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Dynamic Optimization and Collaborative Mechanisms for Value Co-Creation: A Four-Party Evolutionary Game Study in Digital Innovation Ecosystems

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Abstract

Value co-creation among diverse actors in digital innovation ecosystems (DIEs) exhibits characteristics of high complexity and dynamic evolution. Grounded in the Quadruple Helix Theory, this study develops a conceptual model that interlinks "supervisory guides, knowledge providers, technology transformers, and user demand parties." This model is defined by organizational oversight as its nexus, knowledge and technology as its foundation, outcome transformation as its core, and user needs as its orientation. Building upon this conceptual foundation, we establish a four-party evolutionary game model involving "innovation regulators (government), innovation producers (academic/research institutions), innovation decomposers (enterprises), and innovation consumers (users)." This analytical framework is then applied to systematically investigate the dynamic evolutionary mechanisms and collaborative pathways for value co-creation in DIEs. We construct the payoff matrix and replicator dynamics to derive the system's Evolutionarily Stable Strategies (ESSs). Numerical simulations via MATLAB R2023b identify the stability conditions for each party's strategic choices and unravel the influence mechanisms of key parameters. The results demonstrate nine distinct ESSs, categorized into three types: low-level stability, regulation-dominated transitional stability, and high-level cooperative stability. While the agents' initial strategies do not alter the system's final equilibrium state, they significantly impact the speed of evolutionary convergence. Critical factors—including regulators' intervention costs, subsidy and penalty mechanisms, producers' and decomposers' cooperation and default costs, and consumer feedback behaviors—collectively drive the system toward the ideal (1, 1, 1, 1) equilibrium. Theoretically, this study enriches the perspective on multi-agent collaboration in value co-creation by introducing a dynamic quantitative analytical framework, thereby addressing a notable gap in the literature. Practically, it provides actionable insights for mechanism design and a solid foundation for policy optimization, aiming to foster a synergistic governance system that integrates "regulatory guidance, market incentives, and social feedback."

Keywords: digital innovation ecosystem; quadruple helix theory; evolutionary game; value co-creation

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1. Introduction

Driven by the dual forces of the innovation-driven development strategy and the digital economy, the innovation paradigm is undergoing a structural shift from linear, closed systems toward ecological and networked collaboration. The digital innovation

ecosystems (DIE) has emerged as a core engine for high-quality development at national and regional levels. It constitutes a complex adaptive system formed by diverse, heterogeneous actors—including governments, enterprises, universities, research institutions, and users—who interact through competition, cooperation, resource integration, and relational coordination within an open environment. Within such ecosystems, the logic of value creation has fundamentally transformed: value no longer originates from within a single organization but is generated through a collaborative process characterized by nonlinear interactions among multiple actors, adaptive resource matching, and dynamic adjustment to the environment. This value co-creation process forms the central driving force for the continuous evolution and healthy development of DIEs. To systematically explain the collaborative relationships among these diverse actors, innovation theory has evolved from the "Triple Helix" (university–industry–government) model to the Quadruple Helix model [1], which incorporates the public (users) as a fourth helix. While the Quintuple Helix further adds the natural environment as a fifth helix [2], our study focuses on the socio-economic subsystem of the digital innovation ecosystem and therefore adopts the Quadruple Helix framework (government–academia–industry users). This framework underscores the symbiotic evolution and mutual reinforcement among four key forces: government, industry, academia, and the public. Mapped onto the context of DIE, these forces manifest as four core actor types: innovation regulators (government), innovation producers (universities and research institutions), innovation decomposers (enterprises), and innovation consumers (users) [3].

While value co-creation theoretically promises the synergistic "1 + 1 > 2" effect, its practical implementation faces significant challenges. All actors in the system are boundedly rational decision-makers who base their strategic choices on self-interest and expectations of others' actions. Specifically, innovation regulators weigh "proactive intervention" against "laissez-faire"; innovation producers choose between "open sharing" and "closed protection"; innovation decomposers consider "collaborative innovation" versus "independent innovation"; and innovation consumers oscillate between "proactive participation" and "passive consumption." These strategic choices are deeply intertwined and mutually constraining, forming a dynamic network rife with uncertainty. The emergence of opportunistic behavior can easily precipitate a "tragedy of the commons" or foster "innovation inertia." Such outcomes trap the system in a state of coordination failure, thereby hindering the realization of optimal synergy envisioned by the Quadruple Helix framework in practice.

Accordingly, this study addresses the following core research questions: Within a digital innovation ecosystem (DIE) structured by the Quadruple Helix framework: (1) What are the dynamic evolutionary patterns governing value co-creation behaviors among the four key actors: innovation regulators, producers, decomposers, and consumers? (2) Which key factors determine whether the system evolves towards deep integration or becomes trapped in a low-efficiency equilibrium? (3) How can dynamic optimization and rational mechanism design guide the system to overcome barriers and achieve a high-level, stable state of value co-creation? To answer these questions, this study develops a four-party evolutionary game model to analyze the dynamic process and stability conditions of their strategic interactions. Theoretically, it contributes by integrating the Quadruple Helix framework with evolutionary game theory, thereby providing a dynamic and quantitative analytical framework for understanding multi-agent coordination in DIEs. Practically, it employs systematic simulation to identify pivotal influencing factors. The findings offer a scientific basis for designing precise intervention policies and optimizing participation strategies for diverse actors, ultimately steering the system towards advanced value co-creation.

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2. Literature Review

This study investigates value co-creation behaviors and dynamic coordination mechanisms among multiple actors in digital innovation ecosystems (DIEs). By systematically reviewing the literature across core domains—including the DIE, value co-creation theory, the Quadruple Helix framework, and evolutionary game theory—it aims to clarify the theoretical evolution and identify research gaps, thereby laying a solid theoretical groundwork for constructing a four-party evolutionary game model.

2.1. From Innovation Ecosystems to Digital Innovation Ecosystems: Theoretical Evolution and Real-World Drivers

The theory of innovation ecosystems originates from the intersection of ecology, systems science, and innovation management. It moves beyond the constraints of traditional linear innovation models by emphasizing that value creation arises from the symbiotic coupling and collaborative interactions among diverse actors [4,5]. The theory itself has evolved through stages from "sustainable development" to "open innovation," and further into "value co-creation" [3], reflecting a fundamental shift in logic—from individual-centric to holistic synergy, and from unidirectional output to networked interaction. Propelled by the deepening digital economy, digital technology—as a core driver—has profoundly integrated with innovation ecosystems, giving rise to the digital innovation ecosystem (DIE) as a new paradigm. Existing research commonly defines the DIE as a complex adaptive system built upon digital platforms and infrastructure [6–8], where heterogeneous actors (e.g., governments, enterprises, universities, research institutions, and users) engage in competitive interactions across temporal, spatial, and organizational boundaries [9]. Driven by digital technology and oriented toward value co-creation, the DIE exhibits structural features such as blurred innovation boundaries, digitized innovation elements, and ecological relationships among actors, thereby opening new pathways for value creation [10]. Nevertheless, prevailing studies have predominantly focused on static structures and role definitions. There remains a notable gap in exploring the dynamic strategic interactions and co-evolutionary mechanisms among actors, underscoring the need to introduce dynamic analytical tools for deeper investigation. To distinguish digital innovation ecosystems (DIEs) from innovation ecosystems, we highlight two distinctive features rooted in digitalization. First, platform-enabled coordination: DIEs are built upon digital platforms that facilitate real-time data exchange, modularity, and algorithmic matching among actors, thereby reducing information asymmetry and accelerating collaborative adaptation [11]. Second, user-driven value co-creation: DIEs blur the traditional boundaries between producers and consumers by enabling users to actively participate in innovation processes through feedback, co-design, and user-generated content—a role that is typically more passive in conventional ecosystems [12]. These digital characteristics fundamentally reshape the cost–benefit structure of multi-actor interactions and are operationalized in the proposed model through parameters that capture user engagement costs, reputational feedback, and platform-mediated transaction costs.

2.2. Value Co-Creation: The Logical Leap from Dyadic Interaction to Systemic Synergy

The theory of value co-creation challenges the firm-centric, unidirectional logic of value creation, positing instead that value is jointly created by multiple actors through open collaboration [13]. Within the DIE—a primary vehicle for its practical enactment—the value co-creation process is characterized by high complexity and adaptability. It is shaped by multiple factors, including benefit distribution, collaboration costs, risk mitigation, and opportunistic behavior [14]. The system evolves structurally through nonlinear interactions—including knowledge sharing, resource integration, and risk sharing—progressing from

disorder to order and from lower-order to higher-order states. This dynamic evolution provides continuous structural impetus for value co-creation [15]. However, existing research has yet to sufficiently clarify the specific micro-mechanisms of value co-creation behaviors or delineate clear pathways to achieving systemic synergy, highlighting an area ripe for further investigation.

2.3. Quadruple Helix: A Framework for Multi-Actor Synergy

We situate our conceptual framework within the evolutionary lineage of n-Helix models. The Triple Helix model established the foundational "knowledge triangle" of university–industry–government interactions, emphasizing the recursive and overlapping roles of these spheres in innovation [16]. Subsequent extensions to the Quadruple Helix incorporated civil society (users) as a fourth helix [1], while the Quintuple Helix further added the natural environment [2]. In this study, the Quadruple Helix serves primarily as a justification for actor inclusion—it legitimizes the selection of our four key actors (regulators, producers, decomposers, consumers). However, the specific evolutionary mechanisms inherent to helix dynamics (e.g., co-evolution, institutional logics, recursive interactions) are not directly modeled; instead, we translate these qualitative insights into a game-theoretic payoff structure that captures the strategic choices of boundedly rational agents. This distinction clarifies that our contribution lies in the dynamic quantitative analysis of multi-actor coordination, not in testing or extending helix-specific evolutionary mechanisms. Following Cai [17], we acknowledge that institutional logics and contextual factors shape actor behavior, but we operationalize them through cost–benefit parameters rather than through helix-specific dynamics. The natural environment is not treated as an independent strategic actor in our model; it is considered as part of the broader socio-ecological context that lies outside the current scope. Consequently, our framework is accurately described as operating within a Quadruple Helix logic (government–academia–industry users), providing a robust systemic basis for analyzing actor interactions within digital innovation ecosystems.

2.4. Evolutionary Game Theory: A Dynamic Tool for Analyzing Innovation Synergy and Its Theoretical Boundaries

By integrating classical game theory with dynamic evolutionary processes, evolutionary game theory is well-suited to analyze the behavior of boundedly rational agents. It effectively models both their strategy adjustments and the system's path to equilibrium. It has thus been widely applied to study innovation collaboration and system governance. However, extant applications remain limited. Most studies are confined to dyadic games (e.g., "core vs. non-core enterprises") [18,19] or tripartite frameworks (e.g., "government–enterprises–academia") [20,21], consistently omitting user groups from the analytical scope [22]. This omission not only compromises the comprehensiveness of the Quadruple Helix framework but also impedes a full account of an innovation system's evolutionary dynamics. Consequently, it fails to adequately capture the dynamic adjustment mechanisms of strategies chosen by boundedly rational actors. In summary, while the existing literature provides a solid foundation, three critical avenues for extension emerge: The study of value co-creation in DIEs must evolve from describing static structures to uncovering the micro-mechanisms of dynamic strategic interaction. The Quadruple Helix framework requires integration with dynamic quantitative methods, such as evolutionary game theory, to bridge the gap between theoretical prescription ("ought") and empirical explanation ("is"). Current evolutionary game models lack actor comprehensiveness and dynamic process depth, thereby falling short of reflecting DIE's inherent complexity.

Recent multi-population evolutionary game studies in related domains provide useful comparisons. Wang and Luo [23] develop a tripartite model for digital urban–rural resource

sharing, while Liu et al. [24] examine private sector strategies in green energy PPP projects. Both employ replicator dynamics and numerical simulation, similar to our approach. However, the proposed model differs in three key aspects: (i) it covers four actors (regulators, producers, decomposers, consumers) rather than two or three; (ii) it embeds consumer feedback as an endogenous driver through reputational losses and participation benefits; and (iii) it systematically analyzes asymmetric effects of initial strategies on convergence speed and conducts a numerical search for interior/boundary equilibria. These features extend the existing literature on multi-population evolutionary games.

To address these gaps, this study constructs a four-party evolutionary game model involving innovation regulators, producers, decomposers, and consumers. Using numerical simulation in MATLAB R2023b, it aims to systematically uncover the evolutionary pathways of agent strategies and the conditions for systemic synergy. The goal is twofold: to advance theoretical understanding of multi-actor collaboration in DIEs and to inform the design of mechanisms and policies to mitigate coordination failure.

3. Construction of a Four-Party Evolutionary Game Model

3.1. Analysis of Participating Actors and Their Interests

Grounded in the Quadruple Helix innovation theory, this study constructs a theoretical model to analyze the dynamic optimization and synergistic mechanisms of value co-creation in DIE. The model centers on four core actors within the digital context, examining their respective roles, core interests, and strategic choices: the government (innovation regulators), academic and research institutions (innovation producers), enterprises (innovation decomposers), and users (innovation consumers). Operating under the assumption of bounded rationality, each actor seeks to maximize its own payoff. Their strategic interactions, driven by mutual anticipation and dynamic gameplay, ultimately drive the entire system toward a coordinated set of Evolutionarily Stable Strategies.

As "innovation regulators," the government is responsible for organizing, guiding, and supervising the ecosystem. Its core mission is to foster a stable and efficient innovation environment, playing a pivotal role in planning, coordinating, and sharing risks—especially in advancing breakthroughs in key core technologies [25]. Specifically, it shares R&D costs through innovation subsidies and tax incentives [26], guides the optimal allocation of innovation resources via financial support and intellectual property protection, and deters opportunistic behavior with punitive measures such as fines and license revocations. In the digital context, the government further enhances its capacity by leveraging big data monitoring and mobile government platforms. This improves the precision of its situational analysis and policy responses, strengthens continuous information exchange, and boosts overall governance efficiency [27]. The government's fundamental interests lie in promoting breakthroughs in key technologies, facilitating industrial structure upgrading, and cultivating a healthy, sustainable DIE. Through this process, it aims to achieve steady growth in fiscal revenue and to enhance overall social welfare. While infrastructure provision, platform building, and standard setting are undeniably important government functions, the proposed model deliberately focuses on subsidy and penalty mechanisms—the most direct and commonly used policy instruments for incentivizing collaborative innovation in digital ecosystems. This focus allows the model to isolate the core economic drivers of value co-creation without loss of generality for the mechanisms under investigation. For analytical tractability, the model therefore abstracts from other government roles such as infrastructure provision, platform building, standard setting, or the supply of public goods.

As "innovation producers," academic and research institutions constitute the primary source of knowledge creation and technological R&D within the system. Their core responsibilities encompass fundamental research, knowledge innovation, and talent cultivation.

Capitalizing on their disciplinary depth and talent pool, they supply enterprises with cutting-edge theoretical insights and innovative solutions. Furthermore, they actively facilitate the translation of scientific and technological achievements through industry–academia–research collaborations, thereby aiding enterprises in technological iteration and product innovation [28]. In the digital context, these institutions further harness emerging infrastructures such as blockchain, artificial intelligence, and digital twins. This enhances the modularity of knowledge transfer and the precision of collaborative R&D, cementing their foundational, value-adding role within the ecosystem [29]. Their core interests are threefold: to secure stable funding for R&D, to expand diversified channels for industry–academia–research collaboration, and, through these, to elevate their academic reputation and broader societal influence.

As "innovation decomposers," enterprises play the pivotal role of transforming scientific and technological resources into market value [30]. As hubs for ecosystem aggregation and value realization, they perform a dual function: integrating theoretical knowledge, technical solutions, and digital resources from academia to drive continuous product and service iteration, while providing complementary actors with resource support and capability synergy based on their own strengths in talent, technology, and equipment. Advancements in digitalization significantly reduce innovation uncertainty and information transmission costs. This, in turn, enhances enterprises' responsiveness and dynamic adaptability within collaborative networks. Their primary interests focus on acquiring advanced technological outcomes, mitigating independent innovation risks, strengthening market competitiveness, and, ultimately, maximizing economic benefits [30]. For analytical tractability, the proposed model abstracts from firm heterogeneity, lock-in effects, vested interests, sunk investments, and political power, focusing instead on the fundamental economic trade-off between collaborative and independent innovation. Consequently, the results apply to firms willing to consider collaboration; in settings where incumbent firms defend the status quo due to lock-in or vested interests, the dynamics may differ, and extensions such as heterogeneous agent types or switching costs would be required. This simplification allows the model to establish a clear baseline for understanding value co-creation in digital innovation ecosystems.

As "innovation consumers," users have shifted from being traditional product recipients to being core participants and key enablers in the value co-creation process. In user-driven innovation models, they not only enhance their own efficacy by adopting high-quality outputs but also, via digital platforms and big data, provide real-time feedback on usage experiences, improvement suggestions, and latent needs. This feedback constitutes critical input for enterprises to identify market trends and refine product strategies [31]. This sustained interaction enhances both the market fit and success rate of innovations, while also facilitating the dynamic optimization of resource allocation and innovation pathways within the system [32]. The core interests of users are threefold: to access superior products and services, to amplify their own influence through proactive participation, and to articulate individual and collective values within the framework of collaborative governance. For analytical tractability, the proposed model captures consumer influence primarily through participation costs and benefits. This focus is deliberate: consumer behavior affects the payoffs of producers and decomposers (e.g., via reputational losses and rewards), thereby shaping their strategic choices—a mechanism that constitutes value co-creation even without deeper strategic reasoning from consumers. The proposed model abstracts from broader civil society dimensions such as collective action, public discourse, legitimacy, or institutional feedback, as these fall outside the scope of its evolutionary game framework, which is designed to analyze the economic drivers of multi-actor coordination.

In summary, the four core actors in DIEs—government, academic institutions, enterprises, and users—exhibit roles and interests that are distinct yet profoundly interdependent. Driven by bounded rationality, their strategic choices are not made in isolation but co-evolve through continuous interaction, mutual learning, and adaptation within a dynamic, open digital environment. This complex interplay of strategies constitutes a game-theoretic network with inherent dynamic feedback. Building directly on this analysis, the present study proceeds to construct a four-party evolutionary game model for value co-creation in DIEs. The model aims to elucidate the logic governing actor roles and the structure of their interests, thereby establishing a theoretical foundation and analytical framework for investigating systemic dynamic evolution. The specific logical structure of this research is presented in Figure 1.

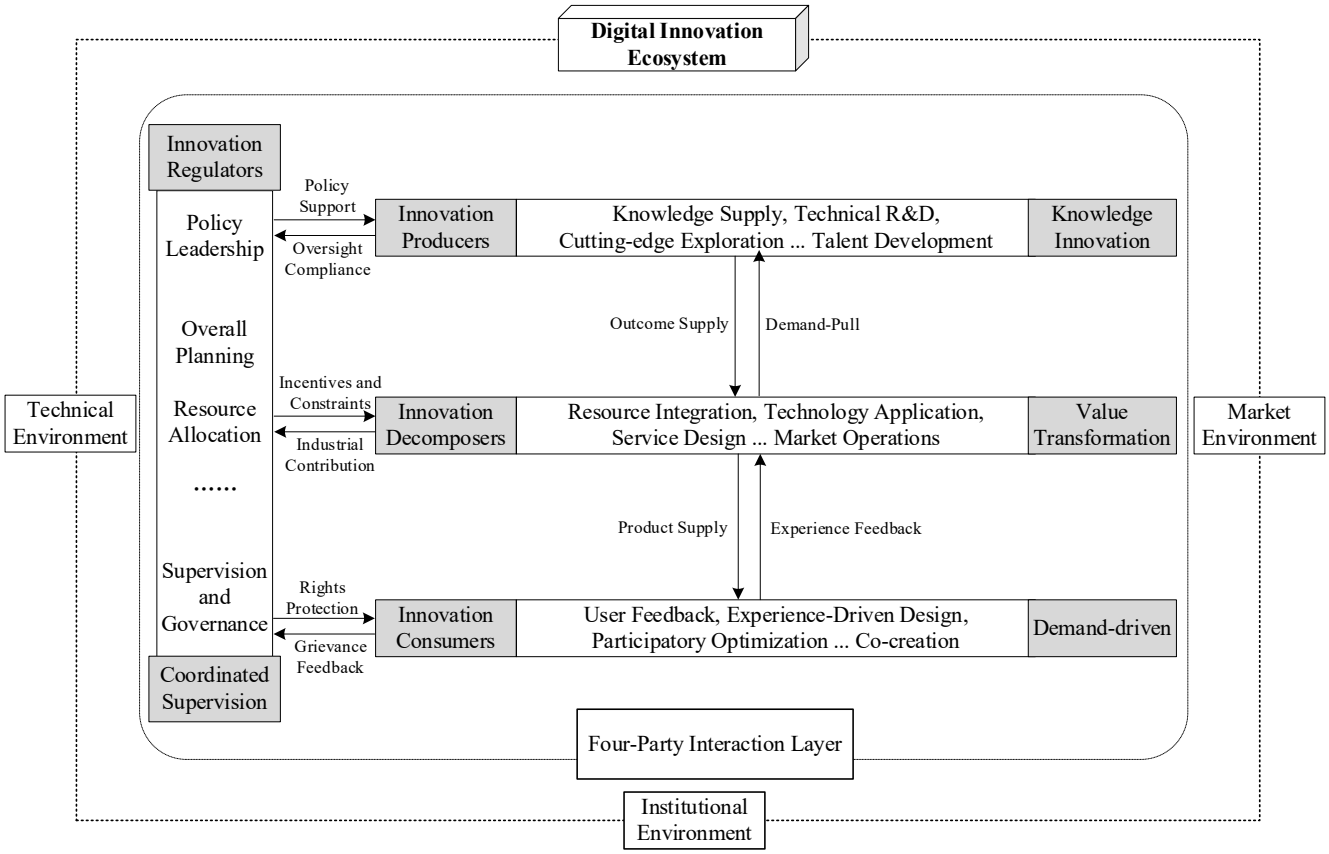


Figure 1. The Four-party evolutionary game framework for co-creating DIE value.

3.2. Model Assumptions

To develop an evolutionary game model that captures the four core actors within DIE, to elucidate the patterns of their strategic interactions, and to solve for the system's evolutionarily stable strategy, this study establishes the following fundamental behavioral assumptions:

Assumption 1. *The participants in the DIE value co-creation game are the innovation regulators (R), the innovation producers (P), the innovation decomposers (D), and the innovation consumers (C). Each actor type was assumed to be boundedly rational and to operate under information asymmetry. Their objective is to maximize their own interests or utility. The system converges on an evolutionarily stable strategy (ESS) through dynamic adjustments to each actor type's strategy. In this paper, "ESS" refers to a locally asymptotically stable equilibrium of the replicator dynamics (all eigenvalues of the Jacobian have negative real parts), a weaker condition than the strict ESS defined by Maynard Smith and Price [33]; see Section 4 for details.*

Assumption 2. *The strategy choices for innovation regulators are (proactive intervention, laissez-faire). Proactive intervention incurs cost C_1 and yields social benefit R_1. To incentivize collaborative innovation, the regulator provides corresponding incentives: subsidies S_1 and S_2 for collaborative innovation between producers and decomposers; compensation S_3 for producers who attempt open sharing but fail; and rewards S_4 for actively participating consumers. If innovation producers and decomposers achieve collaborative innovation, the innovation regulator gains positive utility B_1. If either party fails to cooperate, the regulator incurs negative utility N_1 due to insufficient collaboration and may impose penalties F_1 and F_2 on the defaulting entities. The effectiveness of the intervention is modulated by the intervention intensity coefficient α ($0 < \alpha < 1$). It should be noted that "laissez-faire" in this context does not imply governmental inaction, but rather a strategic posture of regulatory restraint—allowing market mechanisms and autonomous collaboration to function while maintaining basic legal and institutional frameworks.*

Assumption 3. *The strategy choices for innovation producers are (open sharing, closed protection). Opting for open sharing yields subsidies S_1 from innovation regulators and service fees C_5 paid by innovation decomposers, but incurs cooperation costs C_2 and risks knowledge spillovers and diminished exclusivity over outcomes. Choosing closed protection preserves short-term knowledge monopolies and base returns R_2, yet may trigger penalty payments T_1 for breaches and suffer reputational damage N_2 from negative feedback by innovation consumers, thereby undermining long-term collaboration opportunities and reputation accumulation.*

Assumption 4. *The strategy choices for innovation decomposers are (collaborative innovation, independent innovation). Choosing collaborative innovation incurs additional cooperation costs C_4 and service fees C_5 but yields extra returns R_4; choosing independent innovation retains baseline returns R_3 but entails independent innovation costs C_3 and risks paying penalty fees T_2 and reputational losses N_3 due to negative consumer experiences.*

Assumption 5. *The strategy choices for innovation consumers are (proactive participation, passive consumption). Choosing proactive participation incurs participation costs C_6 but yields social benefits R_5 and positive utility B_2 from collaborative innovation. Choosing passive consumption avoids participation costs but entails negative experiences N_4 due to suboptimal system innovation outcomes and forfeits opportunities to influence the innovation process through deep engagement.*

Assumption 6. *The probability that innovation regulators choose "proactive intervention" is x ($0 < x < 1$), while the probability of selecting "laissez-faire" is $1 - x$; the probability that innovation producers choose "open sharing" is y ($0 < y < 1$), while the probability of selecting "closed protection" is $1 - y$. The probability that innovation decomposers choose "collaborative innovation" is z ($0 < z < 1$), and the probability they choose "independent innovation" is $1 - z$. The likelihood that innovation consumers choose "proactive participation" is w ($0 < w < 1$), and the probability they choose "passive consumption" is $1 - w$.*

The relevant parameter settings for the four-party game entities are shown in Table 1.

3.3. Parameter Rationale and Simplification

The proposed model involves a relatively large number of parameters (24 in total), which reflects the complexity of the four-party digital innovation ecosystem. Each parameter corresponds to a real-world economic or institutional factor identified in the literature (see Table 1 for definitions). To improve interpretability and reduce dimensionality, we apply the following simplifications without loss of generality:

Table 1. Parameter settings and definitions.

Subject	Parameter	Meaning (Technical Definition)	Economic Interpretation (Plain Language)
Innovation Regulators	C_1	Costs incurred by innovation regulators for adopting a proactive intervention strategy	Administrative and operational expenses of active regulation (e.g., monitoring systems, personnel)
	R_1	Social benefits obtained by innovation regulators from proactive intervention	Improved innovation climate, industrial upgrading, and overall welfare gains
	S_1	Innovation regulators' subsidy to producers for collaborative innovation	R&D funding or tax breaks given to academic/research institutions for open sharing
	S_2	Innovation regulators' subsidy to decomposers for collaborative innovation	Financial incentives for enterprises to engage in joint innovation projects
	S_3	Innovation regulators' compensation to producers for attempted open sharing	Partial reimbursement to producers who try open sharing but fail (risk mitigation)
	S_4	Benefits provided by innovation regulators to consumers who actively participate in the system's value co-creation	Rewards (monetary or non-monetary) for user feedback and co-design activities
	B_1	Positive utility gained by regulators from the collaborative innovation between innovation producers and decomposers	Regulatory satisfaction from successful industry–academia collaboration
	N_1	Negative utility incurred by innovation regulators due to independent innovation by either producers or decomposers	Regulatory disappointment or political cost when collaboration fails
	F_1	Fine imposed by innovation regulators on producers who fail to fulfill cooperative responsibilities	Monetary penalty for closed-protection behavior by research institutions
	F_2	Fine imposed by innovation regulators on decomposers due to the lack of cooperation between producers and decomposers	Monetary penalty for enterprises choosing independent innovation over collaboration
	α	Intervention intensity coefficient of innovation regulators	Degree of regulatory activeness ($0 < \alpha < 1$); higher α means stronger policy enforcement
Innovation Producers	C_2	Costs incurred by innovation producers for cooperating with decomposers	Transaction and coordination costs in open sharing (e.g., IP negotiation, technology transfer)
	R_2	Base revenue for innovation producers from open sharing	Baseline income from knowledge dissemination (e.g., licensing fees, research grants)
	T_1	Breach penalty payable by closed-protection innovation producers to cooperative-innovation decomposers	Compensation paid by non-cooperative producers to enterprises that expected collaboration
	N_2	Reputation loss inflicted upon closed-protection producers due to feedback from innovation consumers	Loss of academic prestige or public trust from negative user reviews

Table 1. *Cont.*

Subject	Parameter	Meaning (Technical Definition)	Economic Interpretation (Plain Language)
Innovation Decomposers	C_3	Costs incurred by innovation decomposers for independent innovation	R&D expenses when innovating alone (without external collaboration)
	C_4	Additional costs required by innovation decomposers for collaborative innovation	Extra coordination and integration costs when working with producers
	C_5	Service fees paid by innovation decomposers to access producers' knowledge/technical services	Payment for technology transfer or consulting from academic institutions
	R_3	Base revenue for innovation decomposers from independent innovation	Baseline profit from in-house innovation (used as numéraire)
	R_4	Additional revenue obtained by innovation decomposers from collaborative innovation	Extra profit from joint projects (e.g., faster time-to-market, shared resources)
	T_2	Breach penalty payable by independent-innovation decomposers to producers	Compensation paid by enterprises that abandon agreed collaboration
	N_3	Reputation loss inflicted upon independent-innovation decomposers due to feedback from innovation consumers	Brand damage or customer distrust from negative user experiences
Innovation Consumers	C_6	Costs incurred by innovation consumers for actively participating in the system's value co-creation	Time, effort, or data privacy costs of providing feedback and co-design
	R_5	Social benefits for proactive innovation consumers from producer–decomposer collaboration	Social recognition, improved user experience, or community rewards
	B_2	Positive utility provided to consumers by the collaborative innovation between producers and decomposers	Personal satisfaction from contributing to innovation (intrinsic motivation)
	N_4	Negative experience imposed on consumers by the independent innovation of producers and decomposers	Frustration from using inferior products due to lack of collaboration

Aggregation: Parameters that play similar functional roles are combined where possible. For instance, the two subsidy terms S_1 and S_2 are aggregated into a single subsidy level $S = S_1 + S_2$ when analyzing the total incentive effect on cooperation; similarly, the two penalty terms F_1 and F_2 are aggregated into $F = F_1 + F_2$ for the regulator's deterrence capacity. The separate effects are discussed only when asymmetric treatment between producers and decomposers is essential.

Parameter fixing: Sensitivity analysis shows that the convergence pattern is primarily driven by a subset of key parameters (intervention cost C_1, subsidies S_1, S_2, S_4, penalties F_1, F_2, cooperation costs C_2, C_4, additional revenue R_4, participation cost C_6, and feedback losses N_2, N_3). The remaining parameters (e.g., B_1, B_2, N_1, N_4) affect only the magnitude of payoffs but not the direction of stability; they are fixed at baseline values derived from field surveys and expert interviews.

These simplifications preserve the essential trade-offs and strategic interactions while making the model more tractable and the results easier to interpret.

3.4. Model Construction

Based on the above assumptions and parameter settings, a payoff matrix for the game involving four decision-making entities—the innovation regulator (R), innovation producer (P), innovation decomposer (D), and innovation consumer (C)—is constructed, as shown in Table 2.

Table 2. Payoff matrix for the four-party game in the system value co-creation.

		Collaborative Innovation by Innovation Decomposers (z)		**Independent Innovation by Innovation Decomposers (1 − z)**	
		Proactive participation by innovation consumers (w)	Passive consumption by innovation consumers (1 − w)	Proactive participation by innovation consumers (w)	Passive consumption by innovation Consumers (1 − w)
Proactive intervention by innovation regulators (x)	Open sharing by innovation producers (y)	$r_1 = R_1 + B_1 - C_1 - S_1 - S_2 - S_4$ $p_1 = R_2 + C_5 + S_1 - C_2$ $d_1 = R_3 + R_4 + S_2 - C_3 - C_4$ $c_1 = R_5 + B_2 + S_4 - C_6$	$r_2 = R_1 + B_1 - C_1 - S_1 - S_2$ $p_2 = R_2 + C_5 + S_1 - C_2$ $d_2 = R_3 + R_4 + S_2 - C_3 - C_4$ $c_2 = B_2$	$r_3 = R_1 + F_1 + F_2 - C_1 - S_4 - N_1$ $p_3 = R_2 + S_3 + T_2$ $d_3 = R_3 - C_3 - T_2 - N_3 - F_2$ $c_3 = S_4 - C_6 - N_4$	$r_4 = R_1 + F_1 + F_2 - C_1 - N_1$ $p_4 = R_2 + S_3 + T_2$ $d_4 = R_3 - C_3 - T_2 - F_2$ $c_4 = -N_4$
	Closed protection by innovation producers (1 − y)	$r_5 = R_1 + F_2 - C_1 - S_3 - S_4 - N_1$ $p_5 = R_2 - T_1 - N_2 - F_1$ $d_5 = R_3 + T_1 - C_3 - F_2$ $c_5 = S_4 - C_6 - N_4$	$r_6 = R_1 + F_2 - C_1 - S_3 - N_1$ $p_6 = R_2 - T_1 - F_1$ $d_6 = R_3 + T_1 - C_3 - F_2$ $c_6 = -N_4$	$r_7 = R_1 + F_1 + F_2 - C_1 - S_4 - N_1$ $p_7 = R_2 - N_2 - F_1$ $d_7 = R_3 - C_3 - N_3 - F_2$ $c_7 = S_4 - C_6 - N_4$	$r_8 = R_1 + F_1 + F_2 - C_1 - N_1$ $p_8 = R_2 - F_1$ $d_8 = R_3 - C_3 - F_2$ $c_8 = -N_4$
Laissez-faire by innovation regulators (1 − x)	Open sharing by innovation producers (y)	$r_9 = \alpha R_1 + B_1 - \alpha C_1 - \alpha S_1 - \alpha S_2 - \alpha S_4$ $p_9 = R_2 + C_5 + \alpha S_1 - C_2$ $d_9 = R_3 + R_4 + \alpha S_2 - C_3 - C_4$ $c_9 = R_5 + B_2 + \alpha S_4 - C_6$	$r_{10} = \alpha R_1 + B_1 - \alpha C_1 - \alpha S_1 - \alpha S_2$ $p_{10} = R_2 + C_5 + \alpha S_1 - C_2$ $d_{10} = R_3 + R_4 + \alpha S_2 - C_3 - C_4$ $c_{10} = B_2$	$r_{11} = \alpha R_1 + \alpha F_1 + \alpha F_2 - \alpha C_1 - \alpha S_4 - N_1$ $p_{11} = R_2 + \alpha S_3 + T_2$ $d_{11} = R_3 - C_3 - T_2 - N_3 - \alpha F_2$ $c_{11} = \alpha S_4 - C_6 - N_4$	$r_{12} = \alpha R_1 + \alpha F_1 + \alpha F_2 - \alpha C_1 - N_1$ $p_{12} = R_2 + \alpha S_3 + T_2$ $d_{12} = R_3 - C_3 - T_2 - \alpha F_2$ $c_{12} = -N_4$
	Closed protection by innovation producers (1 − y)	$r_{13} = \alpha R_1 + \alpha F_2 - \alpha C_1 - \alpha S_3 - \alpha S_4 - N_1$ $p_{13} = R_2 - T_1 - N_2 - \alpha F_1$ $d_{13} = R_3 + T_1 - C_3 - \alpha F_2$ $c_{13} = \alpha S_4 - C_6 - N_4$	$r_{14} = \alpha R_1 + \alpha F_2 - \alpha C_1 - \alpha S_3 - N_1$ $p_{14} = R_2 - T_1 - \alpha F_1$ $d_{14} = R_3 + T_1 - C_3 - \alpha F_2$ $c_{14} = -N_4$	$r_{15} = \alpha R_1 + \alpha F_1 + \alpha F_2 - \alpha C_1 - \alpha S_4 - N_1$ $p_{15} = R_2 - N_2 - \alpha F_1$ $d_{15} = R_3 - C_3 - N_3 - \alpha F_2$ $c_{15} = \alpha S_4 - C_6 - N_4$	$r_{16} = \alpha R_1 + \alpha F_1 + \alpha F_2 - \alpha C_1 - N_1$ $p_{16} = R_2 - \alpha F_1$ $d_{16} = R_3 - C_3 - \alpha F_2$ $c_{16} = -N_4$

Every cell in Table 2 is constructed by linearly adding or subtracting the relevant parameters according to the strategy profile of the four actors. For instance, the regulator's payoff always includes the social benefit R1 and the intervention cost C_1 when $x = 1$; it adds the positive utility B_1 only when both the producer and the decomposer cooperate $y = 1, z = 1$; it subtracts subsidies S_1, S_2, S_4 only when the corresponding recipients adopt the cooperative/proactive strategy; and it adds fines F_1, F_2 when the non-cooperative party is penalized. Thus, the 16 entries are not independently defined but are generated from a unified parametric formula—the same formula that underlies the replicator dynamics in Section 4. This additive, linear form is a deliberate choice for analytical tractability: it yields closed-form stability conditions and allows systematic sensitivity analysis.

We recognize that real-world digital innovation ecosystems often exhibit non-linearities and emergent phenomena (e.g., threshold effects or positive feedback loops) that a purely linear payoff structure does not directly encode. However, two features of our analysis partially mitigate this limitation. First, the replicator dynamics themselves generate non-linear evolutionary paths, where small changes in parameters or initial conditions can produce non-linear adjustments in convergence speed and path shape. Second, our numerical simulations reveal non-monotonic relationships that emerge from the linear payoff structure combined with the replicator dynamics—a well-known property of evolutionary game models.

4. Stability Analysis of Strategies in the Four-Party Game

Before presenting the detailed stability analysis, we first specify the key concepts used throughout this paper.

Nash equilibrium and local asymptotic stability. A strategy profile (x, y, z, w) is a Nash equilibrium if no player can unilaterally deviate to obtain a higher payoff. In this paper, all 16 pure-strategy vertices of the state space (where each x, y, z, w is either 0 or 1) are Nash equilibria by construction. For the replicator dynamic system (Sections 4.1–4.4), an equilibrium point is locally asymptotically stable if all eigenvalues of the Jacobian matrix evaluated at that point have negative real parts. For pure-strategy vertices, the Jacobian matrix is triangular; hence, its eigenvalues are the diagonal entries (real numbers), and the condition simplifies to all diagonal entries being negative. For interior or boundary equilibria, eigenvalues may be complex, and we require their real parts to be negative.

Distinction from strict ESS. It is important to distinguish the above concept from the evolutionarily stable strategy (ESS) in the strict sense [33]. A strict ESS requires that a strategy be resistant to invasion by any rare mutant, a condition that is sufficient but not necessary for local asymptotic stability in asymmetric multi-population games [34]. In this paper, we do not claim that our stable equilibria satisfy the strict ESS conditions. Instead, all stability results are stated in terms of local asymptotic stability of the replicator dynamics (all eigenvalues with negative real parts).

Due to the symmetrical structure of the derivations for the four actors, the detailed derivations for Sections 4.2–4.4 are provided in Appendix B.

4.1. Stability Analysis of the Innovation Regulators' Strategy

The expected payoffs for the innovation regulators choosing proactive intervention and laissez-faire are U_{R1} and U_{R2}, respectively, with the average expected payoff denoted as $\overline{U}_R$. The replicator dynamic equation for this behavioral strategy is $F(x)$, and its first derivative is $F'(x)$, as given by Equations (4) and (5), respectively.

$$\begin{aligned} U_{R1} = {} & yzwr_1 + yz(1-w)r_2 + y(1-z)wr_3 + y(1-z)(1-w)r_4 + (1-y)zwr_5 + (1-y)z(1-w)r_6 \\ & + (1-y)(1-z)wr_7 + (1-y)(1-z)(1-w)r_8 \end{aligned} \tag{1}$$

$$\begin{aligned} U_{R2} = {} & yzwr_9 + yz(1-w)r_{10} + y(1-z)wr_{11} + y(1-z)(1-w)r_{12} + (1-y)zwr_{13} + (1-y)z(1-w)r_{14} \\ & + (1-y)(1-z)wr_{15} + (1-y)(1-z)(1-w)r_{16} \end{aligned} \tag{2}$$

$$\overline{U}_R = xU_{R1} + (1-x)U_{R2} \tag{3}$$

$$\begin{aligned} F(x) = x(U_{R1} - \overline{U}_R) &= x(1-x)(U_{R1} - U_{R2}) \\ &= x(1-x)(1-\alpha)[F_1 + F_2 + R_1 - C_1 - z(F_1 + S_3) - yz(F_2 + S_1 + S_2 - S_3) - wS_4] \end{aligned} \tag{4}$$

$$F'(x) = (1-2x)(1-\alpha)[F_1 + F_2 + R_1 - C_1 - z(F_1 + S_3) - yz(F_2 + S_1 + S_2 - S_3) - wS_4] \tag{5}$$

According to the stability theorem of differential equations, the innovation regulators' strategy reaches a stable state if and only if $F(x) = 0$ and $F'(x) < 0$.

Proposition 1. *When* $z < z_1$, *the evolutionarily stable strategy (ESS) for the innovation regulators is proactive; when* $z > z_1$, *it is laissez-faire; when* $z = z_1$, *the stability is indeterminate. The threshold* z_1 *is given by:* $z_1 = [F_1 + F_2 + R_1 - C_1 - wS_4]/[F_1 + S_3 + y(F_2 + S_1 + S_2 - S_3)]$.

Proof. Let $R(y,z,w) = (1-\alpha)[F_1 + F_2 + R_1 - C_1 - z(F_1 + S_3) - yz(F_2 + S_1 + S_2 - S_3) - wS_4]$. Since $\partial R(y,z,w)/\partial z < 0$, $R(y,z,w)$ is a decreasing function of z. When $z < z_1$, $R(y,z,w) > 0$. Given $F(x)|_{x=1} = 0$ and $F'(x)|_{x=1} < 0$, $x = 1$ is stable. When $z > z_1$, $R(y,z,w) < 0$. Given $F(x)|_{x=0} = 0$ and $F'(x)|_{x=0} < 0$, $x = 0$ is stable. When $z = z_1$, $F(x) = 0$ and $F'(x) = 0$. In this case, any $x \in [0,1]$ is stable, and no evolutionarily stable strategy can be determined. □

Proposition 1 shows that in a DIE, if innovation decomposers and producers exhibit a strong willingness to cooperate and consumers participate actively, the system is likely to achieve high-level value co-creation. Under such conditions, the market mechanism functions well. If the innovation regulators nevertheless intervene aggressively, it may fall into a "government failure" dilemma, in which the benefits fall short of expectations while regulatory costs remain high. This reveals a counterintuitive policy insight: aggressive regulatory intervention becomes counterproductive when endogenous synergy is already strong. Therefore, regulators should adopt a contingent strategy—intervene only when cooperative willingness falls below the threshold z_1, and otherwise withdraw to a facilitative or monitoring role.

Based on Proposition 1, the phase diagram illustrating the innovation regulators' strategic choices is presented in Figure 2.

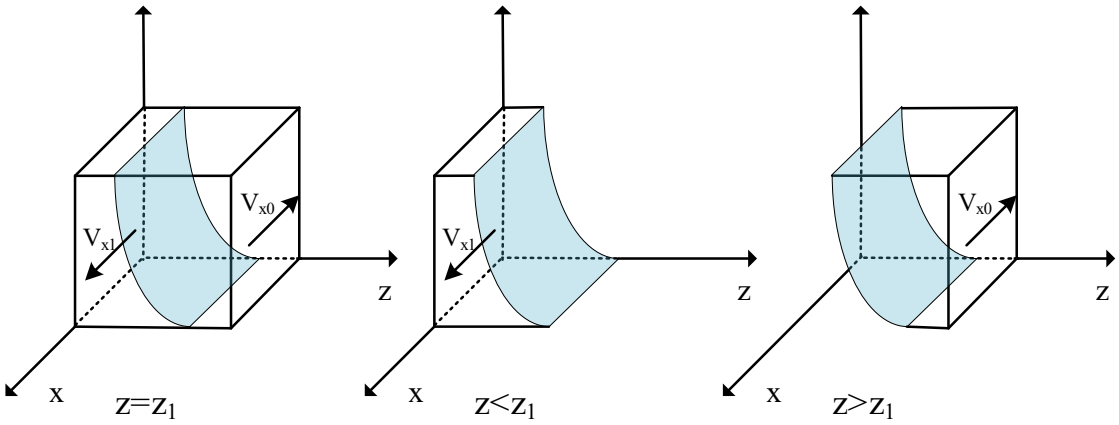


Figure 2. The phase diagram illustrating the innovation regulators' strategic choices.

As illustrated in Figure 2, the volume of region V_{x0} corresponds to the probability that the innovation regulators adopt a proactive intervention strategy. In contrast, the volume of region V_{x1} corresponds to the probability of laissez-faire. The calculated results lead to the following corollary:

$$V_{x0} = \int_0^1 \int_0^1 \frac{F_1 + F_2 + R_1 - C_1 - wS_4}{y(F_2 + S_1 + S_2 - S_3) + F_1 + S_3} dydx = (F_1 + F_2 + R_1 - C_1 - wS_4) \frac{\ln(F_1 + F_2 + S_1 + S_2 / F_1 + S_3)}{F_2 + S_1 + S_2 - S_3} \quad (6)$$

$$V_{x1} = 1 - V_{x0} = 1 - (F_1 + F_2 + R_1 - C_1 - wS_4) \frac{\ln(F_1 + F_2 + S_1 + S_2 / F_1 + S_3)}{F_2 + S_1 + S_2 - S_3} \quad (7)$$

Corollary 1. *Increasing the penalties imposed by the innovation regulators on innovation producers and decomposers raises the probability that the regulator will choose a proactive intervention strategy.*

Proof. Taking the first-order partial derivatives of the active-intervention probability V_{x0} with respect to F_1 and F_2 gives $\partial V_{x0}/\partial F_1 > 0$. Thus, as the penalty standards rise, the probability that the regulators select proactive intervention also increases. The underlying economic logic is as follows: Higher penalties directly raise the marginal cost of default for the relevant actors, which incentivizes cooperative behavior. At the same time, the increased penalty revenue provides stronger cost coverage and institutional justification for the regulators' intervention, making oversight and guidance more sustainable and feasible. □

4.2. Stability Analysis of the Innovation Producers' Strategy

Following the same derivation procedure as in Section 4.1 (see Appendix B for details), the replicator dynamic equation for innovation producers is given by:

$$\begin{aligned} F(y) = y(U_{P1} - \overline{U}_P) &= y(1-y)(U_{P1} - U_{P2}) \\ &= y(1-y)[T_2 + \alpha F_1 + \alpha S_3 + x(F_1 + S_3 - \alpha F_1 - \alpha S_3) + z(T_1 - T_2 + \alpha S_1 - \alpha S_3 - C_2 + C_5) \\ &+ xz(S_1 - S_3 - \alpha S_1 + \alpha S_3) + wN_2] \end{aligned} \tag{8}$$

Proposition 2. *When* $w < w_1$*, the evolutionarily stable strategy (ESS) for the innovation producers is closed protection; when* $w > w_1$*, it is open sharing; when* $w = w_1$*, the stability is indeterminate. The threshold* w_1 *is given by:*

$$w_1 = \left[-T_2 - \alpha F_1 - \alpha S_3 - x(F_1 + S_3 - \alpha F_1 - \alpha S_3) - z\begin{pmatrix} T_1 - T_2 + \alpha S_1 \\ -\alpha S_3 - C_2 + C_5 \end{pmatrix} - xz\begin{pmatrix} S_1 - S_3 \\ -\alpha S_1 + \alpha S_3 \end{pmatrix}\right]/N_2.$$

Proof. See Appendix B. □

Proposition 2 shows that the level of participation of innovation consumers influences the innovation producers' strategic choice. Insufficient consumer participation leads producers to favor a closed protection strategy. Conversely, when consumers actively participate and provide feedback, producers are more inclined toward open sharing to capture collaboration benefits and avoid reputational losses.

Based on Proposition 2, the phase diagram for the innovation producers' strategy selection is presented in Figure 3.

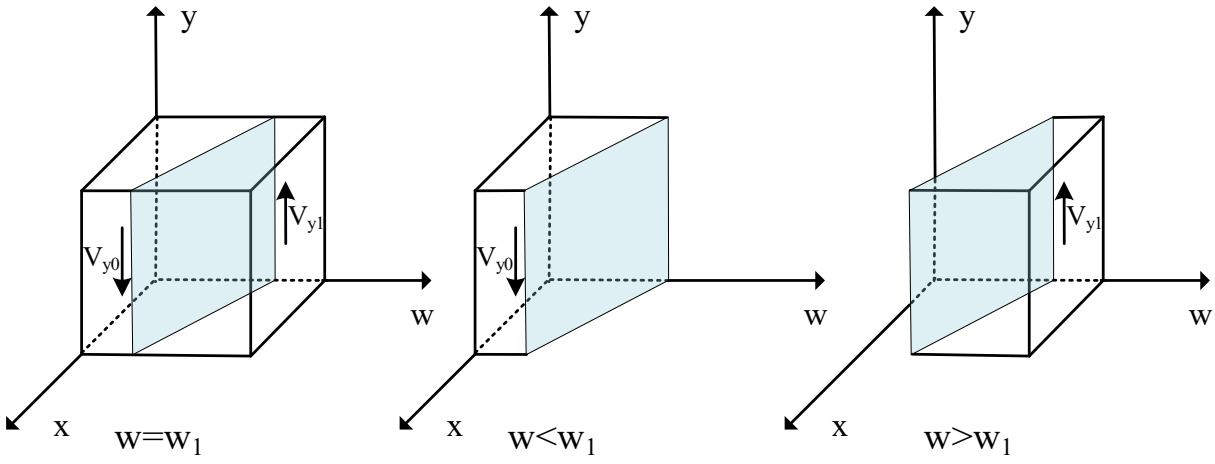


Figure 3. The phase diagram for the innovation producers' strategy selection.

Corollary 2. *When the innovation regulators increase penalties on innovation producers, or when feedback from innovation consumers amplifies the reputational damage inflicted by producers adopting closed protection strategies, the probability that producers will choose open sharing strategies will rise accordingly.*

4.3. Stability Analysis of the Innovation Decomposers' Strategy

Similarly, the replicator dynamic equation for innovation decomposers (derived in Appendix B) is:

$$\begin{aligned} F(z) = z\left(U_{D1} - \overline{U}_D\right) &= z(1-z)(U_{D1} - U_{D2}) \\ &= z(1-z)[T_1 + y(R_4 - C_4 - T_1 + T_2 + \alpha F_2 + \alpha S_2) + xy(F_2 + S_2 - \alpha S_2 - \alpha F_2) + wN_3] \end{aligned} \tag{9}$$

Proposition 3. *When* $w < w_2$*, the evolutionarily stable strategy (ESS) for the innovation decomposers is independent innovation; when* $w > w_2$*, it is collaborative innovation; when* $w = w_2$*, the stability is indeterminate. The threshold* w_2 *is given by:* $w_2 = -T_1 - y(R_4 - C_4 - T_1 + T_2 + \alpha F_2 + \alpha S_2) - xy(F_2 + S_2 - \alpha S_2 - \alpha F_2)/N_3$.

Proof. See Appendix B. □

Proposition 3 shows that consumer feedback is the pivotal driver of the decomposers' strategic shift. When consumers actively participate and provide feedback, the decomposers' stable strategy tends toward collaborative innovation to gain market recognition and access to demand information. Conversely, insufficient consumer participation leads the decomposers to prefer an independent innovation mode.

Based on Proposition 3, the phase diagram for the innovation decomposers' strategy selection is shown in Figure 4.

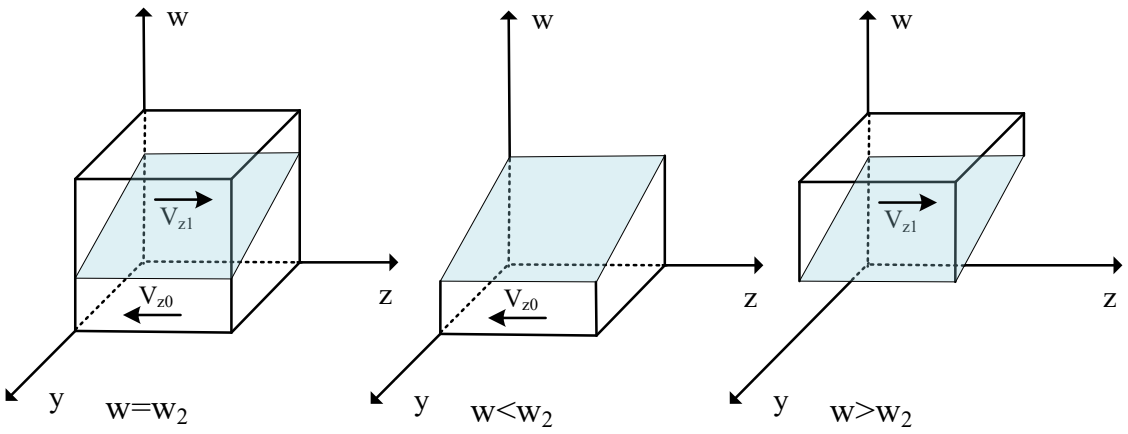


Figure 4. The phase diagram for the innovation decomposers' strategy selection.

Corollary 3. *An increase in the subsidy provided to the decomposers by the regulators, or an increase in the breach penalty payable for independent innovation, raises the probability that the decomposers will choose the collaborative innovation strategy.*

4.4. Stability Analysis of the Innovation Consumers' Strategy

Analogously, the replicator dynamic equation for innovation consumers (see Appendix B for the full derivation) is:

$$F(w) = w\left(U_{C1} - \overline{U}_C\right) = w(1-w)(U_{C1} - U_{C2}) = w(1-w)[\alpha S_4 - C_6 + x(S_4 - \alpha S_4) + yzR_5] \tag{10}$$

Proposition 4. *When* $x < x_1$*, the evolutionarily stable strategy (ESS) for the innovation consumers is passive consumption; when* $x > x_1$*, it is proactive participation; when* $x = x_1$*, the stability is indeterminate. The threshold* x_1 *is given by:* $x_1 = (C_6 - \alpha S_4 - yzR_{5)}/(S_4 - \alpha S_4)$.

Proof. See Appendix B. □

Proposition 4 shows that as the regulators' intervention probability rises, the consumers' stable strategy shifts from passive consumption to proactive participation. The rationale is that effective regulatory intervention enhances the efficiency of cooperation and the translation of outcomes among innovation actors. Consequently, by participating actively, consumers can gain prioritized access to innovation value and policy incentives. Driven by this rational calculus, they turn to proactive engagement, thereby propelling the DIE toward higher synergy.

Based on Proposition 4, the phase diagram for the innovation consumers' strategy selection is presented in Figure 5.

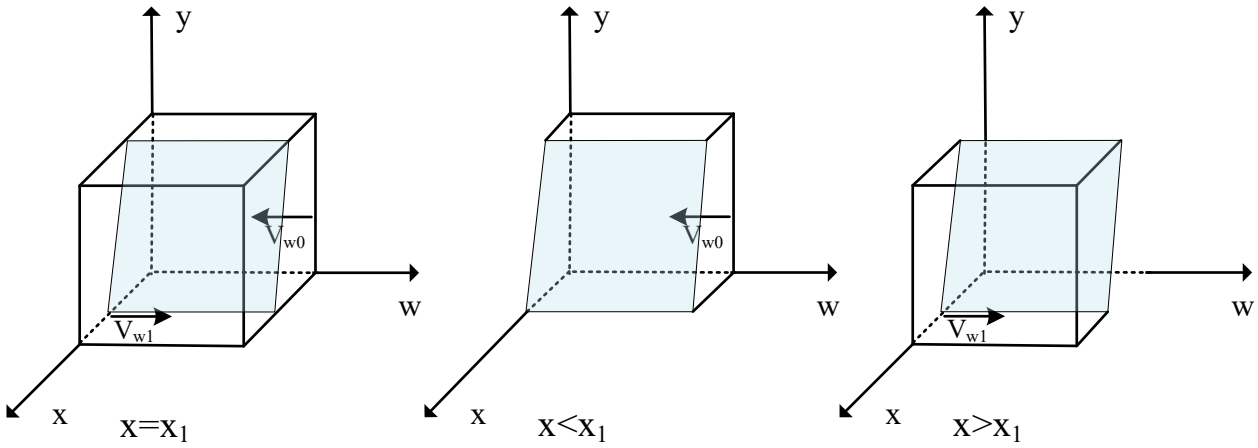


Figure 5. The phase diagram for the innovation consumers' strategy selection.

Corollary 4. *The probability of proactive participation by the innovation consumers increases with the social benefit derived from collaborative innovation and decreases with the consumers' own participation cost.*

5. Stability Analysis of Strategy Profiles

5.1. Pure-Strategy Equilibria

For pure-strategy vertices, the Jacobian matrix of the replicator dynamics is triangular. Hence, its eigenvalues are the diagonal entries (real numbers). According to the stability criterion defined in Section 4, a vertex is locally asymptotically stable if and only if all diagonal entries are negative (i.e., all eigenvalues have negative real parts). The following analysis applies this criterion to the 16 vertices. To reveal the formation conditions and dynamic processes of stable strategies in DIE value co-creation, this study constructs a four-party evolutionary game model involving innovation regulators, producers, decomposers, and consumers, and solves the corresponding replicator dynamic system. By setting $F(x) = 0, F(y) = 0, F(z) = 0, F(w) = 0$, several equilibrium points of the system can be obtained. Adhering to the view that stable solutions in multi-population evolutionary games correspond to strict Nash equilibria and following Lyapunov's first method (indirect method) for stability determination [35], this analysis focuses on evaluating the stability of the system's 16 pure-strategy equilibrium points. Furthermore, based on the replicator

dynamics equations of the four game actors, the Jacobian matrix of the system is derived, which takes the following form:

$$J = \begin{bmatrix} \partial F(x)/\partial x & \partial F(x)/\partial y & \partial F(x)/\partial z & \partial F(x)/\partial w \\ \partial F(y)/\partial x & \partial F(y)/\partial y & \partial F(y)/\partial z & \partial F(y)/\partial w \\ \partial F(z)/\partial x & \partial F(z)/\partial y & \partial F(z)/\partial z & \partial F(z)/\partial w \\ \partial F(w)/\partial x & \partial F(w)/\partial y & \partial F(w)/\partial z & \partial F(w)/\partial w \end{bmatrix}$$

Each of the 16 pure-strategy equilibrium points, as identified by the replicator dynamics equations, is subsequently substituted into the Jacobian matrix to solve for the corresponding eigenvalues. The stability of each equilibrium point, along with the conditions for its stability, is then determined based on the signs of these eigenvalues. The results are summarized in Table 3.

Table 3. Stability analysis of equilibrium points.

Equilibrium Points	Eigenvalues $\lambda_1, \lambda_2, \lambda_3, \lambda_4$	Sign Pattern	Stability	Conditions
E_1 (0, 0, 0, 0)	$(1-\alpha)(F_1 - C_1 + F_2 + R_1)$, $T_2 + \alpha F_1 + \alpha S_3$, T_1, $\alpha S_4 - C_6$	(+, +, +, U)	Unstable	\
E_2 (0, 0, 0, 1)	$(1-\alpha)(F_1 - C_1 + F_2 + R_1 - S_4)$, $N_2 + T_2 + \alpha F_1 + \alpha S_3$, $N_3 + T_1$, $-(\alpha S_4 - C_6)$	(U, +, +, U)	Unstable	\
E_3 (0, 0, 1, 0)	$(1-\alpha)(F_2 + R_1 - S_3 - C_1)$, $C_5 - C_2 + T_1 + \alpha F_1 + \alpha S_1$, $-T_1$, $\alpha S_4 - C_6$	(U, U, −, U)	ESS	$F_2 + R_1 < C_1 + S_3 C_5 - C_2 + \alpha S_1 < -T_1 - \alpha F_1$ $\alpha S_4 < C_6$
E_4 (0, 0, 1, 1)	$(1-\alpha)(F_2 + R_1 - S_3 - S_4 - C_1)$, $C_5 - C_2 + N_2 + T_1 + \alpha F_1 + \alpha S_1$, $-(N_3 + T_1)$, $-(\alpha S_4 - C_6)$	(U, U, −, U)	ESS	$F_2 + R_1 < S_3 + S_4 + C_1 C_5 - C_2 + \alpha S_1 < -N_2 - T_1 - \alpha F_1$ $\alpha S_4 > C_6$
E_5 (0, 1, 0, 0)	$(1-\alpha)(F_1 - C_1 + F_2 + R_1)$, $-(T_2 + \alpha F_1 + \alpha S_3)$, $R_4 - C_4 + T_2 + \alpha F_2 + \alpha S_2$, $\alpha S_4 - C_6$	(+, −, U, U)	Unstable	\
E_6 (0, 1, 0, 1)	$(1-\alpha)(F_1 - C_1 + F_2 + R_1 - S_4)$, $-(N_2 + T_2 + \alpha F_1 + \alpha S_3)$, $N_3 - C_4 + R_4 + T_2 + \alpha F_2 + \alpha S_2$, $-(\alpha S_4 - C_6)$	(U, −, U, U)	ESS	$F_1 + F_2 + R_1 < C_1 + S_4 R_4 + \alpha S_2 - C_4 < -T_2 - \alpha F_2 - N_3$ $\alpha S_4 > C_6$
E_7 (0, 1, 1, 0)	$(1-\alpha)(R_1 - S_1 - S_2 - C_1)$, $-(C_5 + T_1 + \alpha F_1 + \alpha S_1 - C_2)$, $-(R_4 + T_2 + \alpha F_2 + \alpha S_2 - C_4)$, $R_5 - C_6 + \alpha S_4$	(U, U, U, +)	Unstable	\
E_8 (0, 1, 1, 1)	$(1-\alpha)(R_1 - C_1 - S_1 - S_2 - S_4)$, $-(C_5 + N_2 + T_1 + \alpha F_1 + \alpha S_1 - C_2)$, $-(N_3 + R_4 + T_2 + \alpha F_2 + \alpha S_2 - C_4)$,$-(R_5 + \alpha S_4 - C_6)$	(U, U, U, −)	ESS	$R_1 < C_1 + S_1 + S_2 + S_4 C_5 + \alpha S_1 - C_2 > -N_2 - T_1 - \alpha F_1 R_4 + \alpha S_2 - C_4 > -N_3 - T_2 - \alpha F_2$
E_9 (1, 0, 0, 0)	$-(1-\alpha)(F_1 - C_1 + F_2 + R_1)$, $F_1 + S_3 + T_2$, T_1, $S_4 - C_6$	(−, +, +, U)	Unstable	\
E_{10} (1, 0, 0, 1)	$-(1-\alpha)(F_1 - C_1 + F_2 + R_1 - S_4)$, $F_1 + N_2 + S_3 + T_2$, $N_3 + T_1$, $-(S_4 - C_6)$	(U, +, +, U)	Unstable	\
E_{11} (1, 0, 1, 0)	$-(1-\alpha)(F_2 + R_1 - S_3 - C_1)$, $C_5 - C_2 + F_1 + S_1 + T_1$, $-T_1$, $S_4 - C_6$	(U, U, −, U)	ESS	$F_2 + R_1 > S_3 + C_1$ $C_5 - C_2 + S_1 < -T_1 - F_1$ $S_4 < C_6$
E_{12} (1, 0, 1, 1)	$-(1-\alpha)(F_2 + R_1 - S_3 - S_4 - C_1)$, $C_5 - C_2 + F_1 + N_2 + S_1 + T_1$, $-(N_3 + T_1)$, $-(S_4 - C_6)$	(U, U, −, U)	ESS	$F_2 + R_1 > S_3 + S_4 + C_1$ $C_5 - C_2 + S_1 < -T_1 - F_1 - N_2$ $S_4 > C_6$
E_{13} (1, 1, 0, 0)	$-(1-\alpha)(F_1 - C_1 + F_2 + R_1)$, $-(F_1 + S_3 + T_2)$, $F_2 - C_4 + R_4 + S_2 + T_2$, $S_4 - C_6$	(−, −, U, U)	ESS	$R_4 + S_2 - C_4 < -T_2 - F_2$ $S_4 < C_6$
E_{14} (1, 1, 0, 1)	$-(1-\alpha)(F_1 - C_1 + F_2 + R_1 - S_4)$, $-(F_1 + N_2 + S_3 + T_2)$, $F_2 - C_4 + N_3 + R_4 + S_2 + T_2$, $-(S_4 - C_6)$	(U, −, U, U)	ESS	$F_1 + F_2 + R_1 > S_4 + C_1$ $R_4 + S_2 - C_4 < -T_2 - N_3 - F_2$ $S_4 > C_6$
E_{15} (1, 1, 1, 0)	$-(1-\alpha)(R_1 - C_1 - S_1 - S_2)$, $-(C_5 + F_1 + S_1 + T_1 - C_2)$, $-(F_2 + R_4 + S_2 + T_2 - C_4)$, $R_5 - C_6 + S_4$	(U, U, U, +)	Unstable	\
E_{16} (1, 1, 1, 1)	$-(1-\alpha)(R_1 - S_1 - S_2 - S_4 - C_1)$, $-(C_5 + F_1 + N_2 + S_1 + T_1 - C_2)$, $-(F_2 + N_3 + R_4 + S_2 + T_2 - C_4)$, $-(R_5 + S_4 - C_6)$	(U, U, U, −)	ESS	$R_1 > S_1 + S_2 + S_4 + C_1$ $C_5 + S_1 - C_2 > -T_1 - F_1 - N_2$ $R_4 + S_2 - C_4 > -F_2 - N_3 - T_2$

Note: For pure-strategy vertices, eigenvalues are real (the diagonal entries of the triangular Jacobian). Local asymptotic stability requires that all eigenvalues have negative real parts, which for real eigenvalues is equivalent to being negative. The "Stability" column in this table is determined based on this criterion. "ESS" in the table refers to locally asymptotically stable pure-strategy equilibria under the replicator dynamics.

Based on the eigenvalue stability criterion applied to the Jacobian matrix, the equilibrium points listed in Table 3 were analyzed. A total of nine equilibrium points were identified as stable under certain parameter conditions, corresponding to Evolutionarily Stable Strategies (ESSs). These can be systematically categorized into three types: low-

level stability (E_3, E_4, E_6), transitional stability dominated by regulation (E_{11}, E_{12}, E_{13}, E_{14}), and high-level stability (E_8, E_{16}). High-level stability is further divided into market-driven synergy, which relies on the system's endogenous dynamics, and the ideal state of regulation-market synergy, which embodies a positive interaction between regulatory and market forces. The latter, representing the optimal evolutionary goal for the DIE, corresponds to the equilibrium point (1, 1, 1, 1) where all agents participate actively. The stability of this state requires the simultaneous fulfillment of three core conditions: the basic payoff for the innovation regulator must exceed its total costs and subsidy expenditures ($R_1 > S_1 + S_2 + S_4 + C_1$); and the net payoffs for both innovation producers and decomposers from participating in coordination must be positive ($C_5 + S_1 - C_2 > -T_1 - F_1 - N_2$, $R_4 + S_2 - C_4 > -F_2 - N_3 - T_2$). Under such a parameter structure, the system develops a dual-driven mechanism of regulation and market forces: innovation regulators effectively empower the market through sustainable governance, while innovation producers and decomposers achieve synergistic gains within this favorable environment. This leads to an organic integration of a "proactive government" and an "efficient market," collectively fostering a fully participatory, healthy, and sustainable value co-creation network. These strategy profiles clearly delineate the diverse and progressive stable pathways of the DIE—from deadlock and transition to synergistic co-creation—under specific cost and benefit structures.

5.2. Interior and Boundary Equilibria

In principle, the replicator dynamic system could possess interior (fully mixed) equilibria with $0 < x, y, z, w < 1$ or boundary equilibria on edges or faces (e.g., (x, 0, 0, 0) or (x, y,0, 0)). Following the approach of Balabanova et al. [36], we first attempt to solve $F(x) = F(y) = F(z) = F(w) = 0$ analytically. Even the candidate interior equilibria, if they exist, involve extremely complicated expressions that do not admit closed-form simplification. We therefore adopt a numerical approach. We conducted an extensive numerical grid search over the four-dimensional unit hypercube (i.e., all strategy frequencies in the open interval (0, 1)) with step size 0.05, complemented by Monte Carlo random sampling (10,000 initial points), to detect any interior or boundary fixed points. For each candidate, we computed the Jacobian eigenvalues to evaluate stability.

Results indicate that no interior equilibrium with all eigenvalues having negative real parts was found under our baseline parameter set. To further explore the possibility of interior equilibria, we randomly sampled parameter values across their feasible ranges (10,000 draws) and numerically solved the replicator dynamics. In none of these samples did we observe a locally stable interior equilibrium. All interior fixed points either lie outside the feasible region or exhibit at least one eigenvalue with a positive real part (i.e., unstable saddle points). For boundary equilibria (edges and faces), any equilibrium not at a vertex is either unstable or a saddle point. For example, on the edge where $y = z = w = 0$, the dynamics reduce to a one-dimensional system; the only locally stable points are $x = 0$ or $x = 1$ depending on parameter conditions, consistent with the vertex analysis. Therefore, the only locally asymptotically stable equilibria are the 16 pure-strategy vertices listed in Table 3. The detailed numerical procedures, including grid search parameters, Monte Carlo settings, and eigenvalue analysis, are provided in Appendix A.

This conclusion is further supported by the numerical simulations in Section 6, where all trajectories from diverse initial conditions converged to vertex equilibria, and no interior or cyclic attractor was observed under the considered parameter regimes. This finding is consistent with the observations in Balabanova et al. [36] and Hofbauer and Sigmund [34] that interior equilibria in multi-population evolutionary games are rare and typically unstable.

6. Simulation Analysis of the Four-Party Evolutionary Game

6.1. Parameter Assignment

To thoroughly investigate the dynamic processes of the four-party evolutionary game and the impact of key parameters on the strategic choices of the four parties, this study employs MATLAB R2023b to numerically simulate the evolutionary paths toward the ideal equilibrium state (1, 1, 1, 1), building on the preceding theoretical analysis. The simulation parameters strictly satisfy the stability conditions for this equilibrium point: $R_1 > S_1 + S_2 + S_4 + C_1$, $C_5 + S_1 - C_2 > -T_1 - F_1 - N_2$, and $R_4 + S_2 - C_4 > -F_2 - N_3 - T_2$. In setting the parameters, a multi-source data fusion strategy is adopted to enhance the reliability and real-world interpretability of the parameter system. Specifically, macro-level data—such as the R&D intensity and profit margins of industrial enterprises above a designated size in 2024 (released by the National Bureau of Statistics)—and statistical bulletins on core digital-economy industries in the Yangtze River Delta region were used to anchor the baseline return standards. Field surveys of smart-manufacturing enterprises in the Pearl River Delta region systematically collected actual cost structures and revenue information. For parameters that are difficult to observe directly or involve commercial sensitivity, multiple rounds of calibration were performed by drawing on the latest research in the field and incorporating expert interviews [37]. Furthermore, the Monte Carlo method was used to conduct large-scale sampling and robustness testing of parameter combinations, thereby identifying and mitigating potential simulation biases arising from parameter coupling. Based on the principles and methods described above, the final parameter values assigned to each participating entity are as follows: $C_1 = 20$, $C_2 = 60$, $C_3 = 40$, $C_4 = 80$, $C_5 = 40$, $C_6 = 22$, $R_1 = 120$, $R_2 = 60$, $R_3 = 65$, $R_4 = 40$, $R_5 = 35$, $S_1 = 30$, $S_2 = 35$, $S_3 = 20$, $S_4 = 25$, $B_1 = 20$, $B_2 = 15$, $N_1 = 20$, $N_2 = 8$, $N_3 = 10$, $N_4 = 12$, $F_1 = 20$, $F_2 = 25$, $T_1 = 10$, $T_2 = 10$, $\alpha = 0.6$.

To ensure transparency and reproducibility, Appendix C provides a detailed mapping of each parameter, including its baseline value, plausible range, data source, and the sensitivity/robustness settings used in the simulations (Section 6.4 and the Monte Carlo sampling in Appendix A).

6.2. Analysis of Initial System Evolutionary Paths

To verify the rationality of the parameter system and the stability of the equilibrium point, this study first conducted numerical simulations using the benchmark parameters. The resulting evolutionary paths of the system are shown in Figure 6. The simulations show that under the given parameter conditions, the strategy choices of the innovation regulator (x), producer (y), decomposer (z), and consumer (w) all evolve toward 1 over time, eventually converging to the ideal equilibrium state (1, 1, 1, 1). This result confirms the sufficiency of the stability conditions identified in the theoretical analysis, demonstrating that when the parameter configuration meets those conditions, the system indeed exhibits an inherent tendency to evolve toward the high-level synergistic state. Importantly, the simulations also reveal the non-linear adjustment paths and the relative convergence speeds of different actors, which are not directly observable from the analytical stability conditions alone.

A closer examination of the evolutionary trajectories indicates that, although the initial strategy values differ among agents, their evolutionary paths all converge toward the stable equilibrium point. This suggests that the convergence outcome is highly robust with respect to the initial strategy values. It is noteworthy that while the initial values do not alter the final stable state of the system, they significantly affect convergence speed: the closer the initial strategy values are to the target equilibrium, the less time it takes for the system to stabilize, highlighting a clear path-dependence characteristic of the evolutionary process. These simulation results dynamically reveal the feasible pathways

for the DIE to evolve toward its ideal state. They offer an intuitive basis for understanding the strategic interactions and synergistic mechanisms among multiple agents in value co-creation, thereby laying the groundwork for further investigation into the impact of key parameters on the system's evolutionary behavior.

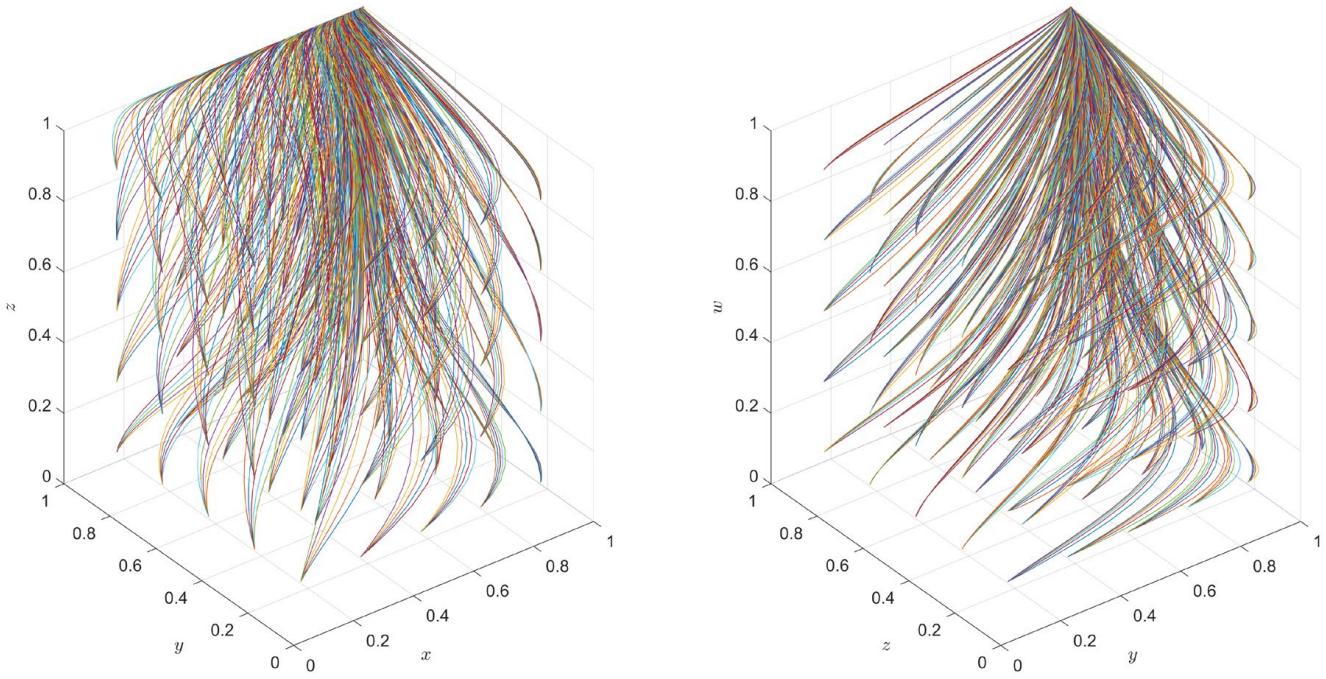


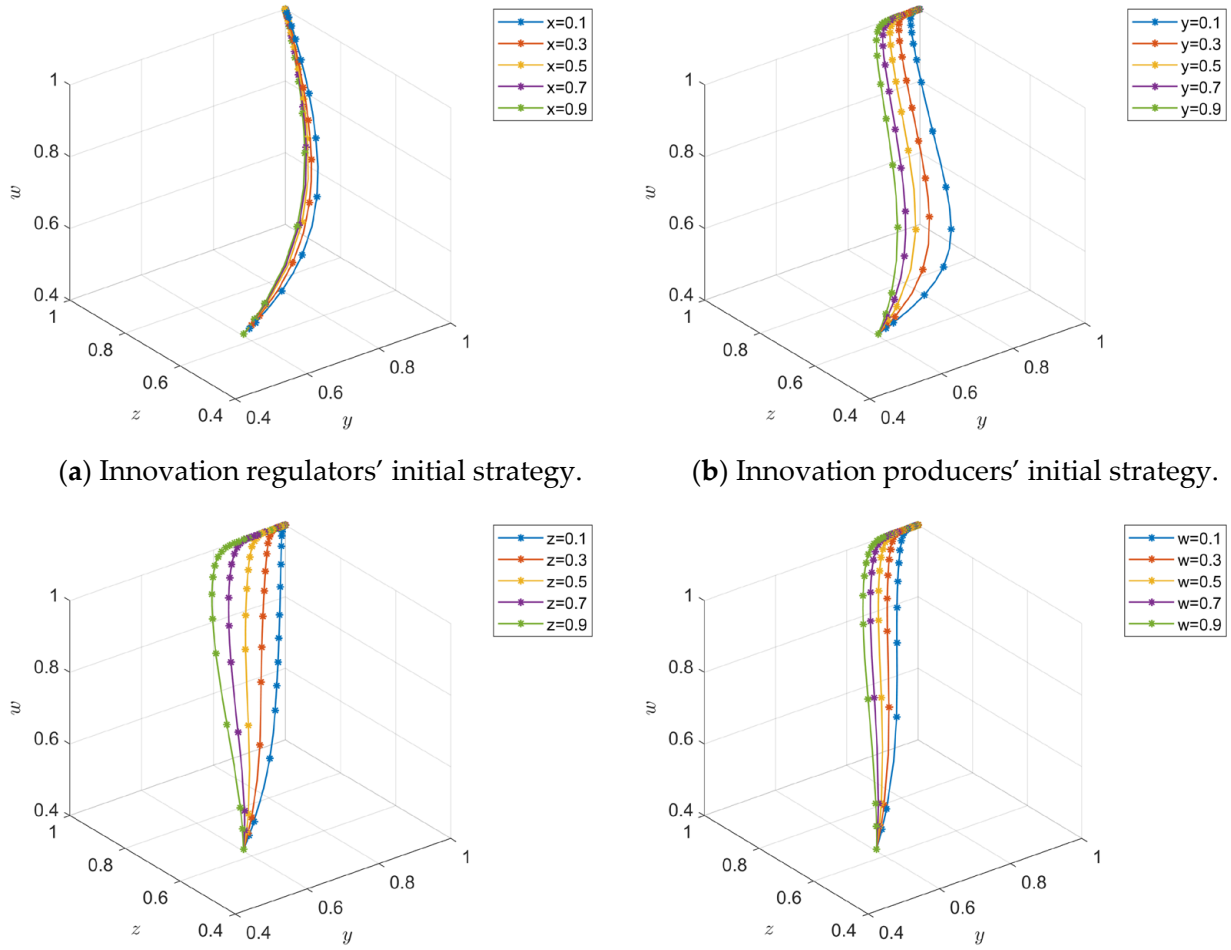
Figure 6. Initial evolutionary paths of the system.

6.3. Impact of Initial Strategies on System Evolution Paths

To examine the influence of different initial strategies on the system's evolutionary paths, the initial strategy probabilities for the four parties (x, y, z, w) were set to [0.1, 0.3, 0.5, 0.7, 0.9], respectively, while all other parameters were kept at their baseline values. The resulting evolutionary trajectories of the system are shown in Figure 7.

Simulation results show that under the baseline parameter settings, the system consistently converges to the ideal equilibrium (1, 1, 1, 1), regardless of the initial strategies, further corroborating the equilibrium's stability and robustness. However, the influence of the initial strategy on convergence speed varies markedly across agents. As shown in Figure 7a,b, a higher initial strategy value (greater willingness) for the innovation regulator and producer accelerates system convergence, indicating that their early active engagement can effectively pull the system toward the ideal state. In contrast, Figure 7c,d reveal that an increase in the initial willingness of the innovation decomposer and consumer, conversely, slows down the overall convergence process.

This asymmetry in convergence speed can be understood through the structure of the replicator dynamics. The payoffs of regulators and producers enter more directly into the incentive terms affecting the other actors (e.g., through subsidies S_1, S_2 and service fees C_5), whereas the payoffs of decomposers and consumers are more dependent on the prior cooperation of others. Consequently, when decomposers or consumers start with high cooperative willingness while other actors lag behind, the marginal benefit of further cooperation for those lagging actors is reduced, leading to slower adjustment. This observation is a direct consequence of the assumed payoff structure and does not invoke any additional behavioral mechanisms such as strategic waiting or option valuation.



(**a**) Innovation regulators' initial strategy.

(**b**) Innovation producers' initial strategy.

(**c**) Innovation decomposers' initial strategy.

(**d**) Innovation consumers' initial strategy.

Figure 7. Impact of initial strategies on system evolution.

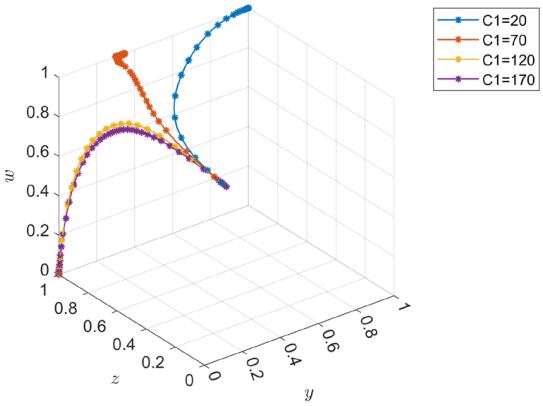
6.4. Impact of Parameter Variations on System Evolutionary Paths

To assess the robustness of our findings and identify the most influential drivers, we systematically vary each key parameter while holding others at their baseline values. The following subsections report the effects on convergence speed and equilibrium selection. All simulations satisfy the stability conditions for the (1, 1, 1, 1) equilibrium; therefore, the observed variations affect only the convergence speed and transient dynamics, not the final equilibrium.

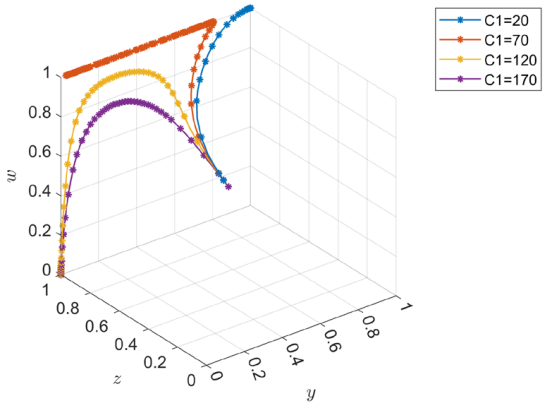
6.4.1. Effect of Innovation Regulators' Behavioral Changes on Evolutionary Paths

Figure 8 illustrates the effect of changes in the intervention cost (C_1) of innovation regulators on the system's evolutionary paths. The simulation results show that as intervention costs rise, the convergence speed decreases across all actors—a negative effect on system dynamics. Furthermore, a higher probability of proactive intervention by regulators (x) leads to a more pronounced impact of intervention costs on the evolutionary outcome, as seen in Figure 8a–c. This confirms the pivotal role of innovation regulators as "coordination hubs" in accelerating system convergence. Specifically, when the probability of proactive intervention by regulators is high (x = 0.9) and intervention costs are low, the convergence speed of all agents increases markedly. Figure 8e further uncovers the underlying mechanism: when intervention costs are low, regulators tend to adopt proactive intervention strategies, which in turn drive the strategy values of innovation producers,

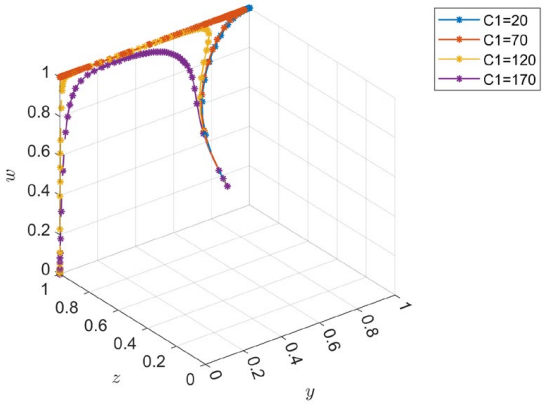
decomposers, and consumers rapidly toward 1, resulting in swift, high-level coordination. This outcome indicates that regulators' strategy choices exert a notable influence within the system—their actions not only shape their own evolutionary path but also transmit effects to other agents through the payoff structure of the replicator dynamics.



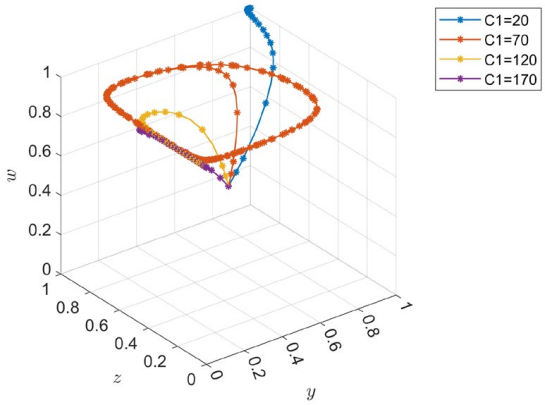
(**a**) x = 0.1.



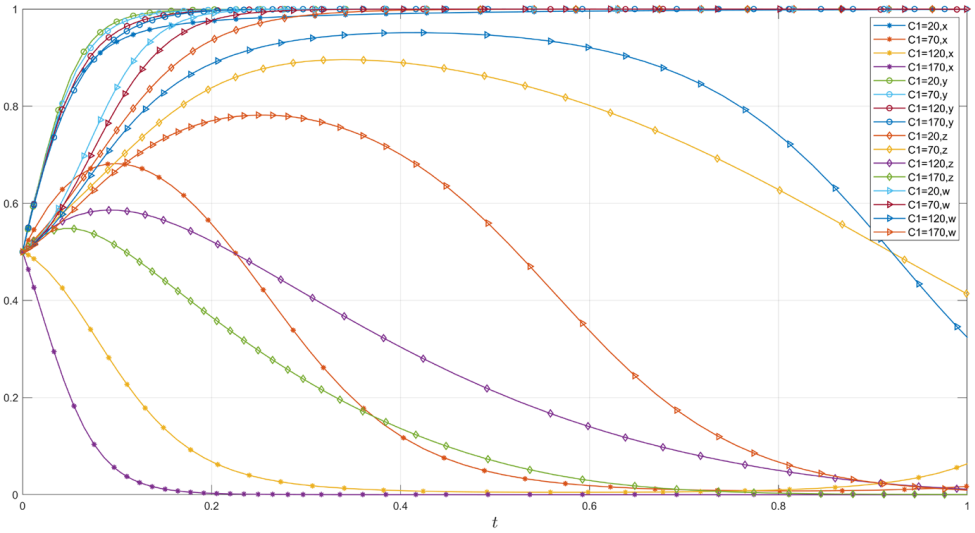
(**b**) x = 0.5.



(**c**) x = 0.9.



(**d**) x = 0.5 (concerning the x, y, and z axes).

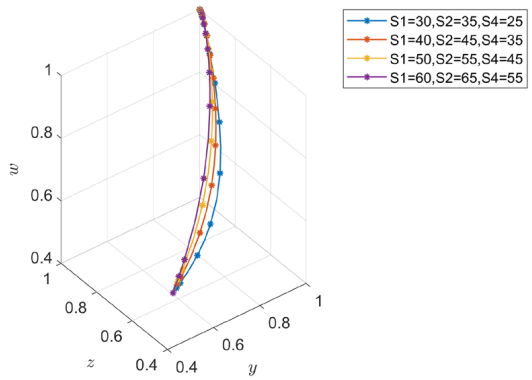


(**e**) Impact of C_1 variation on the strategy selection of the four agents.

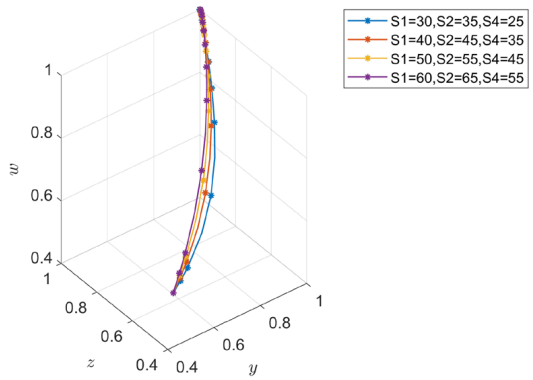
Figure 8. Effect of C_1 on evolutionary outcomes for x = 0.1, 0.5, and 0.9.

As shown in Figure 9a–c, raising the subsidy levels for innovation regulators (S_1, S_2, S_4) significantly accelerates the system's convergence toward the ideal equilibrium state.

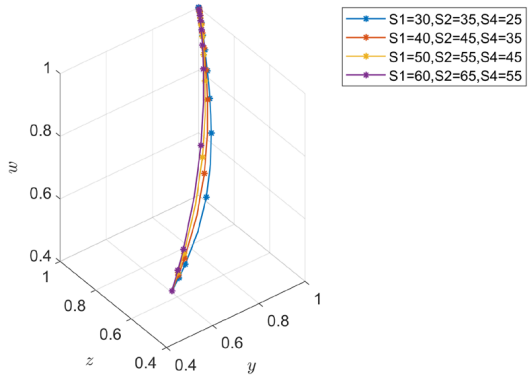
Moreover, a higher probability of proactive intervention by regulators leads to a more pronounced influence of subsidies on the evolutionary outcome. These results highlight the key regulatory role of subsidy policies in system evolution. Even when innovation regulators show low willingness to participate (x = 0.1), sufficient subsidies can effectively motivate all agents and drive the system to converge rapidly to the ideal equilibrium. In contrast, when regulators engage proactively (x = 0.9) under high-subsidy policies, the system attains the fastest convergence speed and the strongest stability.



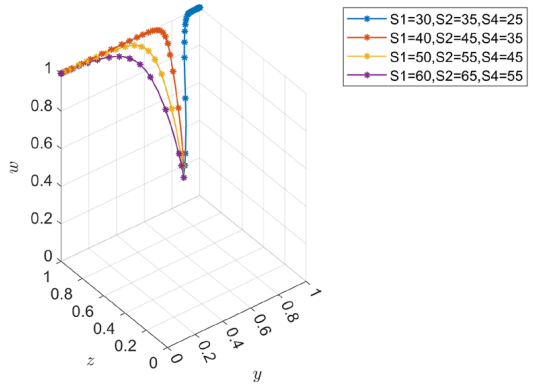
(**a**) x = 0.1.



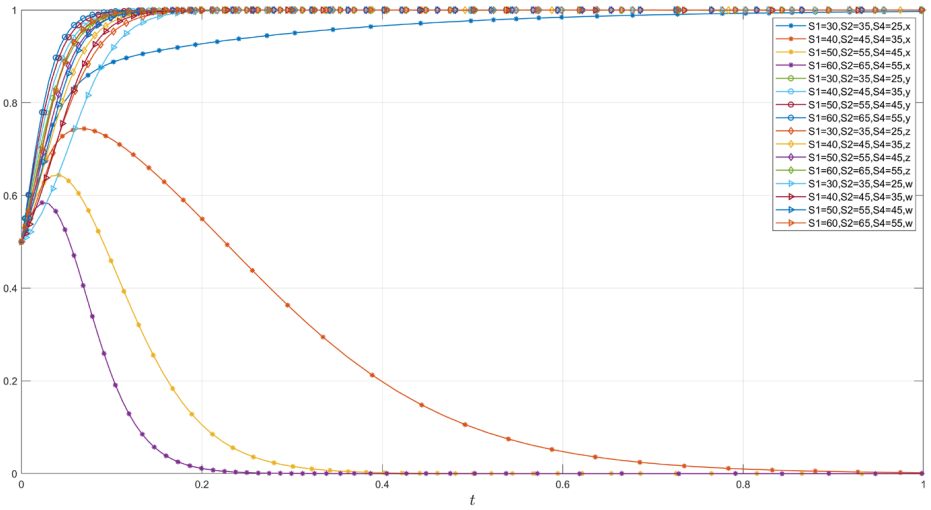
(**b**) x = 0.5.



(**c**) x = 0.9.



(**d**) x = 0.5 (concerning the x, y, and z axes).



(**e**) Impact of S_1, S_2 and S_4 variations on the strategy selection of the four agents.

Figure 9. Effects of S_1, S_2 and S_4 on evolutionary outcomes for x = 0.1, 0.5, and 0.9.

Figure 9d,e further illustrate the dual impact of subsidies. Even with low subsidies, the system can still converge cooperatively to the ideal stable point (1, 1, 1, 1) under sustained guidance from innovation regulators. Under high subsidies, however, while innovation producers (y), decomposers (z), and consumers (w) are strongly motivated and quickly move toward cooperation, innovation regulators (x) exhibit slower convergence due to the high fiscal cost of subsidies. This contrast shows that although subsidies stimulate other agents, they may also impose a cost burden on the regulators, affecting the relative speed of their strategy adjustment.

As shown in Figure 10, penalties (F_1, F_2) significantly accelerate the system's evolution toward the ideal equilibrium. Furthermore, a stronger willingness for proactive intervention by the innovation regulator leads to a more pronounced regulatory effect of the penalties. When the innovation regulator shows low participation willingness (x = 0.1), high penalties act as a critical external constraint, compensating for the lack of intervention impetus and maintaining the system's tendency to converge toward the ideal equilibrium (1, 1, 1, 1). Conversely, when the innovation regulator engages proactively (x = 0.9) under high penalty levels, both convergence speed and stability are enhanced simultaneously.

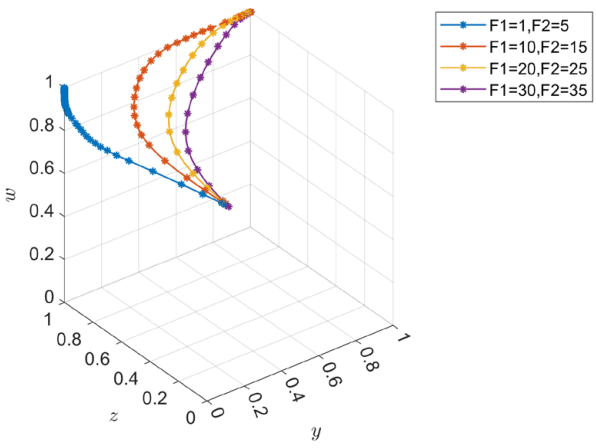
Specifically, the convergence path of innovation producers (y) varies systematically with the penalty level: under low penalties, their stable strategy tends toward 0; as penalties rise, the relative payoff for cooperation increases, driving their strategy toward 1. Innovation decomposers (z) are also highly sensitive to penalty changes; their strategy curve becomes steeper as penalties increase, indicating that penalties effectively accelerate their convergence toward cooperation. This contrast reveals that penalties, as an external constraint mechanism, primarily guide strategic transformation by reshaping the payoff structure and exerting a direct and significant influence on behavior on both the production and decomposition sides.

6.4.2. Impact of Innovation Producers' Behavioral Changes on Evolutionary Trajectories

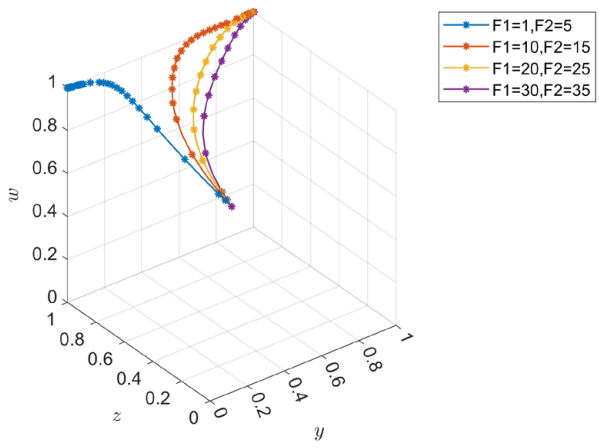
As shown in Figure 11a–c, the system's convergence speed toward stable strategies exhibits a non-monotonic trend—first accelerating and then decelerating—as the collaboration cost (C_2) for innovation producers increases. Furthermore, a higher probability of open sharing among producers leads to a more pronounced impact of these costs on the evolutionary outcome. This non-linear relationship implies the existence of an optimal range for collaboration costs, within which the system balances convergence speed with stability. Figure 11e further reveals significant heterogeneity in how different agents respond to changes in collaboration cost. When costs are low, innovation decomposers and consumers converge more rapidly toward the ideal equilibrium. In contrast, as costs rise, innovation regulators show accelerated convergence toward the equilibrium state. Notably, the strategies of innovation decomposers are most strongly affected by producers' collaboration costs, indicating their high sensitivity within the synergistic network. This result demonstrates that collaboration costs generate asymmetric effects through the interconnected payoff functions, thereby shaping the overall evolutionary trajectory.

6.4.3. Impact of Innovation Decomposers' Behavioral Changes on Evolutionary Trajectories

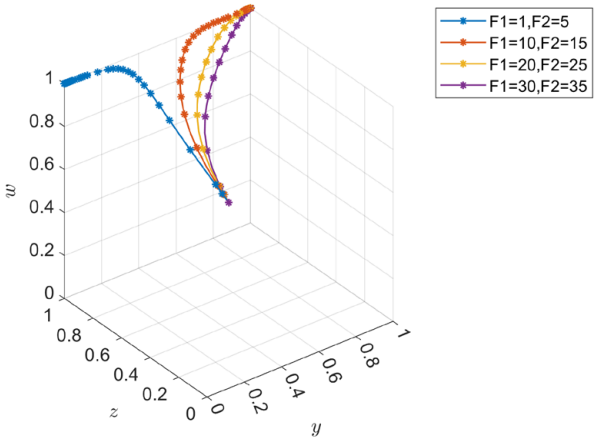
As shown in Figure 12a–c, lower collaborative innovation cost (C_4) for innovation decomposers leads to faster system convergence toward stable strategies. Furthermore, a higher probability of collaborative innovation by decomposers amplifies the influence of cost on the evolutionary outcome. This indicates that collaboration cost directly affects the convergence speed of innovation decomposers: when costs are low, they converge more rapidly toward collaborative strategies, thereby driving the system more quickly toward a stable equilibrium; conversely, excessively high costs markedly slow their convergence.



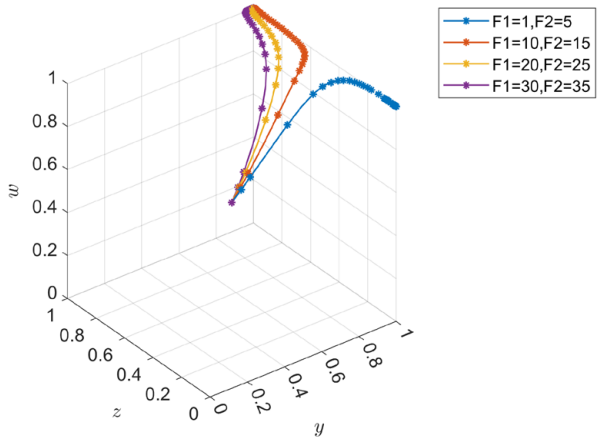
(**a**) x = 0.1.



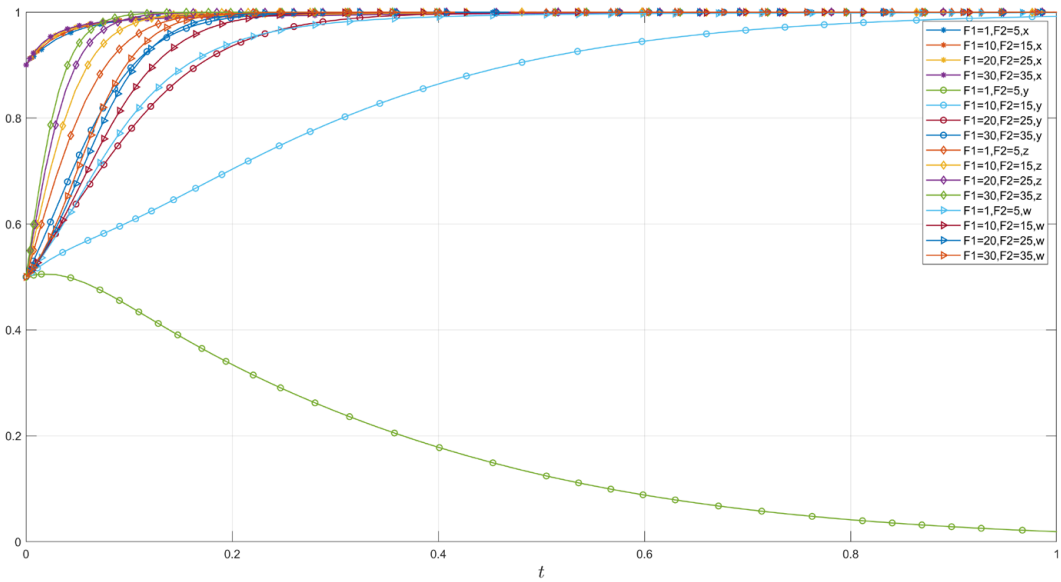
(**b**) x = 0.5.



(**c**) x = 0.9.

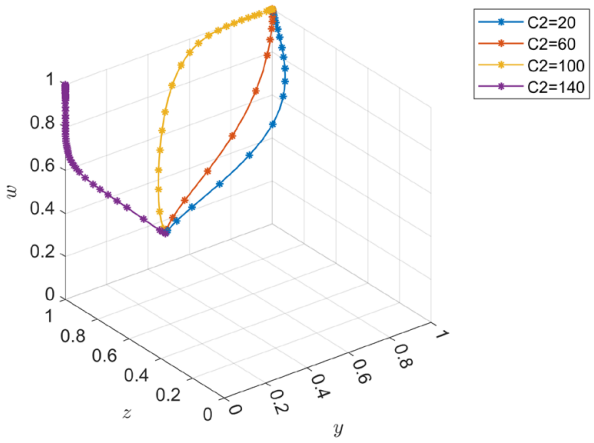


(**d**) x = 0.5 (concerning the x, y, and z axes).

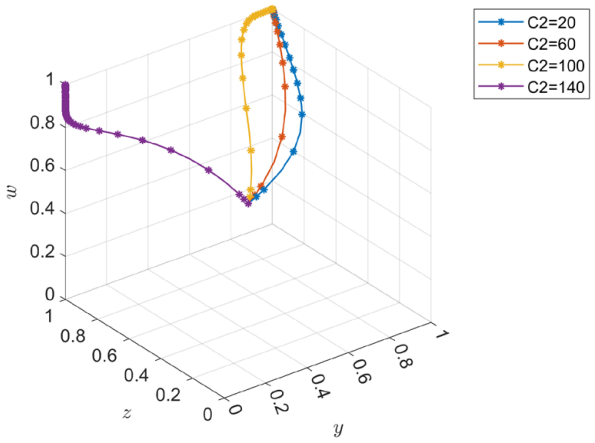


(**e**) Impact of F_1 and F_2 variations on the strategy selection of the four agents.

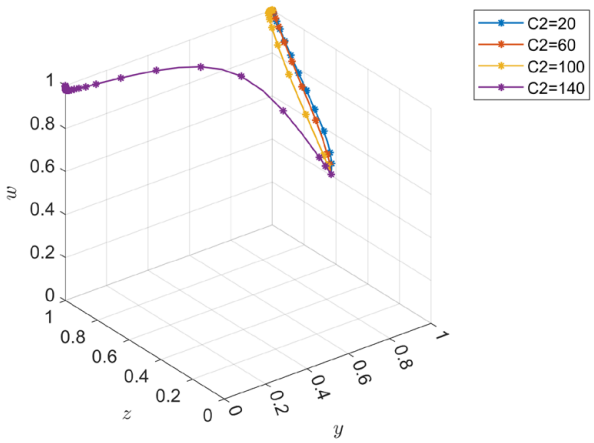
Figure 10. Effects of F_1 and F_2 on evolutionary outcomes for x = 0.1, 0.5, and 0.9.



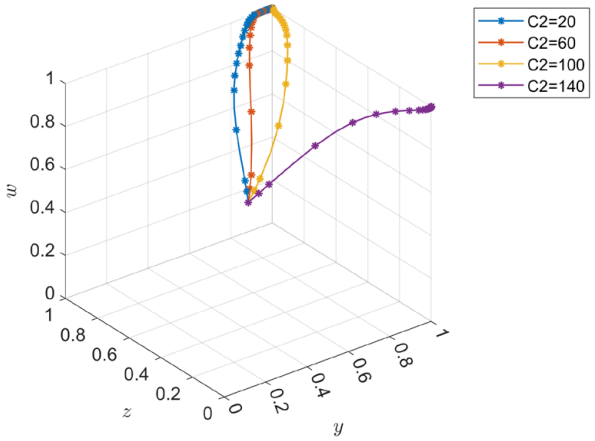
(**a**) y = 0.1.



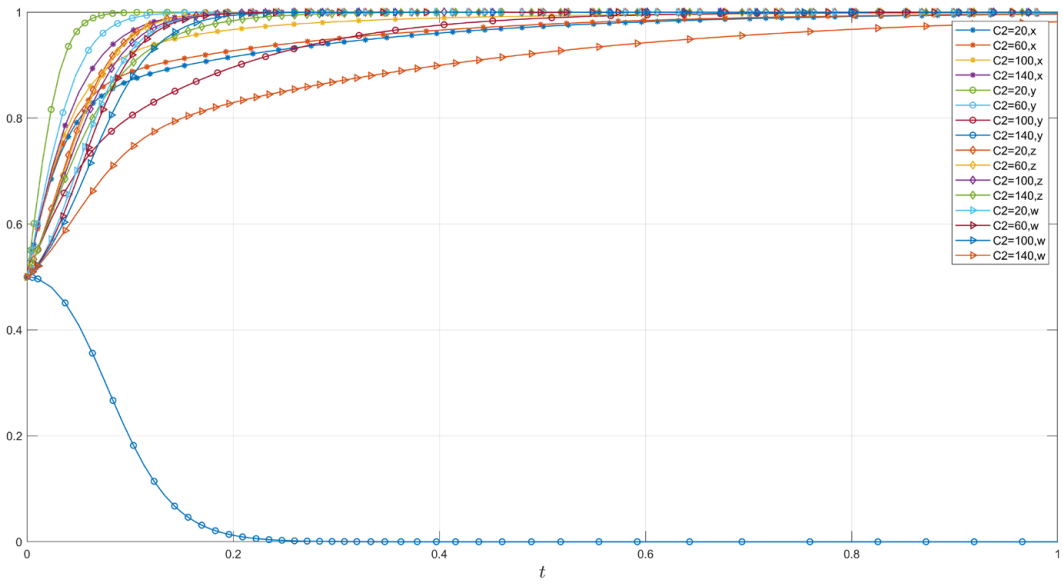
(**b**) y = 0.5.



(**c**) y = 0.9.

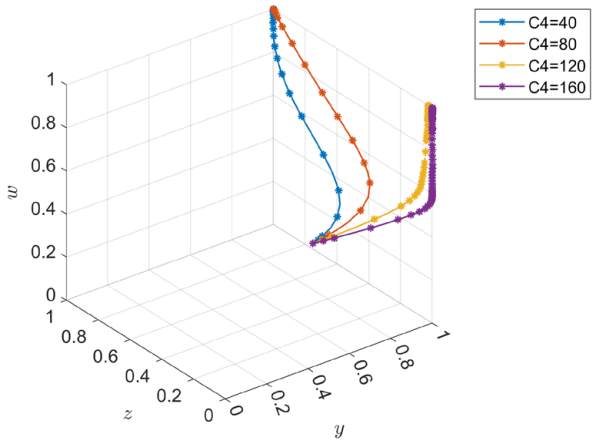


(**d**) y = 0.5 (concerning the x, y, and z axes).

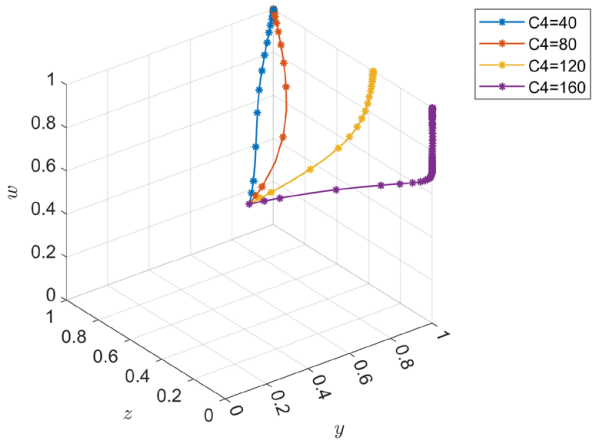


(**e**) Impact of C_2 variation on the strategy selection of the four agents.

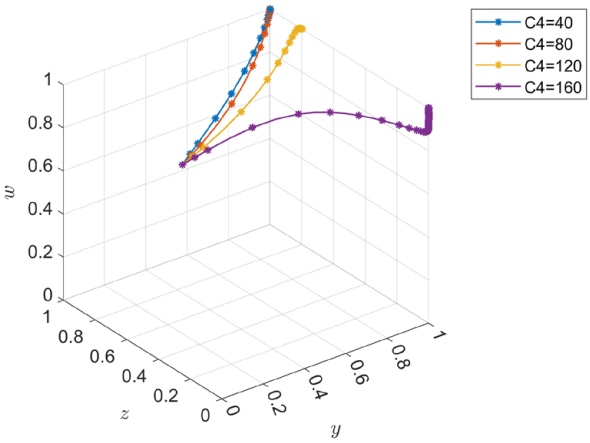
Figure 11. Effect of C_2 on evolutionary outcomes for y = 0.1, 0.5, and 0.9.



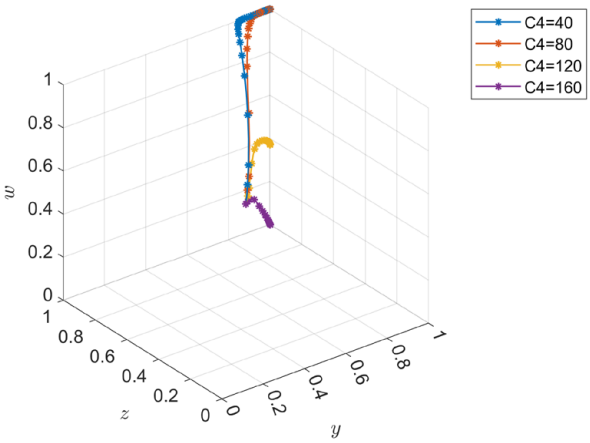
(**a**) z = 0.1.



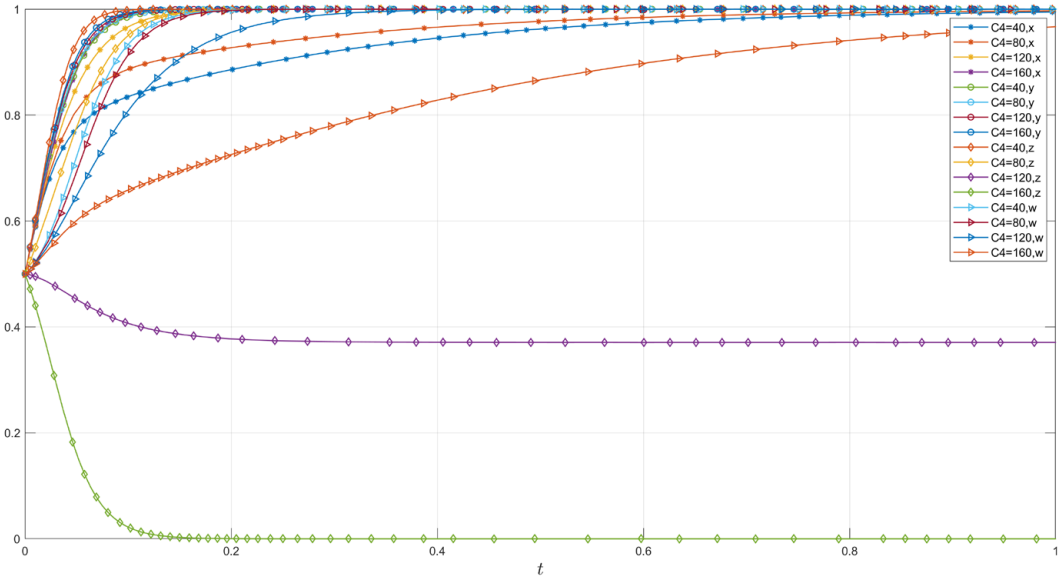
(**b**) z = 0.5.



(**c**) z = 0.9.



(**d**) z = 0.5 (concerning the x, y, and z axes).



(**e**) Impact of C_4 variation on the strategy selection of the four agents.

Figure 12. Effect of C_4 on evolutionary outcomes for z = 0.1, 0.5, and 0.9.

Further analysis shows that variation in the collaborative innovation cost of decomposers asymmetrically influences the convergence speeds of other agents. As illustrated in Figure 12e, when collaboration costs are high, innovation producers and regulators actually converge toward stable strategies more quickly. In contrast, innovation consumers approach the ideal equilibrium faster when collaboration costs are low. These findings demonstrate that the collaboration cost of innovation decomposers not only shapes their own strategy choice but also differentially modulates the evolutionary dynamics of producers, regulators, and consumers through the interconnected payoff structure, ultimately affecting the convergence efficiency of system-wide coordination.

Figure 13 shows that the system converges significantly faster toward the ideal equilibrium state as the additional payoff (R_4) from collaborative innovation for innovation decomposers increases. This effect is more pronounced when decomposers have a higher probability of innovation. These results indicate that additional payoffs incentivize collaborative behavior: when payoffs are low, decomposers lack sufficient motivation, resulting in slow system evolution; raising the payoffs effectively stimulates their participation and thus accelerates overall system convergence. This implies that a well-designed payoff-sharing mechanism is key to fostering collaborative vitality and lowering barriers to participation.

Further analysis reveals that increased additional payoffs exert asymmetric effects on other agents through payoff spillover. As shown in Figure 13e, higher additional payoffs lead to markedly faster convergence of innovation consumers toward the ideal equilibrium, demonstrating that a high-payoff environment effectively encourages their engagement. At the same time, the intervention propensity of innovation regulators declines accordingly, reflecting strengthened endogenous synergistic forces within the system and reduced reliance on external intervention. Notably, the strategy of innovation producers remains relatively insensitive to changes in additional payoffs. Their behavior is shaped mainly by their own cost structure and direct interactions with other agents, suggesting that payoff spillovers have a limited influence on them.

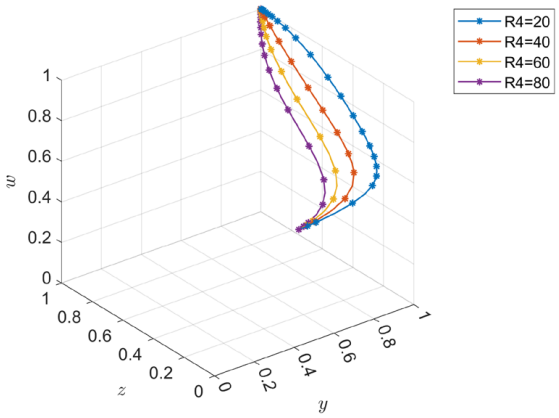
6.4.4. Impact of Innovation Consumers' Behavioral Changes on Evolutionary Trajectories

As shown in Figure 14a–d, lower participation costs (C_6) for innovation consumers lead to faster system convergence toward a stable equilibrium. Furthermore, a higher probability of proactive participation by consumers amplifies the influence of these costs on the evolutionary outcome. This demonstrates that consumers' participation costs are a key factor affecting the system's convergence efficiency: lower costs reduce entry barriers, thereby accelerating convergence; conversely, higher costs slow the system's convergence.

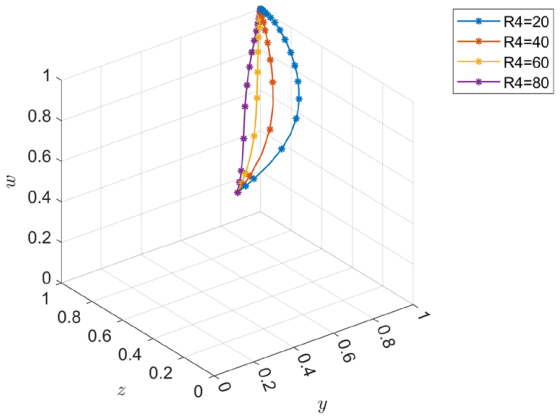
Figure 14e further reveals the differential responses across agents. When participation costs are high, innovation regulators converge toward stable strategies more quickly. In contrast, innovation decomposers converge faster toward the ideal equilibrium when participation costs are low. Notably, innovation producers show little sensitivity to changes in participation costs. Their behavior is governed mainly by their own collaboration costs and direct cooperative relationships with innovation decomposers. This highlights how different agents follow distinct response patterns to the same external parameter during system coordination.

Figure 15a–d show that the system converges toward stable strategies significantly faster with increasing feedback losses (N_2, N_3) imposed by innovation consumers. Furthermore, a higher probability of proactive participation by consumers leads to a more pronounced influence of these losses on the evolutionary outcome. This indicates that consumer feedback, through its impact on the payoff structure, can effectively accelerate the convergence of other agents toward cooperative strategies. Figure 15e further shows that under higher feedback losses, both innovation producers and decomposers converge

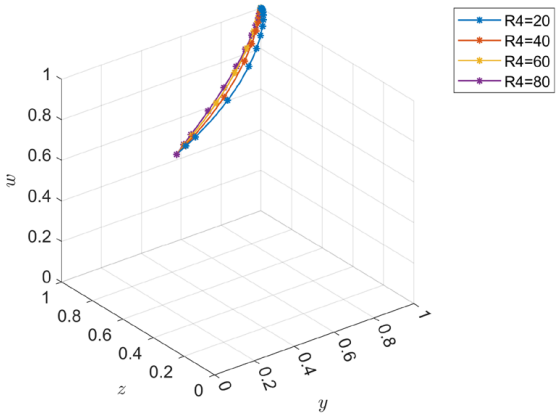
toward stable strategies more quickly. In contrast, innovation regulators approach the ideal equilibrium faster when feedback losses are lower.



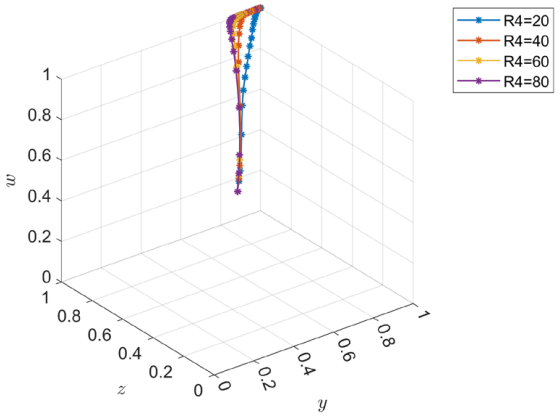
(**a**) z = 0.1.



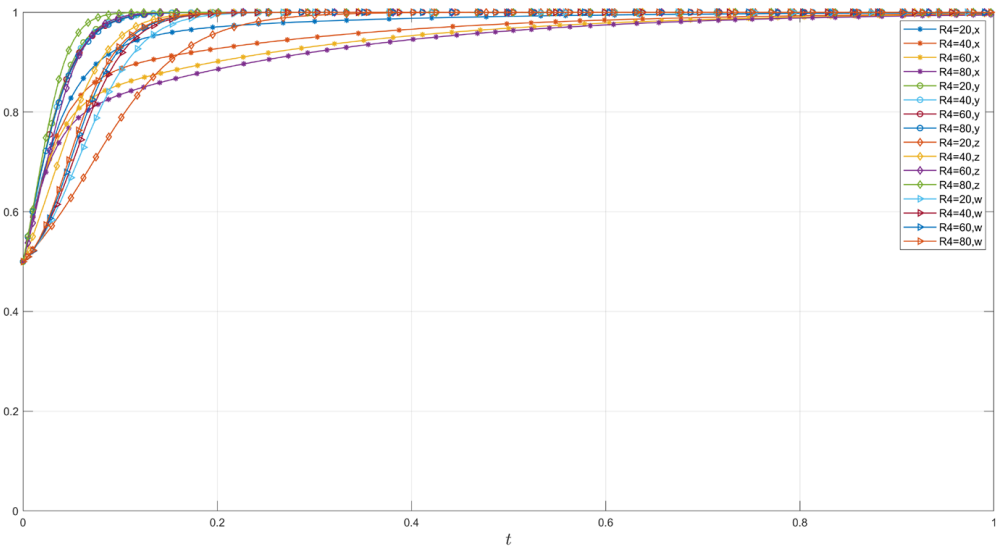
(**b**) z = 0.5.



(**c**) z = 0.9.

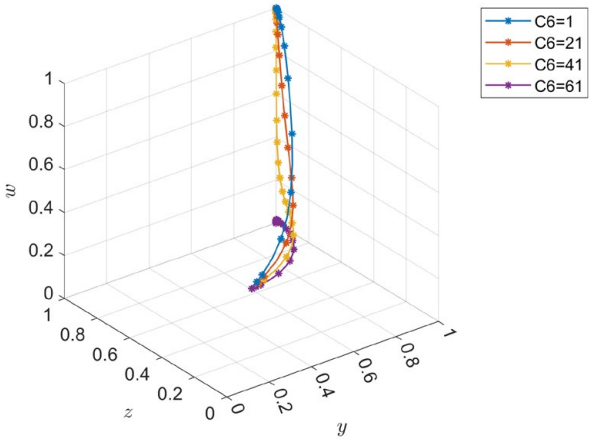


(**d**) z = 0.5 (concerning the x, y, and z axes).

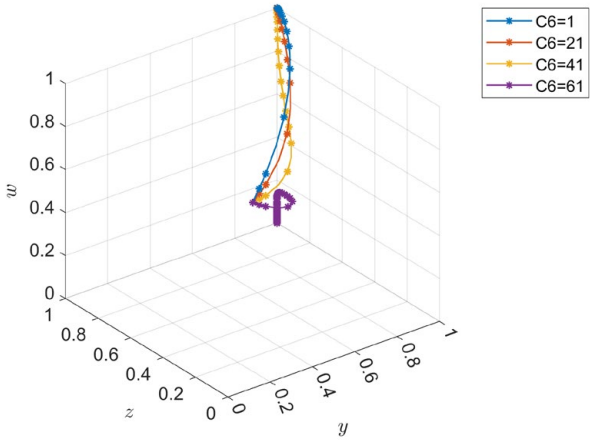


(**e**) Impact of R_4 variation on the strategy selection of the four agents.

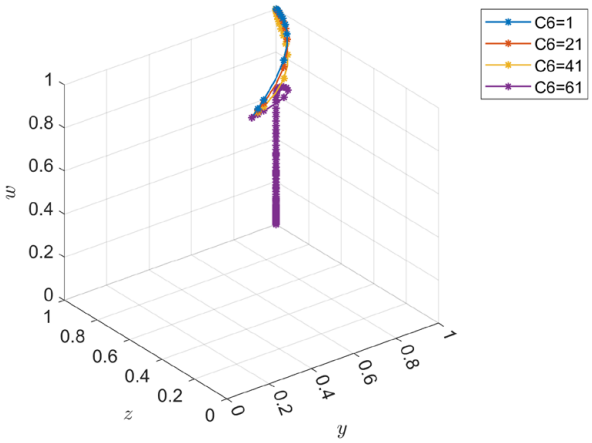
Figure 13. Effect of R_4 on evolutionary outcomes for z = 0.1, 0.5, and 0.9.



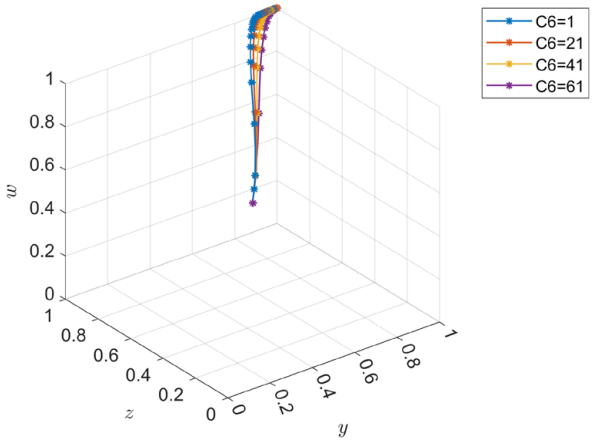
(**a**) w = 0.1.



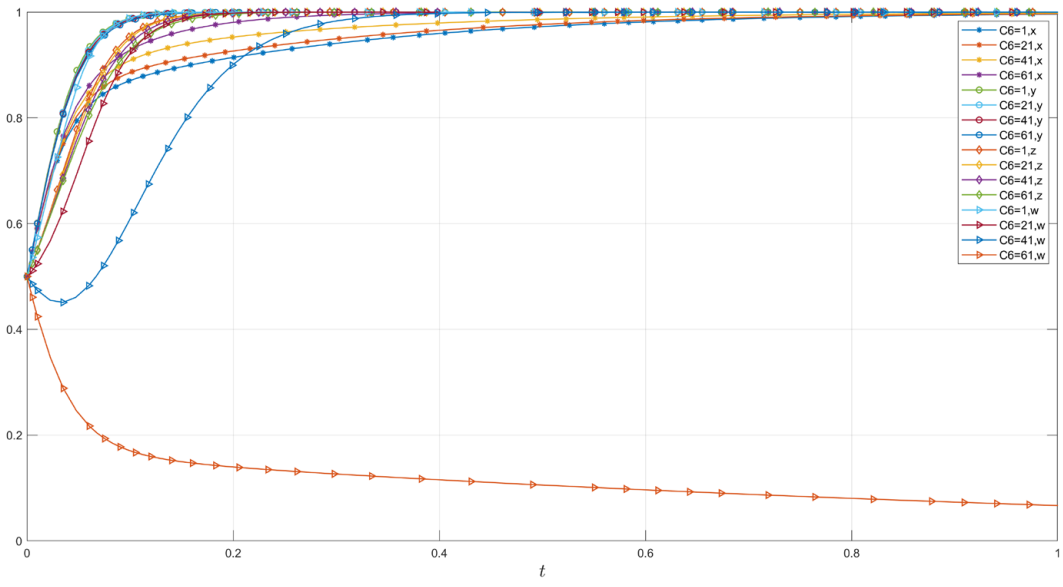
(**b**) w = 0.5.



(**c**) w = 0.9.

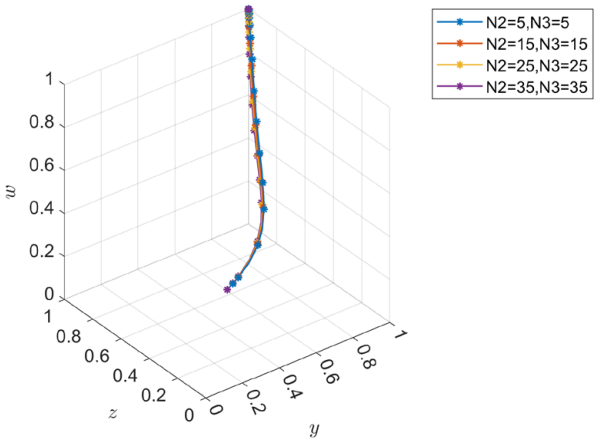


(**d**) w = 0.5 (concerning the x, y, and z axes).

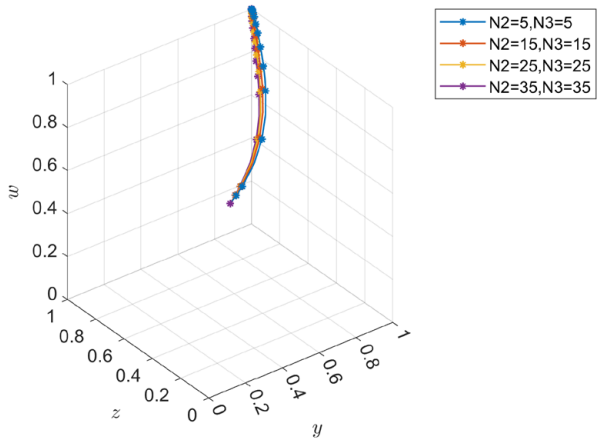


(**e**) Impact of C_6 variation on the strategy selection of the four agents.

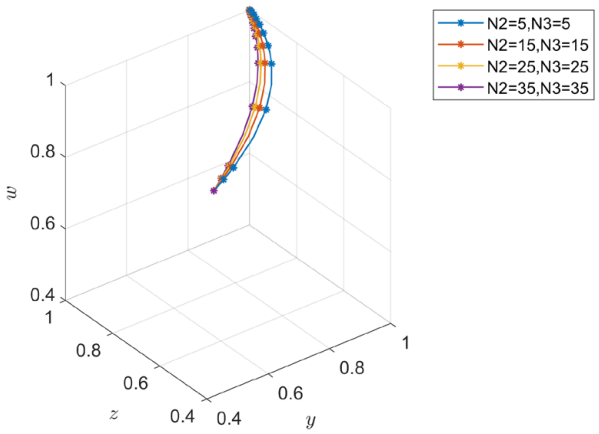
Figure 14. Effect of C_6 on evolutionary outcomes for w = 0.1, 0.5, and 0.9.



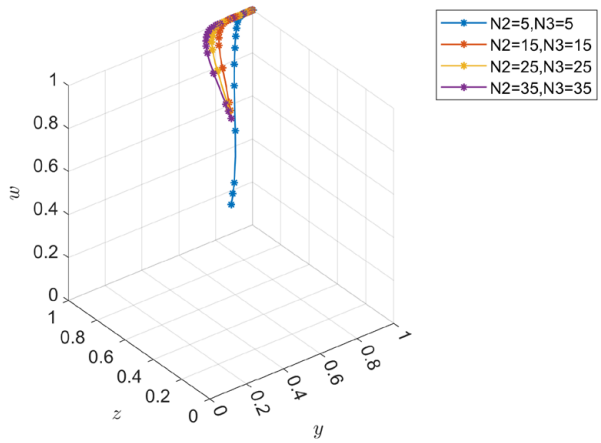
(**a**) w = 0.1.



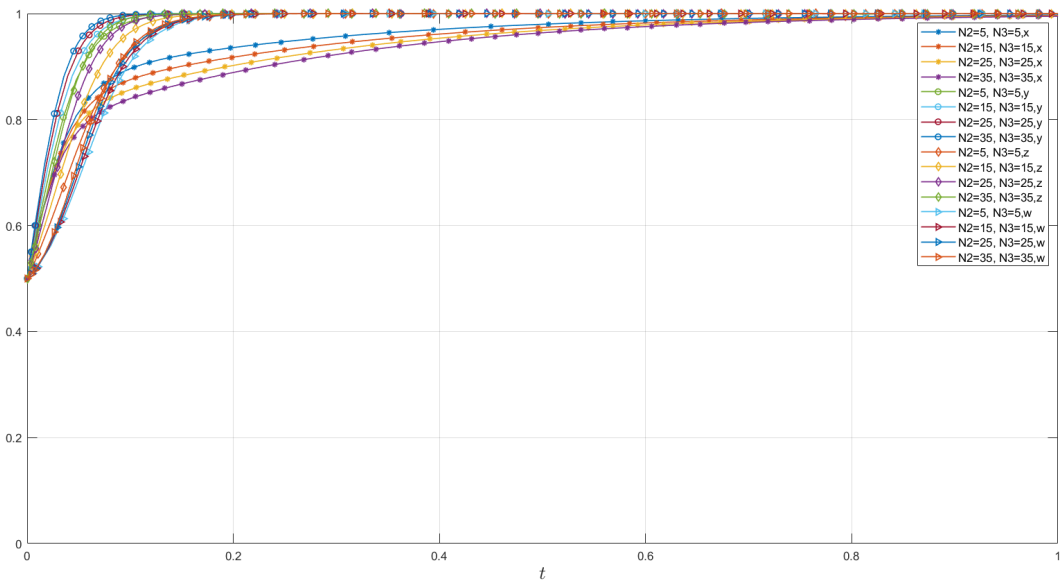
(**b**) w = 0.5.



(**c**) w = 0.9.



(**d**) w = 0.5 (concerning the x, y, and z axes).



(**e**) Impact of N_2 and N_3 variations on the strategy selection of the four agents.

Figure 15. Effects of N_2 and N_3 on evolutionary outcomes for w = 0.1, 0.5, and 0.9.

7. Conclusions and Implications

7.1. Research Findings

This study systematically uncovers the strategic interaction patterns and evolutionary pathways of value co-creation among multiple agents in the DIE by constructing a four-party evolutionary game model involving innovation regulators, producers, decomposers, and consumers. Combined with numerical simulations that analyze the impact of initial strategies and key parameters, this study yields the following main conclusions:

(1) The key factors and intrinsic mechanisms influencing value co-creation in the DIE are revealed. Each agent's strategy selection is systematically moderated by its payoff-cost structure. The strategy of innovation regulators is shaped by intervention costs, social benefits, and fiscal instruments (such as subsidies and penalties). The choices of innovation producers and decomposers are primarily driven by collaboration costs, synergy benefits, breach penalties, and consumer feedback losses. Innovation consumers' strategy selection depends on participation costs and regulator incentives. Within the dynamic feedback loop formed by the strategic interactions of all agents, subsidy and penalty mechanisms exert differentiated contextual regulatory effects on system synergy.

(2) Multiple stable strategies and their convergence conditions in system evolution are identified. Among the 16 pure-strategy equilibrium points, nine are conditionally stable and can be categorized into three types: low-level stability, regulator-dominated transitional stability, and high-level stability. Considering payoff maximization for all participating agents and stability against parameter perturbations, the state (1, 1, 1, 1)—where all four agents adopt proactive participation strategies—is identified as the system's optimal stable point. Under a reasonable incentive and cost structure, this state possesses the intrinsic impetus and stability to evolve toward a high-level synergistic state.

(3) The asymmetric mechanism through which initial strategies influence the system's evolutionary path is elucidated. Simulation results show that while the initial strategy of each agent does not alter the final equilibrium state (1, 1, 1, 1) of system convergence, it significantly affects the convergence speed and path characteristics. Specifically, high initial strategies of innovation regulators and producers can accelerate system convergence, playing a core role in driving it. In contrast, excessively high initial strategies of innovation decomposers and consumers may delay the process due to a "wait-and-see effect," reflecting the asymmetric roles of different agents in system evolution. This provides a theoretical basis for phased policy guidance in DIE development.

(4) A composite driving logic for enhancing synergistic efficacy is extracted. The research finds that: the intervention of innovation regulators has a notable influence, with their costs, subsidies, and penalty policies collectively steering system evolution, though the high fiscal cost of excessive subsidies may slow regulators' own convergence. Importantly, a contingent regulation principle is observed: proactive intervention is more effective when cooperative willingness is low ($z < z_1$); otherwise, a less intensive regulatory approach may be sufficient, as strong endogenous cooperation reduces the need for aggressive intervention; the strategy choices of innovation producers and decomposers are dually moderated by external incentives and internal constraints, with breach penalties and consumer feedback being particularly significant in accelerating convergence when cooperative willingness is low; the participation of innovation consumers exhibits sensitivity to participation costs and regulatory incentives, with their role aligning more with that of "responders" to the payoff environment created by other actors. Achieving a high-level synergistic steady state does not rely on a

single mechanism but requires building a synergistic governance system integrating "regulatory guidance, market incentives, and social feedback." This system guides the strategies of diverse agents toward the ideal equilibrium by optimizing cost structures, precisely designing incentive constraints, and lowering participation barriers.

(5) A counterintuitive yet policy-critical finding emerges from Proposition 1 and its corollary: when innovation decomposers cooperate strongly enough (i.e., $z > z_1$), the market mechanism can drive high-level value co-creation on its own. In this situation, aggressive regulatory intervention becomes not only unnecessary but counterproductive, risking a "government failure" dilemma in which costs rise without commensurate benefits. This finding challenges the conventional assumption that more regulation always improves outcomes, and it implies that effective governance should be contingent on the system's evolutionary stage—intervening actively only when cooperative willingness is low, and otherwise adopting a facilitative or monitoring role.

7.2. Theoretical Contributions

This study offers several potential theoretical contributions. First, it expands the research perspective on value co-creation by shifting from a "dyadic interaction" framework to a "networked synergy" paradigm. Prior research has predominantly focused on value co-creation between dyadic actors (e.g., producer–consumer or firm–user), which fails to fully capture the complex networked nature of multi-actor collaboration in digital innovation ecosystems. Grounded in the Quadruple Helix theory, this study constructs a four-party evolutionary game model involving innovation regulators, producers, decomposers, and consumers. By extending the analytical framework from bilateral interactions to a multi-actor, multi-level systemic network, it better aligns with the synergistic essence of innovation ecosystems in the digital age and enriches the explanatory power of value co-creation theory in complex-system contexts.

Second, this study addresses a gap in dynamic quantitative analysis within DIE research. Existing work has largely emphasized theoretical framing or qualitative case studies, lacking a quantitative depiction of the dynamic process of strategic interaction among multiple actors. By introducing evolutionary game theory and building a four-party dynamic game model combined with MATLAB R2023b-based numerical simulation, this research uncovers the stability conditions and path-dependence features of system evolution. This approach not only bridges "static structural description" and "dynamic process simulation," but also supplies a quantitative basis for identifying key parameters that affect system synergy, thereby advancing digital-innovation research from normative "ought-to-be" reasoning toward positive "as-is" analysis.

Third, the work systematically identifies and elucidates the key influencing factors and mechanistic pathways of multi-actor collaborative evolution. Through evolutionary game modeling and stability analysis, it pinpoints the core parameters that shape the strategic choices of the four parties and clarifies their differentiated roles across various evolutionary stages. Further simulation analysis delineates multiple evolutionary paths—from "low-level equilibrium" to "high-level synergy"—along with their stage-specific characteristics, and clarifies the asymmetric mechanisms through which different actors influence system progression. These findings provide a mechanistic explanation for "how synergy emerges and sustains itself" in DIEs, laying a theoretical foundation for subsequent research to develop multi-level, multi-stage collaborative governance models.

7.3. Management Implications

By constructing a four-party evolutionary game model, this study reveals the dynamic evolutionary logic of value co-creation in DIEs. To steer the system toward a high-level synergistic steady state, management practice should balance the interests of all actors and strive to build an integrated governance system that synergizes "regulatory guidance, market incentives, and social feedback." Based on the findings, the following managerial implications are proposed:

(1) Optimize the regulatory toolkit for targeted empowerment and sustainable governance. Innovation regulators should actively employ digital governance tools (e.g., big data, AI) to effectively reduce intervention costs (C_1) and improve policy-implementation efficiency, thereby avoiding "crowding-out effect" caused by excessive costs. Subsidy mechanisms should shift from a "universal" to a "performance-oriented" approach, implementing variable incentives to enhance precision and fiscal sustainability. Penalty standards must carry sufficient deterrent force, especially in early-stage collaboration or when regulatory participation is low, to serve as an effective external constraint. Furthermore, a flexible intervention mechanism should be established to dynamically adjust the intensity and strategy of intervention according to the system's evolutionary stage (e.g., low-level deadlock, transitional adjustment, or approaching ideal synergy). This facilitates an orderly transition from proactive intervention to "maintenance-oriented regulation," ultimately fostering a virtuous cycle between an "effective market" and a "capable government."

(2) Strengthen innovation producers' willingness to share openly and build a long-term knowledge-conversion mechanism. Innovation producers should refine internal incentive systems by incorporating collaborative benefits (e.g., horizontal funding C_5, government subsidies S_1) into performance assessment and distribution schemes, thereby offsetting the pressure of collaboration costs (C_2). At the same time, they ought to establish regular communication channels with innovation consumers to promptly integrate user feedback (N_2) into R&D optimization and social-impact enhancement. In designing collaboration agreements, reasonable breach penalties (T_1) can be set to stabilize partnerships; however, excessively high penalties should be avoided when cooperative willingness is already strong, so as not to create an inhibitory effect.

(3) Guide innovation decomposers to focus on collaborative innovation and enhance value-realization capacity and risk resilience. Innovation decomposers should make full use of government subsidies for collaborative innovation (S_2) to reduce additional collaboration costs (C_4) and raise net collaborative benefits. They must also systematically evaluate the comprehensive risks of independent innovation, looking beyond breach penalties (T_2) to consider potential brand-reputation damage and lost market opportunities arising from negative consumer feedback (N_3). Collaborative innovation should be elevated to a strategic level by building efficient, stable collaborative networks that accelerate the conversion of knowledge resources into market returns (R_4). Cooperation agreements should clearly specify rights, responsibilities, and breach clauses to curb opportunistic behavior.

(4) Activate innovation consumers' participation and strengthen demand-side traction and feedback. Regulators should enhance the convenience of "proactive participation" by optimizing interaction processes, simplifying feedback channels, and lowering participation costs (C_6). A non-monetary reward system centered on honorary incentives and community recognition—such as contribution awards and co-creator badges—should be established to boost consumers' sense of fulfillment (B_2) and perceived social value (R_5). Moreover, robust mechanisms for collecting, responding to, and

implementing user feedback must be put in place to ensure that feedback tangibly shapes innovation processes and outcomes, thereby reinforcing consumers' stable strategy of active engagement.

7.4. Limitations and Future Research

Although this study systematically uncovers the dynamic evolution of value co-creation in DIEs through a four-party evolutionary game model, several limitations remain. Future research could extend the work in five directions: first, model parameters were calibrated using a multi-source data-fusion strategy, but some idealization bias persists; subsequent studies could integrate operational data from representative regional digital-innovation platforms and employ empirical methods to obtain more accurate estimates. Second, future research could model asymmetric information among actors (e.g., hidden actions or types) using principal–agent frameworks or signaling games to examine its effects on subsidy allocation, penalty enforcement, and trust-building. Third, future research could allow regulatory intervention intensity (α) to vary over time—declining as the system approaches high-level synergy—to capture phase-dependent governance strategies. Fourth, the replicator dynamics framework is suited for incremental adjustments; future research could incorporate stochastic shocks, regime-switching mechanisms, or multi-level perspective concepts to capture the non-linear, discontinuous dynamics of disruptive innovation or socio-technical transitions. Fifth, the proposed model focuses primarily on the economic drivers of value co-creation (e.g., subsidies and penalties) and abstracts from firm heterogeneity, broader government roles, consumer governance mechanisms, and civil society dynamics. Future research could delve deeper into these institutional and socio-political factors to extend the current framework.

Author Contributions: Conceptualization, Y.D. and Y.J.; methodology, Y.D.; software, Y.D.; validation, Y.D. and Y.J.; formal analysis, Y.D.; investigation, Y.D.; resources, Y.J.; data curation, Y.D.; writing—original draft preparation, Y.D.; writing—review and editing, Y.D. and Y.J.; visualization, Y.D.; supervision, Y.J.; project administration, Y.J.; funding acquisition, Y.J. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The simulation data supporting the findings of this study are generated using the parameter settings reported in Appendix B. The R2023b code used for numerical simulations is available from the corresponding author upon reasonable request.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Numerical Procedure for Detecting Interior and Boundary Equilibria

This appendix provides the detailed numerical procedure used in Section 5.2 to search for interior (fully mixed) and non-vertex boundary equilibria of the replicator dynamic system (Equations (4) and (8)–(10) in the main text). The goal is to verify whether any equilibrium point with all eigenvalues having negative real parts (locally asymptotically stable) exists outside the 16 pure-strategy vertices.

Appendix A.1. Grid Search over the Interior of the Hypercube

A systematic grid search was performed over the four-dimensional open hypercube $(0, 1)^4$ with a uniform step size of 0.05. For each grid point $\left(x_i, y_j, z_k, w_l\right)$ where i, j, k, l = 1, . . ., 19 (i.e., 0.05, 0.10, . . ., 0.95), we evaluated the four replicator Equations (4) and (8)–(10) in the main text using the baseline parameter values listed at the end of Section 6.1. A point was considered a candidate fixed point if $|F(x)|, |F(y)|, |F(z)|, |F(w)| < 10^{-6}$. For each candidate, the Jacobian matrix J was constructed analytically (using the derivatives derived in Section 3) and its eigenvalues were computed numerically via standard eigenvalue routines (MATLAB R2023b). A candidate was declared locally asymptotically stable if all eigenvalues had negative real parts (tolerance: real part $<-10^{-6}$).

Result of grid search: Among the 130,321 grid points, no point satisfied the fixed-point criterion with all eigenvalues having negative real parts. All candidates that met the fixed-point condition (fewer than 0.01% of grid points) were either at the boundary of the hypercube (i.e., one or more variables equal to 0 or 1) or had at least one eigenvalue with positive real part.

Appendix A.2. Monte Carlo Random Sampling

To avoid missing equilibria that might lie between grid points, we complemented the grid search with Monte Carlo random sampling. We generated 10,000 random initial points uniformly distributed in $(0, 1)^4$. For each random point, we solved the replicator dynamics using the ode45 solver (relative tolerance 10^{-6}, absolute tolerance 10^{-8}) until convergence (maximum time T = 10,000 or until $|F(x)|, |F(y)|, |F(z)|, |F(w)| < 10^{-8}$). The final point was recorded as a fixed-point candidate, and its Jacobian eigenvalues were computed as above.

Result of Monte Carlo sampling: In all 10,000 runs, the trajectories converged to one of the 16 vertices. No trajectory converged to an interior point or a non-vertex boundary point. For each converged vertex, the Jacobian eigenvalues were negative (or had negative real parts), confirming the stability conditions reported in Table 3.

Appendix A.3. Parameter-Sweeping Monte Carlo

To assess robustness, we performed an additional parameter sweep. Each of the 24 model parameters was randomly sampled from a uniform distribution ±30% around its baseline value. For each of 10,000 parameter draws, we repeated the fixed-point search described in Appendix A.2 (solving the ODE from 10 random initial conditions).

Result of parameter sweep: In all 10,000 parameter combinations, no interior or non-vertex boundary equilibrium was observed. All trajectories converged to vertices, and the stable vertices under each parameter draw were consistent with the eigenvalue conditions derived in Section 5.1.

Appendix A.4. Boundary Equilibria (Edges and Faces)

For boundary equilibria, we reduced the system dimension by fixing one or more variables at 0 or 1. For example:

Edge y = 0, z = 0, w = 0: the dynamics reduce to $F(x) = x(1 - x)(1 - \alpha)[F_1 + F_2 + R_1 - C_1]$. The only fixed points are x = 0 and x = 1. Their stability depends on the sign of the bracket; under baseline parameters, x = 1 is stable and x = 0 is unstable.

Face x = 0, y = 0: the system reduces to two dimensions (z, w). A 2D grid search (step size 0.05) over $(0, 1)^2$ found no stable fixed points except the vertices $(z, w) = (0, 0), (0, 1), (1, 0), (1, 1)$, whose stability matches the full 4D analysis.

All non-vertex fixed points found on edges or faces were either unstable (at least one eigenvalue with positive real part) or saddle points (a mix of positive and negative eigenvalues). No locally asymptotically stable equilibrium was found on any edge or face outside the vertices.

Conclusion: Under the baseline parameter set and over a wide range of perturbed parameters, the replicator dynamic system exhibits no locally asymptotically stable equilibrium other than the 16 pure-strategy vertices listed in Table 3. This numerical evidence supports the theoretical conclusion that the only candidates for stable outcomes in the DIE value co-creation game are the vertices, with the ideal cooperative state (1, 1, 1, 1) being achievable under appropriate parameter conditions.

Appendix B. Detailed Derivation for Innovation Producers, Decomposers, and Consumers

Since the full derivation for innovation regulators (Section 4.1) is already presented in the main text, this appendix provides the detailed derivations for the remaining three actors (Sections 4.2–4.4).

Appendix B.1. Innovation Producers

The expected payoffs for the innovation producers choosing open sharing and closed protection are U_{P1} and U_{P2}, respectively, and the average expected payoff is denoted $\overline{U}_P$. The replicator dynamic equation for this behavioral strategy $F(y)$, and its first derivative $F'(y)$ are given by Equations (A4) and (A5), respectively.

$$\begin{aligned} U_{P1} = {} & xzwp_1 + xz(1-w)p_2 + x(1-z)wp_3 + x(1-z)(1-w)p_4 + (1-x)zwp_9 + (1-x)z(1-w)p_{10} \\ & + (1-x)(1-z)wp_{11} + (1-x)(1-z)(1-w)p_{12} \end{aligned} \tag{A1}$$

$$\begin{aligned} U_{P2} = {} & xzwp_5 + xz(1-w)p_6 + x(1-z)wp_7 + x(1-z)(1-w)p_8 + (1-x)zwp_{13} + (1-x)z(1-w)p_{14} \\ & + (1-x)(1-z)wp_{15} + (1-x)(1-z)(1-w)p_{16} \end{aligned} \tag{A2}$$

$$\overline{U}_P = yU_{P1} + (1-y)U_{P2} \tag{A3}$$

$$\begin{aligned} F(y) = y(U_{P1} - \overline{U}_P) &= y(1-y)(U_{P1} - U_{P2}) \\ &= y(1-y)[T_2 + \alpha F_1 + \alpha S_3 + x(F_1 + S_3 - \alpha F_1 - \alpha S_3) + z(T_1 - T_2 + \alpha S_1 - \alpha S_3 - C_2 + C_5) \\ &\quad + xz(S_1 - S_3 - \alpha S_1 + \alpha S_3) + wN_2] \end{aligned} \tag{A4}$$

$$\begin{aligned} F'(y) = (1-2y)[{} & T_2 + \alpha F_1 + \alpha S_3 + x(F_1 + S_3 - \alpha F_1 - \alpha S_3) + z(T_1 - T_2 + \alpha S_1 - \alpha S_3 - C_2 + C_5) \\ & + xz(S_1 - S_3 - \alpha S_1 + \alpha S_3) + wN_2] \end{aligned} \tag{A5}$$

Proof of Proposition 2. Define $P(x,z,w) = T_2 + \alpha F_1 + \alpha S_3 + x(F_1 + S_3 - \alpha F_1 - \alpha S_3) + z(T_1 - T_2 + \alpha S_1 - \alpha S_3 - C_2 + C_5) + xz(S_1 - S_3 - \alpha S_1 + \alpha S_3) + wN_2$. Since $\partial P(x,z,w)/\partial w > 0$, $P(x,z,w)$ is a strictly increasing function of w. If $w < w_1$, then $P(x,z,w) < 0$. Given $F(y)|_{y=0} = 0$ and $F'(y)|_{y=0} < 0$, the point $y = 0$ is stable. If $w > w_1$, then $P(x,z,w) > 0$. Given $F(y)|_{y=1} = 0$ and $F'(y)|_{y=1} < 0$, the point $y = 1$ is stable. If $w = w_1$, $F(y) = 0$ and $F'(y) = 0$. In this case, any $y \in [0,1]$ is a stable point, and no ESS can be determined. □

Volume calculations for Figure 3. As illustrated in Figure 3, the volume of region V_{y0} corresponds to the probability that the innovation producers adopt a closed protection strategy. In contrast, the volume of region V_{y1} corresponds to the probability of open sharing. The calculations yield:

$$\begin{aligned} V_{y0} &= \int_0^1 \int_0^1 \left[-T_2 - \alpha F_1 - \alpha S_3 - x\begin{pmatrix} F_1 + S_3 \\ -\alpha F_1 - \alpha S_3 \end{pmatrix} - z\begin{pmatrix} T_1 - T_2 + \alpha S_1 \\ -\alpha S_3 - C_2 + C_5 \end{pmatrix} - xz\begin{pmatrix} S_1 - S_3 \\ -\alpha S_1 + \alpha S_3 \end{pmatrix} / N_2\right] dydx \\ &= \frac{1}{N_2}\left[-T_2 - \frac{1}{2}(1+\alpha)(F_1 + S_3) - z(T_1 - T_2 - C_2 + C_5) - \frac{z}{2}(1+\alpha)(S_1 - S_3)\right] \end{aligned} \tag{A6}$$

$$V_{y1} = 1 - V_{y0} = \frac{1}{N_2}\left[N_2 + T_2 + \frac{1}{2}(1+\alpha)(F_1 + S_3) + z(T_1 - T_2 - C_2 + C_5) + \frac{z}{2}(1+\alpha)(S_1 - S_3)\right] \tag{A7}$$

Proof of Corollary 2. From the open-sharing probability V_{y1}, the first-order partial derivatives with respect to F_1 and N_2 are $\partial V_{y1}/\partial F_1 > 0$, and $\partial V_{y1}/\partial N_2 > 0$. Hence, the probability of open sharing increases with a higher regulatory penalty F_1 and a larger reputational loss N_2 from consumer feedback. The underlying economic mechanism is as follows: The dual "economic–social" constraint operates through two distinct channels. First, a higher penalty F_1 directly increases the financial cost (or economic cost) of choosing closed protection, thereby incentivizing the producers to shift toward open sharing. Second, active consumer feedback and public scrutiny amplify the social-reputational cost N_2 associated with closed behavior, providing a strong non-economic incentive for openness. Together, these channels form a mutually reinforcing mechanism that steers the producers' strategy toward collaborative outcomes. □

Appendix B.2. Innovation Decomposers

The expected payoffs for the innovation decomposers choosing collaborative innovation and independent innovation are U_{D1} and U_{D2}, respectively, and the average expected payoff is denoted $\overline{U}_D$. The replicator dynamic equation for this behavioral strategy $F(z)$, and its first derivative $F'(z)$, are given by Equations (A11) and (A12).

$$\begin{aligned} U_{D1} = {} & xywd_1 + xy(1-w)d_2 + x(1-y)wd_5 + x(1-y)(1-w)d_6 + (1-x)ywd_9 + (1-x)y(1-w)d_{10} \\ & + (1-x)(1-y)wd_{13} + (1-x)(1-y)(1-w)d_{14} \end{aligned} \tag{A8}$$

$$\begin{aligned} U_{D2} = {} & xywd_3 + xy(1-w)d_4 + x(1-y)wd_7 + x(1-y)(1-w)d_8 + (1-x)ywd_{11} + (1-x)y(1-w)d_{12} \\ & + (1-x)(1-y)wd_{15} + (1-x)(1-y)(1-w)d_{16} \end{aligned} \tag{A9}$$

$$\overline{U}_D = xU_{D1} + (1-x)U_{D2} \tag{A10}$$

$$\begin{aligned} F(z) &= z\left(U_{D1} - \overline{U}_D\right) = z(1-z)(U_{D1} - U_{D2}) \\ &= z(1-z)[T_1 + y(R_4 - C_4 - T_1 + T_2 + \alpha F_2 + \alpha S_2) + xy(F_2 + S_2 - \alpha S_2 - \alpha F_2) + wN_3] \end{aligned} \tag{A11}$$

$$F'(z) = (1-2z)[T_1 + y(R_4 - C_4 - T_1 + T_2 + \alpha F_2 + \alpha S_2) + xy(F_2 + S_2 - \alpha S_2 - \alpha F_2) + wN_3] \tag{A12}$$

Proof of Proposition 3. Define $D(x, y, w) = T_1 + y(R_4 - C_4 - T_1 + T_2 + \alpha F_2 + \alpha S_2) + xy(F_2 + S_2 - \alpha S_2 - \alpha F_2) + wN_3$. Since $\partial D(x, y, w)/\partial w > 0$, $D(x, y, w)$ is a strictly increasing function of w. If $w < w_2$, then $D(x, y, w) < 0$. Given $F(z)|_{z=0} = 0$ and $F'(z)|_{z=0} < 0$, the point $z = 0$ is stable. If $w > w_2$, then $D(x, y, w) > 0$. Given $F(z)|_{z=1} = 0$ and $F'(z)|_{z=1} < 0$, the point $z = 1$ is stable. If $w = w_2$, $F(z) = 0$ and $F'(z) = 0$. In this case, any $z \in [0, 1]$ is a stable point, and no ESS can be determined. □

Volume calculations for Figure 4. As shown in Figure 4, the volume of region V_{z0} corresponds to the probability that the innovation decomposers choose independent innovation, while the volume of region V_{z1} correspond to the probability of collaborative innovation. The calculations yield:

$$V_{z0} = \int_0^1 \int_0^1 [-T_1 - y(R_4 - C_4 - T_1 + T_2 + \alpha F_2 + \alpha S_2) - xy(F_2 + S_2 - \alpha S_2 - \alpha F_2)/N_3]dydz = -\frac{1}{2N_3}[R_4 - C_4 + T_1 + T_2 + (x - \alpha x + \alpha)(F_2 + S_2)] \quad (A13)$$

$$V_{z1} = 1 - V_{z0} = \frac{1}{2N_3}[2N_3 + R_4 - C_4 + T_1 + T_2 + (x - \alpha x + \alpha)(F_2 + S_2)] \quad (A14)$$

Proof of Corollary 3. The first-order partial derivatives of the collaborative-innovation probability V_{z1} with respect to S_2 and T_2 are $\partial V_{z1}/\partial S_2 > 0$, and $\partial V_{z1}/\partial T_2 > 0$. Hence, the probability of collaborative innovation is positively correlated with both the subsidy and the independent-innovation penalty. Mechanically, a higher subsidy directly raises the expected payoff of collaboration, creating a "pull" effect. Conversely, a higher breach penalty increases the cost and risk of independent innovation, generating a "push" effect. These two forces jointly reshape the decomposers' cost–benefit structure, making collaborative innovation the more rational choice. This result illustrates the effectiveness of the regulators' dual incentive-and-constraint mechanism in steering the system toward synergy. □

Appendix B.3. Innovation Consumers

The expected payoffs for the innovation consumers choosing proactive participation and passive consumption are U_{C1} and U_{C2}, respectively, and the average expected payoff is denoted $\overline{U}_C$. The replicator dynamic equation for this behavioral strategy $F(w)$, and its first derivative $F'(w)$, are given by Equations (A18) and (A19).

$$U_{C1} = xyzc_1 + xy(1-z)c_3 + x(1-y)zc_5 + x(1-y)(1-z)c_7 + (1-x)yzc_9 + (1-x)y(1-z)c_{11} + (1-x)(1-y)zc_{13} + (1-x)(1-y)(1-z)c_{15} \quad (A15)$$

$$U_{C2} = xyzc_2 + xy(1-z)c_4 + x(1-y)zc_6 + x(1-y)(1-z)c_8 + (1-x)yzc_{10} + (1-x)y(1-z)c_{12} + (1-x)(1-y)zc_{14} + (1-x)(1-y)(1-z)c_{16} \quad (A16)$$

$$\overline{U}_C = wU_{C1} + (1-w)U_{C2} \quad (A17)$$

$$F(w) = w(U_{C1} - \overline{U}_C) = w(1-w)(U_{C1} - U_{C2}) = w(1-w)[\alpha S_4 - C_6 + x(S_4 - \alpha S_4) + yzR_5] \quad (A18)$$

$$F'(w) = (1-2w)[\alpha S_4 - C_6 + x(S_4 - \alpha S_4) + yzR_5] \quad (A19)$$

Proof of Proposition 4. Define $C(x,y,z) = \alpha S_4 - C_6 + x(S_4 - \alpha S_4) + yzR_5$. Since $\partial C(x,y,z)/\partial x > 0$, $C(x,y,z)$ is a strictly increasing function of x. If $x < x_1$, then $C(x,y,z) < 0$. Given $F(w)|_{w=0} = 0$ and $F'(w)|_{w=0} < 0$, the point $w = 0$ is stable. If $x > x_1$, then $C(x,y,z) > 0$. Given $F(w)|_{w=1} = 0$ and $F'(w)|_{w=1} < 0$, the point $w = 1$ is stable. If $x = x_1$, $F(w) = 0$ and $F'(w) = 0$. In this case, any $w \in [0,1]$ is a stable point, and no ESS can be determined. □

Volume calculations for Figure 5. As shown in Figure 5, the volume of region V_{w0} corresponds to the probability that the innovation consumers adopt passive consumption, while the volume of region V_{w1} corresponds to the probability of proactive participation. The calculations yield:

$$V_{w0} = \int_0^1 \int_0^1 \frac{C_6 - \alpha S_4 - yzR_5}{S_4 - \alpha S_4} dydw = \frac{2C_6 - 2\alpha S_4 - zR_5}{2(S_4 - \alpha S_4)} \tag{A20}$$

$$V_{w1} = 1 - V_{w0} = 1 - \frac{2C_6 - 2\alpha S_4 - zR_5}{2(S_4 - \alpha S_4)} \tag{A21}$$

Proof of Corollary 4. The first-order partial derivatives of the active-participation probability V_{w1} with respect to R_5 and C_6 are $\partial V_{w1}/\partial R_5 > 0$ and $\partial V_{w1}/\partial C_6 < 0$. Hence, the participation probability is positively correlated with the social benefit and negatively correlated with the participation cost. Intuitively, a higher social benefit raises the expected return from participation, creating a positive incentive. Conversely, a higher participation cost dampens the willingness to engage. Therefore, building a collaborative innovation ecosystem requires both enhancing social benefits and lowering participation costs. Effective mechanism design that addresses these two aspects is essential for stimulating and sustaining consumers' innovative vitality. □

Appendix C. Parameter Values, Ranges, Data Sources, and Sensitivity Settings

Table A1 below reports the baseline value, plausible range, data source, and sensitivity/robustness setting for every parameter used in the model. The baseline values are derived from a multi-source data fusion strategy: macro-level data (e.g., R&D intensity and profit margins of industrial enterprises above a designated size in 2024, released by the National Bureau of Statistics) and statistical bulletins on core digital-economy industries in the Yangtze River Delta region were used to anchor baseline return standards. Field surveys of smart-manufacturing enterprises in the Pearl River Delta region systematically collected actual cost structures and revenue information. For parameters that are difficult to observe directly or involve commercial sensitivity, multiple rounds of calibration were performed by drawing on the latest research and incorporating expert interviews. The ranges are chosen as ±20% of the baseline for most cost/benefit parameters, or based on literature-reported variation. Sensitivity analysis (Section 6.4) systematically varies each key parameter within its range, while Monte Carlo sampling (Appendix A) randomly draws parameter combinations from these ranges to test robustness.

Table A1. Parameter mapping.

Subject	Parameter	Baseline Value	Range	Data Source/Basis	Sensitivity Setting
Innovation Regulators	C_1	20	[10, 30]	Average administrative cost of regional innovation policies (Provincial Statistical Yearbook, 2024)	Varied ±50% (Figure 8)
	R_1	120	[100, 140]	Estimated social benefit from innovation output (National Bureau of Statistics, 2024)	Fixed in main analysis; tested via Monte Carlo
	S_1	30	[15, 45]	Typical R&D subsidy rate for universities (Ministry of Science and Technology, 2023)	Varied ±50% (Figure 9)

Table A1. *Cont.*

Subject	Parameter	Baseline Value	Range	Data Source/Basis	Sensitivity Setting
Innovation Regulators	S_2	35	[20, 50]	Typical R&D subsidy rate for enterprises (same source)	Varied ±50% (Figure 9)
	S_3	20	[10, 30]	Compensation for failed collaboration (expert interview)	Fixed
	S_4	25	[15, 35]	Reward for user participation (platform data, 2024)	Varied ±50% (Figure 9)
	B_1	20	[10, 30]	Regulatory satisfaction from successful collaboration (the literature: [25])	Fixed
	N_1	20	[10, 30]	Negative utility from collaboration failure (expert interview)	Fixed
	F_1	20	[10, 30]	Penalty for non-cooperative producers (based on IPR law enforcement)	Varied ±50% (Figure 10)
	F_2	25	[15, 35]	Penalty for non-cooperative decomposers (same source)	Varied ±50% (Figure 10)
	α	0.6	[0.4, 0.8]	Intervention intensity (survey of policy effectiveness)	Fixed in main analysis
Innovation Producers	C_2	60	[40, 80]	Transaction and coordination cost for open sharing (field survey)	Varied ±33% (Figure 11)
	R_2	60	[50, 70]	Baseline revenue from knowledge dissemination (the literature: [28])	Fixed
	T_1	10	[5, 15]	Breach penalty from producer to decomposer (contract data)	Fixed
	N_2	8	[4, 12]	Reputational loss from negative consumer feedback (social media analysis)	Varied ±50% (Figure 15)
Innovation Decomposers	C_3	40	[30, 50]	Independent R&D cost (survey)	Fixed
	C_4	80	[60, 100]	Extra collaboration cost (survey)	Varied ±25% (Figure 12)
	C_5	40	[30, 50]	Service fee paid to producers (survey)	Fixed
	R_3	65	[55, 75]	Baseline revenue from independent innovation (National Bureau of Statistics)	Fixed
	R_4	40	[20, 60]	Additional revenue from collaboration (survey)	Varied ±50% (Figure 13)
	T_2	10	[5, 15]	Breach penalty from decomposer to producer (contract data)	Fixed
	N_3	10	[5, 15]	Reputational loss from consumer feedback (social media analysis)	Varied ±50% (Figure 15)

Table A1. *Cont.*

Subject	Parameter	Baseline Value	Range	Data Source/Basis	Sensitivity Setting
Innovation Consumers	C_6	22	[11, 33]	Participation cost (time/effort) for feedback (survey)	Varied ±50% (Figure 14)
	R_5	35	[25, 45]	Social benefit from collaboration (the literature: [32])	Fixed
	B_2	15	[10, 20]	Positive utility from participation (expert interview)	Fixed
	N_4	12	[6, 18]	Negative experience from independent innovation (consumer survey)	Fixed

Notes: (1) The "sensitivity setting" column indicates whether the parameter is varied in Section 6.4; the corresponding figure number is given in parentheses. Parameters marked "Fixed" are held at their baseline values in the main simulations but are also tested via Monte Carlo sampling (10,000 draws, Appendix A) to ensure robustness. (2) Ranges are derived from the 20th–80th percentiles of the collected data or from literature-based plausible intervals. (3) The Monte Carlo method samples uniformly from these ranges to verify that the qualitative conclusions (e.g., convergence to (1, 1, 1, 1) under the stability conditions) remain unchanged.

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