Journal of Industrial and Management Optimization

https://www.aimspress.com/journal/jimo

JIMO, 22 (3): 1539–1570.
DOI: 10.3934/jimo.2026057
Received: 21 November 2025
Revised: 21 January 2026
Accepted: 05 February 2026
Published: 28 February 2026

Research article

How to enhance collaborative innovation resilience? A game-theoretic analysis of triple-helix synergies in high-tech sectors

Yawen Liu, Jia-Hui Meng*, Fang Ji and Jian Wang*

School of Management, Harbin Institute of Technology, Harbin, 150001, China

* **Correspondence:** Email: chrismjh@outlook.com, wang_jian@hit.edu.cn.

Abstract: In increasingly dynamic and complex innovation ecosystems, the resilience of collaborative innovation systems has become a critical determinant of sustainable technological advancement. This study developed an evolutionary game-theoretic model involving three key actors—government, enterprises, and universities (or research institutions)—to analyze how bounded rationality, policy interventions, cost-benefit structures, and opportunistic behaviors jointly influence the evolution of collaborative innovation resilience (CIR). Unlike previous triple helix studies that primarily focus on synergy measurement or network stability, this work explicitly incorporated collaborative innovation resilience into an evolutionary dynamic framework, thereby linking system stability with adaptive capacity under policy and behavioral uncertainty. The findings indicated that stronger governmental incentives, coupled with well-calibrated supervisory and punitive mechanisms, significantly enhance the willingness of enterprises and universities to collaborate, improving both systemic stability and resilience. Furthermore, reducing collaboration costs, optimizing the distribution of excess returns, and mitigating free-riding behaviors were shown to foster sustainable cooperation and strengthen CIR. To enhance empirical relevance, the model was embedded in a representative high-tech manufacturing region, and numerical simulations using policy-calibrated parameters verified the effects of key strategic variables on evolutionary trajectories and equilibrium states. The results demonstrated that active and adaptive government participation not only stimulates the collaborative motivation of enterprises and universities but also amplifies the overall innovation system's resilience and social benefits. This study extends the triple helix literature by linking dynamic stability and innovation resilience through an evolutionary lens, offering both theoretical insights and practical guidance for policy design in high-tech and other innovation-intensive sectors.

Keywords: collaborative innovation resilience; triple helix; high-tech innovation; multi-actor cooperation; evolutionary game
Mathematics Subject Classification: 91B38, 91A22, 37N40

1. Introduction

In recent years, the rapid advancement of frontier technologies, such as artificial intelligence, semiconductors, biotechnology, and quantum computing, has accelerated the digital, intelligent, and networked transformation of high-tech sectors. These changes are reshaping industrial organizational structures while making technological innovation increasingly dependent on cross-organizational and cross-sectoral collaboration mechanisms [1]. Against this backdrop, collaborative innovation networks involving enterprises, universities (or research institutions), and governments have emerged as a critical engine for boosting national innovation capacity and fostering high-tech industrial upgrading [2]. Effective interactions among these actors facilitate knowledge sharing, accelerate the commercialization of scientific results, and improve both innovation performance and system adaptability [3].

However, in high-tech sectors characterized by rapid iteration and high uncertainty, innovation systems often struggle to sustain collaboration over time. Beyond efficiency and output, their long-term viability depends on their ability to absorb shocks, adapt to disruptions, and recover from instability—a property defined as collaborative innovation resilience (CIR) [4]. Compared with traditional industries, high-tech enterprises face shorter product life cycles, higher R&D risks, and stronger technological dependencies [5]. These features amplify the impact of opportunistic behavior, misaligned incentives, and coordination failures, making CIR essential for maintaining system stability and sustainable cooperation [6].

In such multi-actor game environments, the government plays a pivotal role in shaping collaborative behavior [7] through policy interventions such as fiscal incentives, regulatory frameworks, or contract enforcement that significantly influence system stability and resilience. While an increasing body of research has examined collaborative innovation mechanisms, few studies have addressed, from a resilience perspective, the dynamic interplay among policy incentives, collaboration costs, and opportunistic behaviors. Moreover, existing research often lacks formalized modeling frameworks and empirical validation grounded in high-tech industry contexts [8–10].

To address this gap, this study develops an evolutionary game-theoretic model involving governments, enterprises, and universities to explore how policy incentives, penalties, and opportunistic behaviors affect the evolution of collaborative innovation resilience. The model incorporates bounded rationality and adaptive learning to simulate the strategic interactions of triple helix actors and identify the conditions that lead to stable, resilient equilibria. By embedding the model in a representative high-tech manufacturing region and calibrating it with policy-based parameters, this research aims to provide both theoretical insight and policy-oriented evidence for enhancing collaborative innovation resilience and optimizing institutional design in high-tech sectors.

2. Literature review

2.1. Collaborative innovation resilience

In recent years, research on collaborative innovation has gradually shifted from static knowledge transfer models to dynamic and adaptive system perspectives, with increasing attention on how multi-actor cooperation can sustain innovation performance under uncertain environments. An emerging and critical concept in this context is collaborative innovation resilience (CIR), which refers to the ability of an innovation system to maintain cooperative relationships, adjust strategies, and continuously generate innovation outcomes in the face of external shocks, policy changes, or partner withdrawal [11–13]. CIR emphasizes not only the robustness of collaborative networks but also their adaptability, learning capacity, and self-recovery mechanisms, which are particularly crucial for high-tech sectors characterized by rapid technological iteration and frequent market fluctuations [14,15]. Existing studies suggest that CIR encompasses multiple dimensions, such as absorptive capacity, flexibility, and knowledge integration, each being highly dependent on the intensity and quality of interactions among key actors [16]. While prior works often treat network robustness or stability as proxies for resilience, this paper distinguishes collaborative innovation resilience as the dynamic capability of sustaining cooperation under bounded rationality and policy uncertainty.

Traditional resilience research has mainly focused on organizational management and supply chain systems, emphasizing redundancy, agility, and responsiveness [17,18]. However, its application to collaborative innovation remains limited, often relying on qualitative cases rather than formal mechanism modeling [19]. Scholars increasingly argue that CIR can be conceptualized as a dynamic equilibrium emerging from continuous strategic interactions among multiple actors [20]. From this view, evolutionary stability in game dynamics reflects the system's capacity to recover from disturbances, aligning with the essence of resilience. Recent studies on dynamic decision-making in supply chain systems further illustrate how long-term performance and stability emerge from intertemporal strategic adjustments. For example, a continuous-time Stackelberg game shows that optimal timing and dynamic investment paths jointly shape equilibrium outcomes over time [21]. Yet, there remains a lack of comprehensive theoretical frameworks that formally connect strategic co-evolution, policy incentives, and system resilience.

2.2. Triple helix and multi-actor innovation systems

The triple helix model describes the institutional interactions among universities, industries, and governments and serves as a fundamental framework for analyzing multi-actor collaborative innovation [22–25]. While the original formulation provided a foundational conceptualization of university–industry–government relations, subsequent studies have substantially extended and refined the triple helix framework. Recent research emphasizes the evolving and context-dependent roles of triple helix actors in response to technological change, societal challenges, and sustainability concerns, and highlights the dynamic nature of innovation systems [26,27]. In addition, extensions toward quadruple and quintuple helix models further broaden the analytical scope by incorporating civil society and environmental dimensions into innovation analysis [28]. Empirical reviews and network-based analyses also clarify the thematic evolution and diversification of triple helix research over time, underscoring the need to revisit the framework in light of contemporary innovation dynamics [29].

Against this backdrop, this model emphasizes institutional complementarity and coupling as drivers of innovation efficiency, but it often assumes stable collaboration and overlooks real-world challenges such as behavioral heterogeneity, incentive asymmetry, and opportunistic behavior, which are critical to the formation and maintenance of CIR in high-tech sectors [30].

2.3. Evolutionary game theory and policy-driven behavioral dynamics

Evolutionary game theory (EGT) has recently gained prominence as an analytical tool to study strategy co-evolution under bounded rationality [31]. It effectively captures how incentives, penalties, and free-riding behaviors evolve over time and influence system stability [32]. Related advances in operations research employ continuous-time dynamic game models to analyze multi-actor strategic interactions under uncertainty, showing that equilibrium strategies and system performance can be highly sensitive to evolving interaction effects and system conditions [33]. Prior works have used EGT to examine incentive alignment in university–industry–government collaborations [34] and the effects of policy instruments on cooperative behavior [35]. Recent studies further demonstrate how policy-related incentives and reputational mechanisms dynamically interact with firms' strategic investment decisions, jointly shaping long-run equilibrium outcomes in competitive and cooperative settings [36]. Moreover, opportunistic behaviors, such as free-riding and information asymmetry, are widely recognized as major threats to collaboration stability, requiring adaptive policy mechanisms to mitigate their impact [37,38]. However, most studies have not explicitly incorporated resilience indicators into EGT frameworks or treated government as an endogenous, adaptive actor [39].

Therefore, it remains essential to build an integrated framework combining triple helix interactions, CIR dynamics, and policy-driven behavioral evolution. This study conceptualizes collaborative innovation resilience (CIR) not as a static performance outcome but as a dynamic property emerging from repeated strategic interactions among triple helix actors. Within an evolutionary game-theoretic framework, CIR is operationalized through the stability and convergence properties of the evolutionary dynamics, where evolutionarily stable strategies (ESS) indicate the system's capacity to sustain cooperation and recover from behavioral disturbances under bounded rationality and policy uncertainty [40]. This study addresses this gap by developing an evolutionary game model that links policy incentives, penalties, and opportunistic behavior to the formation of CIR. By situating the analysis in high-tech industry contexts, it contributes to the cross-disciplinary integration of innovation policy, evolutionary dynamics, and system resilience, offering new insights into how government interventions and adaptive behaviors jointly enhance collaborative innovation resilience.

3. Research assumptions and model construction

3.1. Overview of methodological approach

This study employs an evolutionary game-theoretic framework to characterize the dynamic interactions within a multi-actor collaborative innovation system. This framework can simulate how governments, enterprises, and universities (or research institutions) continually adjust their strategic choices under uncertain conditions [41]. Evolutionary game theory is grounded in the assumption of bounded rationality, whereby participants iteratively revise their strategies based on historical payoffs in repeated games, ultimately converging toward a stable equilibrium state [42]. This behavioral assumption is also consistent with recent extensions of the triple helix framework, which explicitly emphasize bounded rationality, adaptive learning, and behavioral diversity as key drivers of innovation dynamics in university–industry–government interactions [43].

In the innovation ecosystem of high-tech sectors, heightened uncertainty and accelerated technological iteration make collaboration among government, industry, and academia highly dynamic. These actors do not make one-off, fixed decisions but instead engage in continuous strategic interactions, repeated games, and iterative evolution, learning from experience and adjusting strategies to reduce collaboration costs and enhance expected payoffs. Prior to constructing the triadic game model, it is essential to clarify the roles, responsibilities, and benefit linkages among the triple helix actors—government, enterprises, and universities—in order to identify the key factors influencing collaborative innovation resilience. Based on this foundation, the proposed model aims to simulate the strategy selection paths and equilibrium outcomes of governments, enterprises, and universities/research institutions under a co-innovation setting.

3.2. Fundamental assumptions

Assumption 1: Agents and behavioral attributes. The model considers three core agents involved in technology-driven industrial transformation: the government, enterprises, and universities (including research institutions). Each is modeled as a boundedly rational actor with independent decision-making capacity and self-interested objectives. Drawing upon the triple helix framework [44], the model defines their functional roles as follows:

1) The government acts as a system coordinator and policy architect. It intervenes by establishing incentive mechanisms (e.g., subsidies, tax relief) and constraint mechanisms (e.g., penalties, regulatory restrictions) to foster collaboration between firms and universities. The government's objective is to enhance collaborative efficiency and systemic innovation capacity through reward-punishment structures.

2) The enterprise is the executor of innovation. It provides critical resources, technology, and application contexts for collaborative innovation, aiming to improve operational efficiency, develop new products, and commercialize technological outcomes.

3) The university or research institution functions as the knowledge contributor. It focuses on frontier research, theoretical advancement, and talent development, supplying the scientific foundation and intellectual capital needed for industrial upgrading and long-term innovation.

These three agents form a structurally interdependent configuration within the collaborative innovation network. Their behavior is shaped by payoff structures, institutional incentives, and real-time feedback mechanisms. The strategic interactions and evolutionary pathways among the actors are illustrated in Figure 1.

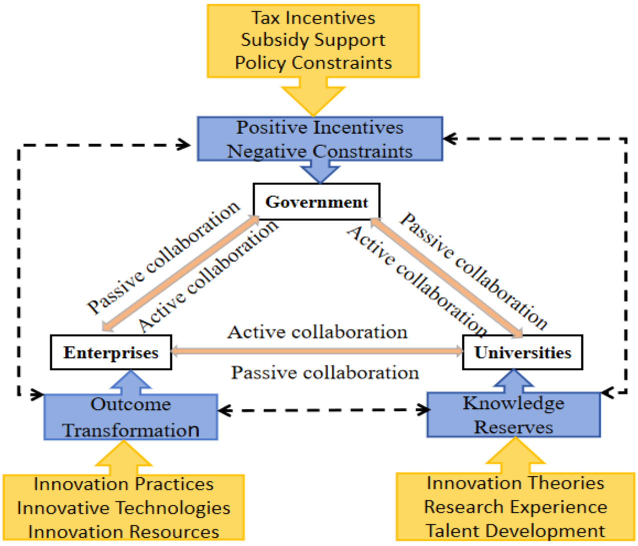


Figure 1. Evolutionary logic process of the three parties.

Assumption 2: Strategy sets. Each agent in the system has a discrete strategy set. For the government, two options are available: {promote collaborative innovation, no promotion}. Let z denote the probability that the government chooses to actively promote collaboration; thus, the probability of not promoting collaboration is $(1 - z)$.

The enterprise also has two strategies: {active collaboration, passive collaboration}. Let x represent the probability that a firm actively engages in collaborative innovation, with $(1 - x)$ denoting the probability of passive or non-collaborative behavior.

Similarly, the university (or research institution) has a strategy set: {active collaboration, passive collaboration}, with y denoting the probability of active participation in collaborative innovation and $(1 - y)$ the probability of opting out.

Throughout the evolutionary game process, all agents iteratively update their strategies based on expected payoffs and observed behaviors, aiming to converge toward a stable Nash equilibrium. The parameters x, y, and z are continuous and bounded within the interval [0,1].

In this context, the government's strategy of promoting collaboration implies the adoption of positive incentive policies, such as financial subsidies, tax relief, or institutional support, to stimulate joint innovation activities. Conversely, a non-promotion strategy reflects insufficient support or a neutral stance, possibly accompanied by restrictive regulations that hinder collaborative initiatives.

Assumption 3: Input costs. Although the government does not directly participate in the collaborative innovation process, it provides financial support or tax incentives to enterprises and universities (or research institutions) and monitors their collaborative activities. When the government adopts the "promotion" strategy, its cost for supervision and policy implementation is denoted as $Cg(Cg \geq 0)$. $a(0 < a \leq 1)$ represents the proportion of the cost incurred when the government adopts the "non-promotion" strategy relative to the "promotion" cost; therefore, the cost of the "non-promotion" strategy is aCg.

As direct participants in collaborative innovation, enterprises and universities (research institutions) must invest resources such as labor, materials, and capital. The total initial costs associated with these inputs are denoted as $Cc(Cc \geq 0)$ for enterprises and $Cu(Cu \geq 0)$ for universities (research institutions).

Assumption 4: Collaboration payoffs. Opportunistic behavior is often a significant obstacle to sustained collaborative innovation; therefore, this model incorporates the concept of opportunistic gains, i.e., the benefits from free-riding on the efforts of others, while ignoring the costs of such behavior [9]. When both enterprises and universities (or research institutions) choose not to collaborate, their initial payoffs are denoted as $Wc\ Wu$.

When both enterprises and universities (or research institutions) actively collaborate, they share knowledge, integrate technologies, and benefit from the successful implementation of innovation projects, resulting in considerable excess returns. The enterprise gains additional returns through improved productivity and enhanced market competitiveness, denoted as Ec, while the university obtains extra returns through technology transfer and knowledge spillovers, denoted as Eu. Thus, $Ec > Cc$ and $Eu > Cu$.

When an enterprise chooses to actively collaborate while the university (or research institution) opts not to, the enterprise incurs its own cost Cc, while the university earns only its baseline return Wu plus an opportunistic gain Lu, with $Lu < Eu$. Conversely, when the university chooses to actively collaborate while the enterprise does not, the university incurs cost Cu, while the enterprise gains its baseline return Wc plus an opportunistic gain Lc, where $Lc < Ec$. Here, Lu and Lc represent the benefits arising from free-riding behavior. The variable Wg represents the social value created by collaborative innovation between enterprises and universities (or research institutions) when supported by the government. In this model, Wg is treated as an exogenous parameter that captures the potential (policy-relevant) social value associated with enterprise–university collaborative innovation under a given regional/sectoral context; government willingness *z* affects the government's expected payoff through the extent to which this social value can be realized (as reflected by the coefficient *b* under non-promotion).

Let $b(0 < b \leq 1)$ denote the proportion of social value realized when the government adopts the "non-promotion" strategy relative to the "promotion" strategy. Thus, the social value under the "non-promotion" scenario is bWg. In addition, the government provides financial support Gc and Gu to enterprises and universities (or research institutions), respectively, when they actively engage in collaborative innovation. If either party fails to collaborate, the government imposes penalties (such as reduced subsidies, increased taxes, or the withdrawal of research funding), denoted as Fc for enterprises and Fu for universities (or research institutions). All parameter definitions and value ranges are summarized in Table 1.

In the model, opportunistic gains for enterprises and universities (*Lc, Lu*) are specified as exogenous and time-invariant parameters. Although opportunistic benefits may vary with the evolution of cooperative relationships in practice, this specification reflects a standard abstraction in evolutionary game modeling, where payoff parameters represent long-run average incentives associated with a given behavior. Recent studies on opportunistic behavior similarly adopt fixed payoff structures to examine strategic selection and equilibrium properties under different incentive environments [45,46]. By varying the magnitude of opportunistic gains while keeping their structural form unchanged, the model enables a transparent and interpretable analysis of how incentive intensity shapes convergence dynamics and stability outcomes. This abstraction improves analytical tractability and enhances the interpretability of the simulation results.

Table 1. Explanation of parameters and their value ranges.

Parameter	Description	Range
Cg	The total cost incurred by the government when adopting the "promotion" strategy, including supervision and policy execution costs.	$Cg \geq 0$
Cc	The total cost incurred by the enterprise when adopting the "active collaboration" strategy.	$Cc \geq 0$
Cu	The total cost incurred by the university (or research institution) when adopting the "active collaboration" strategy.	$Cu \geq 0$
a	The ratio of the government's cost when adopting the "non-promotion" strategy to the cost under the "promotion" strategy.	$0 < a \leq 1$
b	The proportion of social value generated under the "non-promotion" strategy relative to that under the "promotion" strategy.	$0 < b \leq 1$
Wg	The social value generated from collaborative innovation between enterprises and universities (or research institutions) when the government provides incentives.	$Wg \geq 0$
Wc	The baseline payoff obtained by the enterprise when it chooses not to collaborate, derived from competing strategies of other players.	$Wc \geq 0$
Wu	The baseline payoff obtained by the university (or research institution) when it chooses not to collaborate, derived from competing strategies of other players.	$Wu \geq 0$
Ec	The additional (excess) return obtained by the enterprise when both the enterprise and the university (or research institution) actively collaborate, sharing knowledge and technology.	$Ec \geq 0$, $Ec > Cc$
Eu	The additional (excess) return obtained by the university (or research institution) when both sides actively collaborate, sharing knowledge and technology.	$Eu \geq 0$, $Eu > Cu$
Gc	The financial support provided by the government to the enterprise when it actively collaborates.	$Gc \geq 0$
Gu	The financial support provided by the government to the university (or research institution) when it actively collaborates.	$Gu \geq 0$
Fc	The penalty imposed on the enterprise if it fails to participate in collaborative innovation.	$Fc \geq 0$
Fu	The penalty imposed on the university (or research institution) if it fails to participate in collaborative innovation.	$Fu \geq 0$
Lc	The opportunistic gain (free-riding benefit) obtained by the enterprise when it does not collaborate but leverages the collaborative outcomes of the other party.	$Lc < Ec$
Lu	The opportunistic gain (free-riding benefit) obtained by the university (or research institution) when it does not collaborate but leverages the collaborative outcomes of the other party.	$Lu < Eu$

Note: The above assumptions and parameter values are derived from theoretical model analysis and do not fully reflect all real-world complexities.

3.3. Model construction and solution

3.3.1. Construction of the payoff matrix

Table 2. Payoff matrix of the tripartite game among enterprises, universities (research institutions), and government.

Collaboration strategy		Government			
		Active response (*z*)		Passive response (*1-z*)	
		University (research institution)			
		Active collaboration (*y*)	Passive collaboration (*1-y*)	Active collaboration (*y*)	Passive collaboration (*1-y*)
Enterprise	Active collaboration (*x*)	$\begin{bmatrix} Wc+Ec+Gc-Cc \\ Wu+Eu+Gu-Cu \\ Wg-Cg-Gc-Gu \end{bmatrix}$	$\begin{bmatrix} Wc+Gc-Cc \\ Wu+Lu-Fu \\ Wg-Cg-Gc+Fu \end{bmatrix}$	$\begin{bmatrix} Wc+Ec-Cc \\ Wu+Eu-Cu \\ bWg-aCg \end{bmatrix}$	$\begin{bmatrix} Wc-Cc \\ Wu+Lu \\ bWg-aCg \end{bmatrix}$
	Passive collaboration (*1-x*)	$\begin{bmatrix} Wc+Lc-Fc \\ Wu+Gu-Cu \\ Wg-Gu-Cg+Fc \end{bmatrix}$	$\begin{bmatrix} Wc-Fc \\ Wu-Fu \\ Wg-Cg+Fc+Fu \end{bmatrix}$	$\begin{bmatrix} Wc+Lc \\ Wu-Cu \\ bWg-aCg \end{bmatrix}$	$\begin{bmatrix} Wc \\ Wu \\ bWg-aCg \end{bmatrix}$

Note 1: For brevity, the algebraic payoffs for all eight outcomes are structurally similar and derived by substituting the parameters (*Cc, Cu, Ec, Eu, Gc, Gu, Fc, Fu, Lc, Lu*) into the corresponding payoff functions. Full derivations are available upon request.

Note 2: For clarity, each payoff term represents the net benefit of a given strategic combination. *Wc+Ec+Gc-Cc* denotes the enterprise's net payoff under mutual active collaboration. *Wu+Eu+Gu-Cu* represents the corresponding net payoff for the university under mutual active collaboration. Other payoff expressions follow the same construction logic.

3.3.2. Formulation of the expected payoff functions

To analyze the evolutionary game dynamics among enterprises, universities (or research institutions), and the government, this study employs evolutionary game theory combined with expected payoff computation methods. Let U_1, U_2, and U_3 denote the average expected payoffs of enterprises, universities (or research institutions), and the government, respectively. Based on the calculations derived from Table 2, the results are as follows:

(1) Expected payoffs of enterprises under collaboration and non-collaboration

The expected payoff for an enterprise adopting the active collaborative innovation strategy is:

$$\begin{aligned} U_{11} &= yz(Wc+Ec+Gc-Cc)+z(1-y)(Wc+Gc-Cc) \\ &+y(1-z)(Wc+Ec-Cc)+(1-y)(1-z)(Wc-Cc) \end{aligned} \tag{3.1}$$

The expected payoff for an enterprise adopting the non-collaborative strategy is:

$$\begin{aligned} U_{12} &= yz(Wc+Lc-Fc)+z(1-y)(Wc-Fc)+y(1-z)(Wc+Lc) \\ &+(1-y)(1-z)Wc \end{aligned} \tag{3.2}$$

The average expected payoff of the enterprise is therefore calculated as:

$$\overline{U_1} = xU_{11} + (1-x)U_{12} \tag{3.3}$$

(2) Expected payoffs of universities (or research institutions)

The expected payoff for a university (or research institution) adopting the active collaborative innovation strategy is:

$$\begin{aligned} U_{21} &= xz(Wu + Eu + Gu - Cu) + x(1-z)(Wu + Eu - Cu) \\ &+ z(1-x)(Wu + Gu - Cu) + (1-x)(1-z)(Wu - Cu) \end{aligned} \tag{3.4}$$

The expected payoff for a university (or research institution) adopting the non-collaborative strategy is:

$$\begin{aligned} U_{22} &= xz(Wu + Lu - Fu) + x(1-z)(Wu + Lu) + z(1-x)(Wu - Fu) \\ &+ (1-x)(1-z)Wu \end{aligned} \tag{3.5}$$

The average expected payoff of the university (or research institution) is therefore calculated as:

$$\overline{U_2} = yU_{21} + (1-y)U_{22} \tag{3.6}$$

(3) Expected payoffs of government strategies

The expected payoff for the government adopting the promotion strategy is:

$$\begin{aligned} U_{31} &= xy(Wg - Cg - Gc - Gu) + x(1-y)(Wg - Cg - Gc + Fu) \\ &+ y(1-x)(Wg - Gu - Cg + Fc) + (1-x)(1-y)(Wg - Cg + Fc + Fu) \end{aligned} \tag{3.7}$$

The expected payoff for the government adopting the non-promotion strategy is:

$$\begin{aligned} U_{32} &= xy(bWg - aCg) + x(1-y)(bWg - aCg) + y(1-x)(bWg - aCg) \\ &+ (1-x)(1-y)(bWg - aCg) \end{aligned} \tag{3.8}$$

The average expected payoff of the government is therefore calculated as:

$$\overline{U_3} = zU_{31} + (1-z)U_{32} \tag{3.9}$$

3.3.3. Solution of the Malthusian replicator dynamic equations

(1) Tripartite replicator dynamic equations

The replicator dynamic equation for enterprises choosing the collaborative strategy is:

$$P(x) = \frac{dx}{dt} = x\left[U_{11} - \overline{U_1}\right] = x(1-x)\left[y(Ec - Lc) + z(Gc + Fc) - Cc\right] \tag{3.10}$$

Similarly, the replicator dynamic equation for universities (or research institutions) is:

$$Q(y) = \frac{dy}{dt} = y\left[U_{21} - \overline{U_2}\right] = y(1-y)\left[x(Eu - Lu) + z(Gu + Fu) - Cu\right] \tag{3.11}$$

The replicator dynamic equation for the government is:

$$N(z) = \frac{dz}{dt} = z\left[U_{31} - \overline{U_3}\right] = z(1-z)\left[x(-Gc - Fc) + y(-Gu - Fu) + Fc + Fu\right] \tag{3.12}$$

(2) Replicator dynamic system

By combining the replicator dynamic equations of enterprises, universities (or research institutions), and the government, we obtain the replicator dynamic system:

$$\begin{cases} P(x) = x(1-x)\left[y(Ec-Lc)+z(Gc+Fc)-Cc\right] \\ Q(y) = y(1-y)\left[x(Eu-Lu)+z(Gu+Fu)-Cu\right] \\ N(z) = z(1-z)\left[x(-Gc-Fc)+y(-Gu-Fu)+Fc+Fu\right] \end{cases} \tag{3.13}$$

Using the Friedman method [47], the local stability of the evolutionary equilibrium can be determined via the Jacobian matrix of the system. By simultaneously solving the equations, we derive the replicator dynamic system of enterprises, universities (or research institutions), and the government, and compute the Jacobian matrix J to further assess the stability of each equilibrium point:

$$J = \begin{pmatrix} \frac{(dx/dt)}{dx} & \frac{(dx/dt)}{dy} & \frac{(dx/dt)}{dz} \\ \frac{(dy/dt)}{dx} & \frac{(dy/dt)}{dy} & \frac{(dy/dt)}{dz} \\ \frac{(dz/dt)}{dx} & \frac{(dz/dt)}{dy} & \frac{(dz/dt)}{dz} \end{pmatrix} \tag{3.14}$$

Substituting into the system, we obtain:

$$\begin{pmatrix} (1-2x)\left[y(Ec-Lc)+z(Gc+Fc)-Cc\right] & x(1-x)(Ec-Lc) & x(1-x)(Gc+Fc) \\ y(1-y)(Eu-Lu) & (1-2y)\left[x(Eu-Lu)+z(Gu+Fu)-Cu\right] & y(1-y)(Gu+Fu) \\ z(z-1)(Gc+Fc) & z(z-1)(Gu+Fu) & (1-2z)\left[Fc+Fu-x(Gc+Fc)-y(Gu+Fu)\right] \end{pmatrix} \tag{3.15}$$

3.3.4. Stability analysis of equilibrium points

According to the stability conditions of differential equations, the system involving the government, enterprises, and universities (or research institutions) reaches stability when the following conditions are satisfied:

$$P(\mathrm{x}) = 0, \quad \frac{dP(x)}{dx} < 0, \quad Q(y) = 0, \quad \frac{dQ(\mathrm{y})}{dy} < 0, \quad N(z) = 0, \quad \frac{dN(\mathrm{z})}{dz} < 0$$

By setting P(x) = Q(y) = N(z) = 0, the eigenvalues of the local equilibrium points of the system can be obtained, as summarized in Table 3. There are eight equilibrium points, denoted as H1 (0,0,0), H2 (0,0,1), H3 (0,1,0), H4 (0,1,1), H5 (1,0,0), H6 (1,0,1), H7 (1,1,0), and H8 (1,1,1).

According to evolutionary game theory, when all eigenvalues of the system's Jacobian matrix are non-positive, the corresponding point is referred to as an evolutionarily stable strategy (ESS). If at least one eigenvalue is positive and one is negative, the point is classified as a saddle point. If at least one eigenvalue is positive (or all are positive), the point is considered unstable.

Table 3. Local stability of equilibrium points.

Equilibrium point	Eigenvalue λ_1	Eigenvalue λ_2	Eigenvalue λ_3	Stability
(0,0,0)	$-Cc$ (-)	$-Cu$ (-)	$Fc+Fu$ (+)	Saddle point
(0,0,1)	$Gc+Fc-Cc$ (?)	$Gu+Fu-Cu$ (?)	$-Fc-Fu$ (-)	Saddle point/ESS
(0,1,0)	$Ec-Cc-Lc$ (+)	Cu (+)	$Fc-Gu$ (?)	Unstable point
(0,1,1)	$Ec-Lc+Gc+Fc-Cc$ (+)	$-Gu-Fu+Cu$ (+)	$-Fc+Gu$ (?)	Unstable point
(1,0,0)	Cc (+)	$Cu-Eu-Lu$ (+)	$Fu-Gc$ (?)	Unstable point
(1,0,1)	$-Gc-Fc+Cc$ (?)	$Eu-Lu+Gu+Fu-Cu$ (+)	$-Fu+Gc$ (?)	Unstable point
(1,1,0)	$Lc-Ec+Cc$ (?)	$-Eu+Cu+Lu$ (?)	$-Gc-Gu$ (-)	Unstable point/ESS
(1,1,1)	$Lc-Ec-Gc-Fc+Cc$ (-)	$Lu-Eu-Gu-Fu+Cu$ (-)	$Gc+Gu$ (+)	Saddle point

From Table 3, it can be observed that due to the large number and complexity of parameters in the model, the system exhibits evolutionarily stable strategies (ESS). The stability of equilibrium points (0,0,1) and (1,1,0) needs to be discussed as follows:

1. When the point (0,0,1) is an ESS, and the condition $Gc+Fc-Cc<0$ and $Gu+Fu-Cu<0$ holds. This means that when the government's incentives or penalties for enterprises and universities (or research institutions) are less than the cost required for them to initiate collaborative innovation on their own, the stable point (0,0,1) exists. In other words, if both enterprises and universities are unwilling to actively collaborate, the government must expend substantial effort to actively promote and encourage their participation in collaborative innovation for industrial transformation.

2. When the point (1,1,0) is an ESS, and the condition $Lc+Cc-Ec<0$ and $Lu+Cu-Eu<0$ holds. This implies that when the sum of the input costs and the opportunistic free-riding benefits of enterprises and universities (or research institutions) is less than their excess returns, the system reaches the stable point (1,1,0). In other words, if the opportunistic gains from free-riding due to passive collaboration are lower than the net payoff from active collaboration (excess returns minus costs), enterprises and universities will voluntarily participate in collaborative innovation without the need for direct government intervention. Conversely, if this condition is not met, their collaborative willingness will decline, leading to systemic instability.

3. Through deduction and analysis, two evolutionarily stable strategies are obtained: (0,0,1) and (1,1,0). From the perspective of the overall logic of the collaborative innovation system, the second strategy (1,1,0), is more aligned with practical objectives, where enterprises and universities actively engage in collaboration, while the government maintains a relatively low level of intervention. In this scenario, the system achieves improved collaborative willingness and operational efficiency, and the government can focus its resources on strategic guidance rather than continuous intervention. This evolutionary outcome suggests that when market actors possess strong intrinsic incentives and collaborative momentum, the government can transition from a direct incentivizing role to one of institutional design and supervisory support, fostering a self-adaptive collaborative mechanism led primarily by enterprises and research institutions. This approach not only reduces institutional

resource expenditure but also enhances the overall self-organizing and resilient capacity of the system.

From a resilience perspective, the identified evolutionarily stable strategies represent distinct resilience states of the collaborative innovation system. Specifically, the ESS (1,1,0) corresponds to a high-resilience configuration, in which enterprises and universities sustain collaboration endogenously with limited reliance on continuous government intervention, indicating strong self-organization and recovery capacity [11].

By contrast, the ESS (0,0,1) reflects a low-resilience or fragile state, where collaborative behavior cannot be maintained without persistent policy support. Importantly, robustness and convergence are intrinsic properties of evolutionary dynamics rather than additional constructs; therefore, collaborative innovation resilience is inferred from the system's endogenous evolutionary behavior rather than imposed through an external measurement.

3.4. The impact of governmental willingness z on social value Wg

The social value *Wg* serves as an important indicator for assessing the overall impact of collaborative innovation on macro-level systems. It encompasses multiple dimensions, including technological progress, economic growth, knowledge diffusion, social welfare enhancement, and environmental improvement [48], thereby providing a comprehensive reflection of the overall value contribution of collaborative mechanisms within socio-economic systems. In this study, *Wg* is regarded as a key reference metric for evaluating the triple-helix synergy value.

The triple-helix synergy value refers to the integrated innovation capacity and incremental value generated through the dynamic interactions among the government, industry, and universities (or research institutions). It captures the efficient transformation of knowledge into economic and social value, underpinned by resource integration, cross-sector collaboration, and institutional innovation. This concept places particular emphasis on the multiplicative effects of multi-actor collaboration and the achievement of sustainable development goals.

According to the assumptions outlined in Section 3.2, the social value *Wg* is dynamically associated with the government's willingness to incentivize collaboration (*z*). Note that *Wg* itself is not assumed to be a function of *z* in the model; instead, z determines whether the system operates under a promotion or non-promotion policy regime, which changes the extent to which the (exogenously given) social value *Wg* can be realized (i.e., *Wg* vs. *bWg*). Therefore, the causal chain in Section 3.4 is specified as z → policy regime → realized social value term in the government payoff → $\overline{U_3}$. An increase in government participation enhances the overall value creation capacity of the triple-helix collaborative innovation system, thereby boosting the triple-helix synergy value. Consequently, exploring the relationship between *Wg* and *z* helps reveal the marginal impact of government involvement on THSV and further assess its contribution to collaborative innovation resilience.

Based on the derivation from equations (3.7), (3.8), and (3.9), the final $\overline{U_3}$ expression is obtained as follows:

$$\overline{U_3} = zU_{31} + (1-z)U_{32} = Wg[b + z(1-b)] - Cg[a + z(1-a)] - zxGc - zyGu \\ +z(1-x)Fc + z(1-y)Fu \tag{3.16}$$

Since $\overline{U_3}$ and Wg are positively correlated, to examine the relationship between Wg and *z*, we take the partial derivative of $\overline{U_3}$ with respect to *z*:

$$\frac{\partial\overline{U_3}}{\partial z}=U_{31}-U_{32} \tag{3.17}$$

The sign of this derivative $\partial\overline{U_3}/\partial z$ can be determined by comparing the magnitudes of the relevant terms U_{31} and U_{32}.

$$\begin{aligned}U_{31}&=xy(Wg-Cg-Gc-Gu)+x(1-y)(Wg-Cg-Gc+Fu)\\&+y(1-x)(Wg-Gu-Cg+Fc)+(1-x)(1-y)(Wg-Cg+Fc+Fu)\end{aligned} \tag{3.18}$$

By simplifying equation (3.8), we obtain U_{32}:

$$U_{32}=bWg-aCg \tag{3.19}$$

From equation (3.7), it can be seen that the coefficient of Wg in the term U_{31} is determined by the combination of x and y, and this coefficient is denoted as μ.

$$\mu=xy+x(1-y)+y(1-x)+(1-x)(1-y) \tag{3.20}$$

Given the possible values of $0\le x\le 1$ and $0\le y\le 1$, we analyze several extreme cases:

(1) When x = 1 and y = 1, μ = 1;

(2) When x = 1 and y = 0, μ = 1;

(3) When x = 0 and y = 1, μ = 1;

(4) When x = 0 and y = 0, μ = 1.

From equation (3.8), it is known that the coefficient of Wg in U_{32} is b, where $0<b\le 1$.

Therefore, it can be inferred that U_{31} generally has a stronger dependence on Wg compared with U_{32}. Under normal circumstances, this implies that:

$$\frac{\partial\overline{U_3}}{\partial z}=U_{31}-U_{32}>0 \tag{3.21}$$

It can thus be inferred that as the government's willingness z increases, the social value Wg also rises, and, in turn, the triple-helix synergy value improves. With an increase in the government's promotion willingness (z), the realized social-value component entering the government payoff function increases (i.e., shifting from bWg to Wg), which in turn reinforces the government's incentive to promote collaborative innovation. It is important to note that this derivation focuses on the partial (direct) effect of z on the social-value term in the government payoff, conditional on given collaboration probabilities of enterprises and universities. The indirect effect of z, operating through the evolutionary adjustment of enterprise and university strategies (captured by changes in x and y), is analyzed in the subsequent stability and simulation sections. Governmental actions—through financial support, policy incentives, and institutional guidance—strengthen the collaborative relationships between enterprises and universities, improve coordination efficiency, and enhance innovation output value, leading to higher levels of social benefits and system resilience. Conversely, a lack of government involvement or insufficient incentives may destabilize the collaborative system, resulting in diminished value creation and reduced resilience. This logic suggests that the enhancement of the triple-helix synergy value not only reflects the overall collaborative performance of the triple-helix innovation ecosystem but also serves as an important quantitative indicator of collaborative innovation resilience: when the three actors achieve greater value increments through collaboration, the system's adaptive capacity and resilience are simultaneously reinforced.

4. Evolutionary game simulation analysis

Based on the tripartite payoff matrix of the game, the evolutionary resilience (i.e., stability) of the system is influenced by several key factors: the input costs of enterprises and universities (or research institutions) when choosing collaborative innovation (*Cc,Cu*); the excess returns obtained from collaboration (*Ec,Eu*); the positive incentives provided by the government (e.g., tax incentives or financial subsidies) to enterprises and universities (*Gc,Gu*); the penalties imposed by the government on non-collaborating enterprises or universities, e.g., increased taxation or regulatory restrictions, denoted as (*Fc,Fu*); and the opportunistic gains (free-riding benefits) derived from exploiting the other party's efforts (*Lc,Lu*). Therefore, it is essential to further investigate how these parameters affect the stability of strategy selection in the evolutionary game in order to visualize the system's evolutionary trajectory more intuitively.

This study draws on parameter settings and methodological approaches from the literature on industry–academia–research collaborative innovation. We implemented numerical simulations of the tripartite evolutionary game using Python 3.10, combined with expert interviews and the collection of policy documents, to ensure that the model is grounded in realistic contexts [3,34,49].

To enhance the relevance of high-tech industry application scenarios, this study selects the Yangtze River Delta region of China as a representative case [50,51]. Over the past decade, this region has advanced the construction of collaborative innovation mechanisms in high-tech sectors through regional cooperation, institutional integration, and resource sharing. It has effectively mitigated collaboration barriers and facilitated industry-research linkages, thereby supporting the transformation and upgrading of local high-tech industries from factor-driven to innovation-driven development. Local governments have introduced multi-dimensional incentive policies to promote technological collaboration in high-tech industries. For example, basic R&D subsidies of RMB 400,000 and RMB 200,000 are granted to provincial research institutes and high-tech enterprises, respectively. Cross-institutional technology innovation platforms are strongly supported, and universities, research institutions, and leading domestic and international high-tech companies are encouraged to jointly build technology R&D infrastructures. For the actual collaborative R&D expenses borne by enterprises, the government provides a 20% financial subsidy. High-tech-related projects typically receive stronger support, though the subsidy for a single project generally does not exceed RMB 300,000, and the annual total subsidy for a single enterprise is capped at RMB 500,000.

Furthermore, the government also supports enterprises in establishing joint training bases, innovation laboratories, and industry-education integration platforms with vocational institutions. A 20% reimbursement policy is implemented for expenses incurred through enterprise-university collaboration, such as training or R&D. For projects that receive recognition at national, provincial, or municipal levels, performance-based rewards of RMB 100,000, RMB 80,000, and RMB 50,000, respectively, are granted. If an enterprise leads the creation of a newly approved provincial key laboratory, a one-time reward of up to RMB 1 million is provided. For major technological projects, "task-based bidding" mechanisms can receive funding of up to RMB 10 million, while national-level research projects receive local matching funds of 25% of actual funding (up to RMB 5 million). Horizontal cooperation projects between enterprises and universities with actual expenditures reaching RMB 3 million may be treated as municipal-level key scientific plans.

To strengthen the empirical interpretability of the simulation parameters, key policy variables are linked to commonly adopted metrics in innovation policy practice. Government subsidies for collaborative R&D are typically implemented as cost-based post-subsidy schemes, in which eligible enterprises receive fiscal support calculated as a fixed proportion of their verified R&D expenditure, thereby reflecting subsidy intensity relative to innovation cost rather than absolute monetary transfers [52]. Accordingly, subsidy-related parameters in the model are interpreted in relative terms with respect to collaboration cost.

In contrast, government-imposed penalties in collaborative innovation are inherently multi-dimensional and extend beyond direct financial fines. In practice, penalties may involve contractual liability, withdrawal of subsidies, administrative accountability, reputational sanctions, or mandatory rectification. Given this heterogeneity, penalties are modeled as an abstract enforcement intensity capturing their overall deterrent effect relative to the expected benefits of collaboration, allowing the analysis to examine how regulatory strictness influences strategic behavior, system stability, and evolutionary outcomes.

Based on this policy background, the initial simulation state is set as $t = 0$, with the probabilities of collaboration among high-tech enterprises, universities (or research institutions), and the government all initialized at 0.5. The initial parameter values are set as follows:

$Cc = 40, Cu = 34, Ec = 42, Eu = 38, Gc = 18, Gu = 16, Fc = 14, Fu = 12, Lc = 1, Lu = 1$

To enhance methodological transparency, policy documents are used to identify the types and relative roles of key policy instruments relevant to collaborative innovation, rather than to determine exact numerical values. The baseline parameter setting reflects the qualitative policy emphasis on collaboration costs, incentives, penalties, and supervision intensity, ensuring internal consistency with the policy environment. This qualitative calibration strategy allows the simulation to capture the structural logic of policy intervention without imposing a direct or literal mapping from policy texts to numerical parameters [53].

Subsequently, we examine how factors such as the input cost C of enterprises and universities in collaborative innovation, the additional revenue E, the government's financial support G, penalties F for non-participating actors, and opportunistic gains L from free-riding behaviors influence the evolutionary trajectory and stability of collaborative innovation systems in high-tech sectors.

4.1. The impact of collaboration cost C on system evolution

Under the condition that all other parameters remain constant, six groups of simulation experiments are conducted to examine how varying levels of input costs for enterprises and universities (or research institutions) affect the evolutionary trajectory of the system.

Group 1: $Cc = 40, Cu = 34$; Group 2: $Cc = 26, Cu = 24$, with the corresponding two-dimensional evolutionary paths shown in Figures 2(a) and 2(b); Group 3: $Cc = 26, Cc = 32, Cc = 36$, depicting the three-dimensional evolutionary path under high enterprise cost, as shown in Figure 2(c); Group 4: $Cu = 28, Cu = 34, Cu = 40$, representing the high university cost scenario, as shown in Figure 2(d); Group 5: $Cc = 8, Cc = 12, Cc = 16$, representing the low enterprise cost scenario, as shown in Figure 2(e); and Group 6: $Cu = 8, Cu = 12, Cu = 16$, representing the low university cost scenario, as shown in Figure 2(f).

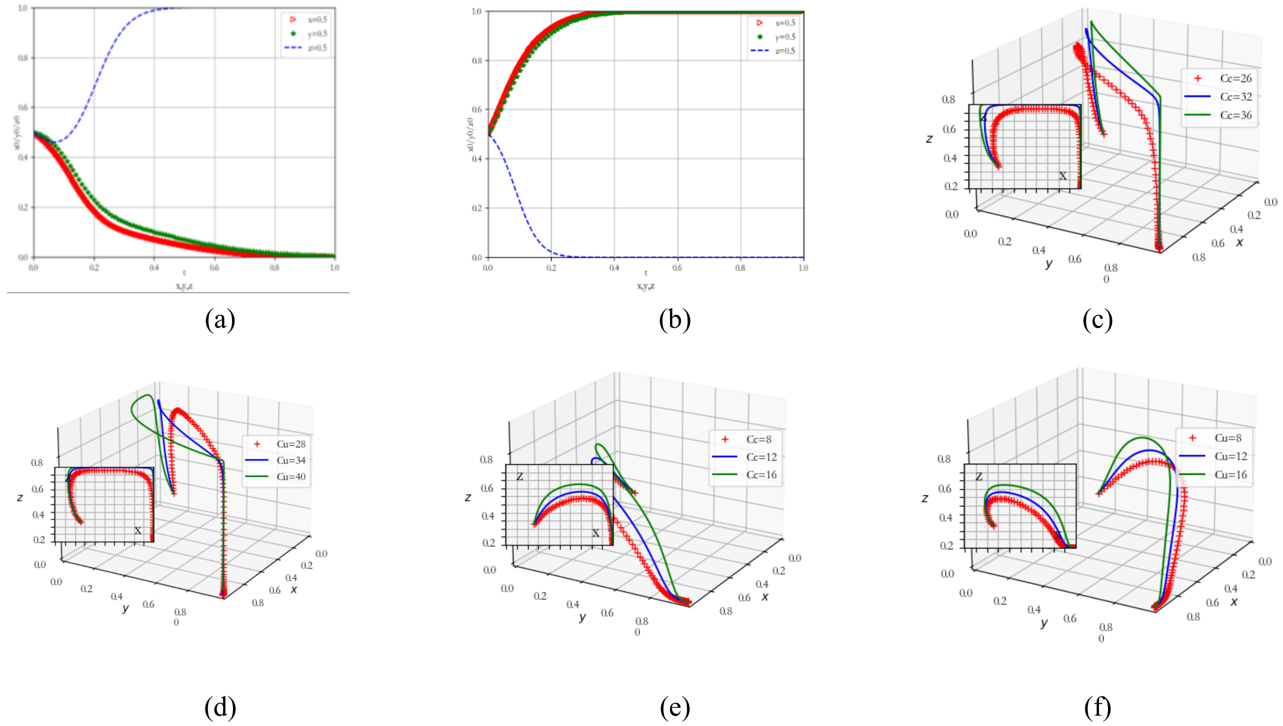


Figure 2. Impact of changes in input cost (C) on system evolution.

Note: x, y, and z denote the probabilities that enterprises, universities, and the government adopt collaborative strategies, respectively. All variables are normalized and dimensionless.

The simulation results confirm the presence of two equilibrium points, (1,1,0) and (0,0,1), which correspond to two distinct stable states, as follows: (1,1,0): Enterprises and universities actively collaborate while the government maintains low intervention. (0,0,1): Enterprises and universities lack collaborative motivation, resulting in high government involvement. The findings indicate that when collaboration costs are low, enterprises and universities are more likely to proactively choose collaborative strategies, allowing the system to naturally converge to the stable state (1,1,0) without significant government intervention. Conversely, when collaboration costs are high, insufficient government incentives may lead to declining collaborative willingness, and the system shifts toward the (0,0,1) configuration, where government-led collaboration becomes dominant. Further analysis reveals that, with the government incentive level held constant, a continuous increase in the costs borne by either enterprises or universities significantly weakens their willingness to participate in collaboration. This trend suggests that the higher the collaboration cost, the greater the system's dependence on government fiscal support and policy guidance to achieve stable multi-party collaboration and maintain technological innovation efficiency.

A senior representative from a provincial industry–academia–research association commented: "Increasing the share of government funding helps alleviate the R&D investment burden borne by universities and small- and medium-sized enterprises, which in turn facilitates deeper industry-academia-research collaboration and enhances the transformation and output of scientific and technological achievements."

This mechanism is particularly salient in high-tech industries. Firms engaging in collaborative innovation often face high R&D costs and uncertainties in technology commercialization, especially in areas such as artificial intelligence, integrated circuits, and advanced manufacturing. Rising costs directly discourage enterprise participation; consistent with insights from expert interviews, increasing the share of government funding is widely regarded as an effective way to alleviate the R&D investment burden faced by universities and small- and medium-sized enterprises; therefore, governmental financial support (e.g., targeted subsidies and tax incentives) serves as a critical lever for maintaining collaboration activity, enhancing system resilience, and increasing the overall triple-helix synergy value.

4.2. The impact of excess return E on system evolution

With all other parameters held constant, six groups of simulation experiments are conducted to evaluate how varying levels of excess returns affect the collaborative evolution of the system:

Group 1: $Ec = 42, Eu = 38$; Group 2: $Ec = 70, Eu = 66,$ resulting in two-dimensional evolutionary trajectories as shown in Figures 3(a) and 3(b); Group 3: $Ec = 38, Ec = 60, Ec = 80$, representing high excess returns for enterprises, with the corresponding three-dimensional evolutionary trajectory shown in Figure 3(c); Group 4: $Eu = 36, Eu = 55, Eu = 80$, representing high excess returns for universities (or research institutions), as shown in Figure 3(d); Group 5: $Ec = 12, Ec = 20, Ec = 34$, representing low excess returns for enterprises, as shown in Figure 3(e); and Group 6: $Eu = 10, Eu = 20, Eu = 30$, representing low excess returns for universities (or research institutions), as shown in Figure 3(f).

The simulation results confirm that the system exhibits two evolutionary equilibrium points, (1,1,0) and (0,0,1). When excess returns are low, the probability of enterprises and universities opting out of collaboration increases sharply. In this case, the system tends to rely on government-led strategies to compensate for insufficient incentives, moving toward the (0,0,1) configuration. Conversely, as the collaborative excess returns for enterprises and universities increase, both parties exhibit a stronger willingness to collaborate voluntarily, and the system ultimately evolves toward the stable equilibrium (1,1,0), allowing the degree of government intervention to diminish.

When government incentives (z) remain constant, excess returns (Ec,Eu) serve as the primary driving force behind collaborative behaviors. Higher returns increase the marginal attractiveness of collaboration, while lower returns, if not supplemented by subsidies or compensatory incentives, can easily lead to a “collaboration failure” path dependence.

This mechanism is particularly salient in high-tech sectors. Enterprises are highly sensitive to the return on investment from collaborative projects, especially in domains characterized by short product life cycles, rapid technological iteration, and high R&D risk. If collaboration fails to yield significant economic returns, firms are likely to avoid engagement, resulting in reduced triple-helix synergy value and weakened system resilience. Therefore, enhancing the tangible returns of collaborative projects, such as improving knowledge conversion and technology transfer efficiency, or implementing targeted incentives, is critical to ensuring effective collaborative innovation and sustaining collaborative innovation resilience in high-tech industries.

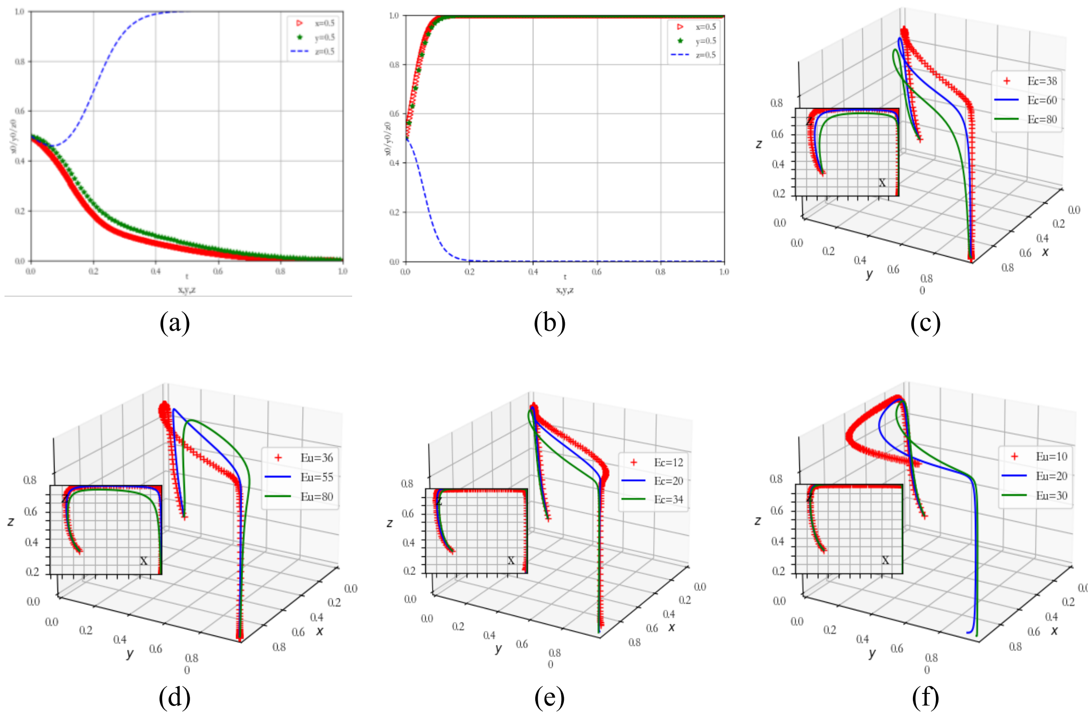


Figure 3. Impact of changes in extra benefit (E) on system evolution.

Note: x, y, and z denote the probabilities that enterprises, universities, and the government adopt collaborative strategies, respectively. All variables are normalized and dimensionless.

4.3. The impact of government funding G on system evolution

With all other parameters held constant, six groups of simulation experiments are conducted to examine how varying levels of government subsidies influence the evolutionary trajectory of collaboration:

Group 1: $Gc = 18, Gu = 16$; Group 2: $Gc = 46, Gu = 42$, resulting in the two-dimensional evolutionary paths shown in Figures 4(a) and 4(b); Group 3: $Gc = 18, Gc = 26, Gc = 34$, representing high financial support for enterprises, with the corresponding three-dimensional trajectory shown in Figure 4(c); Group 4: $Gu = 16, Gu = 24, Gu = 32$, representing high financial support for universities (or research institutions), as shown in Figure 4(d); Group 5: $Gc = 12, Gc = 15, Gc = 18$, representing low financial support for enterprises, as shown in Figure 4(e); and Group 6: $Gu = 10, Gu = 13, Gu = 16$, representing low financial support for universities (or research institutions), as shown in Figure 4(f).

The simulation results indicate that the system has two primary evolutionary stable states: (1,1,0) and (0,0,1), as follows: (1,1,0): Enterprises and universities actively collaborate, with minimal government intervention. (0,0,1): Both parties lack collaborative motivation, requiring strong government intervention. When government subsidies are at a low level, enterprises and universities tend to avoid collaboration, causing the system to evolve toward (0,0,1). This suggests that, under insufficient incentives, multi-agent collaboration is difficult to form spontaneously and requires institutional intervention or resource compensation from the government to maintain stability. As the intensity of government financial support increases, the potential for collaboration is activated, and the collaboration probabilities of enterprises and universities rise simultaneously. Eventually, the system evolves to the (1,1,0) equilibrium, where government intervention can be gradually reduced, and stable collaboration is achieved autonomously.

Further analysis shows that, with the government participation probability z held constant, the level of fiscal incentives has a significant impact on the collaborative decisions of enterprises and universities. Higher subsidies increase collaborative willingness, while insufficient subsidies (which fail to offset costs or opportunity expenses) lead to a strong tendency toward non-collaboration, causing the system's evolution to depend on persistent external intervention. This incentive structure is particularly critical in high-tech sectors. Enterprises engaging in collaborative innovation often face high R&D risks, long commercialization cycles, and uncertain resource allocation. Without effective financial compensation or policy incentives, their willingness to collaborate diminishes significantly. Especially during the early stage of industrial transformation or in major technological breakthrough projects, fiscal incentives not only lower the threshold for collaboration but also serve as a core policy lever to stimulate triple-helix synergistic activity, enhance system resilience, and increase the triple-helix synergy value. Therefore, the magnitude and allocation of government funding directly shape the incentive alignment and resilience of collaborative networks, making it an indispensable parameter in designing effective collaborative innovation policies.

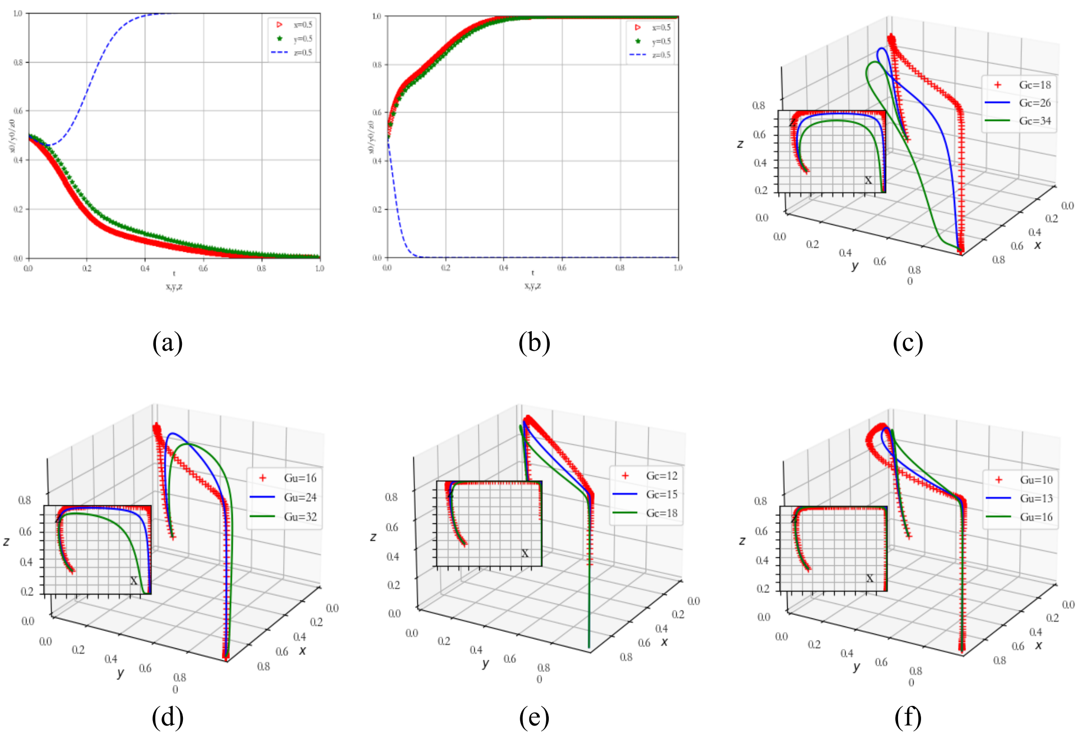


Figure 4. Impact of changes in funding support (G) on system evolution.

Note: x, y, and z denote the probabilities that enterprises, universities, and the government adopt collaborative strategies, respectively. All variables are normalized and dimensionless.

4.4. The impact of government-imposed penalties F on system evolution

With all other parameters held constant, six groups of simulation experiments are conducted to analyze how different levels of government-imposed penalties affect the evolutionary trajectory of collaboration:

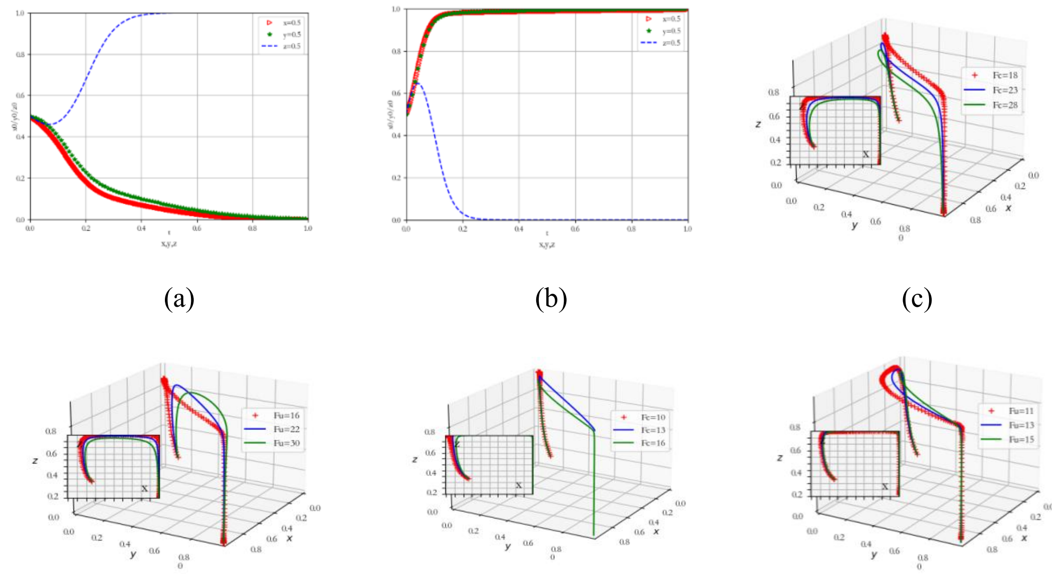
Group 1: $Fc = 14, Fu = 12$, Group 2: $Fc = 46, Fu = 42$, with the corresponding two-dimensional evolutionary paths shown in Figures 5(a) and 5(b); Group 3: $Fc = 18, Fc = 23, Fc = 28$, representing high penalty levels for enterprises, as shown in Figure 5(c); Group 4: $Fu = 16, Fu = 22, Fu = 30$, representing high penalty levels for universities (or research institutions), as shown in Figure 5(d); Group 5: $Fc = 10, Fc = 13, Fc = 16$, representing low penalty levels for enterprises, as shown in Figure 5(e); and Group 6: $Fu = 11, Fu = 13, Fu = 15$, representing low penalty levels for universities (or research institutions), as shown in Figure 5(f).

The simulation results reveal that the system exhibits two evolutionary stable states, (1,1,0) and (0,0,1), as follows: (1,1,0): Active collaboration between enterprises and universities with minimal government intervention; (0,0,1): Lack of collaboration between enterprises and universities, requiring strong government intervention. When the penalty level is low, enterprises and universities tend to select non-collaborative strategies, and the system evolves toward (0,0,1). In this case, the government must increase its level of intervention to maintain cooperation. As the penalty intensity increases, the cost of non-collaboration rises, making enterprises and universities more likely to choose active collaboration. The system then gradually converges to (1,1,0), where stable collaboration can be achieved with reduced government involvement.

A policy expert involved in the governance of collaborative innovation programs noted: “Effective regulatory oversight and appropriately calibrated penalties play an essential role in shaping collaborative behavior. When penalties for opportunistic or non-cooperative actions are sufficiently strong relative to potential gains, participating actors are more likely to adhere to collaborative commitments, which helps reduce strategic deviation and enhances overall coordination efficiency.”

When the government participation probability z remains constant, the penalty parameters Fc and Fu have a significant regulatory effect on the probability of collaboration. Higher penalty levels accelerate convergence toward a collaborative equilibrium, whereas insufficient penalties weaken system stability and sustainability.

In high-tech industries, this mechanism is particularly important. Firms undertaking collaborative innovation projects often face high R&D investment and technical risk. Without effective accountability measures, enterprises may engage in free-riding or adopt a wait-and-see approach, weakening system resilience and the overall triple-helix synergy value. This observation is consistent with insights from policy experts involved in collaborative innovation governance, who emphasize that penalties must be sufficiently strong relative to potential opportunistic gains in order to discipline strategic behavior and reduce deviation from collaborative commitments. Well-designed penalty mechanisms not only suppress opportunistic behavior and improve behavioral consistency but also promote the evolution of collaborative innovation systems toward higher collaborative innovation resilience and greater value creation. Hence, penalty policies are an essential instrument for sustaining a resilient and value-driven collaborative innovation ecosystem in high-tech sectors.



(a) (b) (c)

(d) (e) (f)

Figure 5. Impact of changes in penalty amount (F) on system evolution.

Note: x, y, and z denote the probabilities that enterprises, universities, and the government adopt collaborative strategies, respectively. All variables are normalized and dimensionless.

4.5. The impact of opportunistic free-riding gains L on system evolution

To intuitively analyze how free-riding behavior and the resulting opportunistic gains influence the evolutionary trajectory of the system, a higher level of excess returns is set with all other initial parameters held constant, specifically $Ec = 70$ and $Eu = 66$. Six groups of simulation experiments are then conducted by assigning different values to the opportunistic gains, observing their effects on collaborative evolution:

Group 1: $Lc = 1, Lu = 1;$ Group 2: $Lc = 36, Lu = 33$, yielding two-dimensional evolutionary paths as shown in Figures 6(a) and 6(b); Group 3: $Lc = 36, Lc = 46, Lc = 56$, representing high opportunistic gains for enterprises, with the three-dimensional evolutionary trajectory shown in Figure 6(c); Group 4: $Lu = 32, Lu = 45, Lu = 56$, representing high opportunistic gains for universities (or research institutions), as shown in Figure 6(d); Group 5: $Lc = 1, Lc = 15, Lc = 30$, representing low opportunistic gains for enterprises, as shown in Figure 6(e); and Group 6: $Lu = 1, Lu = 15, Lu = 28$, representing low opportunistic gains for universities (or research institutions), as shown in Figure 6(f).

The results demonstrate that the system maintains two evolutionary equilibrium points: (1,1,0) and (0,0,1). When the opportunistic gains from free-riding are relatively low, enterprises and universities exhibit a stronger willingness to collaborate, and the system converges to the stable state (1,1,0), requiring minimal government intervention. Conversely, when opportunistic gains are high, the incentive for proactive collaboration weakens, and the system shifts toward (0,0,1), where active government intervention is necessary to sustain collaboration.

With other parameters fixed, opportunistic gains Lc and Lu are negatively correlated with the probability of collaboration: higher opportunistic gains reduce collaboration incentives, while lower opportunistic gains encourage spontaneous participation by both parties. This indicates that free-riding behavior undermines the overall fairness and efficiency of the system, posing risks to the sustainability of collaborative innovation. Therefore, the government must introduce appropriate regulatory mechanisms and institutional constraints to minimize unreasonable opportunistic gains, ensure fair alignment between contributions and returns, and maintain the stability and healthy evolution of the system.

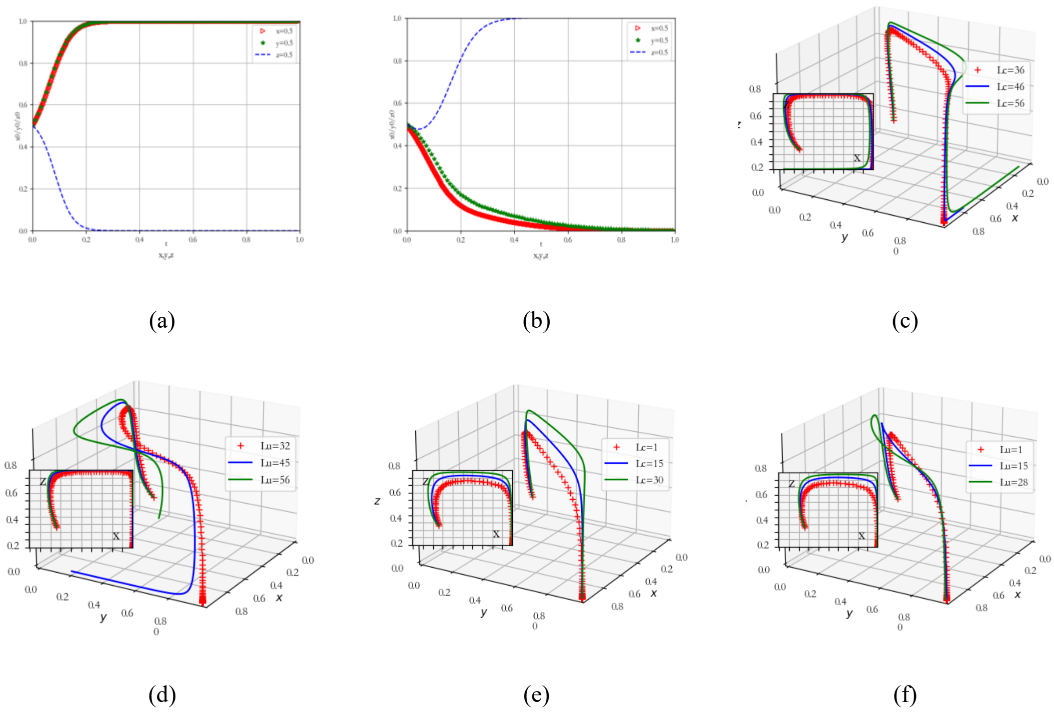


Figure 6. Impact of changes in opportunistic gains (L) on system evolution.

Note: x, y, and z denote the probabilities that enterprises, universities, and the government adopt collaborative strategies, respectively. All variables are normalized and dimensionless.

5. Further discussion and policy implications

5.1. Further discussion

In the context of industrial upgrading and rapidly evolving technological paradigms, this study finds that governments play a pivotal role in orchestrating collaborative innovation among firms, universities, and research institutions. Beyond equilibrium outcomes, the evolutionary trajectories observed in the simulation analysis provide qualitative insights into the strength of collaborative innovation resilience. Specifically, faster convergence toward the collaborative ESS indicates a stronger recovery capability after disturbances, while a wider basin of attraction reflects higher robustness against parameter fluctuations; conversely, frequent shifts toward non-collaborative equilibria signal weaker resilience [54].

From a broader contextual perspective, recent research on innovation and organizational resilience emphasizes that major disruptions, such as the COVID-19 pandemic and increasing geopolitical uncertainty, have reshaped the conditions under which collaborative innovation systems operate. In crisis contexts, resilience is increasingly understood as the capacity of multi-actor systems to absorb shocks, reconfigure interactions, and sustain cooperation under abrupt environmental change [55,8]. This perspective aligns with the evolutionary interpretation adopted in this study, which conceptualizes collaborative innovation resilience as an emergent property of adaptive strategic adjustments over time, reflected in convergence behavior, stability regions, and recovery dynamics following disturbances.

Compared with the mainstream triple helix literature, which typically evaluates collaboration through relatively static indicators such as synergy intensity, network structure, or institutional coupling, this study adopts a more explicitly dynamic perspective. Existing studies provide important insights into institutional configuration and coordination efficiency [24,26,29], but offer limited explanation of how collaborative systems adapt when coordination is disrupted. By contrast, the evolutionary game framework employed here highlights how collaborative innovation resilience is reflected in the stability properties and convergence behavior of strategic interactions under policy intervention and bounded rationality. This dynamic interpretation responds to recent calls in the triple helix literature to move beyond static representations and to analyze innovation systems as adaptive processes shaped by behavioral adjustment and policy feedback [27,28].

By deploying a portfolio of policy instruments, such as fiscal subsidies, tax incentives, technological support, and punitive measures, governments can effectively enhance multi-actor participation in collaborative innovation, facilitate the efficient cross-organizational and cross-sector allocation of innovation resources, and embed knowledge diffusion and technology transfer into production processes, product development, and market commercialization. These findings are consistent with previous research emphasizing the catalytic role of government in innovation ecosystems [56,57] and further suggest that a balanced portfolio of incentives and constraints outperforms single-instrument approaches in sustaining network vitality and system resilience [58].

This study adopts a simplifying assumption that enterprises and universities within each group are homogeneous. While this abstraction facilitates identification of the core evolutionary mechanisms underlying collaborative innovation resilience, it necessarily abstracts from intra-group heterogeneity observed in practice, such as differences in R&D capacity, risk preferences, or absorptive capability. Introducing heterogeneous actors may affect the evolutionary pathways toward CIR by altering convergence speed, strategy adoption order, or sensitivity to policy instruments, even if the existence of collaborative equilibria remains unchanged. For example, firms with stronger R&D capabilities or higher risk tolerance may engage in collaborative strategies earlier and play a disproportionate stabilizing role in the innovation network, whereas smaller or resource-constrained firms may depend more heavily on policy incentives or external supervision to sustain participation. Exploring such heterogeneity through extended evolutionary or agent-based frameworks represents a promising direction for future research.

Beyond the marginal effects of individual parameters, several interaction effects may also shape the evolutionary dynamics of collaborative innovation. First, the effectiveness of subsidies depends on the level of opportunistic gains: when opportunistic incentives are low, subsidies mainly accelerate convergence toward collaborative equilibria, whereas under high opportunistic gains, their impact may weaken unless complemented by effective supervision or penalties. Second, supervision intensity and penalty mechanisms interact with opportunistic gains by reducing the relative attractiveness of free-riding strategies, thereby enhancing equilibrium stability rather than convergence speed. Third, reductions in collaboration costs and increases in policy incentives tend to reinforce each other, jointly lowering entry barriers to cooperation and expanding the basin of attraction of collaborative equilibria. These interaction effects suggest that policy instruments operate in a complementary manner, and their effectiveness should be evaluated jointly within different incentive environments.

The results also reveal that collaboration costs and surplus returns are decisive factors shaping the strategic behavior of innovation actors. When costs are high, targeted subsidies and risk-sharing mechanisms are necessary to encourage engagement; when costs are low, cooperation may emerge spontaneously even under weaker external incentives. Similarly, higher collaborative payoffs motivate proactive participation, while insufficient returns can trigger "collaboration failure" unless compensated by policy support. These dynamics highlight the importance of fine-tuning fiscal incentives to balance efficiency and sustainability [59,60].

Moreover, opportunistic behavior remains a critical threat to stable collaboration. Performance-oriented monitoring and accountability mechanisms can effectively suppress free-riding and information asymmetry, reinforcing behavioral consistency and strategic stability. This finding complements studies on relational governance [61,62].

From a broader perspective, this study refines the understanding of the government's multi-role function in collaborative innovation systems [7,63]. By clarifying behavioral norms and aligning incentive-constraint boundaries, governments can transition from direct intervention to adaptive institutional governance, fostering self-organizing and resilient innovation networks. Particularly in high-tech and capital-intensive sectors, multi-layered and dynamic policy frameworks are essential to enhance responsiveness, prevent collaboration fragmentation, and sustain innovation continuity under uncertainty.

5.2. Policy implications and institutional interpretation

For high-technology industries and other sectors characterized by complex collaboration and high technological uncertainty, governments should employ multi-layered incentive-constraint mechanisms to enhance the willingness of firms and universities to engage in collaborative innovation while effectively curbing opportunistic behaviors. Meanwhile, establishing performance-based monitoring and result-sharing mechanisms can strengthen the resilience and stability of collaboration networks, ensuring that innovation activities can be sustained even in high-risk environments. Such institutionalized support provides a critical foundation for the long-term sustainable development of collaborative innovation in high-technology industries.

The policy implications of this study are directly grounded in the simulation outcomes. The results indicate that increasing subsidy intensity or reducing collaboration costs enlarges the basin of attraction of collaborative equilibria and accelerates convergence toward cooperation, suggesting that cost- and incentive-based policies are particularly effective in facilitating the formation of collaboration. By contrast, stronger supervision and penalty mechanisms primarily enhance the stability of collaborative equilibria by reducing the attractiveness of opportunistic strategies, rather than by altering equilibrium existence. This implies that governance-oriented instruments play a critical role in sustaining collaboration once it has been established. Overall, the findings highlight the importance of aligning policy instruments with different evolutionary functions, combining cost-sharing measures for collaboration formation with monitoring and governance mechanisms for long-term resilience.

In high-tech sectors, digital platforms, standardized data-sharing protocols, and AI-mediated coordination mechanisms can be understood as institutional features that reshape the environment in which triple-helix collaboration takes place. Prior studies on digital innovation emphasize that platform-based and data-enabled infrastructures reduce coordination frictions and facilitate inter-organizational interaction, thereby altering the effective costs of collaboration [64]. From a governance perspective, advances in digital and analytical technologies are often associated with enhanced information availability and oversight capacity, which are widely recognized as key factors in constraining opportunistic behavior in collaborative arrangements [65].

Within the modeling framework of this study, such technological developments do not introduce new strategic actors or incentives but can be conceptually mapped onto changes in existing parameters, such as lower collaboration costs or more effective monitoring. Consequently, they may shift the evolutionary dynamics toward regions in which collaborative equilibria are more stable and resilient. This interpretation highlights how digital and AI-enabled infrastructures can complement traditional policy instruments by modifying the institutional conditions that support collaborative innovation resilience.

6. Conclusion

This paper explores how to enhance collaborative innovation resilience (CIR) in high-tech sectors through an evolutionary game framework involving governments, enterprises, and universities. The results show that lower collaboration costs, higher surplus returns, stronger policy incentives, and effective penalties significantly increase the likelihood of stable cooperation, while excessive costs or weak incentives lead to non-cooperative equilibria. Government participation, particularly through coordinated reward-punishment mechanisms, plays a decisive role in sustaining CIR.

The study contributes to the literature by (1) incorporating resilience into the triple helix–based evolutionary game model, (2) linking dynamic stability with adaptive policy design, and (3) providing simulation-based evidence from a representative high-tech manufacturing region. These insights enrich the theoretical understanding of how bounded rationality and policy intervention jointly shape collaborative stability and system resilience.

In practice, the findings suggest that well-calibrated government incentives and penalties, supported by transparent monitoring, can enhance cooperation efficiency while reducing dependence on continuous state intervention. Policymakers should focus on building adaptive, self-reinforcing collaborative mechanisms that promote sustainable innovation rather than short-term participation. Moreover, the results imply that policy effectiveness depends on the interaction between incentive intensity, opportunistic gains, and collaboration costs, suggesting that "one-size-fits-all" instruments are unlikely to sustain resilience across different stages of collaboration.

Despite these contributions, this study has several limitations. The model assumes homogeneous agents and deterministic evolution, which may not fully capture real-world heterogeneity or stochastic shocks. First, the analysis primarily relies on simulated evolutionary dynamics; future research could complement this framework with longitudinal collaboration data or case-based evidence to examine whether enterprises and universities operating under comparable policy regimes exhibit behavioral adjustments consistent with the simulated trajectories. Second, the homogeneity assumption simplifies variation in R&D capacity, risk tolerance, and absorptive capability across actors; extending the model toward heterogeneous or agent-based formulations would allow a more refined representation of differentiated collaborative pathways. Third, strategy adjustment is modeled without explicitly incorporating path-dependent factors such as sunk costs, reputational lock-in, or switching frictions, which in practice may constrain transitions and slow convergence toward collaborative equilibria. Fourth, the current formulation assumes complete information; incorporating information asymmetry or belief-updating mechanisms would enable future studies to better capture coordination challenges in collaborative settings.

Additional considerations concern the representation of government behavior and temporal interpretation. Government strategy adjustment is modeled in an aggregated manner, and future work could formalize feedback rules based on observed collaboration outcomes to reflect adaptive policy learning. Moreover, while evolutionary trajectories illustrate relative convergence dynamics, the model does not directly map simulation time to real-world durations, limiting direct interpretation of policy timing. Finally, comparative analyses with alternative game-theoretic approaches, such as cooperative or contract-based models, could further clarify the strengths and boundaries of the triadic evolutionary framework.

Overall, these limitations do not undermine the core insights of the study but rather delineate a clear agenda for future research aimed at bridging formal evolutionary modeling with empirical validation, heterogeneous agent dynamics, and policy learning processes in complex innovation systems.

Acknowledgments

This work was supported by the National Social Science Foundation of China (Grant No. 23VRC021 and 25&ZD203).

Author contributions

Yawen Liu: Conceptualization, Data curation, Software, Validation, Writing - original draft, Writing - review & editing.

Jia-Hui Meng: Formal analysis, Writing - review & editing.

Fang Ji: Methodology, Writing - review & editing.

Jian Wang: Project administration, Supervision, Funding acquisition.

Conflict of interest

The authors have no competing interests to declare that are relevant to the content of this article.

Use of Generative-AI tools declaration

The authors declare no use of AI in this study.

Availability of data and materials

Not applicable.

References

1. X. Duan, P. F. Sun, X. Wang, B. S. Zhan, Evolutionary game analysis of industry-university-research cooperative innovation in digital media enterprise cluster based on GS algorithm, *Wirel. Commun. Mob. Comput.*, (2022), 1–10. https://doi.org/10.1155/2022/5701917
2. N. Su, Z. Q. Shi, X. Q. Zhu, Y. S. Xin, An evolutionary game model of collaborative innovation between enterprises and colleges under government participation of China, *Sage Open,* **11** (2021), 1–16. https://doi.org/10.1177/2158244021994854
3. B. J. Hou, J. Hong, H. Y. Wang, C. Y. Zhou, Academia-industry collaboration, government funding and innovation efficiency in Chinese industrial enterprises, *Technol. Anal. Strateg. Manag.*, **31** (2019), 692–706. https://doi.org/10.1080/09537325.2018.1543868
4. X. Y. Qi, G. Mei, Network Resilience: Definitions, approaches, and applications, *King Saud Univ. - Comput. Inf. Sci.,* **36** (2024), 101882. https://doi.org/10.1016/j.jksuci.2023.101882
5. H. G. Bo, Y. G. Zheng, Y. F. Li, S. Q. He, Manufacturing resource outsourcing and matching: Service mode selection and equilibrium evolution, *J. Oper. Res. Soc.,* **76** (2025), 772–789. https://doi.org/10.1080/01605682.2024.2392797
6. X. M. Xie, M. G. Wang, Firm' digital capabilities and green collaborative innovation: The role of green relationship learning, *J. Innov. Knowl.*, **10** (2025), 100663. https://doi.org/10.1016/j.jik.2025.100663
7. J. H. Meng, J. Wang, Y. W. Liu, How is government embedded in innovation process for breakthroughs? A meta-synthesis of qualitative case studies, *Technol. Forecast. Soc. Change*, **194** (2023), 122735. https://doi.org/10.1016/j.techfore.2023.122735
8. L. Hollands, L. Haensse, N. Lin-Hi, The how and why of organizational resilience: A mixed-methods study on facilitators and consequences of organizational resilience throughout a crisis, *J. Appl. Behav. Sci.*, **60** (2024), 449–493. https://doi.org/10.1177/00218863231165785
9. C. G. Schmidt, S. M. Wagner, Blockchain and supply chain relations: A transaction cost theory perspective, *J. Purch. Supply Manag.,* **25** (2019), 100552. https://doi.org/10.1016/j.pursup.2019.100552
10. T. Togoontumur, N. S. Cooray, Does collaboration matter: The effect of university-industry R&D collaboration on economic growth, *J. Knowl. Econ.,* **15** (2023), 9482–9496. https://doi.org/10.1007/s13132-023-01469-5
11. T. Clauss, T. Kesting, M. Franco, Innovation generation through formalisation and fairness in university-industry collaboration, *Technovation,* **134** (2024), 103049. https://doi.org/10.1016/j.technovation.2024.103049
12. G. Melis, S. McCabe, M. Atzeni, G. D. Chiappa, Collaboration and learning processes in value co-creation: A destination perspective, *J. Travel Res.,* **62** (2023), 699–716. https://doi.org/10.1177/00472875211070349
13. Y. Y. Xu, Q. Q. Liang, X. C. Lyu, X. Y. Zang, An evolution analysis of collaborative innovation network considering government subsidies and supervision, *Math. Probl. Eng.,* **2019** (2019), 2906908. https://doi.org/10.1155/2019/2906908
14. D. Q. Gao, S. S. Li, C. Guo, Top management team career experience heterogeneity, digital transformation, and the corporate green innovation: A moderated mediation analysis, *Front. Psychol.,* **14** (2023), 1276812. https://doi.org/10.3389/fpsyg.2023.1276812

15. Y. L. Wan, Y. C. Gao, Y. M. Hu, Blockchain application and collaborative innovation in the manufacturing industry: Based on the perspective of social trust, *Technol. Forecast. Soc. Change,* **177** (2022), 121540. https://doi.org/10.1016/j.techfore.2022.121540
16. S. Sindakis, S. Showkat, G. Showkat, Enhancing resilience and embracing antifragility: The role of innovation in collaborative networks, *Eur. J. Innov. Manag.,* 2025. https://doi.org/10.1108/ejim-12-2023-1129
17. L. Cheng, J. Zhang, Is tourism development a catalyst of economic recovery following natural disaster? An analysis of economic resilience and spatial variability, *Curr. Issues Tour.,* **23** (2020), 2602–2623. https://doi.org/10.1080/13683500.2019.1711029
18. A. Mangan, A. M. Ward, Cooperative resilience: Toward a heuristic model of collective action in a crisis, *Financ. Account. Manag.,* **40** (2024), 308–325. https://doi.org/10.1111/faam.12382
19. K. Medel, R. Kousar, T. Masood, A collaboration-resilience framework for disaster management supply networks: A case study of the Philippines, *J. Humanit. Logist. Supply Chain Manag.,* **10** (2020), 509–553. https://doi.org/10.1108/jhlscm-09-2019-0066
20. R. Prijadi, A. S. Santoso, T. E. Balqiah, H. Jung, P. M. Desiana, P. Wulandari, Enhancing resilience in digital multi-sided platform start-ups: An exploration of entrepreneurial logic and open innovation strategies, *Entrep. Bus. Econ. Rev.,* **12** (2024), 35–53. https://doi.org/10.15678/eber.2024.120103
21. X. Y. Wang, Y. X. Zhang, S. H. Zhang, Dynamic advertising, pricing, and the optimal elongation timing of the supply chain, *Int. J. Prod. Res.,* (2025), 1–22. https://doi.org/10.1080/00207543.2025.2553833
22. H. Etzkowitz, L. Leydesdorff, The dynamics of innovation: From national systems and "Mode 2" to a triple helix of university-industry-government relations, *Res. Policy,* **29** (2000), 109–123. https://doi.org/10.1016/S0048-7333(99)00055-4
23. G. Linton, Triple helix dynamics and hybrid organizations: An analysis of value creation processes, *J. Knowl. Econ.,* **15** (2024), 20797–20822. https://doi.org/10.1007/s13132-024-01911-2
24. M. Ranga, H. Etzkowitz, Triple helix systems: An analytical framework for innovation policy and practice in the knowledge society, *Ind. High. Educ.,* **27** (2013), 237–262. https://doi.org/10.5367/ihe.2013.0165
25. N. Testi, A triple helix model for the diffusion of industry 4.0 technologies in firms in the Marche region, *Open Res. Eur.,* **3** (2023), 89. https://doi.org/10.12688/openreseurope.15706.2
26. Y. Z. Cai, H. Etzkowitz, Theorizing the triple helix model: Past, present, and future, *Triple Helix,* **7** (2020), 189–226. https://doi.org/10.1163/21971927-bja10003
27. Y. Z. Cai, M. Amaral, The triple helix model and the future of innovation: A reflection on the triple helix research agenda, *Triple Helix,* **8** (2021), 217–229. https://doi.org/10.1163/21971927-12340004
28. E. G. Carayannis, D. F. Campbell, E. Grigoroudis, Helix trilogy: The triple, quadruple, and quintuple innovation helices from a theory, policy, and practice set of perspectives, *J. Knowl. Econ.,* **13** (2022), 2272–2301. https://doi.org/10.1007/s13132-021-00813-x
29. M. M. Schocair, A. A. Dias, S. V. R. Galina, M. Amaral, The evolution of the triple helix thematic: A social networks analysis, *Triple Helix,* **9** (2023), 325–368. https://doi.org/10.1163/21971927-bja10037
30. L. Leydesdorff, The triple helix model and the study of knowledge-based innovation systems, *Int. J. Contemp. Sociol.,* **42** (2005), 12–27. https://doi.org/10.48550/arXiv.0911.4291

31. H. Yin, J. X. Liu, N. M. Zeng, How to promote the digital business model innovation of high-tech SMEs through government venture capital? An evolutionary game perspective, *Manag. Decis. Econ.,* **45** (2024), 3193–3216. https://doi.org/10.1002/mde.41855
32. W. W. Liu, J. N. Yang, The evolutionary game theoretic analysis for sustainable cooperation relationship of collaborative innovation network in strategic emerging industries, *Sustainability,* **10** (2018), 4585. https://doi.org/10.3390/su10124585
33. X. Y. Wang, Y. X. Zhang, S. H. Zhang, Dynamic order allocation in a duopoly hybrid workforce of competition: A machine learning approach, *Eur. J. Oper. Res.,* **315** (2024), 668–690. https://doi.org/10.1016/j.ejor.2023.12.026
34. A. Zan, Y. H. Yao, H. H. Chen, University-industry collaborative innovation evolutionary game and simulation research: The agent coupling and group size view, *IEEE Trans. Eng. Manag.,* **68** (2021), 1406–1417. https://doi.org/10.1109/tem.2019.2908206
35. N. Yuan, M. J. Li, Research on collaborative innovation behavior of enterprise innovation ecosystem under evolutionary game, *Technol. Forecast. Soc. Change,* **206** (2024), 123508. https://doi.org/10.1016/j.techfore.2024.123508
36. X. Y. Wang, Y. L. Li, S. H. Zhang, The interplay between green product production and advertising investment under green reputation, *IEEE Trans. Eng. Manag.,* **72** (2025). https://doi.org/10.1109/TEM.2025.3582257
37. X. D. Liu, Corruption culture and corporate misconduct, *J. Financ. Econ.,* **122** (2016), 307–327. https://doi.org/10.1016/j.jfineco.2016.06.005
38. W. Z. Sun, S. N. Chen, Y. Q. Jiao, X. Feng, How does ESG constrain corporate earnings management? Evidence from China, *Finance Res. Lett.,* **61** (2024), 104983. https://doi.org/10.1016/j.frl.2024.104983
39. M. X. Li, X. M. Chi, J. L. Su, H. Z. Sun, O. A. Anaba, A. U. Khan, Evolutionary game theory in patent alliance dynamics: Strategy and policy implications, *Technol. Anal. Strateg. Manag.,* **37** (2024), 1–16. https://doi.org/10.1080/09537325.2024.2361424
40. W. H. Sandholm, Population games and evolutionary dynamics, MIT Press, Cambridge, 2010.
41. X. S. Peng, S. Y. Wang, C. Zhao, Government subsidy policies for industrial internet adoption: A tripartite evolutionary game analysis, *Manag. Decis. Econ.,* **46** (2025), 1392–1404. https://doi.org/10.1002/mde.4440
42. H. P. Young, Commentary: John Nash and evolutionary game theory, *Games Econ. Behav.,* **71** (2011), 12–13. https://doi.org/10.1016/j.geb.2008.12.007
43. R. Viale, V. Cucchiarini, Behavioral triple helix for innovation, *Triple Helix,* 2025, 1–23. https://doi.org/10.1163/21971927-bja10065
44. H. Etzkowitz, Innovation in innovation: The triple helix of university-industry-government relations, *Soc. Sci. Inf.,* **42** (2003), 293–337. https://doi.org/10.1177/05390184030423002
45. E. K. Wang, C. M. Chen, S. M. Yiu, M. M. Hassan, M. Alrubaian, G. Fortino, Incentive evolutionary game model for opportunistic social networks, *Future Gener. Comput. Syst.,* **102** (2020), 14–29. https://doi.org/10.1016/j.future.2019.07.034
46. O. Nazih, N. Benamar, M. Younis, InAn evolutionary bargaining-based approach for incentivized cooperation in opportunistic networkst. *J. Commun. Syst.,* **33** (2020), e4377. https://doi.org/10.1002/dac.4377
47. D. Friedman, On economic applications of evolutionary game theory, *J. Evol. Econ.,* **8** (1998), 15–43. https://doi.org/10.1007/s001910050054

48. E. A. Lindquist, The digital era and public sector reforms: Transformation or new tools for competing values? *Can. Public Adm.,* **65** (2022), 547–568. https://doi.org/10.1111/capa.12493
49. N. Zaharia, University-industry knowledge transfer: Channels of sport research interaction, *Int. J. Bus. Manag.,* **12** (2017), 1. https://doi.org/10.5539/ijbm.v12n9p1
50. Pingyang county people's government office, Several policy opinions of Pingyang county on accelerating technological innovation to promote high-quality development in the manufacturing industry, 2025. Available from: https://www.zjpy.gov.cn/art/2022/5/24/art_1229519551_1999086.html.
51. Hangzhou municipal people's government, Notice of the Hangzhou municipal people's government on issuing several policies to further promote high-quality economic development, 2025. Available from: https://www.hangzhou.gov.cn/art/2024/3/1/art_1229783229_7800.html.
52. Ningxia hui autonomous region department of science and technology, R&D post-subsidy support provided to more than 1,700 enterprises in Ningxia, 2024. Available from: https://www.most.gov.cn/dfkj/nx/zxdt/202409/t20240919_191726.html.
53. J. Sterman, *System dynamics: Systems thinking and modeling for a complex world*, McGraw-Hill, 2002. http://hdl.handle.net/1721.1/102741
54. B. Walker, C. S. Holling, S. R. Carpenter, A. Kinzig, Resilience, adaptability and transformability in social-ecological systems, *Ecol. Soc.,* **9** (2004). https://doi.org/10.5751/ES-00650-090205
55. S. Duchek, Organizational resilience: A capability-based conceptualization, *Bus. Res.,* **13** (2020), 215–246. https://doi.org/10.1007/s40685-019-0085-7
56. I. D. Noni, L. Orsi, F. Belussi, The role of collaborative networks in supporting the innovation performances of lagging-behind European regions, *Res. Policy,* **47** (2018), 1–13. https://doi.org/10.1016/j.respol.2017.09.006
57. A. Saz-Carranza, S. M. Ospina, The behavioral dimension of governing interorganizational goal-directed networks—Managing the unity-diversity tension, *J. Public Adm. Res. Theory,* **21** (2011), 327–365. https://doi.org/10.1093/jopart/muq050
58. X. L. Liu, C. J. Xue, F. J. Xie, The impact of policy mix characteristics of multi-level governance on innovation output of the new energy vehicle industry in China, *Technol. Anal. Strateg. Manag.,* **37** (2024), 1–14. https://doi.org/10.1080/09537325.2024.2304729
59. N. I. Okeke, O. A. Bakare, G. O. Achumie, Integrating policy incentives and risk management for effective green finance in emerging markets, *Int. J. Frontiers Sci. Technol. Res.,* **7** (2024), 76–88. https://doi.org/10.53294/ijfstr.2024.7.1.0050
60. C. Rosário, C. Varum, A. Botelho, The role of public incentives in promoting innovation: An analysis of recurrently supported companies, *Economies,* **12** (2024), 148. https://doi.org/10.3390/economies12060148
61. M. Tripsas, S. Schrader, M. Sobrero, Discouraging opportunistic behavior in collaborative R&D: A new role for government, *Res. Policy,* **24** (1995), 367–389. https://doi.org/10.1016/0048-7333(93)00771-k
62. J. Y. You, Y. Q. Chen, W. Q. Wang, C. X. Shi, Uncertainty, opportunistic behavior, and governance in construction projects: The efficacy of contracts, *Int. J. Project Manag.,* **36** (2018), 795–807. https://doi.org/10.1016/j.ijproman.2018.03.002
63. A. Peterman, A. Kourula, R. Levitt, Balancing act: Government roles in an energy conservation network, *Res. Policy,* **43** (2014), 1067–1082. https://doi.org/10.1016/j.respol.2013.12.007

64. S. Nambisan, M. Wright, M. Feldman, The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes, *Res. Policy,* **48** (2019), 103773. https://doi.org/10.1016/j.respol.2019.03.018
65. O. E. Williamson, *The economic institutions of capitalism: Firms, markets, relational contracting,* Free Press, New York, 1985, 61–75. https://doi.org/10.1007/978-3-8349-9320-5_6