
Article

A Complex Systems Approach to NEV Disruptive Innovation Diffusion: Co-Evolution Across Enterprise and Consumer Networks

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Abstract

Consumer attitude uncertainty can hinder disruptive innovation (DI) diffusion in the new energy vehicle (NEV) market and weaken enterprises' incentives to adopt new technologies. This study develops a dual-layer coupled network model linking consumer attitude dissemination and enterprise R&D strategy evolution under bounded observability. Our simulations show three main findings. First, stronger discouragement of counter-attitudinal dissemination markedly suppresses diffusion and lowers steady-state adoption. Second, diffusion strengthens when consumers weight public information more and firm messaging less, particularly under stronger policy support. Third, network structure shapes diffusion: stronger inter-enterprise connectivity increases adoption, and consumer topology and interaction breadth exert different effects under different network types. These results clarify how information environments, policy support, and cross-layer behavioral modulation jointly shape diffusion regimes.

Keywords: new energy vehicle; disruptive innovation diffusion; coupled multilayer networks; consumer attitude dissemination; evolutionary game

1. Introduction

The new energy vehicle (NEV) transition has entered a paradoxical phase. On the one hand, electrification is scaling rapidly and reshaping the global automotive landscape, with China remaining a central growth engine and cost frontier. On the other hand, the NEV market has become increasingly turbulent: intensified competition compresses margins, product cycles shorten, and consumers confront a flood of heterogeneous models and claims that are difficult to evaluate before purchase [1]. Meanwhile, a prolonged price war has further intensified volatility and amplified strategic turbulence, prompting regulatory attention to what has been described as “irrational competition” in the EV industry [2,3]. The International Energy Agency reports that competitive pressure and falling battery and vehicle prices, especially in China, have accelerated adoption, while simultaneously intensifying rivalry and strategic uncertainty across manufacturers [4]. In parallel, policy support is shifting toward a more structured and longer-horizon

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toolkit [5], such as extended purchase tax incentives through 2027—adding new discontinuities in demand formation and enterprise strategy [6].

Taken together, these developments suggest that the turbulence reflects more than intensified competition. When key quality attributes and long-term performance are hard to verify *ex ante* and policy reference points shift, competition increasingly involves the (re)definition of what counts as “credible” and “future-proof” innovation. Enterprises therefore compete not only on cost and engineering performance, but also on shaping expectations, legitimacy, and ecosystem alignment, while consumers and regulators continuously update what they regard as reliable, compliant, and future-proof [1,7,8]. This combination—uncertain performance assessment, shifting benchmarks, and legitimacy-building efforts—is characteristic of DI dynamics.

The above phenomenon aligns closely with the logic of DI. According to previous research, DI describes trajectories that initially underperform on mainstream performance metrics but offer alternative value propositions (e.g., lower cost, convenience, new use contexts), improve over time, and ultimately reshape market structure and incumbent advantages [9,10]. Subsequent scholarship has clarified that disruption is not a mechanical “new technology replaces old technology” story; it is contingent on demand uncertainty, institutional conditions, complementary assets, and ecosystem alignment [11–13]. This “context-conditional” view is particularly relevant for NEVs, where disruptive dynamics typically arise from a bundle of changes rather than a single technical route: electrified powertrains combined with software-defined architectures, new platform strategies, new service models, and fast-scaling digital channels that actively shape user expectations [14–16].

From a DI perspective, the NEV transition is therefore not merely about adoption rates. It is about market re-ordering under uncertainty, where enterprises compete to define what counts as “credible innovation,” consumers update attitudes through social influence and information cues, and governments redesign policy instruments as diffusion and competition evolve. This framing immediately suggests that the relevant unit of analysis is multi-actor and feedback-driven rather than single-sided.

Because disruptive trajectories in the NEV sector are mediated by complementary assets and institutional infrastructures, diffusion and competitive advantage are inseparable from ecosystem alignment [3,7,17]. NEV diffusion is therefore not the diffusion of a single-point technology, but the coordinated diffusion of a complementary system [18], because key complementarities extend across charging networks, battery supply chains, software stacks, standards and regulatory regimes [19], and platform-enabled services; misalignment in any layer can slow diffusion, shift rents, or change which innovation trajectory becomes viable. Innovation ecosystem research accordingly emphasizes that value creation and capture depend on coordinated alignment among focal firms and complementors, and that competition often becomes “ecosystem versus ecosystem” rather than enterprise versus firm [20]. This ecosystem-mediated character motivates a complex-systems interpretation in which diffusion emerges from heterogeneous agents embedded in interacting networks with reinforcing feedback, rather than from a representative adopter responding to average incentives.

Within this ecosystem setting, a central mechanism that has received limited explicit modeling attention is the two-way coupling between enterprises and consumers under DI-stage uncertainty [21]. On the demand side, classic diffusion theory highlights the roles of perceived relative advantage, compatibility, and observability [22], while technology acceptance research underscores perceived usefulness and perceived ease of use as determinants of acceptance in uncertain environments [23]. For NEVs, where long-term reliability, residual value, and the credibility of performance claims are difficult to verify *ex ante*, adoption is therefore shaped not only by price and infrastructure, but also by

social learning and network-embedded attitudes [24,25]. Digital environments can amplify these processes. Online communities and interactive brand ecosystems shape attitude formation and purchase intention, while platform-mediated information, including reviews and recommendation mechanisms, structures how consumers update beliefs about what is credible and future-proof in a rapidly evolving market.

Policy enters this coupled system not merely as a supply-side instrument but also as a salient signal and constraint that shapes demand formation and credibility inference [26]. Consumers revise perceptions of financial risk, convenience, and compliance partly through policy cues and governance signals, including incentive packages, charging support, privilege policies, standards, and regulatory communications. Empirical studies report that incentive policies can affect purchase intention through psychosocial value and perception channels, and that diversified policy mixes may generate differentiated impacts across consumer segments—suggesting that policy visibility and perceived credibility can shape attitudes rather than simply lowering prices [27]. In parallel, enterprises internalize policy evolution in their strategic calculations: as NEV governance shifts from direct subsidies to broader and longer-horizon toolkits, policy changes can alter both innovation incentives and competitive tactics, thereby interacting with the demand-side belief environment [1].

On the supply side, DI-stage enterprises do not passively respond to demand; they actively shape the information environment through visible R&D commitments, market narratives, and community operations intended to stabilize expectations and accelerate endorsement [15]. Under information asymmetry—when key attributes and long-term performance are difficult to verify *ex ante*—such observable actions can function as credibility signals that shape perceived quality and reduce uncertainty [28]. More broadly, expectations are performative in emerging technologies: narratives and public commitments can coordinate beliefs and channel diffusion trajectories, especially when uncertainty is persistent [29]. This yields a closed feedback logic: enterprise actions influence the evolution and diffusion of consumer beliefs, while the evolving distribution of consumer belief states feeds back into enterprises' expected market prospects and payoffs, thereby affecting subsequent strategic adaptation [30]. Taken together, NEV DI diffusion is best understood as a coupled coevolution process in which consumer cognition spreads through social contagion and information processing, enterprises adapt strategically in response to the evolving belief landscape within their reachable market segments, and policy signals condition both layers under a changing governance regime.

However, this coupled coevolution logic is not yet fully reflected in the existing NEV literature. Despite rapid progress in NEV studies, several gaps remain salient.

First, Although NEV research has accumulated extensive demand-side evidence on adoption intention and choice [31], consumer perceptions are often treated as static or measured at a single time point [32], leaving limited understanding of how beliefs and attitudes evolve through intermediate states under persistent uncertainty and social influence. Supply-side and policy-oriented studies have also examined enterprises' innovation investment and competitive responses [1,33], yet these analyses are frequently conducted without endogenizing the demand-side belief landscape. This framing misses a strategic reality of DI-stage competition: enterprises actively manage narratives and deploy visible investment signals to shape perceived credibility under uncertainty [34], and these actions can alter how consumers interpret information and spread beliefs about what is reliable and future-proof. As a result, the feedback mechanism linking enterprise market-shaping actions, consumer belief updating and contagion, and the resulting shifts in market potential is rarely specified as an explicit closed loop, even though empirical work increasingly documents interaction channels and community effects.

Second, theoretical integration remains limited. Disruptive innovation theory links market re-ordering to value propositions that first gain traction outside the mainstream. It further emphasizes that institutional and regulatory conditions and ecosystem alignment shape whether disruption materializes and how it unfolds [35–37]. Diffusion and technology acceptance theories clarify how perceptions form and how social influence affects adoption under uncertainty [38–40]. Ecosystem theory highlights complementarity and alignment constraints that condition value creation and capture. Yet NEV research often discusses these lenses in parallel rather than synthesizing them into an actor-specific, feedback-driven explanation that connects enterprise market-shaping actions, consumer belief contagion, and policy signals within one coherent causal loop. Accordingly, these theoretical gaps have methodological implications. If NEV disruptive diffusion is conceptualized as a feedback system linking strategic enterprise responses and network-embedded belief dynamics under policy signals, modeling approaches should be able to represent multi-state cognition and social transmission and should also endogenize enterprises' adaptive strategy updates as the belief landscape evolves.

Methodologically, NEV diffusion and policy evaluation have been studied using multiple approaches, each capturing only part of the coupled mechanism. Econometric time-series and panel analyses identify the effects of policy incentives and policy mixes, but they typically operate at aggregate outcomes and do not endogenize micro-level belief transmission or enterprises' adaptive responses [41,42]. System dynamics models represent macro feedback among demand, supply, and policy in post-subsidy transitions, yet they often rely on aggregated behavioral rules and do not explicitly capture network-mediated social contagion or the enterprise–consumer strategic loop [43].

Agent-based modeling is well suited for heterogeneous consumers and local interactions and has been increasingly used in NEV diffusion research [44,45]. Within this tradition, epidemic-style spreading provides a parsimonious formalism for information, awareness, and attitude diffusion by modeling state transitions driven by exposure and social contact. It can be implemented as compartmental dynamics or as stochastic simulations on networks and can accommodate multiple intermediate cognitive states under uncertainty [44,46,47]. Evolutionary games and complex-network models capture bounded rationality, imitation, and topology-driven cascades, but existing work often compresses cognition into binary states, treats belief diffusion as separable from enterprise competition, or omits the mechanism by which enterprises update innovation posture based on locally observable consumer-state distributions [48]. Consequently, many single-layer or weakly coupled models struggle to jointly capture multi-stage belief evolution, strategic enterprise adaptation grounded in observable market potential, and cross-layer feedback under evolving policy mixes [49,50].

On this basis, the methodological literature points to a mismatch between the complexity of NEV disruptive diffusion and the representational capacity of fragmented approaches. This motivates modeling frameworks that treat diffusion as an emergent outcome of tightly coupled enterprise–consumer coevolution under policy-conditioned belief formation. Accordingly, this study represents multi-state consumer belief dynamics and enterprises' adaptive strategy updates as mutually reinforcing processes on interconnected networks.

These considerations motivate modeling approaches that can jointly represent multi-state consumer belief dynamics under DI-stage uncertainty, enterprises' adaptive strategy updates based on observable consumer-state distributions, and cross-layer feedback on interconnected networks. Compartmental state-transition models offer a parsimonious formalism for information, awareness, and attitude diffusion by representing how agents move across cognitive states through exposure and social contact [47], which makes them suitable for belief-driven diffusion under uncertainty. Moreover, multilayer and

coevolution spreading research shows that interacting diffusion processes can generate thresholds and discontinuities that single-layer representations typically miss. In summary, these insights motivate coupled modeling frameworks in which cognition transmission and strategic competition evolve as an integrated system rather than as separable modules.

Consistent with this logic, this study asks how disruptive-innovation R&D can diffuse among NEV manufacturers. We focus on a setting in which consumer attitudes evolve through networked dissemination and enterprises' observable strategic posture shapes consumers' willingness to endorse and disseminate attitudes. To address this question, we develop a coupled two-layer enterprise–consumer network model that closes the feedback loop from consumer dissemination to enterprises' perceived market potential and evolutionary strategy updating. We then conduct simulation experiments to examine three factors: enterprise modulation of consumer attitude dissemination dynamics, the consumer information environment under different policy support regimes, and network connectivity and topology. As a mechanism-oriented framework, the findings are interpreted as conditional patterns under the stated assumptions.

The major contribution of our study can be formulated as follows:

1. We reconceptualize NEV disruptive diffusion as an endogenous outcome of strategic enterprise market-shaping actions, network-mediated consumer belief dynamics, and evolving policy signals, rather than as a unilateral adoption curve driven by average incentives.
2. We synthesize DI logic with diffusion and technology acceptance mechanisms and with ecosystem complementarity constraints to build an actor-specific causal loop. In this loop, DI-stage competition operates through credibility construction and shifting evaluation criteria under uncertainty, which are mapped into consumers' perception formation and social transmission mechanisms. These evolving beliefs then translate into changing market prospects that discipline enterprises' strategic adaptation, while policy signals and ecosystem alignment conditions shape transition intensities and competitive viability.
3. We develop a tightly coupled two-layer complex-network framework that links multi-state consumer belief dynamics with adaptive enterprise strategy updating under cross-layer observability. This design addresses limitations of single-layer or weakly coupled approaches in capturing DI-stage uncertainty, feedback-driven coevolution, and policy-conditioned diffusion dynamics in the NEV context.

The remainder of this paper is organized as follows. Section 2 presents the modeling framework. Section 3 reports simulation design and results. Section 4 discusses research conclusions and implications.

2. Methods

This study investigates the impact of China's policy support for disruptive innovations on the R&D decisions of enterprises in the NEV industry, proposing strategies to enhance China's DI technological development. As shown in Figure 1, a dual-layer complex network model, including 20 automaker enterprises and 500 consumers, simulates the interplay between enterprise strategies and consumer attitudes towards DI technology. All simulations were implemented in Python 3.11.9 (Python Software Foundation, Wilmington, DE, USA).

The model consists of two interconnected layers: the automaker network, focusing on the evolution of R&D strategies for disruptive innovation technology, and the consumer network, which applies the SHEIR model to track the spread of DI awareness. The networks are coupled through preferential connections between high-degree nodes,

allowing enterprises to gauge potential vehicle sales from consumer attitudes and adjust their strategies accordingly. Conversely, consumer attitudes towards DI are influenced by the enterprises' R&D decisions. The model posits that the strategic decision-making of enterprises and the diffusion of consumer awareness are dynamically interlinked, evolving towards equilibrium.

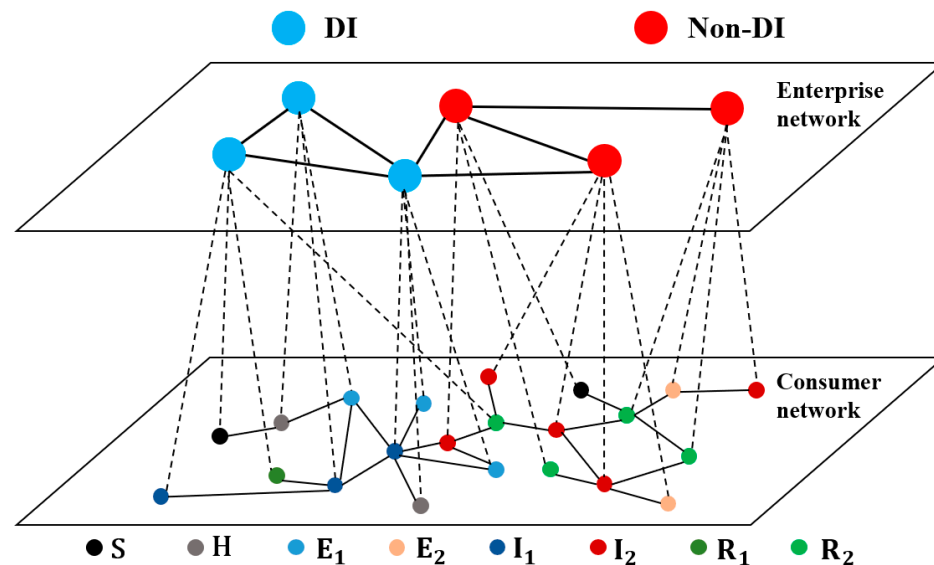


Figure 1. Two-layer enterprise–consumer network with interlayer links. The black solid lines denote intra-layer links between nodes within the same network, and the black dashed lines denote inter-layer links connecting enterprises and consumers across layers.

2.1. Assumption of Model

2.1.1. Assumption of the Enterprise Network

As micro-agents in the enterprise–consumer dual-layer coupled complex network, the connections among enterprises form the enterprise layer network. In order to avoid confounding from firm-specific cost and capability heterogeneity, this model assumes that there is no apparent heterogeneity among enterprises. These enterprises share similar business objectives and risk perceptions, thus a Watts and Strogatz small-world network is used to depict the topological structure of the enterprise layer complex network [51–53].

Enterprises can choose between two strategies: to develop DI products or to not develop DI products and maintain the production of electric vehicles. Moreover, it is assumed that enterprises cannot access all information during the game process, but only the information of the nodes connected to them, to anticipate their profits. Subsequently, enterprises can only engage in games with their neighbor nodes to update their strategies.

2.1.2. Assumption of the Consumer Network

Consumers, as micro-agents in the enterprise–consumer coupled network, form the consumer-layer attitude dissemination network through their social connections. In the new energy vehicle context, attitude expression and peer-to-peer persuasion are increasingly mediated by digitally enabled channels such as social media and online review platforms, where public concerns and sentiments toward NEVs can be observed and measured at scale [54]. We therefore assume substantial heterogeneity in consumers' connectivity and influence, such that a small fraction of highly connected actors can disproportionately shape exposure and attitude transmission. Accordingly, the baseline

consumer layer is modeled as an improved Barabási–Albert scale-free network [55], which provides a parsimonious representation of hub-dominated diffusion in digitally mediated environments [46]. The specific improvement and construction procedure are described in Section 2.2.1.

2.1.3. Assumption of the Inter-Layer Coupling

Physical and interest-based couplings are defined between the enterprise-layer and consumer-layer networks. Under physical coupling, nodes with higher degrees in their respective layers are preferentially connected to form the dual-layer enterprise–consumer network. Under interest-based coupling, enterprises infer expected profits from the strategies of their connected consumers, and consumers infer expected utilities from the strategies of their connected enterprises. This bounded-observability design provides a stylized representation of market processes, in which firms rely on local engagement and community signals and consumers respond to firms’ observable strategic posture, such as technology announcements and market communication. The coupled game evolves through repeated interactions until the system converges to a steady state.

Based on this, edges are added between nodes in the enterprise layer and the consumer layer until the preset number of edges is reached, where the probability of selecting a node is proportional to its degree. Thus, the probabilities of selecting node i from the enterprise layer and node j from the consumer layer are as follows, respectively:

$$\epsilon_i = \frac{k_i}{\sum_{m \in \Omega_E} k_m} \quad (1)$$

$$\epsilon_j = \frac{k_j}{\sum_{n \in \Omega_E} k_n} \quad (2)$$

where k_i and k_j , respectively, denote the degree of node i and node j , and Ω_E and Ω_E , respectively, represent the sets of nodes in the enterprise network and the consumer network.

2.2. Establishment of the Consumer Network

2.2.1. Consumer States

Given that current research on information dissemination models typically does not include individuals insensitive to information, our model also omits this category of people. These individuals are not influenced by the state of others, nor do they influence anyone else. Even if this group were included, their proportion would remain constant over time, not altering the trend of the model. Therefore, we categorize consumers into eight groups.

1. Unaware state (S): This state represents consumers who are not aware or informed about DI. Individuals in this state have not received information about DI and therefore have a neutral attitude towards it.
2. Hesitant state (H): Consumers in this state are aware of DI, but they hold a hesitant attitude about whether to endorse the technology. They require more information or time to form a definitive opinion.
3. Endorsement of DI (E_1): Consumers in the E_1 state endorse DI. Although they endorse it, at this stage, they have not taken any action to disseminate related information.
4. Non-Endorsement of DI (E_2): Consumers in this state do not endorse DI. They may have a negative view of the technology but have also not disseminated their views.

5. Dissemination of Favorable DI Information (I_1): Consumers in the I_1 state not only endorse DI but are also actively spreading favorable information and opinions about the technology to others.
6. Dissemination of Opposing DI Information (I_2): Consumers in the I_2 state oppose DI and actively disseminate information and opinions against the technology.
7. Endorsement without Dissemination (R_1): Consumers in this state endorse DI products but choose not to disseminate any information about the technology.
8. Non-Endorsement without Dissemination (R_2): Consumers in the R_2 state do not endorse DI products and also choose not to disseminate any opposing information.

2.2.2. Spreading Process

As is depicted in Figure 2, the transition rules of the eight states can be summarized as follows:

Initially, consumers are in state S , unaware of DI. As awareness spreads through social interactions, consumers transition to aware states, which include state E_1 , state E_2 , and state H . For consumer i , the probability of transitioning from the state S to the state E_1 is represented by $\lambda_{ij}^{E_1}$ if he contacts a consumer j who is in state I_1 , signifying the inclination towards supporting DI. At this point, if consumer i does not transition to state E_1 , he/she will instead transition to state H , indicating skepticism or uncertainty towards DI products. Conversely, the probability of transitioning from the state S to the state E_2 , denoted as $\lambda_{ij}^{E_2}$, reflects a consumer's skepticism or concerns about the technology. Similarly, if at this time consumer i does not transition to state E_2 , he/she will transition to state H .

A consumer i in state H is at a pivotal point, being aware yet undecided. He/she remains susceptible to influence, continuing to be affected until they transition to either the state E_1 or the state E_2 , denoted by $\lambda_{ij}^{E_1}$ and $\lambda_{ij}^{E_2}$, respectively. The mechanism of transition and the probability of changing states are as described above.

Furthermore, a consumer i in state E_1 can become active proponents, transitioning to the state I_1 with a probability $\mu_i^{I_1}$, actively spreading positive information about DI. Alternatively, he/she might choose to remain passive supporters, not actively disseminating information, denoted by a transition to the state R_1 with a probability $1-\mu_i^{I_1}$. Similarly, a consumer i in the E_2 state might become active critics, moving to the state I_2 with a probability $\mu_i^{I_2}$, or remain passive in their opposition, transitioning to state R_2 with a probability $1-\mu_i^{I_2}$.

After that, a consumer i in state I_1 can potentially return to R_1 if the connected enterprise chooses not to develop DI, with a certain probability of π^{I_1} . This is because when the enterprise's strategy does not align with the attitudes that consumer i endorses and disseminates at that time, their enthusiasm for spreading DI decreases, which facilitates consumer i 's transition from state I_1 to state R_1 . In this case, it is clear that if consumer i is in state I_2 , he/she can also potentially return to state R_2 when the connected enterprise chooses not to develop DI, with a certain probability of π^{I_2} .

As time progresses, consumers become more discerning in their judgment of DI products, especially those in state R_1 and R_2 . They gather various types of information to further analyze whether they should change their attitudes towards DI products. For this reason, a consumer i in state R_1 , after further analysis, will transition to state R_2 with a probability of $\rho_i^{R_2}$. In a similar manner, a consumer i in state R_2 can turn to state R_1 with a probability of $\rho_i^{R_1}$.

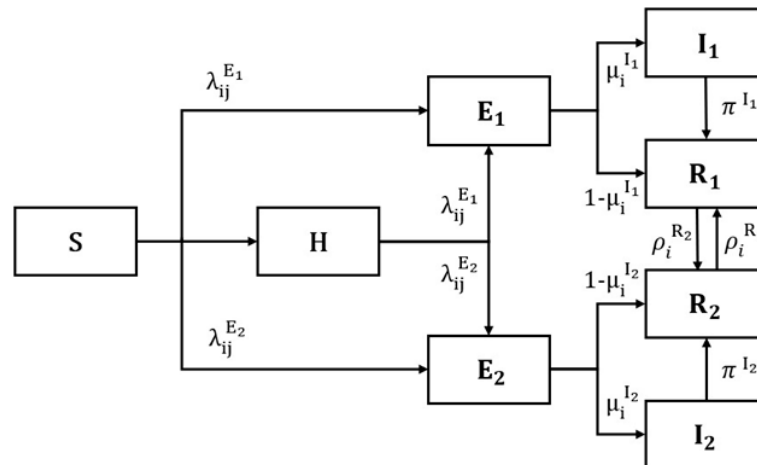


Figure 2. Consumer state-transition diagram in the diffusion process.

2.2.3. Relative Impact Function

In a complex network, nodes often differ in their capacity to influence others [46]. If consumer j is adjacent to consumer i , the impact of consumer j on consumer i can be defined as follows:

$$\theta(i, j) = \frac{k_j}{\sum_{l \in \vartheta(i)} k_l} \quad (3)$$

where $\vartheta(i)$ represents the collective group of consumer i 's neighbors, and k_l denotes the number of connections for individual, who is a part of. It is evident that the more connections consumer j has, the more significant their impact on consumer i . However, $\theta(i, j)$ will be influenced by the average value of k , which makes it impossible to obtain the true impact of j on i . To avoid this impact, the $r\theta(i, j)$ is used to represent the relative impact of j on i , the equation is defined as follows:

$$r\theta(i, j) = \frac{2\theta(i, j)}{\theta(i, j) + \theta(j, i)} \quad (4)$$

2.2.4. Information Perception Function

Drawing on the Technology Acceptance Model and its extensions [56,57], we conceptualize consumers' attitudes toward DI as being shaped by beliefs formed under external cues and social influence, especially when product quality and long-term performance are difficult to verify prior to adoption. Accordingly, we introduce an information perception value to capture consumers' time-varying assessment of DI credibility/usefulness based on public signals and locally transmitted network attitudes, which modulates subsequent attitude reinforcement and updating in the diffusion process.

When consumer i is exposed to the propagation of approval attitudes towards DI products within their social network, they actively gather information to assess the developmental potential of DI. This process results in the formation of a positive information perception value. Conversely, when consumer i encounters the propagation of rejection attitudes towards DI, a similar information collection and assessment process leads to a negative information perception value. A higher information perception value enhances the consumer's conviction in the corresponding attitudes or viewpoints, making them more responsive to encountered social signals. On the other hand, a lower information perception value hinders the spread of those attitudes or viewpoints.

Furthermore, this study also takes into account the role of consumers in state R_1 and state R_2 . These consumers are regarded as calm and rational, reassessing their attitudes based on current social network propagation and public information dissemination. This implies that a consumer in state R_1 , after careful deliberation, may transition to state R_2 , and vice versa. This dynamic process of attitude transformation reveals the consumers' adaptation and reflection mechanisms when faced with a continuously changing information environment, reflecting the complexity and dynamism of consumer attitude formation.

Within this framework, we operationalize the information perception value using public signals (enterprises' DI decisions and government support) and locally transmitted network attitudes. Hence, the positive and negative information perception function which are denoted as $IP_{i1}(t)$ and $IP_{i2}(t)$ at time t can be expressed by the following formulas, respectively:

$$IP_{i1}(t) = \alpha \cdot [ef \cdot Q_1(t) + (1 - ef) \cdot G(t)] + (1 - \alpha) \cdot N_i^1(t) \quad (5)$$

$$IP_{i2}(t) = \alpha \cdot [ef \cdot Q_2(t) + (1 - ef) \cdot 0] + (1 - \alpha) \cdot N_i^2(t) \quad (6)$$

where $Q_1(t)$ and $Q_2(t)$, respectively, represent the proportion of companies that choose to develop DI and not choose to develop DI, $G(t)$ represents the proportion of government development subsidies in the investment made by enterprises, defined as $G(t) = S_g(t)/T_h(t)$. Here, $S_g(t)$ denotes the government subsidy for DI development and $T_h(t)$ denotes the enterprise's DI R&D investment at time t ; both variables are specified in the enterprise-layer payoff and parameter setting (see Section 2.3.1). In addition, $N_i^1(t)$ is the proportion of consumer i 's neighbors in state E_1 , I_1 and R_1 , indicating their support for DI, and $N_i^2(t)$ represents the proportion of consumer i 's neighbors in state E_2 , I_2 , and R_2 . The parameters α and ef are weight coefficients that, respectively, modulate the relative importance of public information and the influence of the social network.

Inspired by prospect theory and reference-dependent evaluation [58], we assume that consumers interpret the perceived information value relative to a neutral reference point. When $IP_{ij}(t)$ exceeds the benchmark (set to 0.5), the corresponding attitude is treated as sufficiently credible and the transition effect is reinforced; when $IP_{ij}(t)$ falls below 0.5, the effect becomes weakening. We operationalise this reference-point mechanism using a smooth logistic mapping centered at 0.5, where L is the maximum utility, m is the consumer sensitivity to the perceived information value.

$$\tau[IP_{i1}(t)] = \frac{L}{1 + e^{-m \cdot (IP_{i1}(t) - 0.5)}} \quad (7)$$

$$\tau[IP_{i2}(t)] = \frac{L}{1 + e^{-m \cdot (IP_{i2}(t) - 0.5)}} \quad (8)$$

2.2.5. Enterprise Consumer Influence Function

The enterprise–consumer influence function formalizes how an enterprise's strategic posture toward DI research and development reshapes the attitude dynamics of its connected consumers through observable market actions and policy related signals. Once an enterprise commits to either continuing or discontinuing DI efforts, it affects consumers via communication, community engagement, and market facing actions such as announcements, promotional activities, and pricing policies. The influence operates through two conceptually distinct mechanisms. When a consumer's prior attitude is aligned with the enterprise's posture, the enterprise's commitment reinforces confidence and increases the propensity for that consumer to endorse and disseminate the aligned

stance. When a consumer's prior attitude is misaligned with the enterprise's posture, the enterprise's actions discourage dissemination of the competing stance by reducing its perceived credibility or attractiveness, or by increasing the perceived costs of maintaining it. In this way, enterprise strategy shifts the distribution of consumer states over time. Following this logic and prior research [59,60], we specify the influence function conditional on the enterprise's strategy.

We model the influence through two modifiers, g_1 and g_2 , which scale the transition from latent attitudes to active dissemination. The positive modifier g_1 applies when enterprise posture and consumer attitude are aligned. It increases the transition probability from E_1 to I_1 when the enterprise develops DI and the consumer already approves of DI. It also increases the transition probability from E_2 to I_2 when the enterprise does not develop DI and the consumer already disapproves of DI. The negative modifier g_2 applies under misalignment. It reduces the transition probability from E_2 to I_2 when the enterprise develops DI and the consumer disapproves of DI. It also reduces the transition probability from E_1 to I_1 when the enterprise does not develop DI and the consumer approves of DI. The functional forms of g_1 and g_2 are given below.

g_1 : This function is used in two scenarios. Firstly, when the enterprise decides to develop DI, it positively impacts its consumers who already approve of DI (affecting the transition from E_1 to I_1). Secondly, when an enterprise decides against DI development, this decision will positively influence its consumers who disapprove of DI (affecting the transition from E_2 to I_2). The function g_1 is formulated as follows:

$$g_1 = 1 + \varphi_1 \cdot e^{-\omega t_\Delta} \quad (9)$$

where φ_1 ($0 < \varphi_1 < 1$) is the rate of positive information inflow, ω ($0 < \omega < 1$) is the enterprise influence coefficient. t_Δ represents the time elapsed since the enterprise's strategy implementation, which ensures that the impact of corporate strategies is not static but evolves with the duration of their implementation.

g_2 : This function is applied in the opposite scenarios: In the first scenario, when an enterprise decides to develop DI, it negatively impacts its consumers who disapprove of DI products (affecting the transition from E_2 to I_2). However, when an enterprise decides against DI development, this negatively influences its consumers who approve of DI products (impacting the transition from E_1 to I_1). The function g_2 is formulated as follows:

$$g_2 = 1 - \varphi_2 \cdot e^{-\omega t_\Delta} \quad (10)$$

where φ_2 ($0 < \varphi_2 < 1$) is the rate of negative information inflow.

2.2.6. Comprehensive Probability Transition Function

In our model, comprehensive probability transition functions are used to capture the complex dynamics of consumer behavior in response to DI. Unlike fixed probabilities, nonlinear comprehensive probability transition functions take into account the complex interplay of factors influencing consumer attitudes. According to the previously established function settings, the comprehensive probability transition function between various states can be summarized.

1. $\lambda_{ij}^{E_1}$ and $\lambda_{ij}^{E_2}$ are defined as follows:

$$\lambda_{ij}^{E_1} = \begin{cases} \lambda_{E_1} \cdot r\theta(i, j) \cdot \tau[IP_{i1}(t)], & \lambda_{E_1} \cdot r\theta(i, j) \cdot \tau[IP_{i1}(t)] < 1 \\ 1, & \lambda_{E_1} \cdot r\theta(i, j) \cdot \tau[IP_{i1}(t)] \geq 1 \end{cases} \quad (11)$$

$$\lambda_{ij}^{E_2} = \begin{cases} \lambda_{E_2} \cdot r\theta(i, j) \cdot \tau[IP_{i2}(t)], & \lambda_{E_2} \cdot r\theta(i, j) \cdot \tau[IP_{i2}(t)] < 1 \\ 1, & \lambda_{E_2} \cdot r\theta(i, j) \cdot \tau[IP_{i2}(t)] \geq 1 \end{cases} \quad (12)$$

2. $\mu_i^{I_1}$ and $\mu_i^{I_2}$ are defined as follows:

When the enterprise associated with consumer i chooses to develop DI, the comprehensive transition functions of $\mu_i^{I_1}$ and $\mu_i^{I_2}$ are defined as follows:

$$\mu_i^{I_1} = \begin{cases} \mu_{I_1} \cdot g_1, & \mu_{I_1} \cdot g_1 < 1 \\ 1, & \mu_{I_1} \cdot g_1 \geq 1 \end{cases} \quad (13)$$

$$\mu_i^{I_2} = \begin{cases} \mu_{I_2} \cdot g_2, & \mu_{I_2} \cdot g_2 < 1 \\ 1, & \mu_{I_2} \cdot g_2 \geq 1 \end{cases} \quad (14)$$

When the enterprise associated with consumer i chooses not to develop DI, the comprehensive transition functions of $\mu_i^{I_1}$ and $\mu_i^{I_2}$ are defined as follows:

$$\mu_i^{I_1} = \begin{cases} \mu_{I_1} \cdot g_2, & \mu_{I_1} \cdot g_2 < 1 \\ 1, & \mu_{I_1} \cdot g_2 \geq 1 \end{cases} \quad (15)$$

$$\mu_i^{I_2} = \begin{cases} \mu_{I_2} \cdot g_1, & \mu_{I_2} \cdot g_1 < 1 \\ 1, & \mu_{I_2} \cdot g_1 \geq 1 \end{cases} \quad (16)$$

3. $\rho_i^{R_2}$ and $\rho_i^{R_1}$ are defined as follows:

$$\rho_i^{R_2} = \begin{cases} \rho^{R_2} \cdot \tau[IP_{I_2}(t)], & \rho^{R_2} \cdot \tau[IP_{I_2}(t)] < 1 \\ 1, & \rho^{R_2} \cdot \tau[IP_{I_2}(t)] \geq 1 \end{cases} \quad (17)$$

$$\rho_i^{R_1} = \begin{cases} \rho^{R_1} \cdot \tau[IP_{I_1}(t)], & \rho^{R_1} \cdot \tau[IP_{I_1}(t)] < 1 \\ 1, & \rho^{R_1} \cdot \tau[IP_{I_1}(t)] \geq 1 \end{cases} \quad (18)$$

where λ_{E_1} , λ_{E_2} , μ_{I_1} , μ_{I_2} , ρ^{R_2} and ρ^{R_1} represent the basic transition probability from state S to state E_1 , from state S to state E_2 from state E_1 to state I_1 , from state E_2 to state I_2 , from state R_1 to state R_2 and from state R_2 to state R_1 , respectively.

2.3. Establishment of the Enterprise Network

2.3.1. Game Model

For enterprises, the primary objective is to maximize their own benefits. The strategic choices of other enterprises can impact an enterprise's benefits, thus creating a clear game relationship among automotive enterprises. Suppose Enterprise A is the decision-maker, and enterprises which it has cooperative or competitive relationships are denoted as Enterprise B. Faced with DI technology, both enterprise A and B will weigh the pros and cons to choose their strategy, leading to three possible decision-making scenarios.

Scenario 1: When enterprise A chooses to develop DI and its neighboring enterprise B also opts for the development of DI, the expected profit function for enterprise A (EP_{HH}) can be expressed as follows:

$$EP_{HH} = c(P_h - C_h)(D_h + b) + (1 - c)(P_e - C_e)D_e - \frac{1}{2}(1 + f_h)W_{h_1}(T_h - S_g)^2 \quad (19)$$

In Equation (19), c represents the success rate of DI products development, b stands for the sales quota granted by the government to enterprises developing DI products. Therefore, $c(P_h - C_h)(D_h + b)$ represents the anticipated revenue for enterprise A from the sales of DI. Here, P_h is the selling price per DI, C_h is the manufacturing cost for producing a DI, and D_h is the expected sales volume of DI for enterprise A. The enterprise adjusts its expectations continuously based on the attitudes of observed consumer nodes and the strategies of neighboring enterprise nodes, thus determining the expected sales volume of DI. The expression for D_h is as follows:

$$D_h = \begin{cases} \frac{\frac{d_{ch}}{d_{ct}} \cdot A_c}{\frac{d_{eh}}{d_{et}} \cdot A_e}, & \frac{\frac{d_{ch}}{d_{ct}} \cdot A_c}{\frac{d_{eh}}{d_{et}} \cdot A_e} < D_t \\ D_t, & \frac{\frac{d_{ch}}{d_{ct}} \cdot A_c}{\frac{d_{eh}}{d_{et}} \cdot A_e} \geq D_t \end{cases} \quad (20)$$

In Equation (20), d_{ch} and d_{ct} , respectively, represent the number of consumers observed by the enterprise A and total number of consumers observable by enterprise A, respectively. Specifically, d_{ch} includes its connected consumers in the state E_1 , I_1 , R_1 , and half of the consumers in state H, who are considered by enterprise A as the target group that may endorse or support DI technology. d_{eh} and d_{et} represent the number of neighboring enterprises adopting the strategy of developing DI technology and the total number of neighboring enterprises, respectively. A_c and A_e represents the total number of consumers and enterprises, respectively. The product of $\frac{d_{ch}}{d_{ct}} \times A_c$ represents the anticipated number of consumers endorsing DI technology among all consumers, as estimated by the enterprise, while the product of $\frac{d_{eh}}{d_{et}} \times A_e$ represents the anticipated number of enterprises developing DI technology among all enterprises. These ratios are then divided to determine the expected sales volume per enterprise adopting DI technology. However, constrained by the total production capacity of the enterprise, the maximum value of this expected sales volume equals the total production capacity.

When enterprise A chooses to develop DI products, it does not completely abandon the production and development of electric vehicles. If the development is successful, the enterprise can sell DI products; if not, it produces electric vehicles. Therefore, when calculating the anticipated revenue under the current situation, the revenue from producing and developing electric vehicles is also considered. $(1 - c)(P_e - C_e)D_e$ represents the expected revenue from selling electric vehicles for company A if the development is unsuccessful, where P_e is the selling price of electric vehicles, C_e is the manufacturing cost of electric vehicles, and D_e is the expected sales volume of electric vehicles. Here, D_e is derived based on the expected sales volume of DI (D_h) and the total vehicle production capacity of each enterprise (D_t). The expression for D_e is as follows:

$$D_e = \begin{cases} \frac{\frac{d_{ce}}{d_{ct}} \cdot A_c}{\frac{d_{ee}}{d_{et}} \cdot A_e}, & \frac{\frac{d_{ce}}{d_{ct}} \cdot A_c}{\frac{d_{ee}}{d_{et}} \cdot A_e} < D_t \\ D_t, & \frac{\frac{d_{ce}}{d_{ct}} \cdot A_c}{\frac{d_{ee}}{d_{et}} \cdot A_e} \geq D_t \end{cases} \quad (21)$$

In Equation (21), d_{ce} represents the number of consumers observed by enterprise A, it includes consumers in the state E_2 , I_2 , R_2 , and half of the consumers in state H. d_{ee} represents the number of neighboring enterprises not adopting the strategy of developing DI technology.

In addition, the term $\frac{1}{2}(1 + f_h)W_{h_1}(T_h - S_g)^2$ represents the investment loss for an automotive company in developing DI. Here, $f_h(0 < f_h < 1)$ is the risk coefficient for developing DI products, and $W_{h_1}(0 < W_{h_1} < 1)$ is the development cost coefficient when both neighboring enterprises are developing DI products technology. T_h and S_g represent the company's investment in DI technology development and the government subsidy for DI technology development, respectively.

Scenario 2: When enterprise A opts to develop DI while its neighboring enterprise B chooses not to develop DI, the expected profit function for enterprise A (EP_{HE}) can be represented as follows:

$$EP_{HE} = c(P_h - C_h)(D_h + b) + (1 - c)(P_e - C_e)D_e - \frac{1}{2}(1 + f_h)W_{h_2}(T_h - S_g)^2 \quad (22)$$

In Equation (22), W_{h_2} ($0 < W_{h_1} < W_{h_2} < 1$) is the development cost coefficient for enterprise A when adjacent enterprise adopts different development strategy. Compared to the situation where both enterprises develop DI technology, this scenario presents greater challenges for enterprise A in terms of research and development, due to the lack of technical collaboration between the enterprises. Consequently, the development cost coefficient for enterprise A in this scenario is higher than in scenario 1.

Scenario 3: When enterprise A maintains the development and production of EV, regardless of whether its neighboring enterprise choose to maintain the incumbent strategy and development or opt for the development of DI technology, the expected profit function for enterprise A (EP_{EH} and EP_{EE}) can be describe as follows:

$$EP_{EH} = EP_{EE} = (P_e - C_e)D_e \quad (23)$$

In this scenario, enterprise A's revenue is exclusively derived from the production and sale of incumbent products. This revenue is calculated based on the market price of electric vehicles minus the production costs. In this way, the payoff matrix of enterprise A can be shown in Table 1.

Table 1. Game payoff matrix of enterprise A.

		Enterprise B	
		DI	Non-DI
Enterprise A	DI	EP_{HH}	EP_{HE}
	Non-DI	EP_{EH}	EP_{EE}

2.3.2. Diffusion Mechanism

During each evolutionary period, each enterprise engages in games with neighboring entities according to three scenarios mentioned above. The cumulative expected revenue is calculated as the aggregate of game revenues accrued from interactions with each neighboring supplier. The formula representing this calculation is as follows:

$$\beta_i = \sum_{j \in N_i} x_i \cdot M \cdot x_j \quad (24)$$

In Equation (24), β_i represent the ultimate revenue of enterprise I, while x_i denotes the strategy vectors, specifically (1,0) and (0,1). When $x_i = (1,0)$, it indicates enterprise i's choose to develop DI, whereas $x_i = (0,1)$ signifies it chooses not to develop DI. M refers to the payoff matrix for the enterprises, and N_i is the set of neighbors of enterprise i. In addition, enterprise j is considered as a neighbor to enterprise i, which means enterprise j is a member of the set N_i .

In the context of technology diffusion for DI within an industry characterized by complex network features, strategies spread among enterprises through the edges in the network. Initially, each enterprise possesses a pure strategy. After that, enterprise i updates its strategy according to the Fermi rule by observing the strategies and cumulative expected revenue of itself and its neighbors from the previous time period:

$$P_{(s_i \leftarrow s_j)} = \frac{1}{1 + \exp\left(\frac{(\beta_i - \beta_j)}{\gamma}\right)} \quad (25)$$

Here, ρ_i denotes the cumulative expected revenue for enterprise i adopting strategy S_i , while ρ_j represents the cumulative expected revenue for neighbor j adopting strategy S_j . γ signifies environmental noise. In the context of the business game between enterprise i and its neighbors, a greater difference in final revenue implies a stronger motivation for learning. However, the transmission of information is subject to risk and may be affected by noise. In this study, γ is set at 0.1. Enterprises in a competitive market environment will actively learn and adjust their strategies based on the game matrix and strategy update rules. This iterative process continues until enterprises reach a stable state of development strategies.

3. Results

3.1. Simulation Settings

To ensure the reliability and validity of the simulation results, we determine the baseline parameter values as follows: (1) Based on the study context, parameters are calibrated within the feasible ranges specified in the model assumptions. (2) We also benchmark our settings against parameter choices and calibration practices commonly adopted in related studies [46,61,62].

The consumer network is built using a Barabási–Albert scale-free network structure with an average degree $k = 20$. The enterprise layer is constructed as a Watts–Strogatz small-world network with an average degree of 4 and a rewiring probability of 0.2, following the baseline parameterization. The linkage mechanism between the enterprise and consumer layers is established by selecting nodes from both layers to create connections until the predetermined number of links is achieved.

The main parameters involve strategic choices in the enterprise game model, probability functions for consumer attitude transitions. Accordingly, we set $P_h = 300$, $P_e = 300$, $D_t = 30$, $C_h = 160$, $C_e = 150$, $T_h = 50$, $S_g = 30$, $f_h = 0.4$, $W_{h_1} = 0.3$, $W_{h_2} = 0.5$, $c = 0.4$, $b = 10$, $\alpha = 0.4$, $ef = 0.4$, $\varphi_1 = 0.3$, $\varphi_2 = 0.3$, $\omega = 0.3$, $L = 2$, $m = 8$. The basic transition probability λ_{E_1} , λ_{E_2} , μ_{I_1} , μ_{I_2} , ρ^{R_1} , ρ^{R_2} , π^{I_1} and π^{I_2} are set to 0.3. In addition, during the entire simulation, the initial values for all parameters are kept constant except for the specific parameters under examination.

Considering the uncertainty and risk in corporate research and development (R&D) strategies for DI, most automakers initially adopt a conservative stance towards DI technology. Therefore, the initial probabilities for automakers to opt for R&D strategies for DI products and to not pursue DI products R&D are set at 0.3 and 0.7, respectively. Furthermore, as consumers have little knowledge about DI products in the early stages of development, most are in the S state at the outset, with an initial probability of 0.8, while the initial probabilities for states E1 and E2 are both 0.1.

3.2. Simulation Steps

During the entire simulation, the initial values for all parameters are kept constant except for the specific parameters under examination.

The simulation process for the disruptive-innovation diffusion model is as follows:

Step 1: Construct a dual-layer coupled complex network of enterprises and consumers.

Step 2: Initialize the strategies of enterprises and the attitudes of consumers with a certain probability.

Step 3: Within the consumer layer, update the states of consumers based on the attitude dissemination mechanism.

Step 4: In the enterprise layer, calculate the cumulative expected revenue for enterprises and update the strategies of all enterprises based on the Fermi rule.

Step 5: Repeat steps 3 and 4 until the preset number of game iterations is reached.

Step 6: Collect and analyze the distribution of enterprise strategies and consumer attitudes.

3.3. Baseline Simulation

Figure 3 reports the baseline co-evolution trajectories of the enterprise strategy composition and consumer states under the initial parameter setting. The left panel shows that the share of DI-adopting enterprises increases rapidly in the early stage and then converges to a stable equilibrium slightly above 0.20, while the non-adopting strategy remains dominant. The right panel displays a consistent consumer diffusion pattern: the uninformed population declines sharply at the beginning, hesitation rises to a transient peak and then decays, and the disseminating and silent states gradually accumulate and stabilize. Taken together, the baseline simulation indicates that, given the initial incentives and network configuration, the coupled system converges to a low-adoption equilibrium for DI rather than a full-diffusion outcome.

The baseline dynamics highlight the core feedback loop in the proposed model. Early consumer exposure generates a temporary surge in belief updating and dissemination, which initially enlarges perceived market potential and supports some enterprise switching toward DI. However, as consumer state proportions stabilize and the incremental demand signal weakens, the payoff advantage of DI is insufficient to overturn the incumbent strategy at the population level, and the enterprise layer settles into a persistent mixed equilibrium with a relatively low DI adoption share. This baseline serves as the reference scenario for the subsequent structural experiments that modify the topology and connectivity of the enterprise and consumer networks.

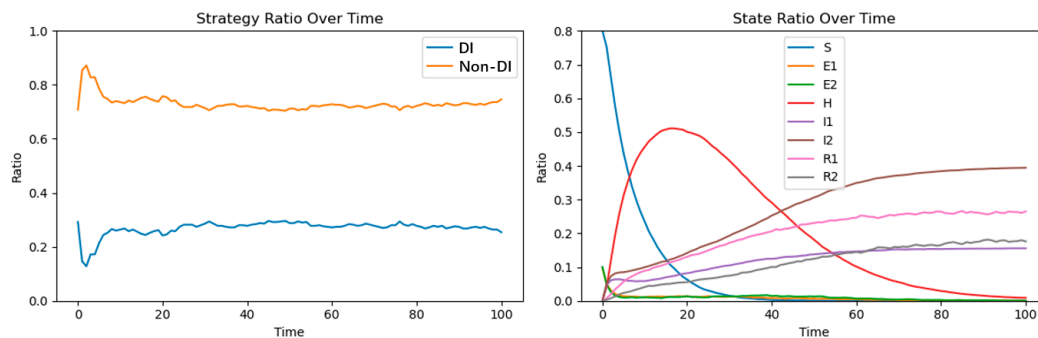


Figure 3. Baseline diffusion dynamics of DI in the coupled enterprise–consumer system. The left panel reports the time evolution of the share of DI-adopting enterprises and non-DI enterprises in the enterprise layer. The right panel reports the time evolution of consumer state proportions in the consumer layer, including 8 states.

3.4. Influence of Enterprise Modulation of Consumer Dissemination

Figure 4 presents how the steady state diffusion outcome of DI in the enterprise layer, quantified by the converged proportion of enterprises adopting DI, varies with enterprises' modulation of consumer dissemination dynamics. In this study, enterprise modulation is operationalized by φ_1 and φ_2 , which govern the extent to which enterprise posture and market facing actions amplify aligned dissemination and discourage counter attitudinal dissemination among connected consumers. Two regularities are observed. First, the equilibrium adoption level varies strongly with φ_2 . For almost any given φ_1 , increasing φ_2 is associated with a systematic reduction in the equilibrium adoption share, indicating high sensitivity to counter attitudinal discouragement intensity. Second, the equilibrium outcome is less responsive to φ_1 .

Changes in aligned mobilization intensity produce comparatively modest variation and do not generate a trend comparable in magnitude to that associated with φ_2 . Taken together, the heatmap indicates that discouragement of counter attitudinal dissemination is the primary determinant of the system level diffusion outcome under the baseline setting.

The mechanism is rooted in how enterprise modulation reshapes the formation of active dissemination in the consumer network and thereby affects perceived market potential. Consumers with latent attitudes can become active disseminators, and dissemination states constitute the principal channel through which initially uninformed consumers become engaged in the diffusion process. Since uninformed consumers can update their state only after exposure to active disseminators, the size and persistence of dissemination states determine whether favorable narratives can propagate widely enough to influence enterprise expectations. Parameter φ_1 captures the extent to which enterprises mobilize attitude aligned consumers into active dissemination through identity-based alignment, community engagement, and incentive compatible advocacy. Parameter φ_2 captures the strength with which dissemination from counter attitudinal consumers is discouraged when enterprise strategy and consumer stance are misaligned. In the early stage, DI is typically not yet dominant among enterprises, and many latent supporters remain connected to enterprises that continue to follow the incumbent strategy. Under this configuration, a higher φ_2 reduces the likelihood that latent supporters become active disseminators, limiting the probability that favorable dissemination reaches the scale required to shift perceived demand. This effect reinforces path dependence and increases the likelihood that the system converges to a low adoption equilibrium.

The dominance of φ_2 has implications for key stakeholders. For enterprises, the results indicate that diffusion is constrained less by marginal improvements in activating supportive dissemination and more by whether countervailing dissemination can circulate sufficiently to reduce uncertainty and support belief revision. For consumers, higher φ_2 corresponds to a more selective communication environment in which cross attitude exchange is attenuated, slowing the formation of shared expectations about DI.

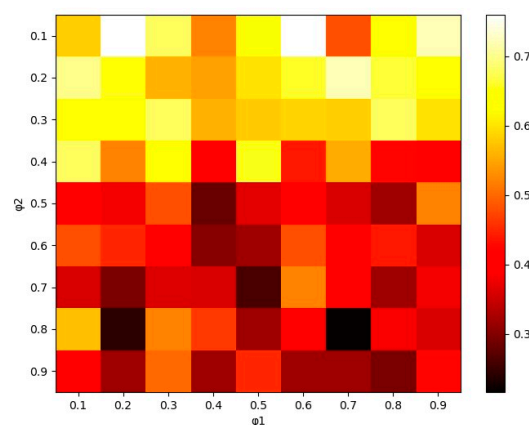


Figure 4. Influence of enterprise modulation of consumer dissemination dynamics on DI diffusion.

3.5. Influence of the Consumer Information Environment on DI Diffusion Under Different Policy Support Regimes

Figure 5a–c report the equilibrium share of enterprises adopting DI as a function of the consumer information parameters, the weight on public information α and the reliance on enterprise information ef , under different subsidy levels. A clear regime

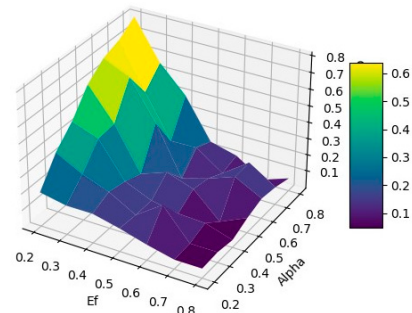
pattern emerges. In Figure 5a, a high adoption region concentrates in the area with high α and low ef . The equilibrium adoption reaches its maximum around $\alpha = 0.8$ and $ef = 0.2$, where the share of DI adopters approaches 0.75. Moving away from this area, either by decreasing α or by increasing ef , shifts the system toward a lower adoption outcome. This indicates that DI diffusion is most likely when consumers anchor their judgements primarily on public policy signals and rely less on enterprise released information. When the subsidy level decreases to $S_g = 20$ in Figure 5b, the location of the high adoption area remains broadly consistent, but the attainable adoption level declines. Even at $\alpha = 0.8$ and $ef = 0.2$, the equilibrium adoption falls to slightly above 0.5. Under the low subsidy setting $S_g = 10$ in Figure 5c, the system converges to a predominantly low adoption outcome across the α and ef domain, with limited responsiveness to further changes in information weights. This suggests that once financial support is sufficiently weak, changing the composition of information reliance alone is not sufficient to lift the system out of a low adoption equilibrium.

These patterns arise from the coupled feedback between consumer belief formation and enterprise strategy updating. A larger α increases the salience of public signals and improves their credibility in consumer judgment, which reduces uncertainty and facilitates the spread of favorable beliefs through social interaction. A smaller ef weakens the role of enterprise released information in shaping expectations, allowing public signals and peer influence to play a greater role in attitude formation. When subsidies are sufficiently strong, these information conditions translate into higher perceived market potential, increase the relative payoff of adopting DI, and support a self reinforcing diffusion process through evolutionary updating. As subsidies decline, the payoff advantage shrinks and path dependence strengthens. Under that condition, even sizeable adjustments in α and ef do not generate sufficient favorable dissemination to raise perceived demand and overturn the incumbent strategy. The results indicate that policy effectiveness depends on the joint operation of material incentives and credible public information, rather than on either component in isolation.

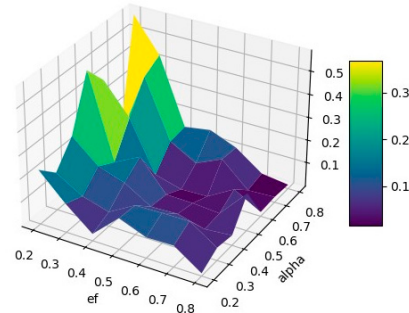
Figure 5d shows that the low subsidy outcome is not fully irreversible when discouragement of counter attitudinal dissemination is reduced. Under $S_g = 10$, lowering φ_2 to 0.2 reintroduces a discernible area of higher adoption. The equilibrium adoption reaches its local maximum when α is around 0.5 and ef remains low, where the adoption share rises to roughly 0.25. Relative to Figure 5c, the diffusion outcome becomes more responsive to information composition when φ_2 is lower, and the area supporting diffusion shifts from requiring very high α toward a more balanced role of public information and social learning, together with limited reliance on enterprise released information.

Mechanistically, a lower φ_2 weakens the extent to which enterprise consumer links discourage the activation of disseminators whose stance is misaligned with the connected enterprise strategy. This increases the likelihood that cross attitude information exchange persists in the consumer network, enabling favorable dissemination to reach a scale that can modify perceived market potential even when subsidies are low. These results highlight, within the simulation setting, that information conditions can complement material incentives in shaping diffusion outcomes, especially under low-subsidy regimes.

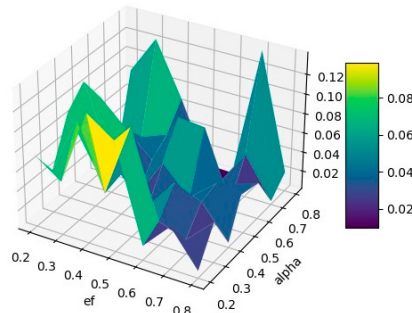
For readability, Table 2 summarizes the key cross-panel contrasts in Figure 5, including the approximate peak adoption levels and their locations under each policy regime and modulation setting. This compact comparison complements the 3D surfaces and facilitates direct interpretation across panels.



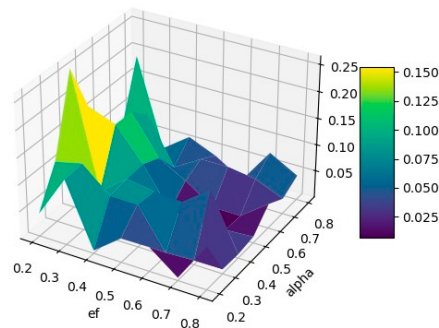
(a)



(b)



(c)



(d)

Figure 5. Equilibrium adoption share of DI under policy support and consumer information conditions. The horizontal axis denotes reliance on enterprise information ef , and the vertical axis denotes the weight on public information α . The color indicates the equilibrium share of DI-adopting enterprises. (a–c) vary the subsidy level sg under baseline enterprise–consumer modulation parameters. (d) reports the low-subsidy case with reduced discouragement intensity $\varphi_2 = 0.2$. Other parameters follow the baseline setting.

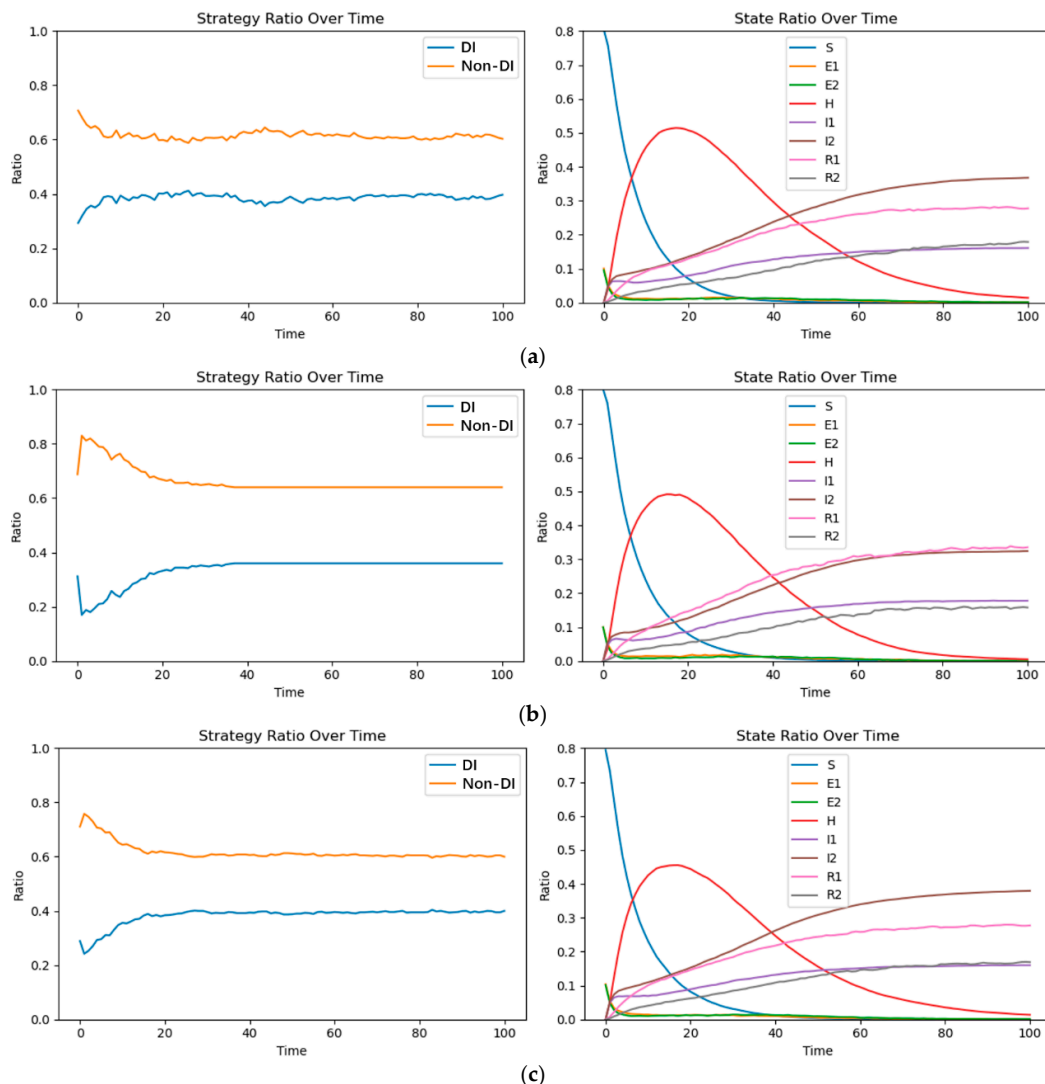
Table 2. Cross-panel comparison for Figure 5.

Panel	S_g	φ_2	High-Adoption Region	Peak Adoption Share	Cross-Panel Contrast
Figure 5a	30	0.3	α high, ef low	about 0.75	Strong diffusion when public signals dominate
Figure 5b	20	0.3	α high, ef low	about 0.50	Same regime shape, lower attainable peak
Figure 5c	10	0.3	no clear peak	about 0.12	Weak sensitivity to α and ef
Figure 5d	10	0.2	α around 0.5, ef low	about 0.25	Diffusion pocket reappears when φ_2 decrease

3.6. Influence of Network Connectivity and Topology on DI Diffusion

3.6.1. Influence of Inter-Enterprise Connectivity on DI Diffusion

Figure 6a examines the effect of stronger inter-enterprise connectivity by increasing the average degree of the enterprise small world network from 4 to 8 while holding all other parameters fixed. The enterprise trajectory converges to a substantially higher equilibrium DI adoption level, approaching 0.40. This indicates that denser inter-enterprise connections facilitate the propagation of the DI strategy across the enterprise layer and lead to a higher steady state diffusion level.



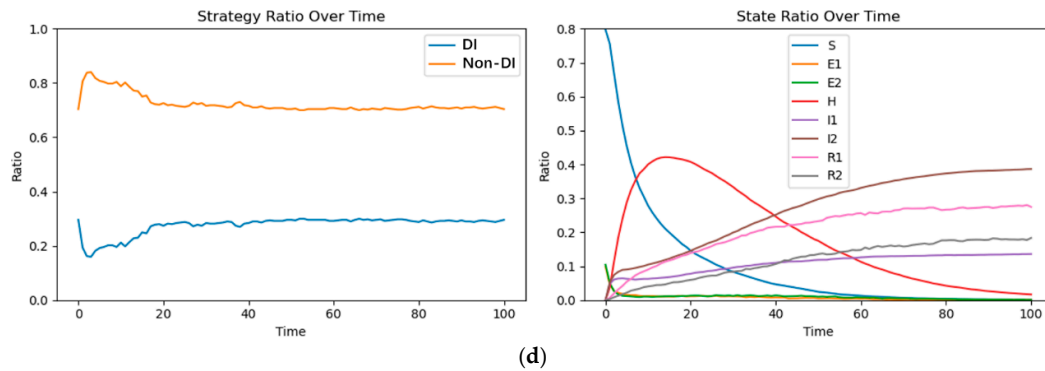


Figure 6. Influence of network connectivity and topology on DI diffusion. (a) Baseline setting: enterprise DI adoption trajectory and consumer state proportions over time. (b) Increased inter-enterprise connectivity, with the average degree of the enterprise small-world network increased from 4 to 8: enterprise DI adoption trajectory and consumer state proportions. (c) Alternative consumer topology, with the consumer layer changed from a scale-free network to a small-world network: enterprise DI adoption trajectory and consumer state proportions. (d) Consumer interaction breadth, with the average degree of the consumer network decreased from 20 to 10: enterprise DI adoption trajectory and consumer state proportions.

Mechanistically, increasing enterprise connectivity enlarges the effective neighborhood through which enterprises observe payoffs and update strategies under the Fermi rule. This accelerates the spread of comparatively advantageous strategies and reduces the persistence of locally trapped configurations. In system terms, higher enterprise connectivity strengthens the link between payoff heterogeneity and evolutionary updating, enabling DI to diffuse more effectively once favorable signals emerge.

3.6.2. Influence of the Consumer Interaction Environment on DI Diffusion

Figure 6b isolates the role of the consumer interaction environment by replacing the consumer layer topology from a scale free network to a small world network while keeping the rest of the model unchanged. The scale free topology reflects a hub dominated online interaction structure, whereas the small world topology approximates locally clustered offline social relationships [46,63]. The equilibrium DI adoption share increases to roughly 0.35 to 0.40, indicating that an offline-like consumer environment can support stronger diffusion of DI at the enterprise level.

This effect is consistent with the structural properties of small world networks. High clustering supports repeated local reinforcement and the formation of coherent attitude clusters. Short path lengths allow information to reach distant parts of the network efficiently through a limited number of bridging links. In the coupled system, these properties increase the likelihood that favorable dissemination reaches a critical scale, improves perceived demand, and feeds back to enterprise payoffs, thereby facilitating DI diffusion.

3.6.3. Influence of the Breadth of Consumer Interaction on DI Diffusion

In this study, we further examine how changes in the average degree of the consumer network, which proxy the breadth of consumer interaction, influence the diffusion of DI. Varying the average degree in an online social environment represented by a scale free network and in an offline social environment represented by a small world network provides a distinct lens for understanding how social network structure conditions technology diffusion.

Comparing Figures 3 and 6c, we observe that diffusion is strengthened when the average degree of the online consumer network decreases. Specifically, when the average degree is reduced from 20 to 10, the equilibrium share of enterprises adopting DI rises from below 0.30 to approximately 0.40. This pattern suggests that, in heterogeneous online environments, reducing the number of information sources can increase the salience of dominant signals and facilitate their propagation, particularly under information overload. The result implies that, to enhance market acceptance of new technologies, enterprises and policymakers may prioritize strategies that leverage influential nodes and credible intermediaries rather than relying on undifferentiated mass broadcasting.

In contrast, comparing Figure 6b,d shows that diffusion weakens when the average degree of the offline consumer network decreases. When the average degree is reduced from 20 to 10 in the small world consumer network, the equilibrium adoption share declines from around 0.40 to roughly 0.30. This finding highlights the diffusion potential of offline social interaction, especially when networks exhibit strong local cohesion and bridging ties across communities. It also underscores the importance of face-to-face engagement in accelerating diffusion and suggests that enterprises may benefit from investing more in experiential and community-based interactions to reinforce beliefs and support adoption. To facilitate comparison of experimental results, we compared the baseline simulation with the four sets of simulations in this section, as shown in Table 3.

Table 3. Comparison of baseline diffusion and structural experiments.

Panel	Enterprise Layer	Consumer Layer	Steady-State DI Share
Figure 3	SW, $k = 4$	BA, $k = 20$	slightly above 0.20
Figure 6a	SW, $k = 8$	BA, $k = 20$	about 0.40
Figure 6b	SW, $k = 4$	SW, $k = 20$	about 0.38
Figure 6c	SW, $k = 4$	BA, $k = 10$	about 0.40
Figure 6d	SW, $k = 4$	SW, $k = 10$	About 0.30

4. Research Conclusions and Implications

4.1. Research Conclusions

This study uses a dual-layer coupled enterprise–consumer network model to explain how DI diffusion unfolds in the NEV sector under policy-driven incentives and heterogeneous information transmission. Three conclusions emerge.

First, enterprise adoption is governed by a co-evolutionary feedback between consumer belief diffusion and enterprise strategy updating. When favorable consumer dissemination expands, enterprises infer stronger market potential, which raises the relative payoff of adopting DI under the evolutionary updating rule. As more enterprises adopt, enterprise-side signals further reshape consumer attitudes, forming a self-reinforcing loop. When this loop is weak, the system remains in a low-adoption equilibrium.

Second, discouragement of counter-attitudinal dissemination is the dominant cross-layer lever shaping the diffusion equilibrium. Variation in the discouragement intensity parameter has a strong and systematic effect on the equilibrium adoption share, whereas aligned mobilization intensity generates comparatively smaller changes. This implies that diffusion barriers arise less from insufficient activation of supportive dissemination at the margin, and more from the suppression of cross-attitude information exchange that would otherwise enable belief updating and uncertainty reduction.

Third, policy support and the consumer information environment jointly determine whether the system can escape low-adoption lock-in. Under higher subsidies, diffusion improves most when consumers place greater weight on public information and rely less

on enterprise-released information. As subsidies decline, the system becomes less responsive to information reweighting and converges to low adoption. However, the low-subsidy regime is not fully irreversible. When discouragement of counter-attitudinal dissemination is reduced, diffusion pockets re-emerge even under weak financial support, indicating that information governance conditions can partially compensate for constrained incentives.

Finally, network structure conditions the strength and direction of these mechanisms. Denser inter-enterprise connectivity increases equilibrium adoption by accelerating imitation and reducing local trapping. On the consumer side, topology matters: a small-world offline-like interaction environment supports stronger diffusion than a scale-free online-like environment under the same parameters, and the effect of reducing interaction breadth is topology dependent, strengthening diffusion in the scale-free case but weakening diffusion in the small-world case. These results highlight that diffusion is shaped not only by incentives and signals, but also by structural constraints on exposure and reinforcement.

4.2. Policy and Managerial Implications

Taken together, these findings yield several important implications for policy design and strategic management.

For government, the results imply that effective NEV transition may benefit from coordinated interventions on incentives and information governance. Subsidies remain important for shifting the payoff landscape, especially in early diffusion stages. Under limited fiscal space, regulators can target the information side by strengthening transparency and independent evaluation and by protecting fair access to technology-related information, so that cross-attitude exchange is not systematically discouraged. Such measures reduce uncertainty and improve the chances that favorable beliefs reach the scale needed to alter market expectations.

For enterprises, the findings suggest that strategy should combine capability building for aligned mobilization with restraint in discouraging countervailing dissemination. Credible engagement and incentive-compatible advocacy can support diffusion, but the simulations also highlight that diffusion can be constrained in environments where opposing views are suppressed and belief revision slows. Enterprises therefore benefit from communication strategies that emphasize verifiable information, third-party validation, and open comparison, which can broaden trust and accelerate convergence toward shared expectations. In addition, managers should leverage inter-enterprise connectivity through alliances, standard-setting, and knowledge exchange to reduce uncertainty and speed up best-practice diffusion.

For consumers and platforms, the model indicates that the diversity and openness of information exposure affect system-level transition. When cross-attitude exchange persists, consumers can update beliefs more effectively, which improves market coordination and reduces the likelihood of being trapped in low-adoption equilibria. Platform governance that curbs manipulation and improves information quality can therefore play a supportive role in NEV diffusion.

4.3. Limitations

Finally, this study has several limitations. First, the framework is mechanism oriented. It is intended to identify conditional diffusion regimes under explicit assumptions rather than to deliver point prediction for the full Chinese NEV market. Relatedly, key behavioral and network parameters are specified as exogenous baseline settings; while the sensitivity and structural experiments support robustness at the mechanism level, empirical calibration with enterprise and consumer data would

strengthen external validity and support stronger quantitative inference. Second, the enterprise layer abstracts from additional market mechanisms, including firm heterogeneity, endogenous pricing, sustained price competition, and supply-side constraints. These factors may affect diffusion speed and shift steady-state adoption levels. Third, the consumer layer represents attitude formation and dissemination through stylized state transitions. It does not explicitly incorporate cognitive biases, platform-specific curation, or more granular psychological processes. These features may affect exposure, belief revision, and the persistence of attitudes. Fourth, network structure and inter-layer linkage are modeled using stylized topologies and simplified coupling rules. Empirically reconstructed networks or alternative coupling logics may lead to different quantitative thresholds. Therefore, the policy and managerial implications should be interpreted as mechanism informed and conditional. Future work may integrate empirical estimation, richer competition mechanisms, and more realistic information environments while preserving the coupled co-evolutionary structure developed here.

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