 to 1), with "passive" cooperation probabilities being $1 - x$ and $1 - y$.

Assumption 3: In the absence of cultivating new farmers, the normal profits for e-Commerce Enterprises and Logistics Companies are R_1 and R_2, respectively.

Assumption 4: Joint cultivation of new farmers by both parties will generate additional profits R based on normal profits, which are divided between the two parties with distribution coefficients β and $1 - \beta$ for the e-Commerce industry chain, respectively.

Assumption 5: Should either party adopt a "passive" stance in cooperation, the initiative to jointly cultivate new farmers may be jeopardized. Under such circumstances, the party choosing a reactive approach will withdraw from the collaboration, leaving the proactively cooperating party to independently carry forward the cultivation of emerging agricultural practitioners. In this scenario of independent cultivation, the additional profits garnered by the proactively cooperating party are denoted as P_1 for the e-Commerce company and P_2 for the logistics enterprise.

Assumption 6: Cultivating new farmers requires various cost inputs, including capital investment, labor input, and risk costs, etc., resulting in a total initial investment cost C. If both parties "actively cooperate," these costs are shared, with cost-sharing coefficients θ and $1 - \theta$ for the e-Commerce industry chain, respectively. If one party actively cooperates and the other does not, the joint cultivation fails, and the initial investment cost is borne solely by the actively cooperating party.

Assumption 7: If a single party chooses "active cooperation," the "passive cooperation" party may incur moral hazard costs to gain speculative profits. The moral hazard costs for "passive cooperation" for the e-Commerce industry chain are D_1 and D_2, respectively.

Assumption 8: If both parties choose "passive cooperation," this should indicate a lack of willingness to cultivate new farmers, hence both have opted not to engage in their cultivation.

To enhance the enthusiasm for cooperation, it is required that: $C > P_1$, $C > P_2$, meaning the total initial investment cost for independent cultivation of new farmers is greater than the profits from independent cultivation. The specific model parameters and their meanings are shown in Tab. 1.

Table 1 Parameters and their definitions

Parameter	Definition
R_1	The revenue of the e-commerce enterprise when not cultivating new farmers
R_2	The revenue of the logistics enterprise when not cultivating new farmers
R	The excess profit generated from the joint cultivation of new farmers by both parties
β	The proportion of excess profits from the joint cultivation of new farmers allocated to the e-Commerce industry.
$1 - \beta$	The proportion of excess profits from the joint cultivation of new farmers allocated to the logistics enterprise.
P_1	The additional profit for the e-Commerce industry in cultivating new farmers independently
P_2	The additional profit for the logistics enterprise in cultivating new farmers independently
C	The initial investment cost for cultivating new farmers
θ	The proportion of initial investment costs for jointly cultivating new farmers borne by the e-Commerce industry.
$1 - \theta$	The proportion of initial investment costs for the joint cultivation of new farmers undertaken by the logistics enterprise.
D_1	The moral hazard cost for the e-Commerce industry choosing "passive cooperation"
D_2	The moral hazard cost for the logistics enterprise choosing "passive cooperation"

2.3 PSO Algorithm and Neural Network Training

PSO algorithm is an evolutionary algorithm derived from the research on the predation behavior of birds [21]. Studies have shown that PSO algorithm is a promising neural network training algorithm [21-33], and the use of PSO instead of directional propagation algorithm to train neural networks has been gradually paid attention to. Like genetic algorithm, PSO algorithm is also based on population and fitness, a possible solution to the problem of individual representation of a particle swarm. Each particle has two characteristics: position and velocity. The objective function corresponding to the position coordinates of the particle can be taken as the fitness of the particle. The algorithm first initializes a group of random particles and finds the optimal solution through iteration. In each iteration the particle updates itself by tracking two polar values. One is the optimal solution found by the particle itself, that is, the individual extremum p Best. The other is the current optimal solution of the entire particle swarm, which is called the global extreme value g_{Best}. After the particle finds the above two extreme values, it updates its speed and position according to the following two formulas.

$$V = w*V + c_1 rand*(p_{\text{Best}} - Present) + c_2*rand*(g_{\text{Best}} - Present)$$
$$Present = Present + V \tag{1}$$

where V is the velocity of the particle, Present is the current position of the particle, *rand* is the random number between [0, 1], c_1 and c_2 are called learning factors. In general, c_1 is equal to c_2 is equal to 2. w is a weighting coefficient, usually between 0.1 and 0.9. During the updating process, the maximum velocity and coordinates of each dimension of the particle are restricted within the allowable range. At the same time, PBSest and g_{Best} are updated continuously in the iterative process, and the final output GBSest is the optimal solution obtained by the algorithm. In order to ensure the convergence of the algorithm, this paper adopts the compression factor method [21]. As a particle, the flying speed V of the new farmer is as follows.

$$V = \chi[w*V + c_1*rand*(p_{\text{Best}} - Present) + c2*rand*(g_{\text{Best}} - Present)] \tag{2}$$

When the neural network is trained by PSO algorithm, the new farmer position represents the total connection weight of the neural network, and the mean square error of the actual output and the expected output of the network.

The difference is used as fitness function, and PSO algorithm is used to search the optimal location of new farmers, that is, the optimal weight of the neural network, so as to minimize the mean square error. The algorithm flow is as follows:

(1) Select the number of new farmers, the maximum number of iterations and the minimum expected error, and initialize the position and speed of new farmers in the group;

(2) The new farmer's p_{Best} is set to the current position, and g_{Best} is set to the position of the Best new farmer in the initial group;

(3) If the maximum number of iterations is reached or the fitness of g_{Best} meets the minimum expected error, turn to (6). Otherwise, perform (4);

(4) For all new farmers in the group, perform the following operations: (a) Update the position and velocity of the particle according to equations (1) and (2); (b) If the fitness of new farmers is better than that of p_{Best}, p_{Best} are set to the new position; (c) If the fitness of new farmers is better than that of g_{Best}, g_{Best} is set as the new position;

(5) If the maximum number of iterations is reached or the fitness of g_{Best} meets the minimum expected error, perform (6). Otherwise, turn to (4).

(6) Output g_{Best}.

3 PAYOFF MATRIX AND EQUILIBRIUM ANALYSIS

Drawing on the model's foundational assumptions and the parameter definitions, the evolutionary game's payoff matrix for the e-Commerce industry chain, each with options for "Active" or "Passive" Cooperation, is formulated (as shown in Tab. 2).

Table 2 The two parties evolutionary game payoff matrix

Game Participants and Strategies		Logistics Enterprise: Active Cooperation (y)	Logistics Enterprise: Passive Cooperation ($1-y$)
e-Commerce industry	Active Cooperation (x)	$R_1 + \beta R - \theta C$; $R_2 + (1-\beta)R - (1-\theta)C$	$R_1 + P_1 - C$; $R_2 - D_2$
	Passive Cooperation ($1-x$)	$R_1 - D_1$; $R_2 + P_2 - C$	R_1; R_2

By applying the calculations from Tab. 2, we ascertain the expected and average payoffs for both entities, enabling the development of replicator dynamics equations for the e-Commerce industry chain.

3.1 Replication Dynamic Equation and Equilibrium Point for e-Commerce Industry

When the e-Commerce industry selects the "Active Cooperation" strategy for cultivating new farmers, the expected payoff is calculated as follows:

$$I_{11} = y\left[\beta R + R_1 - \theta \mathrm{C}\right] + (1-y)\left(P_1 + R_1 - \mathrm{C}\right) \tag{3}$$

The e-Commerce industry's expected revenue from adopting a "Passive Cooperation" strategy in developing new farmers is delineated below.

$$I_{12} = y\left(R_1 - D_1\right) + (1-y)R_1 \tag{4}$$

The average expected payoff for the e-Commerce industry's decision-making behavior is as follows.

$$\overline{I_1} = xI_{11} + (1-x) I_{12} \tag{5}$$

Consequently, the replicator dynamics equation for the e-Commerce industry is deduced from the considerations:

$$\begin{aligned} F(x) &= \frac{\mathrm{d}x}{\mathrm{d}t} = x\left(I_{11} - \overline{I_1}\right) = x(1-x)(I_{11} - I_{12}) \\ &= x(1-x)\left[y\left[\beta R + D_1 + (1-\theta)C - P_1\right] + P_1 - C\right] \end{aligned} \tag{6}$$

According to evolutionary game theory [34], reaching an Evolutionarily Stable Strategy (*ESS*) requires that $F(x) = 0$ and $\mathrm{d}F(x)/\mathrm{d}x < 0$. Therefore, it is necessary to calculate $dF(x)/\mathrm{d}x$ to determine its sign. The formula for calculating $\mathrm{d}F(x)/\mathrm{d}x$ is as follows:

$$\begin{aligned} F^{'}(x) = \frac{\mathrm{d}F(x)}{\mathrm{d}x} = (1-2x) \\ \left[y\left[\beta R + D_1 + (1-\theta)C - P_1\right] + P_1 - C\right] \end{aligned} \tag{7}$$

Solving $f(x) = 0$ yields the possible values $x = 0$, $x = 1$ and $y^* = \dfrac{C - P_1}{\beta R - \theta C_1 + D_1 + C - P_1}$.

(1) At $y = y^*$, $F(x)$ equals zero, indicating that regardless of the e-Commerce industry's "active cooperation" probability x within [0,1], its payoff remains constant when the logistics enterprise has an "active cooperation" probability of y^*. This condition reflects a stable system equilibrium.

(2) For y not equal to y^*, if y is between 0 and y^*, setting $x = 0$ ensures stability with $\mathrm{d}F(x)/\mathrm{d}x < 0$, identifying $x = 0$ as the stable solution. When y is greater than y^* but less than 1, setting $x = 1$ also ensures stability, making $x = 1$ the stable solution [24]. This indicates that a lower active cooperation probability by the logistics enterprise leads to the e-Commerce industry's equilibrium strategy of "passive cooperation," while a higher probability prompts a shift to "active cooperation" as the strategic equilibrium.

3.2 Replication Dynamic Equation and Equilibrium Point for e-Commerce Industry

The expected payoff for the logistics enterprise choosing the "Active Cooperation " strategy is as follows.

$$\begin{aligned} &I_{21} = \\ &x\left[R_2 + (1-\beta)R - (1-\theta)C\right] + (1-x)(R_2 + P_2 - C) \end{aligned} \tag{8}$$

The anticipated profit for the logistics enterprise opting for a "Passive Cooperation" approach is as follows:

$$I_{22} = x(R_2 - D_2) + (1-x)R_2 \tag{9}$$

The average expected payoff for its strategic choices is:

$$\overline{I_2} = yI_{21} + (1-y)I_{22} \tag{10}$$

The equation that describes the evolution of the logistics enterprise's strategy is given by:

$$\begin{aligned} F(y) &= \frac{\mathrm{d}y}{\mathrm{d}t} = y\left(I_{21} - \overline{I_2}\right) \\ &= y(1-y)\left[x\left[D_2 + (1-\beta)R + \theta C - P_2\right] + P_2 - C\right] \end{aligned} \tag{11}$$

Similarly, taking the first derivative of $F(y)$ with respect to y, we obtain the following:

$$\begin{aligned} &F^{'}(y) = \frac{\mathrm{d}F(y)}{\mathrm{d}y} = \\ &(1-2y)\left\{x\left[D_2 + (1-\beta)R + \theta C - P_2\right] + P_2 - C\right\} \end{aligned} \tag{12}$$

By equating $F(y)$ to zero, the solutions for y include $y = 0$, $y = 1$, and $x^* = \dfrac{C - P_2}{D_2 + (1-\beta)R + \theta C - P_2}$.

(1) Given $x = x^*$, $F(y) = 0$ is always satisfied. This implies that when the e-Commerce industry's probability of "active cooperation" is x^*, the logistics enterprise can select any strategy probability within the [0, 1] range without impacting the system's stability.

(2) For $0 < x < x^*$, setting $y = 0$ results in $\mathrm{d}F(y)/\mathrm{d}y < 0$, confirming $y = 0$ as the equation's stable solution. For $x^* < x < 1$, setting $y = 1$ meets the same criterion, making $y = 1$ the stable solution. Thus, if the e-Commerce industry's probability of active cooperation is below x^*, the logistics enterprise's strategy equilibrium is "passive cooperation". Above x^*, the equilibrium shifts to "active cooperation".

3.3 Evolutionary Stability of e-Commerce Industry

Achieving local stability in the evolutionary game occurs at the intersection of $F(x) = 0$ and $F(y) = 0$. This leads to the formulation and resolution of a system of simultaneous equations, denoted as Eq. (11), by setting Eqs. (4) and (9) to zero [24].

$$\begin{cases} F(x) = \dfrac{\mathrm{d}x}{\mathrm{d}t} = x\left(I_{11} - \overline{I_1}\right) = \\ \left(x - x^2\right)\left\{\mathrm{y}\left[D_1 + \beta R + (1-\theta)C - P_1\right] + P_1 - C\right\} = 0 \\ F(y) = \dfrac{\mathrm{d}y}{\mathrm{d}t} = y\left(I_{21} - \overline{I_2}\right) = \\ \left(y - y^2\right)\left\{x\left[D_2 + (1-\beta)R + \theta C - P_2\right] + P_2 - C\right\} = 0 \end{cases} \tag{13}$$

This yields five local equilibrium points for the system of equations: $E_1(0, 0)$, $E_2(0, 1)$, $E_3(1, 0)$, $E_4(1, 1)$, $E_5(x^*, y^*)$, Among them:

$$\begin{aligned} x^* &= \frac{C - P_2}{(1-\beta)R - (1-\theta)C + D_2 + C - P_2} \\ y^* &= \frac{C - P_1}{\beta R - \theta C_1 + D_1 + C - P_1} \end{aligned}$$

By calculating the partial derivatives for x and y, we derive the Jacobian matrix, as presented in Eq. (14).

$$J=\begin{bmatrix}\frac{\mathrm{d}F(x)}{\mathrm{d}x} & \frac{\mathrm{d}F(x)}{\mathrm{d}y}\\ \frac{\mathrm{d}F(y)}{\mathrm{d}x} & \frac{\mathrm{d}F(y)}{\mathrm{d}y}\end{bmatrix} = \begin{bmatrix}(1-2x)\{y[D_1+\beta R+(1-\theta)C-P_1]+P_1-C\} & (x-x^2)[D_1+\beta R+(1-\theta)C-P_1]\\ (y-y^2)[D_2+(1-\beta)R+\theta C-P_2] & (1-2y)\{x[D_2+(1-\beta)R+\theta C-P_2]+P_2-C\}\end{bmatrix} \tag{14}$$

The determinant of the Jacobian matrix, denoted as det(J), is calculated as follows:

$$\begin{aligned}\det(J)&=(1-2x)\{y[D_1+\beta R+(1-\theta)C-P_1]+P_1-C\}\\&(1-2y)\{x[D_2+(1-\beta)R+\theta C-P_2]+P_2-C\}\\&-(x-x^2)[D_1+\beta R+(1-\theta)C-P_1](y-y^2)\\&[D_2+(1-\beta)R+\theta C-P_2]\end{aligned} \tag{15}$$

The trace of the Jacobian matrix, represented by tr(J), is computed as follows:

$$\begin{aligned}tr(J)&=(1-2x)\{y[D_1+\beta R+(1-\theta)C-P_1]+P_1-C\}\\&+(1-2y)\{x[D_2+(1-\beta)R+\theta C-P_2]+P_2-C\}\end{aligned} \tag{16}$$

By calculating the determinant (det(J)) and trace (tr(J)) for each of the five equilibrium points, the results are shown in Tab. 3.

Table 3 The determinant and trace of the pure strategy equilibrium points

Equilibrium Points	det(J)	tr(J)
(0, 0)	$(P_1-C)(P_2-C)$	$(P_1-C)+(P_2-C)$
(0, 1)	$(\beta R-\theta C+D_1)(C-P_2)$	$(\beta R-\theta C+D_1)+(C-P_2)$
(1, 0)	$(C-P_1)[(1-\beta)R-(1-\theta)C+D_2]$	$(C-P_1)+[(1-\beta)R-(1-\theta)C+D_2]$
(1, 1)	$(\beta R+D_1-\theta C)[D_2+(1-\beta)R-(1-\theta)C]$	$-(\beta R+D_1-\theta C)-[D_2+(1-\beta)R-(1-\theta)C]$
(x*, y*)	$\left(\frac{[(1-\beta)R-(1-\theta)C+D_2](C-P_2)}{(1-\beta)R-(1-\theta)C+D_2-(P_2-C)}\right)\times\left(\frac{(\beta R-\theta C+D_1)(C-P_1)}{\beta R-\theta C+D_1-(P_1-C)}\right)$	0

According to Friedman [25], local stability at an equilibrium point is indicated by a positive Jacobian determinant det(J) > 0 and a negative trace tr(J) < 0). Here, $\Delta R_1=\beta R+D_1-\theta C$, $\Delta R_2=(1-\beta)R+D_2-(1-\theta)C$ signify the net earnings for the e-Commerce industry chain in their joint venture to cultivate new farmers. The stability of these equilibria is further analyzed across different cases, with the results summarized in Tab. 4.

(1) In Case 1 ($\Delta R_1>0$, $\Delta R_2>0$), with positive net earnings ΔR_1 and ΔR_2, the system's equilibrium points are delineated in Tab. 4, featuring stable points E_1 (0, 0) and E_4 (1, 1), unstable points E_2 (0, 1) and E_3 (1, 0), and the saddle point E_5 (x*, y*). Fig. 1 illustrates the system's dynamic evolution. The system's trajectory is E_1 for initial cooperation within the E_2-E_5-E_3-E_1 boundary and E_4 for cooperation within the E_2-E_5-E_3-E_4 boundary [4-7]. This case demonstrates that the system's evolutionary direction is contingent upon the initial cooperative levels, with various ranges potentially yielding different outcomes.

Table 4 Evolutionary stability assessment of strategic equilibrium points under different conditions

Equilibrium Points	Criteria for Determination			
	$\Delta R_1>0$, $\Delta R_2>0$	$\Delta R_1<0$, $\Delta R_2>0$	$\Delta R_1>0$, $\Delta R_2<0$	$\Delta R_1<0$, $\Delta R_2<0$
	Results			
(0, 0)	ESS	ESS	ESS	ESS
(0, 1)	U.P	S.P	U.P	S.P
(1, 0)	U.P	U.P	S.P	S.P
(1, 1)	ESS	S.P	S.P	U.P
(x*, y*)	S.P	—	—	—

Note: "U.P" indicates an unstable point; "S.P" denotes a saddle point.

(2) Case 2 ($\Delta R_1<0$, $\Delta R_2>0$), Case 3 ($\Delta R_1>0$, $\Delta R_2<0$), and Case 4 ($\Delta R_1<0$, $\Delta R_2<0$). In these three cases, the evolutionary equilibrium is consistently found at point E_1 (0, 0), signifying that if either party's net earnings are lower than their initial investment, both will ultimately opt for "passive cooperation." Figs. 2, 3, and 4 illustrate the evolutionary phase diagrams for these scenarios.

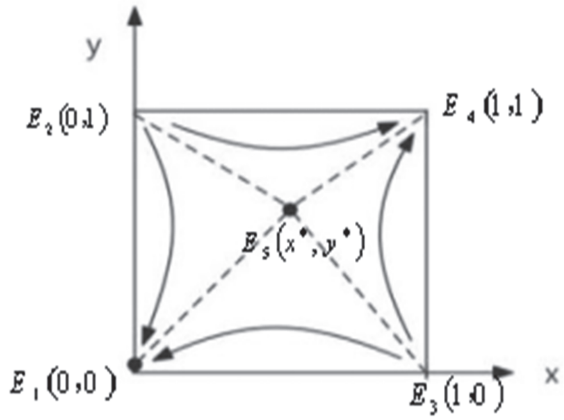

Figure 1 Evolutionary dynamics diagram for case 1

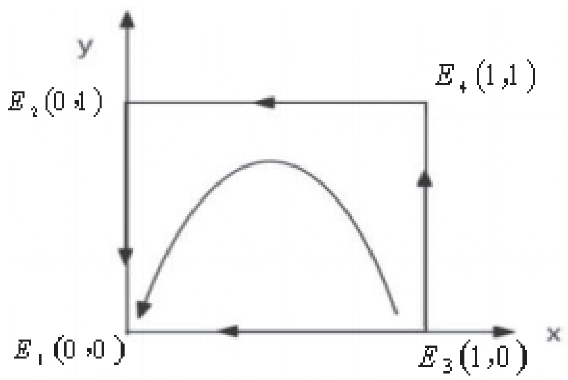

Figure 2 Evolutionary dynamics diagram for case 2

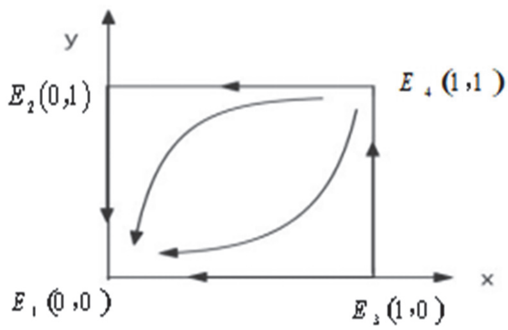

Figure 3 Evolutionary dynamics diagram for case 3

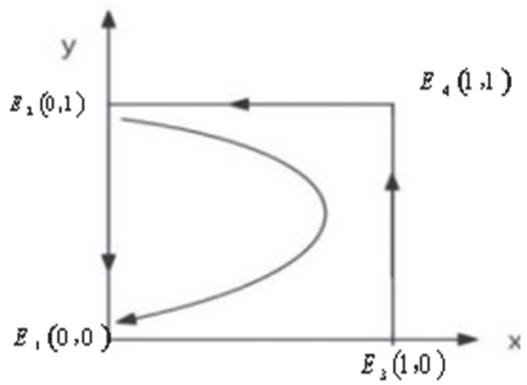

Figure 4 Evolutionary dynamics diagram for case 4

Given this research's aim to investigate the cooperative dynamics between e-Commerce Enterprises and logistics firms in the cultivation of new farmers, the ensuing discussion will hone in on Case 1, examining how the parameters' values influence the evolutionary results.

3.4 Influencing Factors of the Evolutionary Stability

Clearly, the size of the quadrilateral area E_2-E_5-E_3-E_4 in Fig. 1 depends on the probabilities of strategic choices made by the e-Commerce industry and the logistics enterprise. Let the area of quadrilateral E_2-E_5-E_3-E_4 be denoted as S, with the calculation formula given as follows [4].

$$S = 1 - \frac{1}{2}\left(\frac{C-P_1}{D_1+\beta R+(1-\theta)C-P_1}+\frac{C-P_2}{D_2+(1-\beta)R+\theta C-P_2}\right) \tag{17}$$

By analyzing the parameter variations that influence the size of the quadrilateral area S, the factors and mechanisms affecting the collaborative cultivation of new farmers by both parties can be clarified.

(1) *The Effect of Initial Investment Cost C on the Joint Development of New Farmers by Both Parties*

The calculation of S's first derivative with respect to C yields the subsequent result:

$$\frac{\partial S}{\partial C} = -\frac{1}{2}\left(\frac{\beta R+D_1-\theta P_1}{(\beta R+(1-\theta)C+D_1-P_1)^2}+\frac{(1-\beta)R+D_2+(1-\theta)P_2}{\left(R-\beta R-P_2+D_2\right)^2}\right) < 0$$

This suggests that the growth in the initial investment cost C leads to a reduction in the quadrilateral's area, steering both parties' strategic decisions towards point E_1 (0, 0).

Consequently, Proposition 1 can be formulated: The likelihood of e-Commerce Enterprises and Logistics Companies achieving joint cultivation of new farmers is inversely proportional to the initial investment cost. Higher initial costs reduce the probability of selecting a cooperative approach.

(2) *The Effect of Surplus Earnings R on the Joint Development of New Farmers by Both Parties*

By taking the first derivative of S with respect to R, we derive the following expression:

$$\frac{\partial S}{\partial R} = \frac{1}{2}\left[\begin{array}{l}\beta \dfrac{C-P_1}{\left(\beta R-\theta C+D_1+C-P_1\right)^2}+\\ \left(1-\beta\right)\dfrac{C-P_2}{\left[(1-\beta)R-(1-\theta)C+D_2+C-P_2\right]^2}\end{array}\right] > 0$$

This reveals that as the excess profit R grows, the quadrilateral's area S expands, directing the strategic decisions of both parties toward point E_4 (1, 1).

Hence, Proposition 2 is established: The magnitude of excess profits significantly influences the joint cultivation efforts of new farmers, with greater profits increasing the propensity for cooperative strategies.

(3) *The Impact of β and θ on System Evolutionary Stability*

Upon differentiating S with respect to β, the first derivative is determined as follows:

$$\frac{\partial S}{\partial \beta} = \frac{1}{2}\left[\begin{array}{l}R\dfrac{C-P_1}{\left(D_1+\beta R+(1-\theta)C-P_1\right)^2}-\\ R\dfrac{C-P_2}{\left[D_2+(1-\beta)R+\theta C-P_2\right]^2}\end{array}\right]$$

With the first derivative providing insufficient clarity on β's effect on S, the second derivative of S with respect to β is calculated to provide additional insight:

$$\frac{\partial^2 S}{\partial \beta^2} = -\left[\begin{array}{l}R^2\dfrac{C-P_1}{\left(D_1+\beta R+(1-\theta)C-P_1\right)^3}+\\ R^2\dfrac{C-P_2}{\left(D_2+(1-\beta)R+\theta C-P_2\right)^3}\end{array}\right] < 0$$

Hence, it can be determined that S is a convex function with respect to the excess profit distribution coefficient β. Therefore, when the condition $\frac{\partial S}{\partial \beta}=0$ is met, that is, if $R\frac{C_1-P_1}{\left(D_1+\beta R+(1-\theta)C-P_1\right)^2} = R\frac{C-P_2}{\left(D_2+(1-\beta)R+\theta C-P_2\right)^2}$, then S has a maximum value.

Applying a similar method, the calculation of the first derivative of S concerning the initial investment cost-sharing coefficient θ yields the subsequent result:

$$\frac{\partial S}{\partial \theta}=\frac{1}{2}\left[\begin{array}{l} C\dfrac{\left(C-P_1\right)}{\left(\beta R-\theta C+D_1+C-P_1\right)^2}- \\ C\dfrac{\left(C-P_2\right)}{\left[(1-\beta)R-(1-\theta)C+D_2+C-P_2\right]^2} \end{array}\right]$$

Thus, it can be concluded that there is an ideal value for θ that aligns with the interests of all parties involved.

Consequently, we can derive Proposition 3: In the process of collaborative cultivation of new farmers by both players in the game, appropriate excess profit distribution coefficients and suitable initial investment cost sharing coefficients can encourage both parties to choose cooperative strategies with a higher probability.

(4) *The Impact of Moral Hazard Loss on the Joint Cultivation of new farmers by Both Parties*

The calculation of the first derivative of S concerning D_1 yields the following result:

$$\frac{\partial S}{\partial D_1}=\frac{1}{2}\left(\frac{C-P_1}{\left(D_1+\beta R+(1-\theta)C-P_1\right)^2}\right)>0$$

That is, the growth in the moral hazard cost D_1 for the e-Commerce industry's passive role in new farmer cultivation leads to an expansion of area S, enhancing the likelihood of the system's convergence towards E_4 (1, 1). Likewise, a rise in the moral hazard loss D_2 for the logistics enterprise's passive cooperation similarly elevates the odds of system convergence on E_4 (1, 1).

Thus, Proposition 4 is established: The moral hazard losses from a party's passive cooperation significantly influence the evolutionary direction of the joint new farmer cultivation efforts between the e-Commerce industry chain [14]. the growth d moral hazard loss on one side is more likely to incentivize cooperative strategies by both parties.

(5) *The Effect of Passive Cooperation Gains on System Stability Dynamics*

Calculating the initial partial derivative of S relative to P_1 yields the subsequent result:

$$\frac{\partial S}{\partial P_1}=\frac{\beta R-\theta C+D_1}{2\left(D_1+\beta R+(1-\theta)C-P_1\right)^2}>0$$

This outcome suggests that an increment in the unilateral "active cooperation" profit P_1 of the e-Commerce industry in cultivating new farmers leads to an expansion of area S, which in turn raises the likelihood of the system's evolution towards point E_4 (1, 1). Similarly, the growth in the additional profit P_2 from the logistics enterprise's unilateral "active cooperation" also boosts the odds of system convergence on E_4 (1, 1). Essentially, growing additional profits from one party's active strategy enhance the likelihood of collaborative cultivation by both parties.

Hence, Proposition 5 is deduced: The unilateral "active cooperation" profits influence the strategic evolution outcome for both game participants, with greater profits inclining both parties toward active collaboration in new farmer cultivation.

3.5 Prisoner's Dilemma Game

As a second example, we choose the repeated Prisoner's dilemma game, which, although simple, can be used to illustrate many complex problems. The player has two options of C and D, which represent admission and denial, respectively. The benefits are shown in Tab. 5.

Table 5 Prisoner's dilemma game

		Prisoner 2 (Prisoner)	
		C	*D*
Prisoner 1 (e-Commerce Industry Chain)	*C*	(3, 3)	(0, 5)
	D	(5, 0)	(1, 1)

Obviously, strategy C is a severely inferior strategy relative to strategy D. Although the utility of strategy C chosen by both players is greater than that of strategy D, in a single game, both players will reject the severely inferior strategy and choose the dominant strategy, that is, the only Nash equilibrium strategy, which is the prisoner's dilemma. The public goods game is a prisoner's dilemma game in real life. This paper assumes that prisoners adopt Tit2 for 2Tat strategy through neural network training [26]. Currently, the neural network adopts a two-input, single-output structure, and the hidden layer neuron takes H = 40. The input is the strategy of the previous game between the opponent and oneself, and the output is the last strategy of the opponent, that is, the current strategy of oneself. Where, the opponent's strategy is randomly generated, and its first strategy input is D. Fig. 5 shows the steps-error diagram of neural network training. After 256 trainings, the neural network has been able to simulate the adoption of the Tit2 for 2Tat strategy by new farmers.

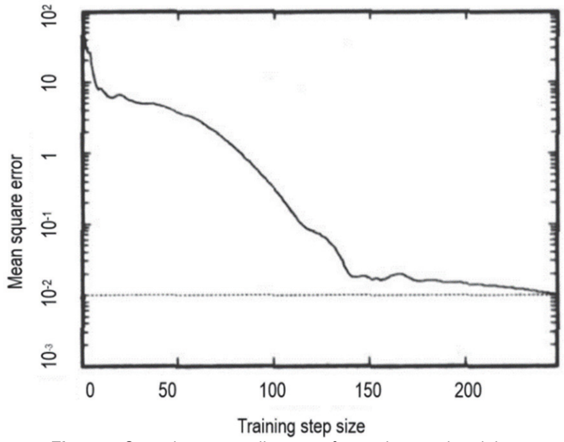

Figure 5 Step size - error diagram of neural network training

4 NUMERICAL ANALYSIS

This paper validates the model's precision and the reliability of the five propositions through numerical simulations using Matlab R2023b. It provides a clear visualization of the strategic game's evolution between e-Commerce Enterprises and Logistics Companies in the joint cultivation of new farmers. Initial parameters are determined under the constraints $C > P_1$, $C > P_2$, $\Delta R_1 > 0$, and $\Delta R_2 > 0$, with detailed initial values listed in Tab. 6.

Table 6 The initial values for each parameter

parameter	R	β	D_1	D_2	P_1	P_2	θ	C
value	100	0.6	15	20	30	25	0.6	50

4.1 The Effect of Varying Initial Strategies

We have chosen two sets of initial probability values for the strategic choices of both parties. The first comprises the pairs (0.1, 0.5), (0.3, 0.4), (0.5, 0.2), (0.6, 0.9), (0.8, 0.7), and (0.9, 0.6); the second includes (0.3, 0.2), (0.35, 0.4), (0.1, 0.6), (0.7, 0.8). We examined how these distinct initial strategy combinations affect the system's evolutionary trajectory and the rate of convergence, as illustrated in Figs. 5 and 6.

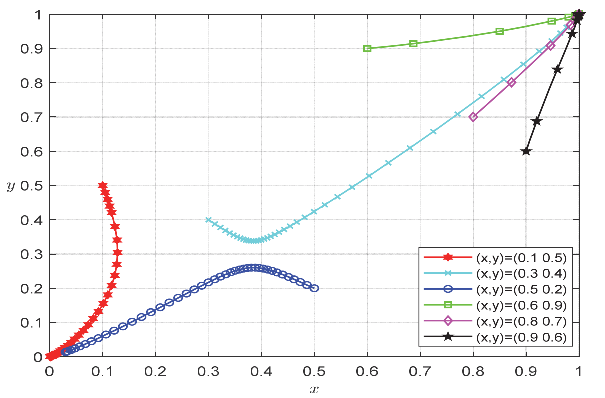

Figure 5 The effect of initial strategy pairings on evolutionary outcomes

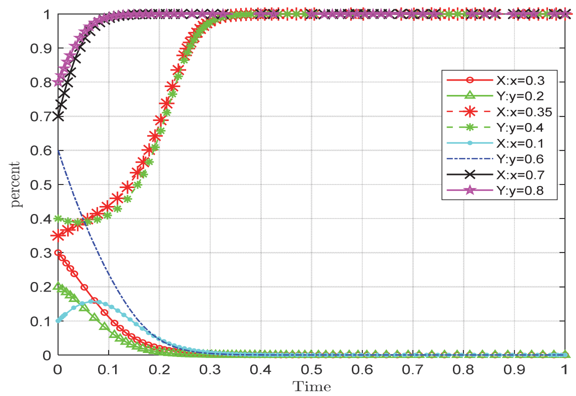

Figure 6 The effect of starting strategies on the rate of convergence

The observations from Figs. 5 and 6 reveal that variations in the initial strategic combinations result in significant differences in both the system's evolutionary outcomes and the speed of convergence. A critical combination of initial probabilities is identified, which in this instance is (0.35, 0.4). Should the initial probability of strategic choice for either party fall below the values in this critical combination, the system's evolutionary result will ultimately converge at the origin (0, 0). Conversely, if the initial probabilities exceed these values, the system's evolution is drawn towards the point (1, 1) [26]. To ascertain the optimal initial cooperation probabilities for both parties at the system's onset, we have calculated the saddle point based on the initial parameter values presented in Tab. 9, yielding the coordinates (0.31, 0.39). This critical threshold signifies the juncture at which the system's evolutionary outcome is altered. All subsequent simulation experiments are predicated on an initial cooperation probability for both parties set at $(x, y) = (0.31, 0.39)$.

4.2 The Role of Initial Investment Cost

With the initial values set at $(x, y) = (0.31, 0.39)$ and all other variables held constant, we manipulated the initial investment cost C by assigning values of 40, 45, 50, 55, 60 and 65. The resultant simulation outcomes are depicted in Fig. 7. A visual analysis of Fig. 7 reveals that as C diminishes, the velocity of convergence for x and y towards (1, 1) increases, indicating a more rapid evolution towards the "active cooperation" strategy for joint cultivation of new farmers by the e-Commerce industry chain. Conversely, the growth in C leads to a strategic convergence at the origin (0, 0) for both game participants.

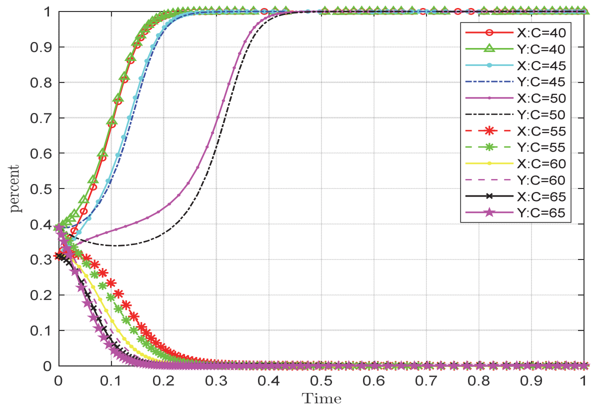

Figure 7 The impact of initial investment cost C on the evolutionary outcomes of the system

Observations confirm Proposition 1, indicating that a higher initial investment cost is negatively correlated with the adoption of "active cooperation" strategies by both e-Commerce industry firms.

4.3 The Effect of Surplus Profits

Maintaining all other initial parameters at a constant level and initiating with the values $(x, y) = (0.31, 0.39)$, the system's evolutionary outcome converges to the point (1, 1) when the excess profit is set at 100, signifying a mutual inclination towards 'active cooperation' in the joint cultivation of new farmers.

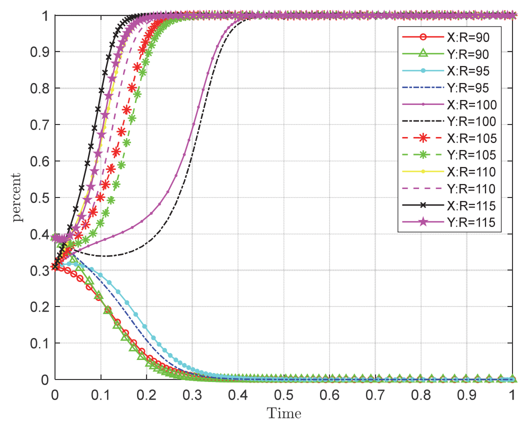

Figure 8 The influence of excess profits R on the evolutionary outcomes of the system

To delve into the influence of excess profits on the evolutionary outcome, simulations were performed with varying R values of 95, 100, and 105, with the findings illustrated in Fig. 8. A discernible pattern from Fig. 8 is that an increment in excess profits correlates with an accelerated rate of convergence towards the "active cooperation" strategy for both game participants.

Proposition 2 is upheld, indicating that greater surplus earnings are likely to promote active cooperation strategies among e-Commerce industry firms in their strategic decision-making.

4.4 The Impact on Participants' Evolutionary Game Path

Maintaining all other initial parameters at a constant state and initiating with the values $(x, y) = (0.31, 0.39)$, the scenario in which the initial investment cost sharing coefficient θ is set to 0.6, thereby assigning the e-Commerce industry a 60% share of the total initial investment cost, fosters a propensity for "active cooperation" among game participants. Subsequently, with other conditions held constant, the initial sharing coefficient θ was varied to 0.3, 0.4, 0.5, 0.6, 0.7, and 0.8, and the resultant simulation curves were plotted, as illustrated in Fig. 9.

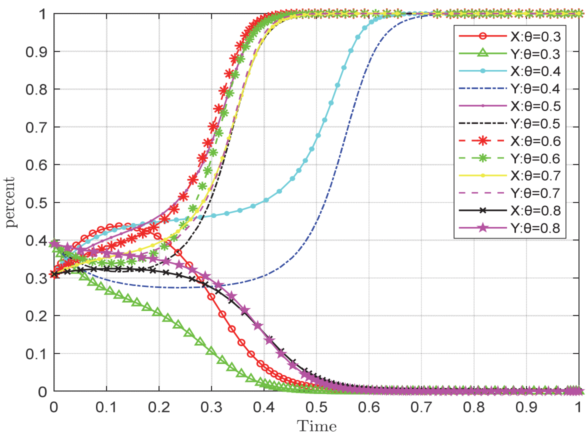

Figure 9 The influence of θ on the system's evolutionary results

Fig. 9 offers a comparative analysis of the simulation diagrams, revealing that when the initial investment cost sharing coefficient θ falls between 0.4 and 0.7, both parties in the game are inclined to evolve towards "active cooperation" in the joint cultivation of new farmers. At $\theta = 0.3$, the e-Commerce industry, shouldering 10% less of the initial investment than at $\theta = 0.4$, exhibits an enhanced propensity for 'active cooperation.' However, the logistics enterprise, despite taking on an additional 10% of the initial cost, faces an unaltered profit distribution, which engenders a "passive cooperation" attitude and leads to a cooperative failure.

Conversely, when $\theta = 0.8$, the e-Commerce industry, bearing 80% of the investment, receives only 60% of the excess profits, a disparity that deters it from pursuing "active cooperation." Meanwhile, the logistics enterprise, despite its minimal 20% cost contribution, is challenged by the e-Commerce industry's lack of zeal, making it difficult to sustain the initiative in new agricultural entrepreneur cultivation alone. This scenario underscores that the cost-sharing coefficient must be balanced. An optimal ratio is essential to achieve a harmonious and effective cooperative dynamic between the two entities.

By maintaining all other initial parameters at a constant and adjusting the excess profit distribution coefficient β to values of 0.3, 0.4, 0.5, 0.6, 0.7, and 0.8, we conducted further simulations to scrutinize the outcomes, as depicted in Fig. 10.

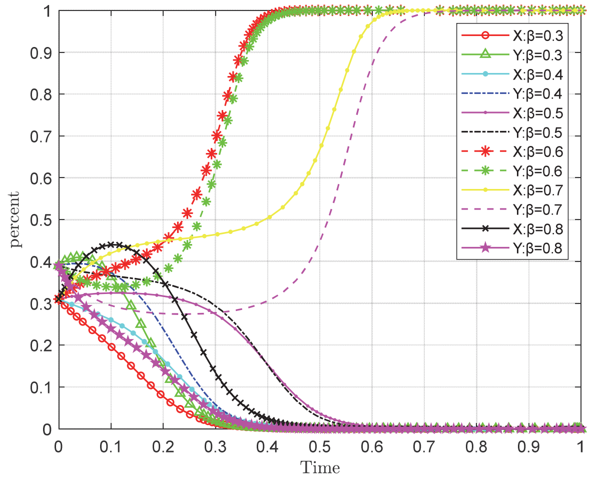

Figure 10 β's influence on the evolutionary results of the system

A careful review of Fig. 10 indicates that when the coefficient β falls within the interval of [0.6, 0.7], the evolutionary trajectory of both game participants converges upon the point (1, 1), signifying a mutual adoption of "active cooperation" in cultivating new farmers. Conversely, at $\beta = 0.8$, the e-Commerce industry garners 80% of the excess profits while incurring only 60% of the initial investment cost, an inequitable arrangement that the logistics enterprise is unwilling to accept, leading to a collapse in cooperative efforts. Despite the e-Commerce industry's initial inclination toward "active cooperation," the logistics enterprise's resolute "passive cooperation" stance culminates in a failure to jointly cultivate new farmers [12]. When the distribution coefficient is $\beta \le 0.5$, the e-Commerce industry, bearing a disproportionate 60% of initial costs, receives a mere equal or lesser share of excess profits, an untenable scenario that precludes the realization of cooperation. Figs. 9 and 10 demonstrate that under the current initial values, the adoption of "active cooperation" strategies by both parties occurs when the initial investment cost and excess profit distribution ratios are 3:7 and 4:6.

The evidence supports Proposition 3, highlighting that setting fair values for θ and β encourages positive cooperation in nurturing new farmers within the game framework.

4.5 The Effect of Moral Hazard Costs

With constant initial parameters and a starting point of $(x, y) = (0.31, 0.39)$, the baseline case stabilizes at (1, 1) for both game participants when $D_1 = 15$ and $D_2 = 20$. A simulation was conducted to examine the effects of varying D_1 and D_2, adjusted from 5 to 30 in steps of 5. The resultant curves in Fig. 11a, b clarify the influence of moral hazard costs on the evolutionary outcomes.

Thus, Proposition 4 is validated: The moral hazard losses borne by the party choosing "passive cooperation" significantly influence the strategic decisions of the logistics enterprise and e-Commerce industry. Paradoxically, the growth in one party's moral hazard losses promotes cooperation in cultivating new farmers.

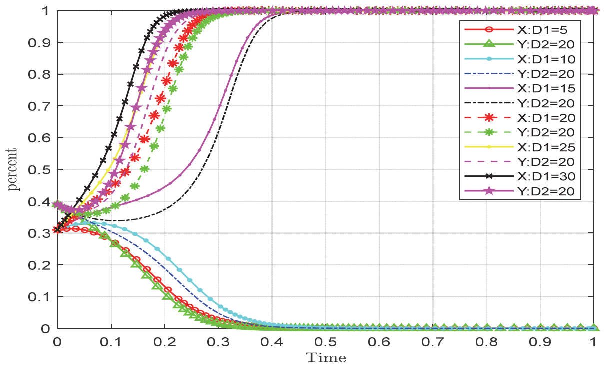

Figure 11a The impact of D_1 on system evolutionary outcomes

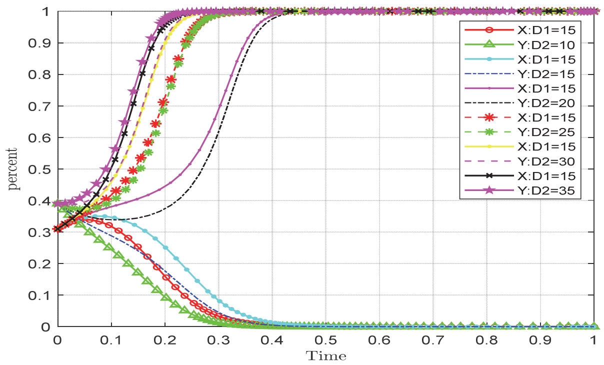

Figure 11b The impact of D_2 on system evolutionary outcomes

4.6 The Impact of Unilateral Additional Profits

With all other initial parameters maintained at a constant, when the e-Commerce industry chain receives additional profits of $P_1 = 30$ and $P_2 = 25$, respectively, for unilateral "active cooperation" in cultivating new farmers, the evolutionary outcome for both game participants converges upon the point (1, 1). A series of simulations were conducted by varying P_1 and P_2 across the values of 15, 20, 25, 30, 35, and 40, with the resulting curves depicted in Fig. 12a and 12b.

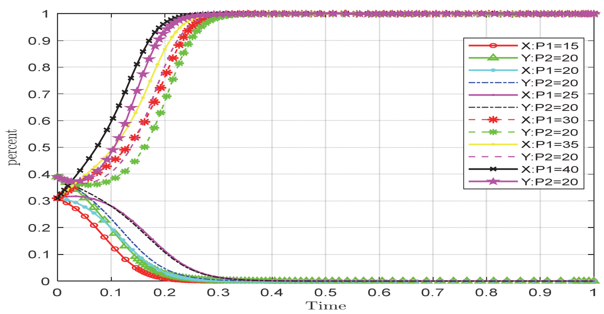

Figure 12a P_1's influence on the system's evolutionary path

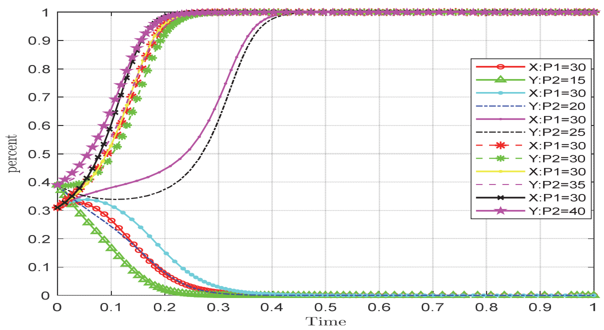

Figure 12b P_2's contribution to the system's evolutionary outcomes

An analysis of these curves indicates that at the threshold of $(P_1, P_2) = (30, 25)$, a decline in P_1 below 30 is associated with an accelerated progression towards "passive cooperation", culminating in a failure to collaboratively cultivate new farmers. In contrast, the growth in P_1 beyond 30 stimulates the logistics enterprise to perceive the profitability in such cultivation, prompting a strategic realignment that hastens the convergence to (1, 1) and a more rapid achievement of collaborative cultivation. Likewise, when P_2 surpasses 25, the enhancement in additional profits accelerates the realization of cooperation.

This examination confirms Proposition 5: Unilateral "active cooperation" profits substantially sway both parties' strategic choices, where increased profits are more inclined to encourage a mutual "active cooperation" strategy in new farmer cultivation.

5 CONCLUSIONS

This study presents a rural e-commerce ecosystem model that underscores the synergistic efforts of multiple stakeholders in cultivating new farmers, a key driver in China's agricultural and rural modernization. By integrating a neural network into the evolutionary game framework and employing particle swarm optimization (PSO) to train it, we simulate the learning and behavior of new farmers, demonstrating the neural network's capacity for evolutionary learning. The model is then applied to analyze the repeated Prisoner's Dilemma, revealing the PSO-trained neural network's efficacy in modeling the learning and strategy adjustment of bounded rational new farmers, thus serving as a robust tool for evolutionary game analysis.

The study's key findings are:

(1) The decision to co-cultivate new farmers is influenced by an initial preference threshold; active cooperation is initiated only when both parties' initial cooperative inclination surpasses this threshold.

(2) Stakeholders' decisions are significantly impacted by initial investment costs and collaborative surplus profits, with high costs hindering and surplus profits fostering cooperation. Establishing effective cost-sharing and profit-distribution mechanisms is crucial for promoting a cooperative strategy in new farmer cultivation.

(3) The strategic choices of logistics companies and e-Commerce Enterprises are influenced by the losses from passive cooperation and profits from active cooperation. Increases in moral hazard losses or additional profits for either party increase the likelihood of active cooperation, accelerating the adoption of strategies that enhance collaborative new farmer cultivation.

The significance of these findings lies in their contribution to rural revitalization and economic prosperity strategies. By understanding the dynamics of cooperation between e-Commerce Enterprises and logistics companies in nurturing new farmers, this research provides actionable insights for policymakers and industry leaders. It highlights the importance of initial cooperative thresholds, cost-sharing, and profit-distribution mechanisms in fostering collaborative efforts, which are essential for the sustainable development of the rural e-Commerce ecosystem. This study thus offers a strategic roadmap for enhancing rural economic growth and modernization through the cultivation of new farmers, aligning with broader goals of rural revitalization and economic prosperity.

The study admits limitations, primarily in the comprehensiveness of factors considered for the joint cultivation of new farmers by e-commerce platforms and logistics enterprises, suggesting the need for additional parameters in future analyses. Additionally, due to the challenge of obtaining precise data for our numerical simulations, we relied on estimated values. Future research should aim to collect more accurate and specific case data through fieldwork to empirically validate and refine the model.

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6 REFERENCES

[1] Chen, M. & Long, Y. (2024). Empowering Rural Revitalization: Unleashing the Potential of E-commerce for Sustainable Industrial Integration. *Journal of the Knowledge Economy*. https://doi.org/10.1007/s13132-024-01813-3

[2] Bai, S. Z., Yu, W. Z., & Jiang, M. (2023). Promoting the Tripartite Cooperative Mechanism of E-Commerce Poverty Alleviation: Based on the Evolutionary Game Method. *Sustainability*, (15), 1-315. https://doi.org/10.3390/su15010315

[3] Bilewicz, A. & Śpiewak, R. (2024). A repeasantisation in Poland? New farmers, the peasant mode of production and their situations in local communities. *The Journal of Peasant Studies*, 1-21. https://doi.org/10.1080/03066150.2023.2300778

[4] Du, S. (2024). An evolutionary game-theoretic analysis of cooperation strategy between SMEs and cross-border e-Commerce Enterprises considering the cross-network effect, *Kybernetes*, *53*(5), 1857-1887. https://doi.org/10.1108/K-09-2022-1316

[5] Xu, X. J., Wang, L., & Wang, X. L. (2024). Evolutionary game analysis of information service quality control of e-commerce platforms under information ecology. *Journal of Management Analytics*, *11*(1), 135-159. https://doi.org/10.1080/23270012.2023.2291836

[6] Zhou, F. L., Zhou, F. L., Zhang, C. C., Chen, T. F., & Lim, M. K. (2023). An evolutionary game analysis on blockchain technology adoption in cross-border e-commerce. *Operations Management Research*, *16*(4), 1766-1780. https://doi.org/10.1007/s12063-023-00382-z

[7] Cheng, Y. Y., Xie, B., & An, K. Y. (2023). Analysis of Omni-Channel Evolution Game Strategy for E-Commerce Enterprises in the Context of Online and Offline Integration. *Systems*, *11*(7), 321. https://doi.org/10.3390/systems11070321

[8] Rashidin, M., Gang, D., Javed, S., & Hasan, M. (2022). The Role of Artificial Intelligence in Sustaining the E-Commerce Ecosystem: Alibaba vs. Tencent. *Journal of Global Information Management (JGIM)*, *30*(8), 1-25. http://doi.org/10.4018/JGIM.304067

[9] Song, Y., Escobar, O., Arzubiaga, U., & Alfredo, D. M. (2022). The digital transformation of a traditional market into an entrepreneurial ecosystem. *Review of Managerial Science*, *16*(1), 65-88. https://doi.org/10.1007/s11846-020-00438-5

[10] Zhang, N. et al. (2024). Does rural e-commerce drive up incomes for rural residents? Evidence from Taobao villages in China. *Economic Analysis and Policy*, *82*(4), 976-998. https://doi.org/10.1016/j.eap.2024.04.023

[11] He, H. Y. & Zhang B. (2023). Strategy Analysis of Multi-Agent Governance on the e-Commerce industry. *Journal of Theoretical & Applied Electronic Commerce Research*, *18*(1), 1-18. https://doi.org/10.3390/jtaer18010001

[12] Huang, L., Huang, Y., Huang, R., Xie, G., & Cai, W. (2022). Factors influencing returning migrants' entrepreneurship intentions for rural e-commerce: An empirical investigation in china. *Sustainability*, *14*(6), 3682-3682. https://doi.org/10.3390/su14063682

[13] Zhao, H. & Li, M., (2023). Study on Joint Distribution Mode and Evolutionary Game of Express Enterprises in Rural Areas. *Sustainability*, *15*, 1520. https://doi.org/10.3390/su15021520

[14] Zhou, J., Yu, L., & Choguill, C. L. (2021). Co-evolution of technology and rural society: The blossoming of taobao villages in the information era, China. *Journal of Rural Studies*, *83*(2), 81-87. https://doi.org/10.1016/j.jrurstud.2021.02.022

[15] Li, X., Jiang, J., & Cifuentes-Faura, J. (2023). The impact of logistic environment and spatial spillover on agricultural economic growth: An empirical study based on east, central and west China. *PLoS ONE*, *18*(7), e0287307. https://doi.org/10.1371/journal.pone.0287307

[16] Shu, H., Zhan, L., Lin, X., & Zhou, X. (2023). Coordination measure for coupling system of digital economy and rural logistics: An evidence from China. *PLoS ONE*, *18*(4), e0281271. https://doi.org/10.1371/journal.pone.0281271

[17] Wang, L. H. & Dong, M. P. (2023). An Entropy Weight-TOPSIS Based Method for e-Commerce Logistics Service Quality Evaluation. *Tehnicki Vjesnik-Technical Gazette*, *30*(4), 1253-1256. https://doi.org/10.17559/TV-20230306000408

[18] Zhang, N., Yang, W. T., & Ke, H.Q. (2024). Does rural e-commerce drive up incomes for rural residents? Evidence from Taobao villages in China. *Economic Analysis and Policy*, *82* (4), 976-998. https://doi.org/10.1016/J.EAP.2024.04.023

[19] Gao, J., Zeng, Y. W., & Liu, M. (2024). Policy interventions and market innovation in rural China: Empirical evidence from Taobao villages. *Economic Analysis and Policy*, *81*(1), 1411-1429. https://doi.org/10.1016/j.eap.2024.02.015

[20] Ma, W. L., Marini, M. A. & Rahut, D. B. (2023). Farmers' organizations and sustainable development: An introduction. *Annals of Public and Cooperative Economics*, *94*(3), 683-700. https://doi.org/10.1111/apce.12449

[21] Zhang, L. L. (2023). An IoT-based English translation and teaching using particle swarm optimization and neural network algorithm. *Soft Computing*, *27*(19), 14431-14450. https://doi.org/10.1109/JLT.2023.3270025

[22] Zuo, X. Y., Pei, L., Bai, B., Wang, J. S., Zheng, J. J., Ning, T. G., Dong, F., & Zhao, Z. L. (2023). Integrated Silicon Photonic Reservoir Computing with PSO Training Algorithm for Fiber Communication Channel Equalization. *Journal of Lightwave Technology*, *41*(18), 5841-5850. https://doi.org/10.1109/JLT.2023.3270025

[23] Chen, H. H., Zhang, J. Y., Jiang, B., Cui, X. R., Zhou, R. R., & Zhang, Y. C. (2023). Multi-source underwater DOA estimation using PSO-BP neural network based on high-order cumulant optimization. *China Communications*, *20*(12), 212-229. https://doi.org/10.23919/JCC.ea.2021-0031.202302

[24] Weibull, J. W. (1995). Evolutionary game theory. Cambridge. *MA: The MIT Press*.

[25] Friedman, D. (1998). On economic applications of evolutionary game theory. *Journal of Evolutionary Economics*, *8*(1), 15-43. https://doi.org/10.1007/s001910050054

[26] Brânzei, S. (2024). Tit-for-tat dynamics and market volatility. *Nonlinearity*, *37*(3), 035006. https://doi.org/10.1088/1361-6544/ad1e26

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