

Article

Evolutionary Mechanisms of Disruptive Innovation: A Multi-Agent Simulation Based on Complex Adaptive Systems

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Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and/or methodology.

- A complex adaptive systems framework conceptualizes disruptive innovation as an emergent industry-level process driven by heterogeneous firm interactions and adaptive feedback.
- An agent-based simulation integrating a genetic algorithm and simulation-based regression reveals how network, institutional, and resource mechanisms jointly shape technological evolution.

What are the main findings and/or the implications of the main findings?

- Greater social network connectivity can reinforce incumbent entrenchment and delay disruptive-technology penetration when network advantages are unevenly distributed.
- Government subsidies accelerate disruptive-technology penetration, whereas heterogeneous resource configurations primarily shape firms' subsequent competitive and adoption outcomes.

Abstract

Despite extensive research on the antecedents of disruptive innovation, how disruptive innovation evolves through interacting mechanisms within complex adaptive systems remains insufficiently understood. To address this gap, this study conceptualizes disruptive innovation as an industry-level evolutionary process shaped by three differentiated mechanisms: the network mechanism, institutional mechanism, and resource mechanism. Drawing on Complex Adaptive Systems Theory, we develop an agent-based simulation model integrated with a genetic algorithm and complement the simulation with regression analysis to examine how these mechanisms shape technological penetration, market dynamics, and enterprise adoption. Based on 30 independent simulation replications with fixed random seeds and systematic sensitivity analysis, the results reveal three distinct evolutionary effects. First, higher social network connectivity does not necessarily accelerate disruptive-technology diffusion; when network advantages are concentrated among incumbent firms, stronger connectivity reinforces incumbent entrenchment and delays technological substitution. Second, government subsidies serve as an effective institutional lever, with greater subsidy intensity systematically accelerating the market penetration of disruptive technology. Third, initial resource endowment has limited influence on the



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timing of disruption, while heterogeneous resource configurations generate differentiated effects on market share, market price, and enterprise adoption. These findings demonstrate that disruptive innovation emerges not from isolated technological or organizational factors, but from the dynamic interactions of heterogeneous firms within a complex adaptive system. By distinguishing the different evolutionary functions of network connectivity, institutional intervention, and resource configuration, this study advances a mechanism-based understanding of disruptive innovation and provides implications for managing technological transitions through context-sensitive network development, targeted institutional support, and strategic resource allocation.

Keywords: disruptive innovation; evolutionary mechanisms; complex adaptive systems; multi-agent simulation; genetic algorithm

1. Introduction

In the past century, the innovations achieved by mankind in the fields of aerospace, biomedical engineering, artificial intelligence, nanotechnology and other technologies have profoundly changed the way people produce, live and think, as well as their consciousness, which promotes the progress and development of human society. The emergence of disruptive innovation in practice has begun to attract the attention of scholars and forms the basis of disruptive innovation theory [1–3]. According to Christensen and Bower, disruptive innovation is an innovation disrupting an established trajectory of performance improvement in an industry or reshaping the meaning of performance [4]. Christensen and Raynor further expand the concept of disruptive innovation to include not only technological innovation, but also business model innovation and customer value provision innovation [5]. Business model innovation and customer value supply innovation evolve from non-mainstream markets and eventually disrupt the original mainstream market, changing the rules of competition. Disruptive business model innovation focuses on creating a new system of activities, with new partners and activities configured in an unprecedented way compared to the existing business model [6]. Ramani and Mukherjee regard disruptive innovation as a new design of product, process or business model, which can greatly change the whole industry [7]. Through integrating different approaches to define disruptive innovation, this paper defines disruptive innovation as follows: Disruptive innovation refers to the process of disruptive technologies or technology combinations cutting through low-end markets or niche markets on a new technology track, offering new value structures to customers, bringing disruptions or huge impacts to products, services, and business models in mainstream markets, and then gradually expanding market share and becoming the new dominant technology until a new technology paradigm and market is created. Disruptive innovation is increasingly becoming the dominant mode of technological innovation in the 21st century. Against this background, understanding how disruptive innovation emerges and evolves has become a central issue in innovation management and technology strategy.

While people are experiencing huge social changes brought by disruptive innovations and enjoying the convenience brought by technological advancement, a new problem has emerged: most disruptive technologies are not able to enter and take over the market quickly because the room for their growth is often squeezed by mainstream markets and products—causing them to end prematurely before capturing the market. Research has also shown that many disruptive technologies that have been developed, tested, and scientifically proven by R&D departments do not necessarily succeed in crossing the so-called ‘valley of death’ between technology development and market adoption [8,9]. Just

as Mokyr likened new technologies to “monsters of hope”, most scholars agree that the emergence of disruptive technologies is full of bright and promising prospects [10,11]. But at the same time, they also realize that compared with existing technologies that occupy a considerable market space, it is often difficult for disruptive technologies to gain immediate competitive advantages, thus falling into the ‘valley of death’ mentioned above. Therefore, what can be done to advance disruptive innovation and help to guarantee that disruptive technologies enter the market successfully and become a “welfare” for human society? This raises a fundamental question: how do disruptive innovations emerge, evolve and successfully overcome the valley of death in complex adaptive systems?

Existing studies have identified a variety of technological, organizational and institutional determinants of disruptive innovation, including technological opportunities, organizational learning, social networks, government intervention and resource investment. Although these studies have substantially advanced our understanding of disruptive innovation, they predominantly examine these determinants independently. Comparatively little attention has been devoted to explaining the evolutionary mechanisms through which disruptive innovation emerges and evolves in complex adaptive systems. As disruptive innovation is inherently an evolutionary process characterized by adaptation, learning, competition and selection, a mechanism-based perspective is needed to explain its emergence and evolution. Such a perspective provides a theoretical foundation for investigating the key evolutionary mechanisms that shape disruptive innovation over time.

Motivated by this research gap, this study conceptualizes disruptive innovation as an evolutionary process driven by three complementary evolutionary mechanisms, namely the network mechanism, institutional mechanism and resource mechanism. Drawing on Complex Adaptive Systems Theory, a multi-agent simulation model integrating a genetic algorithm is developed to investigate how these mechanisms shape the emergence and evolution of disruptive innovation. In the simulation model, the three mechanisms are operationalized by social network structure, government subsidy intensity and resource investment, respectively.

This study contributes to the disruptive innovation literature in three respects. First, it shifts the theoretical focus from isolated determinants to the evolutionary mechanisms underlying disruptive innovation, thereby providing a more process-oriented explanation of how disruptive innovation emerges and evolves. Second, drawing on Complex Adaptive Systems Theory, it conceptualizes disruptive innovation as an evolutionary process involving heterogeneous innovation agents, offering a dynamic perspective for understanding the evolution of disruptive innovation. Third, it develops an integrated multi-agent simulation framework incorporating a genetic algorithm to investigate the dynamic roles of the network, as well as the institutional and resource mechanisms shaping the emergence and evolution of disruptive innovation.

2. Literature Review

One of the more interesting perspectives in existing disruptive innovation theory is the analysis of the evolutionary process of disruptive innovation.

2.1. Disruptive Innovation as an Evolutionary Process

Disruptive innovation has become one of the most influential concepts in innovation management ever since Christensen introduced the theory in *The Innovator's Dilemma* [10]. Christensen argued that disruptive innovations typically originate in non-mainstream or low-end markets and gradually penetrate mainstream markets as technological improvement outpaces customers' performance requirements. Christensen and Raynor [5] further distinguished disruptive innovation from sustaining innovation according to the degree of

organizational and market change. While sustaining innovation improves existing products along performance dimensions valued by mainstream customers, disruptive innovation creates new markets or reshapes existing ones by offering new value propositions, such as lower cost, greater convenience and improved accessibility. Subsequent studies further emphasized that disruptive innovation often originates in niche markets, challenges incumbent firms' core competencies, and eventually transforms industrial competition by reconstructing market demand and technological trajectories [12–15].

Rather than representing a single technological breakthrough, disruptive innovation is increasingly recognized as an evolutionary process. Existing studies have shown that its emergence and diffusion depend not only on technological superiority but also on organizational adaptation, market competition and ecosystem evolution. For example, Georgantzis and Katsamakos demonstrated through simulation that the diffusion of disruptive innovation follows a replicable evolutionary process characterized by continuous user migration from incumbent technologies to emerging alternatives [16]. Similarly, Adner and Levinthal identified different competitive regimes during disruptive innovation, including convergence, isolation and disruption [17]. Based on a multi-agent simulation model, Shi et al. [18] further found that increasing technological opportunities significantly accelerate the replacement of incumbent firms by disruptive innovators. Collectively, these studies suggest that disruptive innovation should be understood as a dynamic process of emergence, competition and adaptation rather than as a discrete innovation event.

The evolutionary nature of disruptive innovation is further reflected in its dynamic development path. Christensen argued that disruptive innovation evolves gradually from non-mainstream markets toward mainstream markets through continuous value network reconstruction, organizational adaptation and market expansion [1]. Gilbert proposed a three-stage evolutionary process consisting of new market creation, rapid market expansion and eventual replacement of incumbent firms [19]. Petrick and Martinelli emphasized that successful disruptive innovation requires firms to anticipate future customer problems and continuously redefine value propositions from users' perspectives [20]. Similar evolutionary paths have also been identified by Vittori et al. [21], Yang [22], and Salenius et al. [23], who consistently demonstrate that disruptive innovation develops through successive stages involving technology accumulation, market expansion, ecosystem evolution and institutional adaptation.

Despite these advances, the transition from technological invention to market success remains highly uncertain. Many disruptive innovations fail to cross the so-called "valley of death", where promising technologies are unable to achieve large-scale commercialization because of limited market acceptance, insufficient resource support or inadequate institutional environments. Existing studies have shown that overcoming this critical transition requires not only technological capability but also continuous interactions among heterogeneous innovation actors throughout the evolutionary process [19,23].

Overall, the existing literature increasingly recognizes disruptive innovation as a dynamic evolutionary process involving adaptation, competition and continuous market selection. Although these studies have substantially advanced our understanding of disruptive innovation, they predominantly explain its emergence by examining isolated technological, organizational and institutional determinants. Comparatively little attention has been devoted to explaining the evolutionary mechanisms through which heterogeneous innovation agents shape the emergence and evolution of disruptive innovation in complex adaptive systems. This research gap motivates the present study to explore disruptive innovation from the perspectives of the network mechanism, institutional mechanism and resource mechanism, thereby providing a mechanism-based explanation for its emergence and evolution.

2.2. Existing Explanations of Disruptive Innovation

2.2.1. Network Perspective

The network perspective explains disruptive innovation as an evolutionary process driven by knowledge diffusion, collaborative learning and adaptive interactions among heterogeneous innovation actors. Rather than relying solely on internal technological capabilities, firms acquire external knowledge and complementary resources through collaborative innovation networks, thereby enhancing their innovation capabilities and facilitating the commercialization of disruptive technologies.

Existing studies consistently suggest that innovation networks play a critical role throughout the evolution of disruptive innovation. Collaborative interactions among heterogeneous actors facilitate knowledge exchange, organizational learning and market development, enabling latecomer firms to achieve innovation catch-up through R&D networks spanning geographical, organizational and knowledge boundaries [24]. Empirical studies further demonstrate that network structural characteristics—including network centrality, stability and structural holes—significantly promote disruptive innovation by improving knowledge diffusion and resource integration [25]. Simulation studies likewise confirm that disruptive innovation evolves through continuous interactions among innovation agents, with organizational behavior, consumer learning and network dynamics jointly influencing technology diffusion, market competition and industry evolution [26].

Although previous studies have substantially advanced our understanding of innovation networks, they mainly emphasize static network characteristics or network effects on innovation performance. Comparatively little attention has been devoted to explaining how adaptive interactions among heterogeneous innovation agents drive the emergence and evolution of disruptive innovation. This limitation highlights the need for a mechanism-based explanation of how adaptive interactions among heterogeneous innovation agents shape the emergence and evolution of disruptive innovation, which is addressed through the network mechanism developed in this study.

2.2.2. Institutional Perspective

The institutional perspective explains disruptive innovation from the standpoint of external institutional environments, emphasizing that innovation is embedded within broader socio-technical systems consisting of policies, regulations, infrastructure, market institutions and social norms. Appropriate institutional support reduces uncertainty, facilitates technology commercialization and enables disruptive innovations to evolve from protected niches toward mainstream markets.

Existing studies consistently demonstrate that institutional environments play a decisive role in helping disruptive technologies overcome the “valley of death”. Research based on Strategic Niche Management (SNM) suggests that protected niches and policy support provide favorable conditions for technological experimentation, capability accumulation and market creation [27]. Empirical evidence further indicates that inadequate infrastructure, weak policy support and institutional constraints constitute major barriers to disruptive innovation [28]. From a broader institutional perspective, governments influence disruptive innovation through policy guidance, institutional arrangements and innovation strategies that facilitate technology commercialization and industrial transformation [29,30]. Meanwhile, socio-technical systems theory emphasizes that disruptive innovation evolves within complex institutional environments involving scientific knowledge, production systems, regulatory frameworks, infrastructure and market demand, all of which jointly shape innovation trajectories [31–34].

Although previous studies have highlighted the importance of policy support and institutional environments, they mainly examine individual policy instruments or institutional

effects. Comparatively little attention has been devoted to explaining how institutional environments continuously shape the adaptive evolution of disruptive innovation. This gap highlights the need for a mechanism-based explanation of how institutional environments continuously shape the evolutionary trajectory of disruptive innovation, which is addressed through the institutional mechanism developed in this study.

2.2.3. Resource Perspective

Resource perspective explains disruptive innovation by emphasizing the acquisition, accumulation and reconfiguration of strategic resources throughout the innovation process. Rather than being determined solely by technological superiority, disruptive innovation depends on firms' capabilities to mobilize financial resources, technological knowledge, human capital and organizational capabilities to support experimentation, technological learning and market expansion.

Existing studies consistently recognize resource support as a prerequisite for overcoming the "valley of death". Insufficient resource allocation has been identified as a major obstacle preventing disruptive technologies from entering mainstream markets, while sustained investment is essential for technological improvement and commercialization [35,36]. Successful disruptive innovation further requires the integration of multiple forms of strategic resources—including physical, intellectual and social capital—as well as effective technology incubation and transfer mechanisms [37]. These studies collectively suggest that resource accumulation and capability development provide essential conditions for the long-term evolution of disruptive innovation.

Although previous studies have substantially improved our understanding of resource availability and allocation, they mainly focus on resource quantity or investment intensity. Comparatively little attention has been devoted to explaining how heterogeneous innovation agents continuously accumulate, integrate and reconfigure strategic resources during the evolutionary process of disruptive innovation. This gap highlights the need for a mechanism-based explanation of how strategic resources are continuously accumulated, integrated and reconfigured throughout the evolutionary process of disruptive innovation, which is addressed through the resource mechanism developed in this study.

2.3. Research Gap and Theoretical Framework

Although existing studies have explained disruptive innovation from the perspectives of innovation networks, institutional environments and strategic resources, they predominantly examine these perspectives separately and provide limited understanding of the evolutionary mechanisms underlying disruptive innovation in complex adaptive systems. As disruptive innovation involves continuous adaptation, learning, competition and selection among heterogeneous innovation agents, a mechanism-based perspective is needed to explain how disruptive innovation emerges and evolves over time.

The selection of these three mechanisms is grounded in the multi-level logic of Complex Adaptive Systems (CAS) and the evolutionary characteristics of disruptive innovation. Specifically, the network mechanism captures the relational structure through which heterogeneous agents interact and exchange knowledge; the institutional mechanism captures the external rules and incentives that shape agents' adaptive behaviors; and the resource mechanism captures the internal capabilities and resource configurations through which firms learn, experiment, and adapt. These mechanisms operate at different but interconnected levels: networks shape interaction and information flows, institutions condition the environment in which such interactions occur, and resources determine firms' capacity to respond to and exploit emerging opportunities. Their interaction therefore provides a

theoretically coherent explanation of how decentralized firm-level adaptation can generate industry-level disruptive innovation.

Building upon the above literature, this study conceptualizes disruptive innovation as an evolutionary process driven by three evolutionary mechanisms: the network mechanism, the institutional mechanism, and the resource mechanism. Drawing on Complex Adaptive Systems (CAS) Theory, the network mechanism explains how adaptive interactions and knowledge diffusion among heterogeneous innovation agents facilitate the emergence and diffusion of disruptive innovation. The institutional mechanism explains how institutional environments shape firms' adaptive behaviors and influence innovation trajectories through policy support and socio-technical conditions. The resource mechanism explains how firms accumulate, integrate and reconfigure strategic resources to sustain technological learning, capability development and market expansion throughout the innovation process. Together, these mechanisms provide a process-oriented explanation of disruptive innovation from the perspective of evolutionary dynamics.

Since these evolutionary mechanisms are theoretical constructs that cannot be directly implemented in computational simulations, they are operationalized through observable variables in the multi-agent simulation model. Specifically, the network mechanism is represented by social network structure, the institutional mechanism by government subsidy intensity, and the resource mechanism by resource investment. A multi-agent simulation integrating a genetic algorithm is then developed to investigate the evolutionary effects of the three mechanisms on disruptive innovation.

Figure 1 presents the theoretical framework of this study and illustrates the relationships among the three evolutionary mechanisms, their operational variables and the multi-agent simulation model.

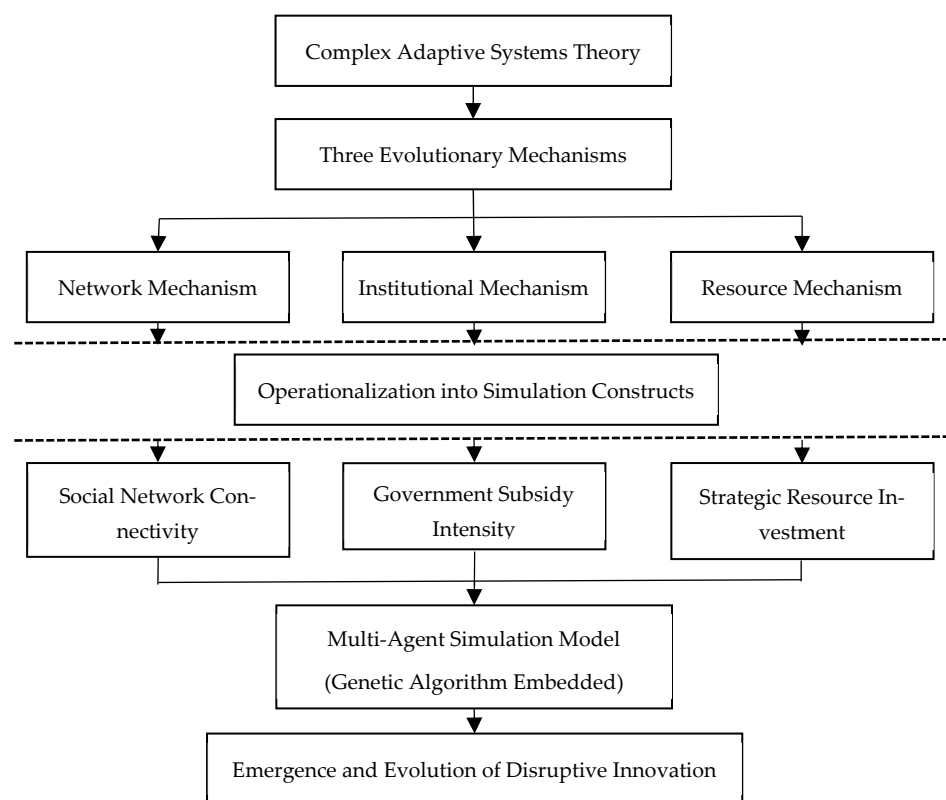


Figure 1. Theoretical framework of three evolutionary mechanisms underlying disruptive innovation. Note: The dashed line is used to distinguish the theoretical layer from the simulation layer. The area above the dashed line represents the theoretical layer, while the area below the dashed line represents the simulation layer.

3. Methodology

3.1. Methodological Rationale

This study investigates disruptive innovation from the perspective of complex adaptive systems, in which innovation is regarded as an evolutionary process emerging from the interactions and adaptive behaviors of heterogeneous innovation agents. Such a process is characterized by decentralized decision-making, continuous learning, resource recombination, market selection and institutional adaptation, making conventional analytical models insufficient for capturing its dynamic evolutionary nature. Therefore, a multi-agent simulation (MAS) approach is adopted as the methodological foundation of this study.

The use of MAS is justified for three reasons. First, disruptive innovation involves multiple heterogeneous agents, including firms, innovators, governments and market participants, whose decisions are autonomous yet interdependent. Innovation outcomes emerge from the continuous interactions among these agents rather than from the behavior of any single actor. Multi-agent simulation provides an appropriate framework for modeling such decentralized interactions and the emergence of system-level innovation dynamics.

Second, disruptive innovation is inherently an adaptive evolutionary process. Innovation agents continuously adjust their technological choices, learning strategies and resource allocation according to market feedback and institutional environments. To capture these adaptive processes, this study incorporates a genetic algorithm into the multi-agent framework. The evolutionary operators of genetic algorithms, including selection, crossover and mutation, provide computational analogies for firms' behavioral adaptation. Specifically, crossover represents knowledge recombination and organizational learning through interactions with other innovation agents, while mutation reflects firms' autonomous R&D activities and exploratory innovation. Population selection further approximates the market competition and selection process through which disruptive innovations survive, diffuse and eventually reshape industrial paradigms.

Third, the integrated MAS–GA framework provides an effective computational platform for operationalizing the proposed three evolutionary mechanisms. In the simulation model, the network mechanism is represented by the social network structure among innovation agents, the institutional mechanism is represented by government subsidy intensity, and the resource mechanism is represented by firms' resource investment. These operational variables allow the theoretical mechanisms to be translated into observable simulation parameters while preserving the evolutionary logic of Complex Adaptive Systems Theory.

Overall, integrating multi-agent simulation with a genetic algorithm enables this study to capture the adaptive learning, decentralized interactions and evolutionary dynamics of disruptive innovation. Compared with traditional analytical models, the proposed framework is better suited to explaining how disruptive innovation emerges and evolves through the combined influences of the network mechanism, institutional mechanism and resource mechanism in complex adaptive systems.

3.2. Model Construction

Building upon the theoretical framework developed in Section 2, this study constructs a multi-agent simulation model to investigate the evolutionary process of disruptive innovation in a complex adaptive system. The model conceptualizes disruptive innovation as an emergent outcome arising from the adaptive interactions among heterogeneous innovation agents under the joint influence of the network mechanism, institutional mechanism, and resource mechanism. Rather than directly representing abstract theoretical constructs, the model operationalizes the three mechanisms through observable simulation variables, which are introduced in Section 3.3.

Following the principles of Complex Adaptive Systems (CAS) Theory, the simulation model consists of three interconnected components: heterogeneous innovation agents, an external innovation environment, and evolutionary interaction rules. Innovation agents possess bounded rationality and heterogeneous capabilities and continuously adjust their innovation strategies through learning, competition, imitation, and adaptation. The external environment provides institutional constraints, market selection, and resource conditions under which innovation activities evolve. Through repeated interactions between agents and their environment, disruptive innovation gradually emerges as a self-organizing evolutionary process rather than as the result of isolated decision-making.

To preserve the essential characteristics of disruptive innovation while maintaining analytical tractability, the model is developed under several simplifying assumptions. First, firms are treated as heterogeneous and boundedly rational innovation agents that continuously adjust their innovation strategies through learning, competition, imitation, and adaptation rather than through perfect optimization. Second, disruptive innovation is assumed to emerge at the industry level from decentralized interactions among firms, rather than from isolated organizational decisions. Third, the three theoretical mechanisms are operationalized through observable simulation variables, namely social network connectivity, government subsidy intensity, and strategic resource investment, allowing their dynamic effects to be explicitly examined. Finally, market outcomes—including technology adoption, market share, technological advancement, and product pricing—are generated endogenously through the evolutionary interactions among heterogeneous agents within a complex adaptive system.

To capture the hierarchical characteristics of disruptive innovation, the proposed model adopts a three-level analytical structure, as illustrated in Figure 2. At the micro level, heterogeneous innovation agents make innovation decisions and adapt their behaviors through learning and competition. At the meso level, innovation agents interact through social networks, facilitating knowledge diffusion and collaborative evolution. At the macro level, the institutional environment provides policy support, market selection, and resource conditions that jointly shape the evolutionary trajectory of disruptive innovation. These three analytical levels constitute the structural foundation of the proposed simulation model.

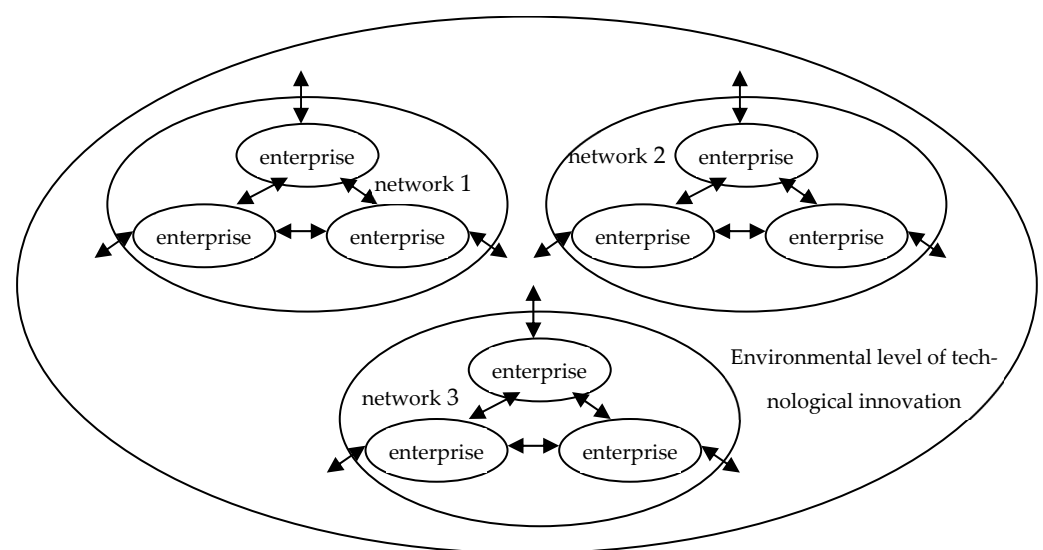


Figure 2. Analytical levels of the disruptive innovation evolution model.

Based on this model architecture, heterogeneous innovation agents repeatedly interact, learn, compete, and evolve within a genetic algorithm framework. Through continuous

adaptation and market selection, the model captures the emergence and evolution of disruptive innovation under different evolutionary conditions. The operationalization of the three evolutionary mechanisms is presented in the following section, while the simulation procedure is described in Section 3.4.

3.3. Operationalization of the Three Evolutionary Mechanisms

To operationalize the proposed theoretical framework, the three evolutionary mechanisms are represented by observable simulation variables. Specifically, the network mechanism, institutional mechanism, and resource mechanism are operationalized by social network structure, government subsidy intensity, and resource investment, respectively. Rather than directly simulating abstract theoretical mechanisms, the model represents them through measurable variables governing agent interactions and environmental conditions. The following subsections explain the theoretical rationale for each operationalization.

3.3.1. Operationalization of the Network Mechanism

The network mechanism describes how interactions among heterogeneous innovation agents facilitate knowledge diffusion, information exchange, collaborative learning, and technological adaptation throughout the innovation process. Since these interaction patterns are determined primarily by the structure of interorganizational relationships, the network mechanism is operationalized by social network structure in the simulation model. Different network structures determine the efficiency of knowledge diffusion, the frequency of agent interaction, and the speed at which disruptive innovations spread across the innovation ecosystem.

3.3.2. Operationalization of the Institutional Mechanism

The institutional mechanism reflects how external institutional environments shape firms' innovation decisions by providing policy incentives, reducing innovation uncertainty, and influencing resource allocation. Among various institutional factors, government support is one of the most direct and observable policy instruments promoting disruptive innovation. Therefore, the institutional mechanism is operationalized by government subsidy intensity, which influences firms' innovation decisions by lowering innovation risks and encouraging technological experimentation under different policy scenarios.

3.3.3. Operationalization of the Resource Mechanism

The resource mechanism explains how firms accumulate, allocate, and reconfigure strategic resources throughout the evolutionary process of disruptive innovation. Resource accumulation directly determines firms' capability to undertake continuous technological exploration and sustain long-term innovation activities. Accordingly, the resource mechanism is operationalized by resource investment, representing firms' investment in innovation-related resources that support capability development, technological accumulation, and market competitiveness.

3.4. Simulation Procedure

The proposed multi-agent simulation models disruptive innovation as an iterative evolutionary process in which heterogeneous innovation agents continuously interact, learn, compete, and adapt under changing environmental conditions. Building upon the operationalization of the three evolutionary mechanisms presented in Section 3.3, the simulation combines multi-agent interactions with a genetic algorithm to capture the dynamic emergence and evolution of disruptive innovation. As illustrated in Figure 3, the simulation procedure consists of six sequential steps.

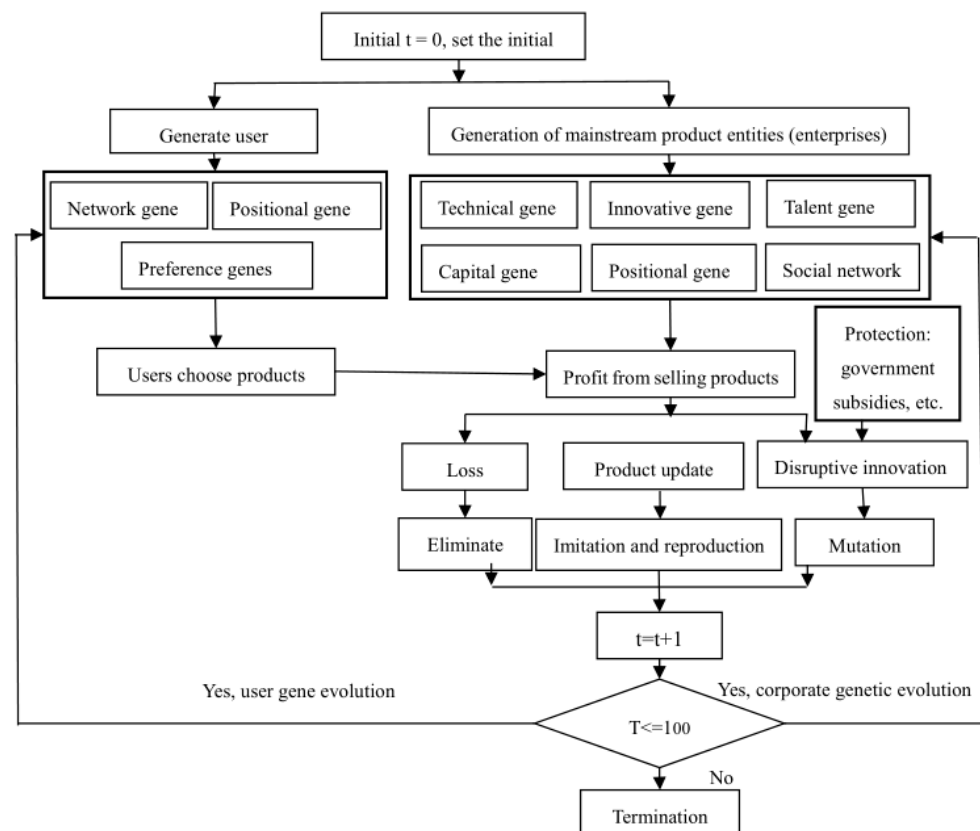


Figure 3. Simulation procedure of disruptive innovation evolution.

Step 1: Initialization. The simulation environment is first initialized by specifying the number of innovation agents, the initial resource endowment, the social network structure, the level of government subsidy, and other environmental parameters. Each innovation agent is assigned heterogeneous characteristics to reflect differences in innovation capability and adaptive behavior.

Step 2: Agent Interaction. Innovation agents interact with neighboring agents through the predefined social network. During these interactions, knowledge is exchanged, information is updated, and collaborative or competitive relationships are established, providing opportunities for adaptive learning and technological diffusion.

Step 3: Adaptive Learning and Innovation. Based on information acquired from the interaction process, innovation agents update their innovation strategies according to their expected returns, accumulated knowledge, and available resources. Learning, imitation, and independent exploration jointly determine the generation of new innovation solutions.

Step 4: Genetic Evolution. The updated innovation strategies are further optimized through the genetic algorithm. Selection, crossover, and mutation operators simulate the evolutionary behaviors of innovation agents, allowing superior innovation strategies to be retained while generating technological diversity through adaptive variation.

Step 5: Market Selection. The performance of each innovation agent is evaluated according to the fitness function defined by market competition and innovation outcomes. Innovation agents with higher fitness are more likely to survive and expand, whereas less competitive agents gradually exit the evolutionary process, reflecting the market selection mechanism underlying disruptive innovation.

Step 6: Iteration and Convergence. The simulation repeats the above procedures until the predetermined stopping criterion is satisfied. Through repeated interactions, adaptive learning, genetic evolution, and market selection, disruptive innovation gradually emerges and evolves as a self-organizing process within the complex adaptive system.

3.5. Parameter Setting of Models

To ensure the reliability and comparability of the simulation experiments, the model parameters are initialized according to the characteristics of disruptive innovation, the assumptions of the proposed multi-agent simulation framework, and the objective of examining the relative effects of different evolutionary mechanisms. Because the purpose of this study is theory development and mechanism identification rather than prediction of a specific industrial system, the parameter settings are theory-driven and scenario-based instead of being empirically calibrated. Unless otherwise specified, all parameters remain unchanged across different simulation scenarios, allowing the independent effects of the network mechanism, institutional mechanism, and resource mechanism to be systematically examined. Accordingly, the initial parameter values should be interpreted as theoretically plausible baseline conditions for comparative evolutionary experiments rather than as empirical estimates of a particular industry.

The simulation is conducted over 30 evolutionary periods, as preliminary simulation experiments indicate that the structural proportions of enterprise types converge to a relatively stable state after approximately 30 iterations. Following the market structure theory [38], the simulation assumes a competitive oligopolistic market in which firms simultaneously compete and cooperate while disruptive innovation emerges under the dominance of old technologies. Accordingly, the initial number of firms is specified between 4 and 40, and the baseline simulation is conducted with 10 firms, which generate stable and representative evolutionary outcomes while maintaining computational efficiency.

Consistent with the operationalization developed in Section 3.3, the institutional mechanism is represented by government subsidy intensity, whereas the network mechanism is represented by the social network coefficient. Rather than reproducing a particular policy regime or industrial environment, the parameter ranges are designed to represent typical evolutionary scenarios commonly observed during the early stages of disruptive innovation. Based on preliminary sensitivity experiments and observed industrial practices, the government subsidy ratio is 50%, representing different levels of institutional intervention, whereas the social network coefficient ranges from 1 to 4, representing innovation networks with different degrees of connectivity and knowledge diffusion. The preliminary sensitivity analysis further indicates that moderate variations in these parameter values do not alter the qualitative evolutionary patterns reported in this study, suggesting that the simulation results are robust to reasonable parameter changes.

Therefore, the selected parameter settings are intended to ensure the internal validity, comparative validity, and theoretical interpretability of the simulation experiments. The model is designed to explain the evolutionary mechanisms underlying disruptive innovation rather than to reproduce or predict the development trajectory of a particular industry. The initial values of the main model parameters are summarized in Table 1.

Table 1. Initial values of the main parameters of the model.

Model Parameter Name	Letter	Meaning of Parameters	Initial Value	Basis
Simulation life	T	Duration of system simulation	30	Preliminary convergence experiments
Number of initial enterprises	m	Number of enterprises in the initial state	4–40	Competitive oligopoly

Table 1. *Cont.*

Model Parameter Name	Letter	Meaning of Parameters	Initial Value	Basis
The proportion of government subsidies	gov	Government subsidies for disruptive innovation by sales	50%	Scenario design and sensitivity experiments
Social network coefficient	Network	Number of agents interacting with the company's social network	1–4	Scenario design and knowledge diffusion theory

3.6. Agent Attributes of Enterprises and Users

To capture the heterogeneity emphasized by Complex Adaptive Systems (CAS) theory, the proposed multi-agent simulation distinguishes between enterprise agents and user agents, each possessing different behavioral characteristics and adaptive capabilities. Enterprise agents represent firms engaging in innovation activities, whereas user agents represent potential adopters whose preferences and adoption decisions jointly determine the market diffusion of disruptive innovation. The interactions between these heterogeneous agents provide the micro-foundation for the emergence and evolution of disruptive innovation.

To distinguish disruptive innovation from generic technology diffusion, this study does not define disruption solely by the diffusion of a new technology. Instead, disruptive innovation is operationally identified as an evolutionary process in which a technology initially competes with an incumbent technological paradigm and, through adaptive learning, market selection, and diffusion, progressively improves its technological performance, expands its market share, and increases enterprise adoption, eventually achieving competitive dominance over the incumbent technology. Accordingly, the simulation tracks four complementary outcomes: technological advancement, market share, enterprise adoption, and relative price dynamics. The emergence of disruptive innovation is therefore reflected not by adoption alone, but by the joint evolution of technological capability, market position, and competitive replacement.

3.6.1. Enterprise Attributes

According to the characteristics of a disruptive innovation system, the enterprise agent in the simulation model contains two types: an enterprise that adopts the old technology and an enterprise that adopts disruptive technology. To reflect the characteristics of disruptive technologies, we have made a typological division of each attribute of the enterprise.

- (1) Technical attributes of enterprises: Polani divides knowledge into tacit knowledge and explicit knowledge [39]. The knowledge that is usually expressed in written words, diagrams and mathematical formulas is called explicit knowledge. Unpresented knowledge contained in actions is called tacit knowledge. Tacit knowledge is highly personalized knowledge that is difficult to standardize [40]. Disruptive innovation is characterized by high risk as well as the uncertainty of benefits and distribution, and tapping into ineffable tacit knowledge at the early stage of innovation is the key to disruptive innovation. In the evolution process of disruptive innovation, the interaction of tacit knowledge and explicit knowledge is constantly transforming and jointly driving the development of enterprises.
- (2) Resource attributes of enterprises: The enterprise resources of the simulation model mainly include capital and talents. According to the Asset Specificity Theory of Williamson [41], we divide capital into the general capital gene and the special capital gene, and the talent gene is divided into general talent and senior talent. In the process

of disruptive innovation, these two types of resource genes will play different roles. Special capital and senior talents have a greater influence on the successful realization of disruptive innovation.

- (3) Location attributes of enterprises: The location of enterprise agent is not only spatial but also based on the relationship with market users. This paper expresses the location gene of enterprises and users with the two-dimensional coordinate axis.
- (4) Social network attributes of enterprises: To simplify the analysis of the model, this paper expresses the degree of interaction between enterprises as social networks. According to the characteristic that the innovation process of enterprises has a herding nature, the greater the number of enterprises refer to other enterprises in the innovation process, the higher the degree of their social network.

3.6.2. User Attributes

(1) Users' location and social network attributes: For users, their location is randomly given on the coordinate axis, the consumption process has a herd mentality, and the users' final product choice is also influenced by the purchase behavior of their neighboring users. Therefore, we set users to modify their preferences by referring to their nearest neighbors, and the number of neighbors (i.e., users' social network indicators) is randomly given in a certain range. (2) Preference attributes of users: The users' preference is the comprehensive attitude towards the enterprises' technology, location, social network and resource attributes, and their preference expresses the form of the enterprise's preference through weighting. The final level of customer satisfaction rises as more user preferences are accommodated.

In the multi-agent simulation of disruptive innovation, enterprises and user agents are living in a certain environment. The environment plays two main roles: first, it provides a space for the interaction between enterprises and user agents, so that each enterprise and user agent can generate interaction or operational behavior; second, it constrains the behavior of enterprises and user agents. There exist many varying factors affecting the agents' behavior in the environment. Apart from the spatial location and the spatial distance, factors such as resources and social network value make sense. These factors can affect all behaviors of the agent, and the structure of the agent is a chromosome represented by several agent attribute genes.

According to the above attribute requirements, we can define the simulation initial value of the agent attribute, as shown in Table 2.

Table 2. Initial definition of agent attributes.

Agent Properties	Agent Attribute Variable	Initial Values
Technical attributes of the enterprises	Technical performance value: Te_0	1-2-3 (Low-Medium-High)
	Ratio of old technology tacit knowledge: Te_1	10–30%
	Ratio of disruptive technology tacit knowledge: Te_2	0–5%
Enterprise resource properties	Ratio of common capital input: $\times 1$	1–40% of random values
	Ratio of dedicated capital input: $\times 2$	1–40% of random values
	Ratio of general talent input: $\times 3$	1–40% of random values
	Ratio of senior talent input: $\times 4$	1–40% of random values

Table 2. Cont.

Agent Properties	Agent Attribute Variable	Initial Values
Location properties	Corporate locations	Random values of (0, 1)
	User location	Random values of (0, 1)
Social network properties	Corporate social network	1–4
	User social network	1–10

The heterogeneous attributes of enterprise and user agents provide the behavioral foundation for the operationalization of the three evolutionary mechanisms. Through repeated interactions, adaptive learning, and market selection, these heterogeneous agents collectively generate the evolutionary dynamics of disruptive innovation examined in the subsequent simulation experiments.

3.7. Agent Behavior and Rules

(1) Agents' imitation of the innovation attribute

Learning behavior is a replication of an innovation with low adaptation to the part of an agent with high adaptation corresponding to their innovation gene, should the innovation agent be able to communicate the innovation with other agents. This generates the willingness to communicate during each period with probability. The communication objectives of the agent are the innovation with the largest market share in the social network that it knows at that time. When the market shares in this period are greater than or equal to the minimum market share allowed by the other party, and they all have the willingness to communicate during this period and have not yet exchanged out-of-date information, they will be matched for learning and communication.

The learning rules adopt the “encircling” mode, that is, the starting point and learning length of the randomly generated innovation gene. If the length exceeds the last gene, it will start from the first round and continue learning until the whole length of learning is completed. An innovation is formed after learning that low fitness, as well as the agents with high fitness, remained unchanged. After each study, the agents with a lower fitness degree pay each other certain resources as learning costs.

The innovation network of a firm is created by creating a two-dimensional space that mimics a real market. In this two-dimensional space, firms and users are randomly or coincidentally distributed within a range defined by a distance threshold h . The agents within the range are called neighbors. In the simulation, firms are influenced by the adoption decisions of these neighbors. m_j denotes the number of agents choosing disruptive innovation behavior in the social network of agent j . The proportion of $(m - 1)$ neighbors around the firm that choose the disruptive innovation is z . The firm's innovation choice behavior is f_j , which can be expressed as the following equation: when this proportion z exceeds d , the firm chooses the disruptive innovation, denoted by 1, and when z is less than d , the firm does not choose the disruptive innovation, denoted by 0.

$$z = \left(\frac{m_j}{m} \right) \times 100\%, \quad (1)$$

$$f_j = \begin{cases} 1, & z > d \\ 0, & z < d \end{cases} \quad (2)$$

$$a_{ij} = \begin{pmatrix} 1 & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mn} \end{pmatrix} \quad (3)$$

The interaction of innovation activities in a firm can be represented by the matrix a_{ij} , representing the interaction of the innovation agents within the evolutionary process of disruptive innovation.

The model assumes that individual firms consider two main factors when deciding whether to accept a disruptive innovation. One is a measure of whether the utility of the innovative innovation meets the requirements; the second is a measure of the impact on the surrounding adjacent population.

(2) Variation of the agent's innovation gene

The variation of the innovation gene by the agent is controlled by three factors: the probability of variation of the agent's innovation gene, the probability of variation of an innovation-related gene, and the magnitude of variation. In each period, the agent changes with specific probability after learning. Giving each gene a mutation probability, the value of the innovation gene is agent to the normal distribution, with the original gene value as the mean value and the variation range as the standard deviation. If the new gene value exceeds the feasible range, the boundary value of the feasible region is taken. The innovation formed by variation replaces the original innovation. After each mutation, the agent will immediately reduce a certain amount of resources as the cost of mutation operation consumption.

The process of variation is similar to Schumpeterian innovation [42], which is an endogenous process driven by the entrepreneur's individual creativity. Innovation comes from a new combination. It is therefore attributed to the subjective imagination or motivation of the entrepreneur. The process can be illustrated by the following example (see Table 3).

Table 3. Examples of the variation process of innovative genes.

Genes	X_1	X_2	X_3	...	X_k	...	X_n
Previous Issue	1	0	1	...	0	...	0
Current Issue	1	0	1	...	1	...	0

The first row of Table 3 shows the current factor usage scheme adopted by the firm. For example, X_k indicates that by applying the variation rule, the entrepreneur innovates the input usage of the X_k th gene factor. 1 indicates that the K th innovative gene is adopted and 0 indicates that the K th innovative gene is not adopted. Then, when deciding the number of innovative genes used, based on the importance of experience, the average value of the existing genes used is selected in this paper.

(3) The agent's study of technical knowledge

The innovation agent in this paper can also adjust and learn the attributes of technical knowledge, with the probability of knowledge learning being P . The knowledge attribute M of the agent is expressed as:

$$M_i = (I_i, m_i^L, T_i, R_i, d_i, P_i) \quad (4)$$

The brackets indicate the learning probability of innovative genes of agents, the lower threshold of market share of learning objects, the probability of variation of agents, the

probability of variation of each gene, the standard deviation of adjusting attribute genes of agents, and the learning probability of technical knowledge in turn.

(4) User satisfaction

In a multi-agent genetic algorithm, the fitness function determines the survival and death of the agent. In the evolutionary model of disruptive innovation, the choice of user agents implies the survival and elimination of product agents. Generally speaking, users will choose the product satisfying them best. Therefore, the satisfaction rating of a product becomes the standard of whether users will choose the product. For the user agents, if the satisfaction of Product A is the highest, Product A is selected; otherwise, Product A is eliminated. This is the same as the fitness function in a multi-agent genetic algorithm, so the user satisfaction evaluation function can be considered the fitness function in the evolutionary model of disruptive innovation.

Due to the non-uniqueness of users and the heterogeneity of users' choice behavior, different satisfaction evaluation rules are also set in the model. Each user has its satisfaction evaluation function, and the fitness function of the model is not unique. Specifically, the user agent selects products of interest within a certain range and scores the degree of satisfaction of each product. First, users measure the weight of each attribute gene in the product agent, score each attribute gene in each product agent, and then obtain the comprehensive score of each product agent by comprehensive weighting, that is, the satisfaction of each product. Finally, after the comparison of the satisfaction scores, users will choose the product with the highest satisfaction.

In the evolutionary model of disruptive innovation, all the product agents entering a certain range of users' selection are the general solutions of the model, and the product agent finally selected by the user agent is the optimal solution corresponding to the fitness function. The enterprise agents can be divided into several attribute genes. Since the fitness function in the model is not unique, the number of optimal solutions in the model is also not unique, and there are multiple optimal solutions in the same period. Its optimization problem can be expressed as follows:

$$\max f(x) = f(x_1, x_2, x_3, \dots, x_n), x_1 \dots x_n \in R, \quad (5)$$

where x denotes the disruptive innovation project and its innovator (not necessarily a firm; a firm can have multiple innovations or multiple firms co-creating a project), corresponding to the chromosomes (agents) of the multi-agent genetic algorithm; $x_1, x_2, x_3, \dots, x_n$ are the n specific innovation elements of x , corresponding to the innovation genes of the genetic algorithm, where n is taken as a constant; $f(x)$ is the value assessment function of the environment (i.e., the market) for the innovation agent x ; and R is the resource, cost, and management constraints of the disruptive innovation.

The fitness function in this genetic algorithm is similar to a satisfaction function. At a certain period, a certain innovation population consists of P disruptive innovations, where a certain disruptive innovation agent is denoted as a_i . The environment where its innovation is located is mainly a market selection mechanism, which is achieved through the fitness function $F(a_i)$. It is assumed that there exists an ideal situation for this certain top innovation, i.e., a better satisfaction rating, which can be referred to as the ideal solution corresponding to the multi-agent genetic algorithm, denoted as r_j , where $j = 1, 2, \dots, N$, which denotes the ideal solution affecting the innovation agent. $F(a_i)$ depends on the degree of coincidence between a_i and r_j , which can be expressed in the model as distance, i.e., the closer a_i is to r_j , the larger the fitness function. Giving the innovation

elements of disruptive innovation the same evaluation weights, their fitness function can be expressed as:

$$F(a_i) = \frac{1}{\sum_{j=1}^N |a_{ij} - r_j|}, \quad (6)$$

The parameter $a_i \in [0, 1]$ represents the weighting factor that balances the relative importance of product performance and product price in determining the overall satisfaction of the agent.

(5) Disruptive innovation adoption decisions and criteria

There are two main factors that individual firms consider when deciding whether to accept a disruptive innovation. The first is whether the utility of the innovation meets the requirements; the second is the influence of the surrounding neighboring agents.

The expected utility of a firm's adoption of a disruptive innovation, computed from the satisfaction (utility) function in Equation (5), must reach a critical level of utility, F (threshold), defined by the adoption decision rule in Equation (7), before the firm will adopt the innovation. When $0 < U_{ij} < U$, although the enterprise adopts the new innovation to obtain certain economic benefits, there is not much difference compared with the original innovation, and the enterprise's motivation to adopt the disruptive innovation is low. Therefore, the decision function for the adoption of innovation by the firm is:

$$f(U_{ij}) = \begin{cases} \text{Adopted, } U_{ij} \geq U_{ij}^* \\ \text{Not adopted, } U_{ij} < U_{ij}^* \end{cases}. \quad (7)$$

When the firm's utility for multiple innovations all exceed U_{ij}^* , the firm selects a particular innovation with a certain probability, based on the principle that the more the threshold is exceeded, the higher the probability of selection.

(6) The elimination of enterprise agents and the emergence of new ones

In the process of disruptive innovation evolution, some enterprises with high adaptability and large resources gradually gain the 'advantageous' position, while the relatively 'inferior' enterprises may be eliminated.

The rule of the agents' death is: when the agent's resources fall below the minimum threshold of resources for several consecutive cycles (i.e., when there are insufficient funds to maintain the technology's continuous development), the agent will die.

The rule for the generation of new agent is that the agent with the largest fitness value will copy a certain number of new agents to describe the diffusion of the excellent gene attributes.

The new agent generation rule is that the agent with the highest fitness value among all innovative agents will replicate a certain number of new agents to describe the diffusion of good innovations. To avoid the phenomenon of "innovation prematurity", each new agent, despite its technical genes coming from the original agent, has all its innovation management method genes reset to a random number between $[0, 1]$ to describe R&D agents that use the same advanced innovation but with different management methods.

3.8. Reproducibility and Computational Details

To enhance reproducibility, this subsection summarizes the model specification and computational protocol. The behavioral rules, including agent imitation, gene variation, knowledge learning, user satisfaction-based fitness evaluation, adoption decisions, and agent entry and exit, are formalized in Section 3.7. The core mathematical components are specified in Equations (4)–(7).

The simulation is implemented in MATLAB 2022 with $n = 200$ consumers, $m = 10$ enterprises (baseline; sensitivity range: 4–40), $x = 4$ client business groups, and a simulation horizon of $T = 30$ periods. Government subsidy intensity $zfbtr$ serves as the institutional lever. Consumer choice follows the satisfaction function in Equation (4), with the new-technology weight amplified fivefold for $t \geq 2$. Enterprise capital and technology stocks evolve according to the learning rules in Section 3.7, with $(C, A) = (15, 40)$ for social network connectivity and $(C, A) = (100, 150)$ for the four resource stocks. The disruptive-technology growth function incorporates the monotonic subsidy term $SUBSIDY_K(zfbtr - 50)$, where $SUBSIDY_K = 0.0008$. The worst-selling firm switches to disruptive technology according to the “valley of death” entry rule, while other firms imitate the best-selling firm’s input ratios.

To improve statistical reliability, this article conducted 30 independent replications, using seeds $2026 + s$, $s = 0, \dots, 29$. Section 4 reports the mean trajectories and corresponding 95% confidence intervals across these replications. All stochastic initializations follow the uniform distributions specified in Tables 1 and 2. For transparency and reproducibility, the simulation code and parameter settings are available upon reasonable request to facilitate independent verification.

4. Simulation Results

This section presents the simulation results and examines the effects of the three evolutionary mechanisms on the emergence and evolution of disruptive innovation.

4.1. Baseline Evolutionary Dynamics

Figure 4 presents the baseline diffusion dynamics of disruptive technology based on 30 independent simulation replications using seeds 2026–2055. Disruptive technology starts with zero market share and follows an S-shaped diffusion trajectory, characterized by an initial stage of gradual adoption followed by a rapid increase in market penetration. The technology crosses the 50% market-share threshold at a mean of 11.0 periods (95% CI: 9.7–12.3). Meanwhile, incumbent technology exhibits a corresponding decline in market share and eventually exits the market, indicating the displacement of incumbent technology by the emerging technology.

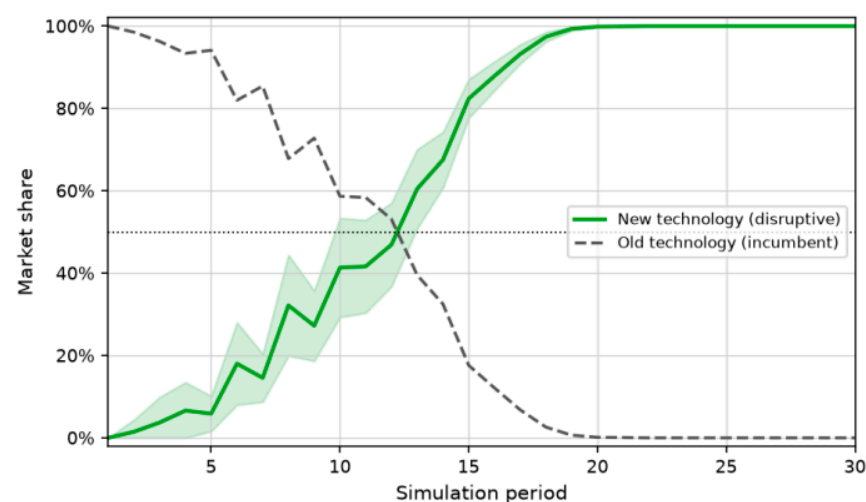


Figure 4. Baseline diffusion dynamics of disruptive technology. Note: Solid green line: mean new-technology market share across $R = 30$ replications; shaded area: 95% confidence interval; dashed grey line: old-technology market share; dotted horizontal line: 50% penetration threshold.

The baseline results establish the model’s ability to reproduce a complete evolutionary transition from technological emergence to market dominance. More specifically, the

observed pattern consists of three successive stages: slow initial emergence, accelerated market transition, and eventual technological dominance. This baseline trajectory provides the reference point for examining how the network, institutional, and resource mechanisms alter the evolutionary path of disruptive innovation in the subsequent analyses.

4.2. Effects of the Network Mechanism

The network mechanism is examined through four complementary dimensions of disruptive innovation evolution: market penetration, enterprise adoption, market-price transition, and technological catch-up. Across these dimensions, social network connectivity captures how network-based interactions and adaptive feedback shape the relative evolutionary positions of incumbent and disruptive technologies.

Proposition 1. *Higher social network connectivity delays the market penetration of disruptive innovation.*

Figure 5 shows that higher social network connectivity substantially delays the market penetration of disruptive innovation. Under low network connectivity, the mean market-penetration time is 8.0 periods (95% CI: 7.2–8.8), whereas under high network connectivity it increases to 14.8 periods (95% CI: 11.6–17.9). Thus, stronger network connectivity is associated with a longer transition from incumbent dominance to disruptive-technology penetration.

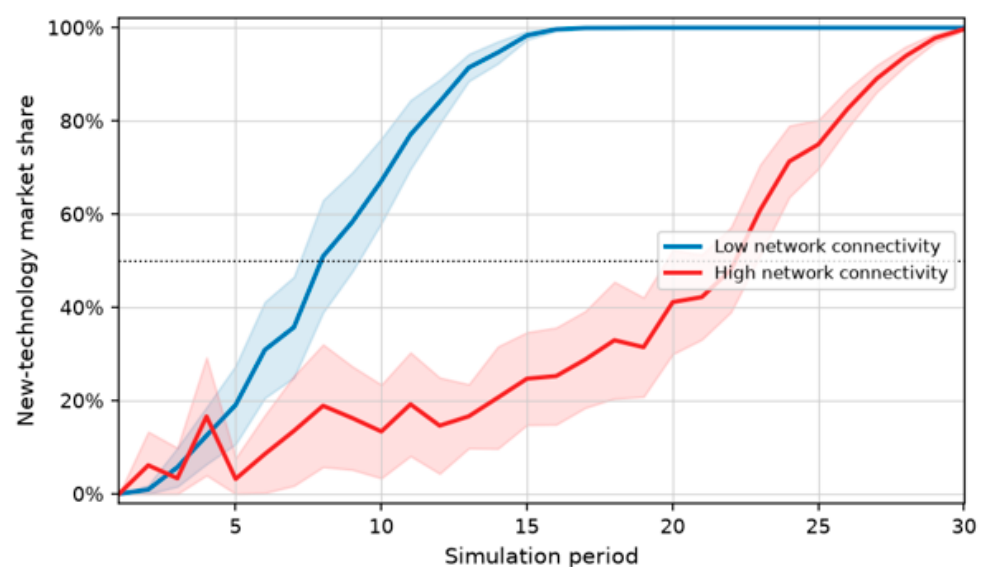


Figure 5. Market-share evolution under low ($\text{net_scale} = 0.5$) and high ($\text{net_scale} = 4.0$) social network connectivity.

This effect arises from the adaptive feedback structure of the model. Because incumbent firms initially hold the market advantage, greater network connectivity increases their sales and, consequently, their capacity to accumulate network connectivity, technological capabilities, and other strategic resources. These reinforcing feedbacks strengthen the incumbents' adaptive position and raise barriers for the disruptive entrant. From a Complex Adaptive Systems perspective, therefore, network connectivity can generate path-dependent incumbent entrenchment when network advantages are concentrated among established firms.

This finding should not be interpreted as indicating that network connectivity inherently constrains disruptive innovation. Rather, the effect depends on how network advantages are distributed across incumbent and emerging firms. In the present model,

network connectivity is introduced as a firm-level initial endowment and subsequently reinforced through adaptive learning; network topology and the openness of incumbent networks to new entrants are not explicitly modeled. Accordingly, Proposition 1 concerns the incumbent-entrenchment effect of social network connectivity under the specified model conditions, rather than a general negative effect of networks on disruptive innovation.

Proposition 2. *Higher social network connectivity reduces enterprise adoption of disruptive innovation.*

Figure 6 shows that higher social network connectivity slows enterprise adoption of disruptive technology. Under low network connectivity, enterprise adoption increases more rapidly, whereas high network connectivity results in a slower transition toward disruptive-technology adoption. This pattern is consistent with the market-level effect observed in Figure 5, indicating that stronger network connectivity delays both market penetration and firms' adoption of disruptive technology.

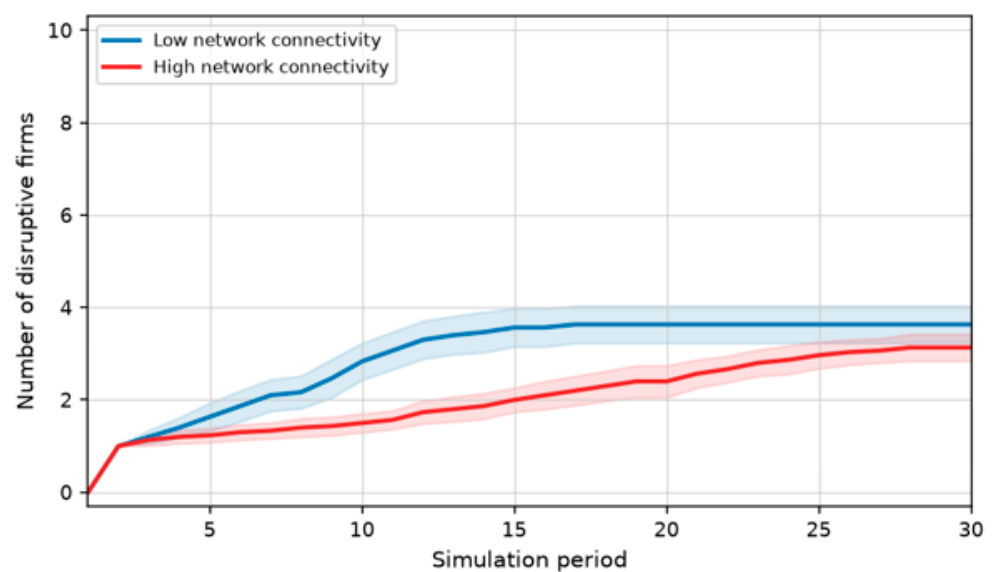


Figure 6. Number of enterprises adopting the disruptive technology under low and high social network connectivity.

This effect can be attributed to the reinforcing feedback between network connectivity and firms' adaptive performance. Incumbent firms with stronger network connectivity are more likely to maintain higher sales and accumulate technological and organizational resources through learning. These advantages reinforce their market position, weakening firms' incentives to switch toward disruptive technology while making it harder for the new technology to attract enterprise adopters. From a Complex Adaptive Systems perspective, enterprise adoption emerges from interactions among firms' network positions, adaptive learning, and market selection rather than technological characteristics alone.

Together with Proposition 1, this result suggests that social network connectivity reinforces incumbent advantage at both the market and firm levels. However, because network connectivity is initially distributed as a firm-level endowment and reinforced through adaptive learning, the finding should be interpreted as an incumbent-entrenchment effect on enterprise adoption under the specified network configuration, rather than a universal negative effect of network connectivity on technology adoption.

Proposition 3. *Higher social network connectivity delays the price transition toward disruptive technology.*

Figure 7 shows that higher social network connectivity delays the price transition toward disruptive technology. Compared with the low-connectivity scenario, the high-connectivity scenario exhibits a slower adjustment in the relative prices of competing technologies, indicating that stronger connectivity prolongs the price transition during technological substitution.

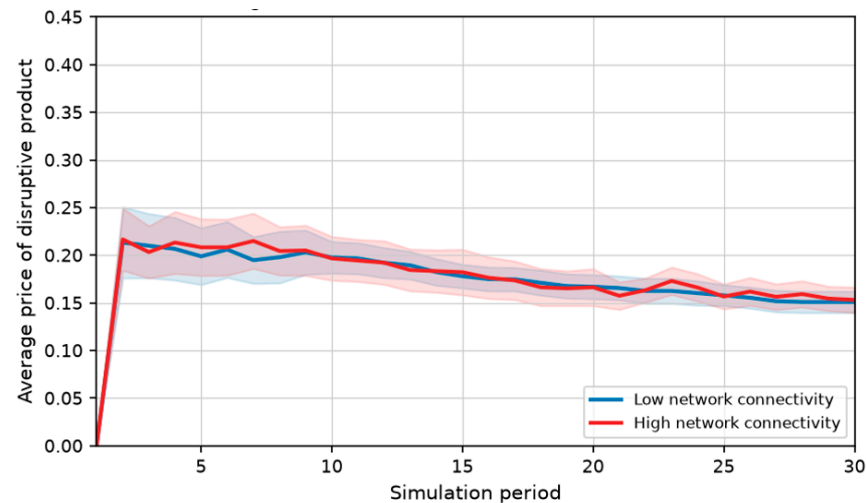


Figure 7. Average price of disruptive-technology products under low and high social network connectivity.

This effect can be understood through the adaptive feedback among firms. Greater network connectivity improves information exchange and market feedback, enabling incumbent firms to adjust pricing and production decisions while maintaining their existing market positions. These adaptive advantages reduce the pressure for rapid price adjustment during the transition and thereby delay the relative price shift toward disruptive technology. From a Complex Adaptive Systems perspective, network connectivity can therefore stabilize incumbent-oriented market configurations even while facilitating information diffusion among heterogeneous agents.

This result suggests that stronger social network connectivity reinforces incumbent advantage across market penetration, enterprise adoption, and price evolution. However, this finding reflects the model's connectivity-endowment setting and should not be interpreted as a universal effect of network connectivity on technology pricing.

Proposition 4. *Higher social network connectivity delays the technological catch-up of disruptive innovation.*

Figure 8 shows that higher social network connectivity delays the technological catch-up of disruptive technology. Compared with the low-connectivity scenario, the high-connectivity scenario exhibits a slower convergence of disruptive technology's technological level toward that of the incumbent. This result indicates that stronger network connectivity does not necessarily accelerate the technological development of disruptive innovation when network advantages are concentrated among incumbent firms.

The underlying mechanism is the cumulative feedback between initial network advantages and adaptive investment. Greater connectivity strengthens incumbents' sales and enables them to accumulate technological and complementary resources more rapidly. These advantages reinforce incumbent technological capabilities and increase the relative gap that disruptive entrants must overcome. From a complex adaptive systems perspective, network connectivity can therefore generate asymmetric learning effects: the same adaptive

interactions that strengthen incumbent capabilities may also increase the technological threshold facing disruptive entrants.

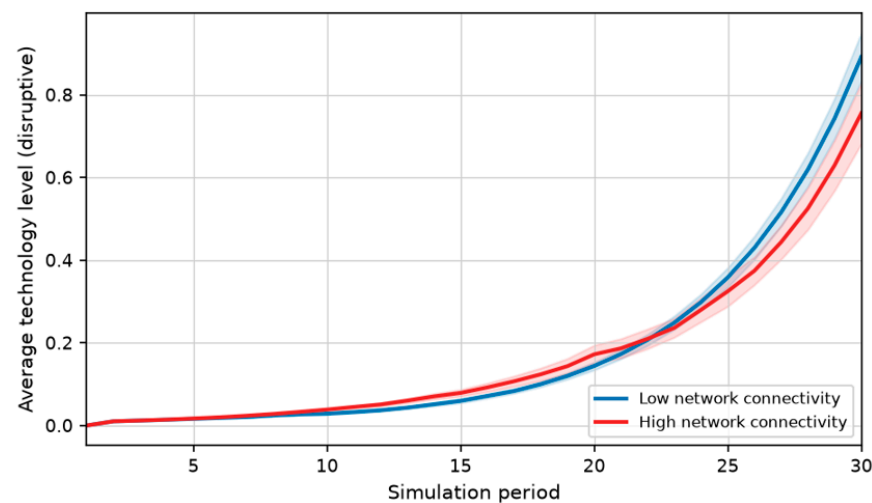


Figure 8. Average technological level of disruptive-technology products under low and high social network connectivity.

This finding suggests that social network connectivity reinforces an incumbent advantage across market, adoption, price, and technological dimensions. However, the result reflects the model's specific connectivity-endowment structure and does not imply that network interaction universally constrains technological learning or innovation.

4.3. Effects of the Institutional Mechanism

Proposition 5. *Higher government subsidy intensity accelerates the market penetration of disruptive innovation.*

Figure 9 shows that higher government subsidy intensity accelerates the market penetration of disruptive innovation. Under low subsidy intensity ($zfbtr = 10$), disruptive technology exhibits a slower increase in market share, whereas under high subsidy intensity ($zfbtr = 90$), its market share rises more rapidly. Figure 10 further shows a monotonic decline in mean market-penetration time, from 13.2 periods at $zfbtr = 10$ to 8.8 periods at $zfbtr = 90$, with non-overlapping 95% confidence intervals.

This effect reflects the role of subsidies in strengthening the growth conditions of firms adopting disruptive technology, thereby facilitating faster accumulation of technological and complementary resources and accelerating market penetration. Higher subsidy intensity increases the growth advantage of firms adopting disruptive technology, enabling them to accumulate technological and complementary resources more rapidly and thereby accelerate market penetration. From a complex adaptive systems perspective, institutional intervention alters the fitness landscape within which heterogeneous firms adapt and compete, shifting market selection in favor of the emerging technology.

The finding also highlights that the effectiveness of institutional support depends on its connection to the evolutionary bottlenecks faced by disruptive entrants. Subsidies therefore function not merely as financial transfers but as an institutional mechanism that can reshape firms' adaptive trajectories and the pace of technological substitution.

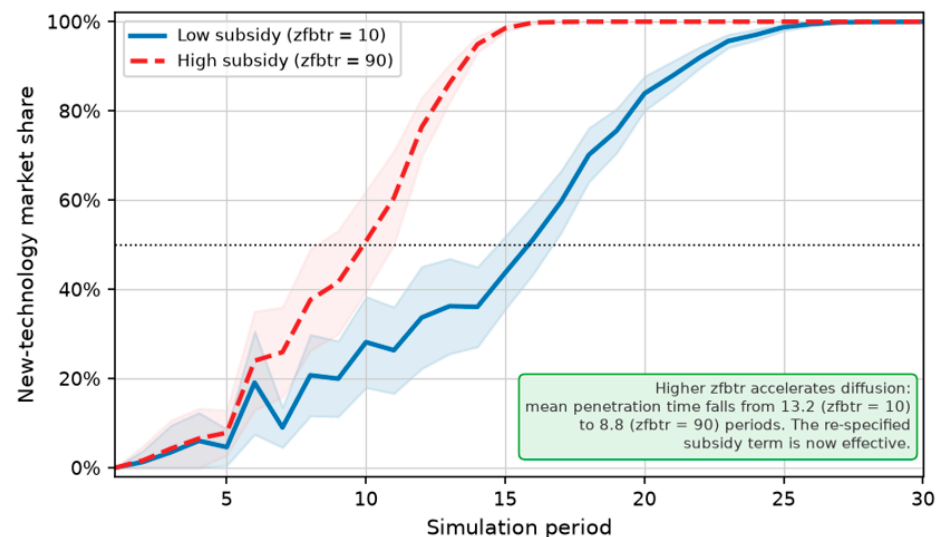


Figure 9. Market-share evolution under low ($zfbtr = 10$) and high ($zfbtr = 90$) government-subsidy intensity. Solid lines and shaded areas are means and 95% confidence intervals across $R = 30$ replications.

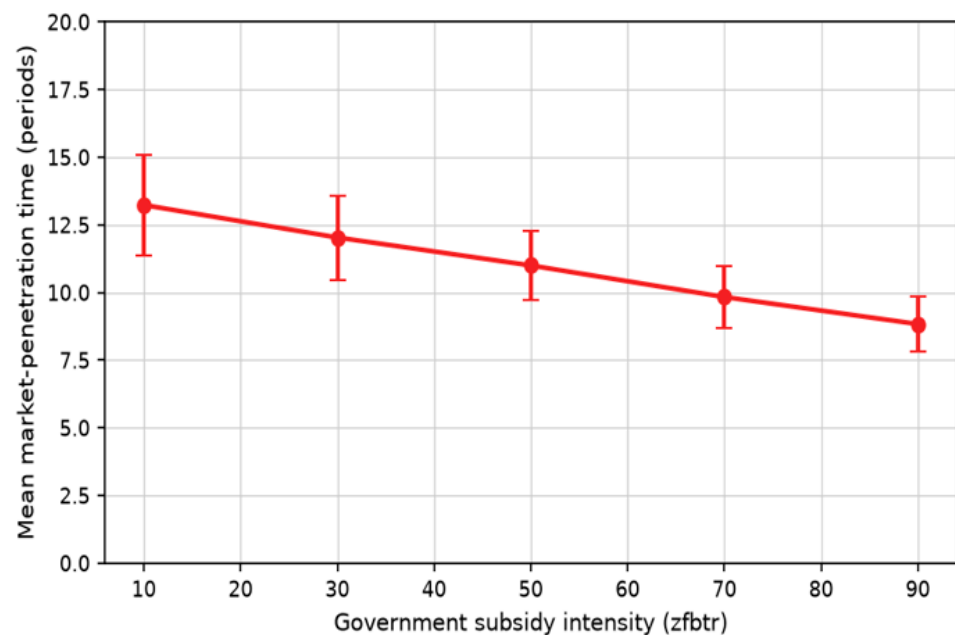


Figure 10. Mean market-penetration time as a function of government-subsidy intensity ($zfbtr$). Error bars show 95% confidence intervals across $R = 30$ replications.

4.4. Effects of the Resource Mechanism

The resource mechanism is examined using a two-stage approach that combines aggregate simulation analysis with regression analysis. This differentiated methodological design reflects the heterogeneous nature of resource effects. Network connectivity and government subsidies are represented by relatively direct scenario-level parameters, allowing their effects to be identified through controlled simulation comparisons. In contrast, resource allocation involves multiple heterogeneous inputs whose effects may differ across firms and evolutionary outcomes. The aggregate simulation results indicate that initial resource endowment has a limited influence on the timing of disruptive-technology penetration. However, this does not imply that resources are unimportant to the subsequent evolution of disruptive innovation. Regression analysis is therefore employed to identify

how heterogeneous resource inputs shape firms' competitive and adoption outcomes after disruptive technology begins to penetrate the market.

Figure 11 examines the aggregate effect of initial senior-talent endowment ($l2_scale$) on market-penetration time. The effect is weak and non-monotonic: a varying $l2_scale$ from 0.5 to 4.0 changes the mean penetration time by less than one period. Thus, senior talent does not substantially determine the timing of disruption under the present model specification. Rather, its effects may become more evident in firms' subsequent competitive and adoption outcomes after disruptive technology enters the market.

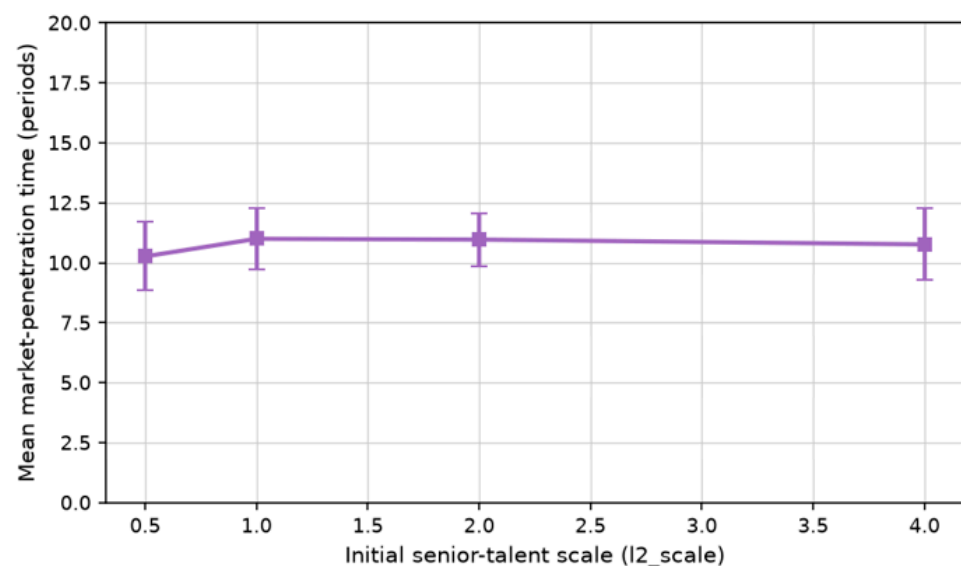


Figure 11. Mean market-penetration time as a function of the initial senior-talent endowment ($l2_scale$). Error bars show 95% confidence intervals across $R = 30$ replications.

The subsequent regression analysis captures these heterogeneous resource effects. The explanatory variables represent four resource types—general capital, specialized capital, general talent, and senior talent—reflecting differences in resource specificity and knowledge intensity. The dependent variables capture three dimensions of evolutionary performance: market share, representing competitive position; market price, representing market positioning and value realization; and enterprise adoption, representing organizational diffusion of disruptive technology. This design allows the analysis to determine how different resource configurations shape firms' adaptive performance rather than treating resource investment as a homogeneous input. The regression models use simulation observations after disruptive technology begins to penetrate the market and therefore complement rather than replace the aggregate simulation analysis. While market-penetration time primarily captures the early-stage dynamics of disruptive-technology penetration, the regression models examine how heterogeneous resource allocation shapes firms' subsequent competitive positions and adoption outcomes.

4.4.1. Effects of the Resource Mechanism on Market Share

The effects of different resource inputs on market share are reported in Table 4.

Table 4. Regression results for the effects of different resource investments on market share.

Ln Market Share	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
General capital	0.066		1.33 **				12.68 ***
Special capital		−0.26 **	−0.29 ***				−1.51 ***

Table 4. Cont.

Ln Market Share	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Ordinary talents				−0.81 ***		−0.75 ***	−3.26 **
Senior talents					0.484 ***	0.45 ***	5.28 ***
Constant term	4.97	4.26	5.15 ***	3.84 ***	5.57 ***	4.53 ***	5.94 ***
Sample size	34	18	18	34	34	34	18
Adjusted R ²	−0.03	0.29 **	0.45 ***	0.31 ***	0.39 ***	0.67 ***	0.92 ***

Note: (1) **, *** represent the critical value of 5% and 10% of significance levels, respectively. (2) Ln market share: a logarithmic indicator of the difference in market share between old and new technologies.

(1) Effects of capital investment

From the perspective of the resource mechanism, capital investment represents a strategic resource whose allocation influences market performance. According to Table 4, general capital investment alone has no significant effect on market share, whereas every 1% increase in the gap in special capital investment reduces the market share gap by 0.26%. Overall, a 1% increase in the gap in general capital investment enlarges the market share gap by 1.33%, while the same increase in special capital investment reduces it by 0.29%, and these effects become stronger when combined with talent investment. As shown in Model 7, every 1% increase in the gap in general capital investment enlarges the market share gap by 12.68, indicating that general capital is the primary resource driving market expansion, whereas the short-term effect of special capital remains limited because of its high specificity and long payback period.

(2) Effects of talent investment

From the perspective of the resource mechanism, talent investment represents a strategic resource supporting the commercialization of disruptive innovation. According to Model 3 in Table 4, every 1% increase in the gap in general talent investment reduces the market share gap by 0.81%, whereas every 1% increase in the gap in senior talent investment enlarges the market share gap by 0.49%. Although the interaction between the two types of talent slightly weakens these effects, their directions remain unchanged, indicating that general talent investment alone does not improve the market share of disruptive technologies, whereas senior talent investment significantly enhances market performance. This pattern reflects the resource mechanism, whereby different types of human capital contribute differently to disruptive innovation. Senior talent provides specialized knowledge and capabilities required for technology commercialization and market diffusion, whereas general talent is more likely to reinforce existing organizational routines and path dependence. Consequently, the resource mechanism enhances market performance through the complementary allocation of talent and capital resources.

(3) Combined effects of capital and talent investment

The combined effects of capital and talent investment on market share are reported in Model 7 of Table 4. The regression results indicate that the interaction between general capital investment and senior talent investment positively affects the market share gap between disruptive and old technologies, whereas the interaction between special capital investment and general talent investment exerts a negative effect. Among the four categories of resource inputs, general capital investment has the strongest effect, followed by senior talent investment, whereas special capital investment exhibits the weakest elasticity. From the perspective of the resource mechanism, these findings suggest that different strategic resources contribute to market performance in distinct ways. The high specificity and long payback period of special capital constrain its short-term market contribution, whereas

senior talent provides the knowledge and adaptive capabilities required for technology commercialization and market diffusion. Consequently, the resource mechanism enhances market performance through the complementary allocation of capital and senior talent, making investment in senior talent particularly critical for the transition from a technology niche to a market niche.

4.4.2. Effects of the Resource Mechanism on Market Price

The effects of different resource investments on market price are reported in Table 5.

Table 5. Regression results for the effects of different resource investments on market price.

The Market Price	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
General capital	−0.01		0.03 *				−0.05
Private capital		−0.007	−0.004				0.007 *
Ordinary people				0.02		−0.01	−0.11 ***
Senior talents					−0.04 ***	−0.04 ***	0.05 ***
Constant term	−0.08	−0.05	−0.02	−0.05 **	−0.14 ***	−0.16 ***	−0.12 ***
Sample size	49	33	33	49	37	37	21
Adjust the R ²	−0.02	0.02	0.10 *	0.01	0.44 ***	0.43 ***	0.99 ***

Note: (1) *, **, *** represent the critical value of 1%, 5% and 10% of significance levels, respectively. (2) Ln market share: a logarithmic indicator of the difference in market share between old and new technologies.

(1) The impact of capital factors on market prices

From the perspective of the resource mechanism, capital investment influences market price through firms' resource allocation. According to the regression results, both general and special capital investment exert negative but statistically insignificant effects on market price when considered separately. However, when examined jointly, every 1% increase in the gap in general capital investment enlarges the market price gap by 0.03 units, whereas the effect of special capital investment remains insignificant. These findings suggest that the resource mechanism shapes market pricing through the efficient allocation of strategic resources, while the short-term contribution of special capital investment remains constrained by its high specificity and long payback period.

(2) Effects of talent investment on market price

From the perspective of the resource mechanism, talent investment influences market price by strengthening firms' innovation capabilities. According to the regression results, general talent investment has no significant effect on market price, whereas every 1% increase in the gap in senior talent investment reduces the market price gap by 0.04 units. The joint effect of general and senior talent investment remains broadly consistent with these individual effects. These findings indicate that senior talent is the primary strategic human resource supporting the market competitiveness of disruptive technologies, enabling firms to achieve more competitive pricing and market returns comparable to those of incumbent technologies.

(3) Combined effects of capital and talent investment on market price

According to the regression results of the combined model in Table 5, general capital investment has no significant effect on market price, whereas special capital investment, general talent investment, and senior talent investment all exert significant effects. Specifically, special capital investment and senior talent investment positively affect the market price gap, whereas general talent investment has a negative effect. These findings suggest that the resource mechanism shapes market pricing through the complementary allocation

of strategic resources, highlighting that the market performance of disruptive technologies depends on the coordinated deployment of capital and talent rather than on any individual resource input.

4.4.3. Effects of the Resource Mechanism on Enterprise Adoption

The effects of different resource investments on enterprise adoption are reported in Table 6.

Table 6. Regression results for the effects of different resource investments on enterprise adoption.

Companies	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
General capital	8.87 ***		4.87 ***				0.59
Private capital		−2.35 ***	−1.96 ***				−0.71 ***
Ordinary people				−8.27 ***		−2.99 ***	−2.43 ***
Senior talents					3.38 ***	3.34 ***	1.80 ***
Constant term	6.04 ***	−6.38 ***	−1.72	−11.09 ***	5.78 ***	1.69 ***	−1.43 ***
Sample size	49	33	33	49	37	37	21
Adjust the R ²	0.21 ***	0.28 ***	0.43 ***	0.54 ***	0.83 ***	0.94 ***	0.99 ***

Note: *** indicate the critical values of 10%.

(1) Effects of capital investment on enterprise adoption

From the perspective of the resource mechanism, capital investment influences firms' willingness to adopt disruptive technologies by shaping resource allocation and investment risk. According to the regression results, every 1% increase in the gap in general capital investment increases the number of firms adopting disruptive technologies by 8.87 units. In contrast, every 1% increase in the gap in special capital investment reduces enterprise adoption by 2.35 units. When the two types of capital investment are considered jointly, their interaction slightly weakens firms' willingness to adopt disruptive technologies, leading to more conservative technology adoption decisions. These findings suggest that while general capital investment facilitates the diffusion of disruptive technologies, the high specificity and investment risk associated with special capital discourage firms from technological transition, thereby reducing enterprise adoption.

(2) Effects of talent investment on enterprise adoption

From the perspective of the resource mechanism, talent investment influences enterprise adoption by shaping firms' human capital and adaptive capability. According to the regression results, every 1% increase in the gap in general talent investment reduces the number of firms adopting disruptive technologies by 8.27 units, whereas every 1% increase in the gap in senior talent investment increases enterprise adoption by 3.38 units. When the two types of talent investment are considered jointly, these effects remain unchanged, but the negative effect of general talent is substantially weakened. Specifically, every 1% reduction in the gap in general talent investment is associated with a decrease of 2.99 units in enterprise adoption. These findings suggest that general talent reinforces firms' dependence on existing technologies, whereas senior talent enhances firms' adaptive capability and willingness to adopt disruptive technologies, thereby facilitating technological transition.

(3) Combined effects of capital and talent investment on enterprise adoption

According to the combined model in Table 6, general capital investment has no significant effect on enterprise adoption, whereas special capital investment and general talent investment jointly reduce firms' willingness to adopt disruptive technologies. These findings suggest that the resource mechanism influences enterprise adoption through the complementary deployment of strategic resources rather than any single resource

input. While the high specificity and long payback period of special capital increase firms' transition costs, senior talent helps overcome organizational inertia and facilitates the adoption of disruptive technologies, highlighting the importance of coordinated capital–talent allocation in technological transition.

Taken together, the regression results demonstrate that the resource mechanism operates through heterogeneous and complementary resource–outcome relationships, rather than through a uniform effect on the timing of disruptive innovation. Different forms of capital and talent exert distinct effects on market share, market price, and enterprise adoption. General capital plays a particularly important role in market expansion, whereas the short-term contribution of specialized capital is constrained by its high specificity and longer payback period. Senior talent consistently supports market performance and enterprise adoption, while general talent tends to reinforce existing technological trajectories. These findings indicate that resource heterogeneity shapes firms' adaptive capabilities and competitive positions in differentiated ways.

Importantly, the resource mechanism differs from the network and institutional mechanisms in its evolutionary role. Whereas network connectivity and government subsidies primarily influence the conditions and speed of disruptive-technology penetration, resource allocation operates more strongly through firms' subsequent competitive adaptation, market positioning, and technology adoption. This distinction also helps explain why the aggregate effect of initial senior-talent endowment on market-penetration time is weak and non-monotonic: resource endowments do not necessarily determine when disruption occurs, but their heterogeneous allocation can substantially influence how firms compete and adapt once disruptive technology enters the market.

These findings suggest that the resource mechanism is best understood as a mechanism of adaptive differentiation and competitive reconfiguration. Rather than simply accelerating the onset of disruptive innovation, heterogeneous resource configurations shape firms' adaptive trajectories and competitive positions after disruptive technology emerges, thereby influencing the subsequent evolution of technological substitution.

4.5. Model Validation and Systematic Sensitivity Analysis

We validate the model by examining convergence, stochastic stability, and the systematic sensitivity of the main outcome to each mechanism lever. All simulations are run for $T = 30$ periods with $R = 30$ independent replications using seeds 2026–2055. The simulation converges to a stable outcome within the specified horizon: after disruptive technology crosses the 50% market-share threshold, its market share remains close to 100%, while the number of firms using the incumbent technology gradually declines to zero.

Figure 12 summarizes the systematic sensitivity of market-penetration time to the three operational levers. Figure 12a shows that social network connectivity has the strongest and most monotonic effect: higher network connectivity consistently delays disruptive-technology penetration. Figure 12b shows that higher subsidy intensity ($zfbtr$) monotonically reduces market-penetration time, confirming the effectiveness of the institutional mechanism in accelerating technological diffusion. Figure 12c shows that initial senior-talent endowment has only a weak and non-monotonic effect. These patterns indicate that aggregate transition dynamics are driven primarily by the distribution of network connectivity and institutional support, whereas the current representation of senior talent has limited influence on the timing of technological transition.

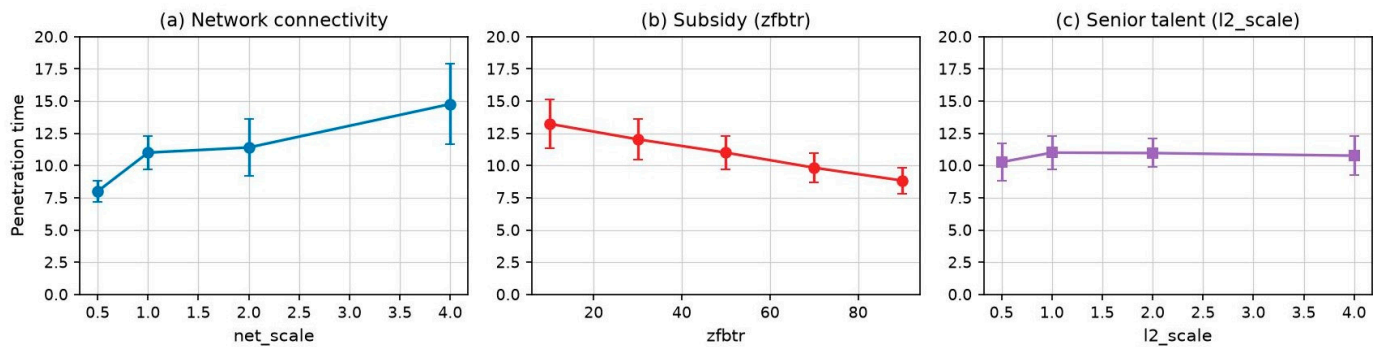


Figure 12. Systematic sensitivity of market-penetration time to (a) social network connectivity, (b) government-subsidy intensity, and (c) senior-talent endowment.

The confidence intervals reported in Figures 4–9 is calculated from the $R = 30$ replications as $\bar{x} \pm 1.96 \frac{\sigma}{\sqrt{R}}$, providing a transparent measure of run-to-run stochastic variation. The qualitative conclusions—including the baseline S-curve diffusion pattern, network-connectivity-driven delay, and the effectiveness of the subsidy channel—remain stable across the independent replications.

5. Discussion

5.1. Discussion of the Network Mechanism

Existing research has consistently recognized social networks as important drivers of innovation diffusion by facilitating knowledge exchange, information transmission, and interorganizational learning [43]. Recent studies further emphasize that network structures shape firms' access to external knowledge, complementary resources, and innovation ecosystem partners, thereby influencing innovation performance [32,44]. However, existing research tends to emphasize the enabling role of networks while paying less attention to how network connectivity may generate adaptive feedback and path dependence during disruptive innovation.

Our simulation results provide a more nuanced perspective on the role of social networks in disruptive innovation. Higher social network connectivity does not necessarily accelerate disruptive-technology penetration; when network advantages are concentrated among incumbent firms, greater connectivity can instead reinforce their existing competitive positions and delay technological substitution. This finding is consistent with Christensen's The Innovator's Dilemma, which emphasizes that established firms can become constrained by established customers, market structures, and resource-allocation patterns, making it difficult for them to respond to disruptive technologies that initially emerge outside the mainstream value network. Our findings extend this argument by showing that network structures can contribute to incumbent entrenchment: stronger connectivity facilitates repeated interactions, knowledge exchange, and resource access among established firms, thereby reinforcing the adaptive advantages embedded in the existing technological and market regime.

From a complex adaptive systems perspective, this process reflects an endogenous feedback mechanism through which network interactions, firm adaptation, and market selection jointly reproduce existing competitive advantages. Rather than viewing networks primarily as channels that facilitate innovation diffusion, our findings suggest that network connectivity can generate path-dependent reinforcement when connectivity is unevenly distributed between incumbent and emerging firms. In this sense, the network mechanism provides a micro-to-macro explanation that extends a central insight of Christensen's disruptive innovation theory: the very structures and relationships that support incumbent firms' success under an existing technological regime may subsequently constrain the diffu-

sion of disruptive alternatives. The network mechanism should therefore be understood as a context-dependent evolutionary force, whose effect depends not simply on the intensity of connectivity but on how network advantages are distributed across incumbent and emerging firms.

5.2. Discussion of the Institutional Mechanism

Institutional environments shape the evolutionary conditions under which emerging technologies develop and compete, while policy support can reduce innovation uncertainty and encourage exploratory investment [11,30]. Innovation policy and Strategic Niche Management research further suggest that government support can create protected spaces in which emerging technologies accumulate capabilities and overcome the “valley of death” [45]. However, existing studies have paid less attention to how institutional support dynamically alters the evolutionary trajectory of disruptive innovation.

Our simulation results demonstrate that government subsidy intensity functions as an effective institutional lever for accelerating disruptive-technology penetration. Higher subsidy intensity systematically increases the growth of disruptive technologies and shortens market-penetration time, indicating that institutional support can strengthen the adaptive capacity of emerging technologies and facilitate their transition from technological emergence to market competition. This finding extends the existing literature by linking policy support to the endogenous evolutionary dynamics of disruptive innovation rather than treating subsidies merely as exogenous financial incentives.

From a complex adaptive systems perspective, the institutional mechanism operates by altering the selection environment in which heterogeneous firms adapt, compete, and learn. Government subsidies reduce the risks associated with disruptive-technology investment and increase firms’ incentives to participate in emerging technological trajectories, thereby accelerating collective market reconfiguration. The institutional mechanism should therefore be understood not simply as a source of financial support, but as an evolutionary lever that reshapes the conditions of technological selection and market penetration. Its effectiveness ultimately depends on how institutional incentives interact with firm adaptation and market selection throughout the evolutionary process.

5.3. Discussion of the Resource Mechanism

The role of strategic resources in disruptive innovation becomes more apparent when resource heterogeneity and evolutionary stage are considered jointly. The resource-based view emphasizes that valuable and difficult-to-imitate resources underpin competitive advantage [46], while dynamic capabilities and strategic human capital enable firms to adapt to technological change [40,41,47]. Our findings extend these perspectives by showing that resource effects are neither uniform nor primarily reflected in the timing of disruption. Although initial senior-talent endowment has only a weak and non-monotonic effect on market-penetration time, heterogeneous resource configurations significantly shape firms’ subsequent market performance and technology adoption.

The regression results reveal distinct evolutionary roles across resource types. General capital is particularly important for market expansion and enterprise adoption, whereas special capital generates limited short-term benefits because its high specificity and longer payback period constrain firms’ flexibility during technological transition. Senior talent consistently strengthens market share, competitive pricing, and enterprise adoption, reflecting its role in knowledge integration, technology commercialization, and adaptive capability. By contrast, general talent may reinforce existing organizational routines and technological trajectories. These findings suggest that the competitive effects of resources depend not simply on their quantity but on their specificity, knowledge intensity, and configuration.

From a complex adaptive systems perspective, resources acquire evolutionary value through their interaction with firm learning, adaptation, and market selection. The resource mechanism therefore operates less as a direct trigger of disruptive-technology emergence than as a mechanism of adaptive differentiation and competitive reconfiguration, through which heterogeneous resource configurations shape firms' trajectories after technological disruption begins. This extends resource-based research from a static endowment perspective toward a dynamic explanation of how resource heterogeneity influences technological substitution.

5.4. Theoretical Implications

This study offers three theoretical contributions to the disruptive innovation literature. First, it advances a mechanism-based view of disruptive innovation. Rather than treating technological, organizational, or market factors as isolated determinants [1,2,4,5], this study conceptualizes disruptive innovation as an emergent evolutionary process shaped by the interaction of network, institutional, and resource mechanisms. More importantly, the findings reveal that these mechanisms play differentiated roles: social network connectivity can reinforce incumbent advantages and delay technological penetration, institutional support can accelerate the diffusion of disruptive technologies, while heterogeneous resources primarily shape firms' subsequent competitive adaptation and adoption. This perspective moves beyond identifying individual drivers toward explaining how distinct mechanisms jointly shape the evolutionary trajectory of disruptive innovation.

Second, this study extends the application of Complex Adaptive Systems (CAS) Theory to disruptive innovation. By incorporating heterogeneous agents, adaptive learning, decentralized interaction, and market selection into a unified computational framework, the study demonstrates how industry-level technological transformation can emerge endogenously from firm-level adaptation and interaction rather than from exogenous technological shocks [20–22]. In particular, the differentiated effects of network connectivity, institutional intervention, and resource configuration illustrate how feedback, path dependence, and adaptive selection generate nonlinear evolutionary outcomes.

Third, this study contributes to simulation-based theory building in innovation research. While prior simulation studies have primarily reproduced diffusion patterns or evaluated policy scenarios [32–34,48], the present model uses multi-agent simulation to identify and compare the evolutionary mechanisms underlying disruptive innovation. The integration of mechanism-based theorizing with computational experimentation demonstrates how simulation can serve not merely as a predictive tool, but as a means of developing, interrogating, and refining theory about complex innovation dynamics.

5.5. Managerial Implications

The findings provide several implications for managers, policymakers, and innovation ecosystem participants seeking to facilitate disruptive innovation.

For firms, disruptive innovation should be managed as an evolutionary process rather than as a one-time technological investment. Managers should focus on the strategic configuration of heterogeneous resources and strengthen senior-talent capabilities in knowledge integration, technology commercialization, and market adaptation. By contrast, highly specialized capital should be deployed selectively because its specificity and longer payback period may constrain strategic flexibility during technological transition. Firms should also manage their network positions strategically. Greater social network connectivity is not inherently beneficial when network advantages are concentrated among incumbents; emerging firms should instead develop diverse and complementary network ties that

provide access to knowledge, resources, and new market opportunities while reducing dependence on established technological trajectories.

For policymakers, government subsidies can serve as an effective institutional lever for accelerating disruptive-technology penetration by reducing investment risks and strengthening the growth of emerging technologies. Policy support should therefore be targeted toward technologies and firms facing substantial early-stage uncertainty, while being complemented by innovation procurement, capability development, and market-oriented institutional arrangements to strengthen longer-term market selection.

For innovation ecosystems, effective governance requires attention to the differentiated roles of networks, institutions, and resources. Universities, research institutes, suppliers, investors, and lead users can help emerging firms build diversified connections and complementary capabilities, while policymakers can facilitate experimentation, technology diffusion, and market entry. Coordinating these mechanisms according to their distinct evolutionary roles, rather than optimizing any single mechanism in isolation, can create more favorable conditions for sustained technological transformation and disruptive innovation.

6. Conclusions

6.1. Summary of Findings

This study investigates the evolutionary mechanisms of disruptive innovation from a complex adaptive systems (CAS) perspective by integrating agent-based simulation with regression analysis. Building on a three-mechanism framework encompassing the network, institutional, and resource mechanisms, the study examines how heterogeneous firms interact, adapt, learn, and compete to shape technological penetration, market dynamics, and enterprise adoption.

The findings demonstrate that disruptive innovation emerges through the differentiated interaction of multiple evolutionary mechanisms rather than through any single determinant. First, the network mechanism reveals a counterintuitive path-dependent effect. Higher social network connectivity does not necessarily accelerate disruptive-technology diffusion. When network advantages are concentrated among incumbent firms, stronger connectivity reinforces their adaptive and competitive advantages, thereby increasing the time required for disruptive technology to penetrate the market. This finding highlights the context-dependent role of networks in technological substitution.

Second, the institutional mechanism demonstrates that government subsidies can serve as an effective evolutionary lever. Higher subsidy intensity systematically strengthens the growth of disruptive technology and shortens its market-penetration time. Rather than functioning merely as a financial incentive, institutional support alters the selection environment faced by heterogeneous firms and facilitates the transition of emerging technologies from technological development to market competition.

Third, the resource mechanism operates primarily through heterogeneous competitive adaptation rather than the timing of disruption. Initial senior-talent endowment has only a weak and non-monotonic effect on market-penetration time, whereas regression results reveal differentiated effects of general capital, specialized capital, general talent, and senior talent on market share, market price, and enterprise adoption. These findings indicate that resource specificity, knowledge intensity, and resource configuration are more consequential than resource accumulation alone, positioning the resource mechanism as one of adaptive differentiation and competitive reconfiguration.

Taken together, these findings advance a mechanism-based understanding of disruptive innovation by showing that network connectivity, institutional intervention, and resource configuration perform distinct evolutionary functions within a complex adaptive system. The study therefore moves beyond identifying isolated determinants and

explains how feedback, adaptation, learning, and selection generate differentiated technological and competitive outcomes. Methodologically, the integration of agent-based simulation and regression analysis demonstrates the value of combining computational experimentation with outcome-level analysis to investigate nonlinear and heterogeneous innovation dynamics.

6.2. Limitations and Future Research

Despite its theoretical and methodological contributions, this study has several limitations that suggest directions for future research.

First, the simulation model necessarily relies on stylized assumptions to represent a complex innovation environment. Although these assumptions facilitate the identification of the three evolutionary mechanisms, they simplify firms' behavioral heterogeneity, institutional conditions, and market structures. Future research could incorporate richer behavioral rules, heterogeneous institutional settings, and industry-specific characteristics to examine whether the identified mechanisms vary across technological and industrial contexts.

Second, the model focuses primarily on industry-level evolutionary dynamics and does not explicitly represent the differentiated roles of broader ecosystem actors. Future research could develop multi-level models incorporating firms, platforms, users, governments, and other participants to examine how micro-level adaptation and meso-level interactions jointly generate macro-level technological transformation.

Finally, the study relies primarily on simulation-based evidence and does not provide direct empirical validation using real-world cases or longitudinal data. Although regression analysis helps identify heterogeneous resource–outcome relationships within the simulation, it does not substitute for external empirical validation. Future research could integrate longitudinal industry data, comparative case studies, or panel data with the proposed simulation framework to assess the robustness, external validity, and boundary conditions of the three-mechanism framework across different technological, industrial, and institutional environments.

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