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The Role of Core Enterprises in Manufacturing Supply Chain Digital Transformation with Industrial Internet Platform Support: A Hypergraph Evolutionary Game Analysis

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Abstract

Digital transformation (DT) is reshaping manufacturing, with core enterprises (CEs) leveraging their resources to build industrial Internet platforms (IIPs) that support ordinary enterprises (OEs) in adopting DT. Differences in enterprise roles lead to varying impacts of government subsidies, necessitating careful policy design. Crucially, IIP adoption involves higher-order, multi-player interactions beyond conventional pairwise relationships—a dimension often overlooked in existing quantitative studies. This research employs hypergraph theory to model these complex interactions on IIPs and applies evolutionary game theory to analyze how enterprise decisions and government subsidies shape DT dynamics in manufacturing supply chains. The findings reveal that: (1) The network effect is the primary driver for DT via IIPs, but its promotional impact exhibits diminishing marginal returns. (2) Governments should prioritize subsidizing CEs for platform establishment, as subsidies directed at OEs for DT adoption are less effective. (3) Before withdrawing subsidies, governments must ensure a sufficiently high IIP adoption rate to sustain DT autonomously. This study introduces a novel methodology for examining DT and offers theoretical insights to guide enterprise strategy and policy implementation.

Keywords: digital transformation; hypergraph evolutionary game; industrial internet platform; complex network; incentive mechanisms

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1. Introduction

Digital technologies, including AI [1], blockchain [2], IoT [3], and cloud computing [4], are advancing rapidly and are increasingly adopted in industrial manufacturing. The implementation of these technologies substantially improves production efficiency, product quality, and operational management. The comprehensive utilization of digital technologies throughout the supply chain to enhance performance and competitive advantage is referred to as digital transformation (DT) [5].

However, DT requires substantial investment in new technologies and involves extended payback periods, which discourages some enterprises from pursuing it [6]. Moreover, financial and technical challenges result in a relatively low transformation success rate, with failure rates reaching 80% [7]. This dilemma is particularly acute for OEs, which are often small to medium-sized with insufficient capital and technical expertise [8]. As a

result, a significant digital divide has emerged between CEs that have completed their transformation and their upstream and downstream OEs, exacerbating transaction costs [9] and reducing overall supply chain efficiency. Therefore, external efforts are needed to alleviate the pressures faced by OEs during digital transformation, increase returns on their investments, enhance overall transformation rates across manufacturing enterprises, and fully leverage the value-creation potential of digital technologies in the manufacturing sector.

IIPs assist enterprises in integrating and optimizing information and resources [10], while strengthening information sharing and collaboration among supply chain partners [11]. Taking China's automotive industry as an example, platformization exists across the entire supply chain, from steel and auto parts to vehicle manufacturers. For instance, Nanjing Iron and Steel Group uses an IIP to enable upstream and downstream users to transact and collaborate on the same platform; Zhejiang Asia-Pacific Electromechanical Co., Ltd. (Hangzhou, China) optimizes procurement and supplier management through the Qilingling Platform; and Chery Automobile leverages the HiGOPlat to help parts suppliers achieve efficient collaboration with Chery in order and production planning systems. These platforms also assist their upstream and downstream partners in digital transformation (DT) [12] and enhance the spillover effect of digital capabilities throughout the supply chain [13].

In the process of CEs establishing IIPs to drive the DT of supply chain partners, all parties involved need to weigh the benefits against the costs. For CEs, assisting supply chain partners through IIPs incurs higher costs than their own DT, but it reduces DT costs and risks for these OEs [14]. Higher levels of digitalization among OEs can also enhance the collaboration benefits that CEs gain when transacting with them [15]. For OEs, DT can improve production and management efficiency and generate benefits through better inter-enterprise collaboration. However, this requires additional investment in R&D—costs that can be mitigated with support from CEs. This trade-off situation leads to hesitations among enterprises when establishing or joining IIPs. In this context, it is imperative to conduct in-depth research on the evolutionary mechanism through which IIPs—driven by CEs—propel the DT of manufacturing supply chains. Such research will help address the DT challenges faced by OEs and comprehensively elevate the overall digital level and collaborative efficiency of the manufacturing industry.

Government policy support also plays a crucial role in this process. Subsidies have been shown to effectively incentivize DT [16], yet excessively high subsidies may place a heavy fiscal burden on the government, ultimately hindering the DT process [17]. Moreover, continuous subsidy policies can lead to blind investment in DT and over-reliance on government support [18]. Therefore, it is essential for the government to choose an appropriate time to withdraw policy support to ensure that the DT of manufacturing enterprises proceeds autonomously and efficiently.

This study centers on how core enterprises drive the DT of the supply chain with the support of IIPs. Enterprise behaviors are interdependent, forming complex game-theoretic relationships, and their strategic interactions directly influence the evolution of DT strategies throughout the supply chain network. Additionally, the game-theoretic relationships among enterprises within the supply chain network, shaped by IIPs and DT, display the following characteristics:

(1) As human decision-makers, managers exhibit bounded rationality, meaning there is a probability that they will not choose the optimal strategy [19]; (2) The game interactions among enterprises are constrained by the topology of the supply chain network [20]; (3) The strategic behavior of one enterprise within an IIP can affect the benefits of all platform members [21], representing a higher-order interaction beyond pairwise relationships. Taking the automotive industry as an example, an IIP established by a core automotive assembly

enterprise can include its upstream component suppliers and downstream distributors. Component suppliers can plan production and inventory based on sales information shared by distributors, while distributors can provide timely feedback to customers regarding product delivery or maintenance progress by accessing production and inventory information shared by suppliers. Thus, efficiency in both production and service is enhanced through the IIP.

Hypergraph theory, which uses hyperlinks to connect two or more nodes, allows a precise definition of group relationships involving multiple entities in a network structure [22]. An evolutionary game based on hypergraphs can capture richer dynamical behaviors than traditional pairwise network structures, while accounting for the bounded rationality of decision-makers and constrained gaming relationships [23]. This makes the approach well-suited for research on the evolutionary dynamics of enterprise DT strategies driven by IIPs.

This study constructs a hypergraph evolutionary game model involving manufacturing CEs and OEs, and addresses the following questions through simulation analysis:

(1) How do enterprises make decisions regarding platform building and DT under the influence of IIPs?

(2) How do different factors (DT benefits and costs, network effect, government subsidies) affect enterprise decisions?

(3) How can the government formulate subsidy policies to promote DT in the manufacturing supply chain, and when can such policies be withdrawn?

The contributions of this study are as follows.

First, the study uses a hypergraph evolutionary game framework to characterize the evolution of DT strategies across enterprises within the supply chain network influenced by IIPs. Unlike traditional networked evolutionary games, which are limited to pairwise interactions, the hypergraph structure enables more accurate modeling of multiplayer interactions and constrained relationships, resulting in simulations that more closely reflect real-world dynamics.

Second, the study quantitatively examines the role of CEs in constructing IIPs to facilitate the DT of upstream and downstream partners, and assesses the resulting enhancement in the overall transformation rate of the manufacturing supply chain. These findings provide theoretical support for the use of IIPs to advance DT in the manufacturing sector.

Third, the study quantitatively investigates the effects of government subsidies directed at supporting IIP development by CEs and DT adoption by OEs, as well as the consequences of policy withdrawal under varying rates of platform construction and DT. This analysis provides a theoretical foundation for the formulation and withdrawal of government subsidy policies.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 presents the hypergraph evolutionary game model and outlines the decision-making mechanisms of the participants. Section 4 analyzes the influence of key factors on evolutionary outcomes through simulation experiments. Section 5 offers conclusions, managerial implications, limitations, and directions for future research.

2. Literature Review

This section reviews four strands of literature pertinent to this study: (1) digital transformation (DT) in manufacturing enterprises; (2) industrial Internet platforms (IIP); (3) supply chain core enterprises (CE); and (4) hypergraph evolutionary games.

2.1. Digital Transformation (DT) in Manufacturing Enterprises

A growing number of manufacturing enterprises are strengthening their DT by implementing digital technologies across the entire business process—from design and production to distribution and after-sales service [24]. DT has become a crucial means for modern manufacturing enterprises to strengthen their market competitiveness [25]. Existing studies have extensively explored DT in manufacturing. Specifically, Tian et al. [26] investigated the impact of DT practices on manufacturers and concluded that DT practices have a significant effect on operational efficiency. Shang et al. [27] examined how the interplay of technological, organizational, and environmental factors jointly enhances DT outcomes. Wu et al. [28] examined how enterprise size, product innovation, and production type affect DT levels. While these studies highlight the positive role of DT from various perspectives, they primarily focus on its impact within individual enterprises, paying insufficient attention to its ripple effects on the supply chain.

Building on this, some scholars have investigated the ripple effects of DT within supply chain networks. Guo et al. [29] demonstrated that the DT of major customers drives upstream digitalization through knowledge spillover and competitive pressure. Geng et al. [13] extended this conclusion to both upstream and downstream relationships, highlighting how DT in CEs facilitates transformation among their customers and suppliers through mechanisms such as reverse driving, knowledge spillover, and eased financing constraints. These conclusions have also been considered in the U.S. market, where government intervention is limited [30]. However, most existing research remains confined to simple dyadic relationships between focal enterprises and their supply chain partners, paying insufficient attention to the role of complex supply chain network structures in shaping the cascading effects of DT.

2.2. Industrial Internet Platform (IIP)

The IIP integrates the platform model with industrial manufacturing, extending Internet platform applications from the consumer domain to the industrial sector [31], and has become a vital tool for manufacturing enterprises to accelerate DT [32]. Li et al. [33] explored, through a case study of ROOTCLOUD, the mediating role of knowledge integration and sharing in promoting DT among SMEs via IIPs. Zhou et al. [32] explained the enabling mechanisms of IIPs for DT from an ecosystem perspective, noting that these platforms help enterprises reduce operational costs, improve product quality, and enhance value creation capabilities, while also driving adjustments in internal structures and external strategies. However, the main focus of existing literature remains on how IIPs create value for individual enterprises, with considerably less exploration into how such platforms, when built by CEs, shape and drive DT across the entire supply chain network.

Furthermore, the benefits of IIPs are shaped by network effects, which indicate that all participants gain greater benefits as the number of platform users grows [34]. This phenomenon is also known as network externality [35]. Using a game-theoretic approach, Zhang et al. [36] examined value-added service levels and pricing strategies for manufacturing platforms under network externalities, concluding that stronger network externalities enhance the value-creation capacity of platform services. Expanding on this research, Han et al. [37] integrated manufacturers' altruistic preferences and utilized differential game theory and Bellman dynamic programming to analyze value-added service strategies for manufacturing platforms that capitalize on network effects.

2.3. Supply Chain Core Enterprise (CE)

CEs are pivotal entities within supply chains, characterized by significant financial and technological advantages and a central position in the supply network [38].

Kang et al. [39] observed that government subsidies can incentivize these CEs to assume social responsibilities, thereby helping alleviate regional poverty. Similarly, Liu et al. [40] used an evolutionary game model to examine the role of platform-based CEs in supporting SME financing. Their study revealed that the effectiveness of CE-led intelligent supply chain finance relies on stringent government oversight. Based on resource dependence theory, Wang et al. [41] examined how CEs' participation motivations influence cooperative behaviors in safety management within supply chains. Yan et al. [42] found that CE involvement in traditional accounts receivable financing models can reduce banks' lending risks to SMEs and enhance the credibility of receivables.

With the advancement of digitization and platformization, the important role of CEs in supply chain DT has also come into focus. Yuan and Sun [43], using supply chain data from listed companies, confirmed that CEs significantly enhance the innovation capabilities of upstream and downstream OEs through spillover effects in funding, digitization, and innovation. Zhang et al. [44] noted that the DT of chain-leading CEs can improve their operational and financial efficiency and risk resilience, thereby boosting the overall efficiency of the supply chain. Further studies indicate that CEs can influence supply chain DT through platform ecosystems. Within platforms, CEs can promote the DT of OEs by providing technological and informational support, helping them improve business processes and market relationships [45]. Leading CEs such as Huawei and JD.com, which rely on IIPs, have facilitated technological innovation and supply chain integration, thereby promoting the emergence of digital value across the entire supply chain [46]. These studies demonstrate the significant position of CEs in DT and IIP ecosystems.

In conclusion, CEs' actions significantly affect other OEs in the supply chain. By providing incentives and implementing regulations targeting CEs, governments can effectively manage the supply chain as a whole. This paper investigates the role of CEs in driving the overall DT of supply chains and examines the effects of government subsidies on their behavior.

2.4. Hypergraph Evolutionary Game

Evolutionary game theory originated from the integration of game theory and biological evolution theory, and was initially used to study limited conflicts among animals of the same species [47]. The theory relaxes the assumption of perfect rationality in classical game theory by examining how boundedly rational players adapt their strategies through learning within a game. This approach allows researchers to model dynamic interactions and uncovers evolutionary patterns in complex environments [48]. For instance, Tang et al. [49] constructed a tripartite evolutionary game model involving manufacturing enterprises, the government, and digital platforms to investigate the driving effect of digital platforms on the green transformation of enterprises under various influencing factors. Yi et al. [50] introduced Gaussian noise to simulate external uncertainties and applied a stochastic evolutionary game to analyze digital collaboration among manufacturing enterprises empowered by IIPs. Their findings also offer insights for designing government subsidy policies to support DT.

Traditional evolutionary game theory assumes that populations are infinite and well-mixed, meaning that any two players in the system interact randomly with equal probability [51]. However, real-world manufacturing enterprises are embedded in complex network relationships, such as supply chains [52], where the probability of interaction between enterprises is not uniform [53]. Nowak and May [54] were among the first to extend evolutionary game theory to network structures, using complex networks to constrain interactions among players and thus better simulate the evolutionary dynamics of real-world complex systems. Networked evolutionary games have been widely applied in industrial

engineering. For instance, Ma et al. [55] used such a framework to study the evolution of knowledge-sharing strategies between manufacturers and service providers in the context of servitization. By comparing outcomes in well-mixed and network-structured populations, they demonstrated that network relationships lead to more diverse equilibrium states. Yang et al. [56] simulated the evolution of green investment strategies among suppliers and manufacturers in a scale-free supply chain network, incorporating the effects of blockchain technology and government intervention on green transformation. Although numerous studies have discussed the ripple effects of DT in supply chain networks [13,29,30], there remains a lack of research that simulates the evolution of enterprise DT strategies within network structures.

While networked evolutionary games constrain interactions among players, they still fall short of fully capturing the complex relationships among enterprises in reality [57]. Take IIPs as an example: most major platforms involve CEs that establish or acquire the platform, along with their upstream suppliers and downstream customers [31]. Within these IIPs, the strategies and payoffs of enterprises are interdependent, forming higher-order interactions that go beyond pairwise relationships [34]. Hypergraph theory offers a methodological framework for defining and analyzing such higher-order interactions. Unlike conventional networks, hypergraphs use hyperlinks to connect multiple nodes simultaneously, allowing a more accurate representation of group interactions [58]. Yin et al. [57] employed hypergraphs to model complex enterprise interactions, enabling more accurate prediction of competitive relationships through deep learning algorithms and demonstrating the superiority of hypergraph theory in modeling enterprise relations. Hypergraph theory has also been integrated into evolutionary game theory. Alvarez-Rodriguez et al. [59] extended evolutionary games to higher-order group interactions by simulating player-strategy evolution in public goods games via hyperlinks, thereby overcoming the limitations of traditional pairwise networks for capturing group dynamics. Nevertheless, few studies have applied hypergraph evolutionary games to investigate strategy evolution among enterprises in supply chain networks.

2.5. Literature Commentary

In summary: (1) Existing studies have sufficiently demonstrated that DT enhances enterprise-level performance and have acknowledged its ripple effects throughout supply chains; however, these works are largely confined to simple linear buyer-supplier relationships and lack consideration of the complex multi-agent interactions within supply chain networks. (2) While the role of IIPs in facilitating DT has been widely discussed—including the network effects they generate—the specific mechanisms through which these platforms promote DT among upstream and downstream enterprises remain underexplored. (3) Although Yi et al. [50] used stochastic evolutionary game theory to simulate digital collaboration among enterprises empowered by industrial Internet platforms, their study does not incorporate the complex structural relationships among enterprises or account for higher-order interactions within multi-agent platform environments. Hypergraph evolutionary game theory offers a promising approach to address this research gap.

3. Methodology

3.1. Problem Description

Supply chains typically include a limited number of CEs that occupy critical positions, operate at larger scales or possess more advanced technological capabilities [38], and have generally achieved DT in their internal production and management processes. On one hand, the DT of these core enterprises exerts a passive influence on non-digitalized upstream and downstream OEs [13]. On the other hand, some CEs establish IIPs to assist

upstream and downstream partners in their DT, thereby enhancing collaboration benefits across the supply chain [14].

Manufacturing enterprises operate within supply chain networks influenced by IIPs, where their strategies and payoffs are interdependent. This interrelationship, combined with the inherent bounded rationality of human decision-makers, makes the evolution of behaviors within the supply chain network difficult to predict. Moreover, as CEs provide a public interaction space via IIPs, the strategies and payoffs of participating enterprises affect one another through network effects, going beyond conventional dyadic supply chain relationships. The collaboration between a CE and its upstream and downstream OEs after establishing an industrial Internet platform is illustrated in Figure 1.

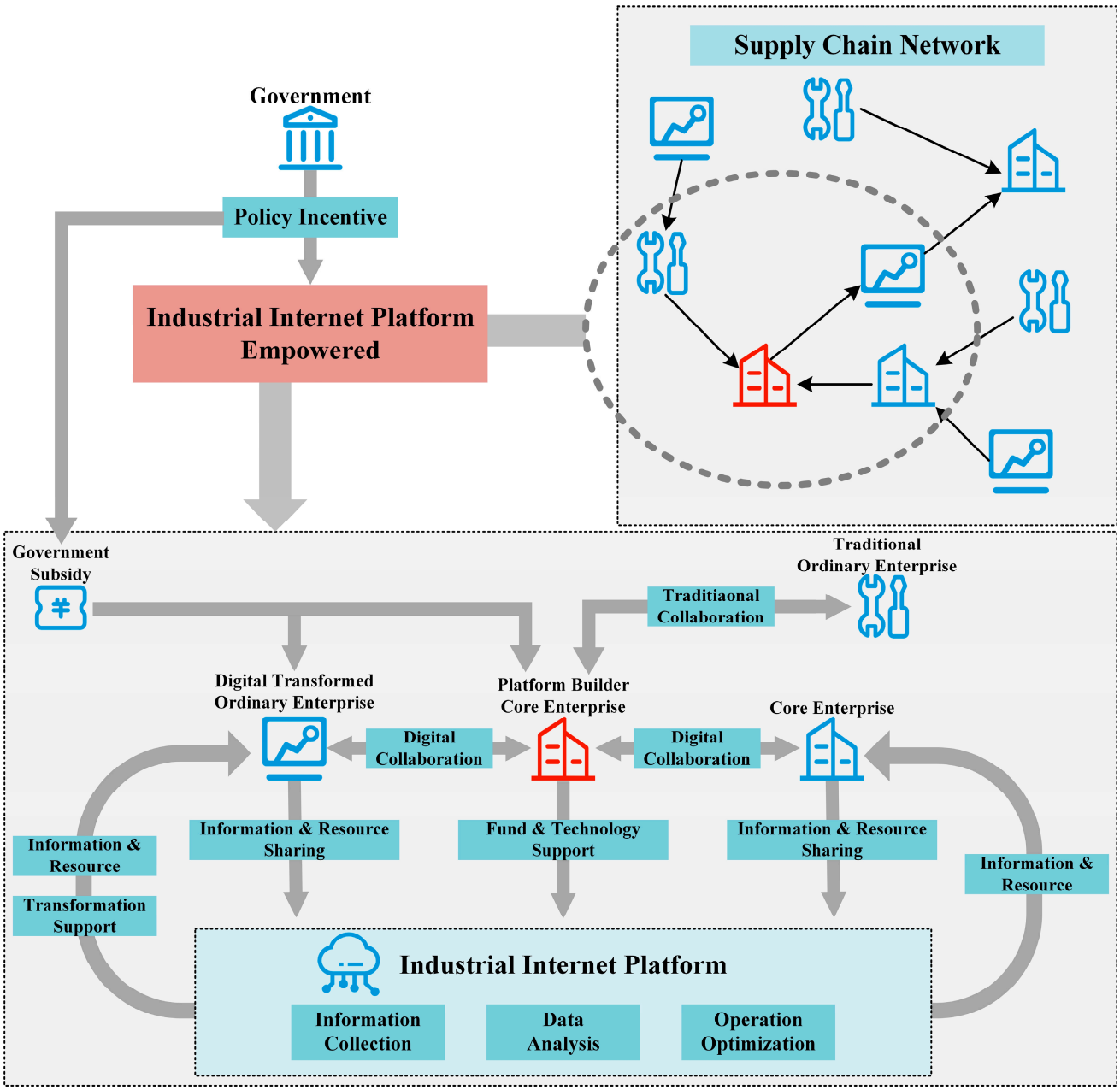


Figure 1. Collaboration mechanism between a CE and its supply chain partners based on the IIP.

This study constructs a multi-platform hypergraph model of the supply chain network using real-world data from S&P Global. The hypergraph includes CEs and OEs as primary actors. Evolutionary game theory is employed to simulate how the construction of IIPs by CE promotes DT among members of the supply chain network.

3.2. Supply Chain Networks and Multi-Platform Hypergraphs

A supply chain network composed of distinct enterprises and their supply relationships can be abstracted as a graph $G = (\mathcal{E}, \mathcal{L})$, consisting of a set N of nodes (or enterprises) $\mathcal{N} = \{n_1, \ldots, n_N\}$ and a set L links (or supply relationships) $\mathcal{L} = \{l_1, \ldots, l_L\}$. Each link connects a pair of nodes (i, j), representing a supply relationship. The connectivity among nodes in the network can be represented by an adjacency matrix $A_{E\times E}$, where $A_{ij} = 1$ if there is a link between nodes i and j, and $A_{ij} = 0$ otherwise. The degree of a node i in the network is defined as $d_i = \sum_{j=1}^{E} A_{ij}$, which corresponds to the number of other nodes directly connected to node i. In general, the role and importance of a node in the network are proportional to its degree [60].

In supply chain networks, CEs that have completed DT and possess advantages in capital and technology may establish IIPs to facilitate communication and collaboration among upstream and downstream enterprises. In this paper, the influence of such potential platforms on inter-enterprise relationships is represented using hypergraphs, specifically referred to as multi-platform hypergraphs for supply chains. A multi-platform hypergraph, composed of CEs, OEs, and their potential platform-enabled higher-order interactions, can be abstracted as a hypergraph $G = (\mathcal{E}, \mathcal{H})$ consisting of a set of N nodes (or enterprises) $\mathcal{N} = \{n_1, \ldots, n_N\}$ and a set of H hyperlinks (or potential platform relationships) $\mathcal{H} = \{h_1, \ldots, h_H\}$. Each hyperlink is a set of two or more nodes, representing the higher-order interactions among enterprises influenced by potential platforms. The structural relationship between nodes and hyperlinks in the hypergraph can be represented by an incidence matrix $B_{N\times H}$, where $B_{N\times H} = 1$ if node i belongs to hyperlink m, and $B_{i\times m} = 0$ otherwise.

CEs typically occupy pivotal positions within supply chain networks, with their representative nodes exhibiting higher degrees [38]. This paper classifies enterprises based on the degree d of their representative nodes. By setting a CE node degree threshold θ, an enterprise node n_i is classified as a core enterprise node ($n_i \in \mathcal{E}_c$) if its degree $d_i \geq \theta$, where $\mathcal{N}_s$ denotes the set of all CE nodes. Conversely, if $d_i > \theta$, the node is categorized as an OR node ($n_i \in \mathcal{E}_s$), with $\mathcal{N}_s$ representing the set of all OE nodes. CEs have generally undergone DT and possess the capability to establish IIPs. These potential platform relationships are represented via hyperlinks in a multi-platform hypergraph, where each hyperlink includes at least one CE node (platform host enterprise, PHE) and its neighboring nodes in the supply chain network, meaning $H = |\mathcal{E}_c|$. The specific generation method of the multi-platform hypergraph is outlined in Algorithm 1. For each CE node $\{n_i,\ d_i \geq \theta\}$, a hyperlink h_m is created to represent its potential platform. This hyperlink comprises that CE node together with all its neighboring nodes $\{n_j,\ A_{ij} = 1\}$.

Algorithm 1 Multi-Platform Hypergraph Generation Algorithm

Input: The set of enterprise nodes $\mathcal{N}$, the network adjacency matrix $A_{E\times E}$, the set of CE nodes $\mathcal{N}_c$, The set of OE nodes $\mathcal{N}_s$ //The input is supply chain network data. Nodes are classified as CEs or OEs based on a CE node degree threshold.

Output: The set of potential platform hyperlinks H, the incidence hypergraph matrix $B_{E\times H}$ //The output is a multi-platform hypergraph.

$i = 1, j = 1, m = 1$
for each $i = 1, 2, \ldots, N$, **do** //Process each node.
  if $e_i \in \mathcal{N}_c$ **then:** //For a CE node (node degree $\geq$ CE node degree threshold).
    $B_{\mathrm{i\times m}} = 1$ //Create a hyperedge containing this CE node.
    for each $j = 1, 2, \ldots, N$, **do** //Process each node.
      if A_{ij}=1 **then:** //Identify the neighbors of this CE node.
        $B_{\mathrm{jm}} = 1$ //Add all neighbors of this CE node to the hyperlink.
      end if
    end for
  end if
  $m = m + 1$
end for
return the hypergraph incidence matrix $B_{N\times H}$ //The final output is a matrix representing the nodes and their connections in the hypergraph.

Figure 2 illustrates the detailed process of generating a multi-platform hypergraph from a supply chain network using Algorithm 1. For the supply chain network shown in the upper part of Figure 2, the CE node degree threshold is set as $\theta = 3$. Accordingly, nodes 4 and 6 are classified as CEs and marked with hexagons, while the remaining nodes are classified as OEs and marked with circles. The potential platform that could be established by node 4 is denoted by hyperlink A, which includes node 4 itself and its neighboring nodes (i.e., upstream and downstream enterprises). To facilitate subsequent analysis, this paper designates the CE that may act as the platform builder within a hyperlink as the PHE f of that hyperlink (e.g., node 4 in hyperedge A), and refers to other CE within the same hyperedge as its "upstream/downstream CE u" (e.g., node 6 in hyperedge A). Similarly, hyperedge B represents the potential platform that could be established by the CE corresponding to node 6. Here, node 6 serves as the PHE of hyperedge B, while node 4 is its upstream/downstream CE.

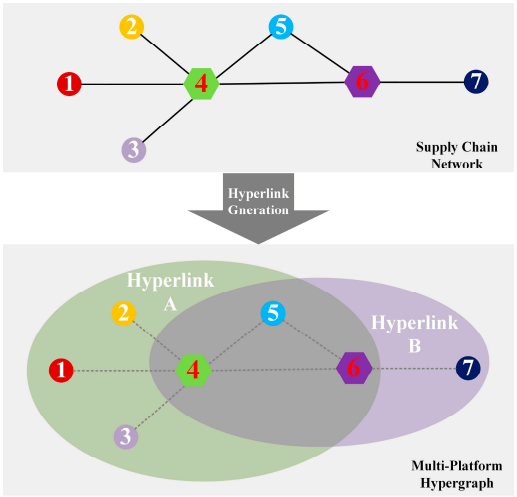


Figure 2. Schematic diagram of the multi-platform hypergraph generation process.

In simple terms, a CE's direct interactions involve all its first-order neighbors within the supply chain network. Its indirect interactions via PHEs encompass all second-order neighbors in the network that are mediated by other CEs. It is also important to note that PHEs and CEs are not two separate sets of nodes. All CEs act as PHEs within their own established platforms—for example, Node 4 in Hyperlink A. This means CEs and PHEs represent the same set of nodes, assuming different roles depending on the hyperlink in which they participate.

3.3. Basic Assumptions

Based on the above analysis and hypergraph structure, this study proposes the following assumptions:

(1) Assumption 1: The multi-platform hypergraph contains two types of heterogeneous players: CEs and OEs. Different players engage in multi-player games within their connected hyperlinks. In its "hosted platform hyperlink", a CE, acting as the PHE, chooses between two strategies: "Build" or "Not Build", determining whether to build an IIP—i.e., whether the potential platform within that hyperlink exists. In other platform hyperlinks, a CE, serving as an "upstream/downstream CE", chooses between two strategies: "Join" or "Not Join", deciding whether to join other platforms led by its upstream or downstream CEs. In all hyperlinks to which it is connected, an OE has the same strategy set: "Transform" or "Not Transform", indicating whether it undergoes DT and joins the platform. Crucially, a CE's choice to "Join" when the PHE adopts "Not Build" does not lead to actual participation. Rather, it signals the CE's willingness to join and represents its preliminary investment of personnel, capital, and technical resources.

(2) Assumption 2: For all enterprises in the hypergraph, the proportion of CEs choosing the "Build" strategy is denoted as x, the proportion of OEs choosing the "Transform" strategy is denoted as y, and the proportion of CEs choosing the "Join" strategy is denoted as z. Here, x_0, y_0 and z_0 represent the respective proportions of these three strategies at the initial state of evolution. For enterprises within a specific hyperlink, y_t represents the number of OEs choosing the "Transform" strategy, y_a represents the total number of OEs; z_j represents the number of upstream/downstream CEs choosing the Join strategy, and z_a represents the total number of upstream/downstream CEs within the hyperlink.

(3) Assumption 3: In the traditional collaboration between enterprises, a CE gains a benefit of R_f, and an OE gains a benefit of R_s. The total benefit obtained by a specific CE from collaborating with all OEs within its hosted platform hyperlink is $y_a R_f$. The cost for an OE to adopt DT is denoted as C_s, and the cost for a CE to build an IIP is denoted as C_f.

(4) Assumption 4: After an OE adopts DT, its internal production, management, and operational efficiency improve [61]. Meanwhile, due to meeting the DT requirements of upstream and downstream CEs [13], it experiences increased sales or reduced costs, resulting in a gain α in collaboration benefit, i.e., $(1+\alpha)R_s$. Through an IIP, the CE can support both upstream and downstream OEs in their digital transformation. This support includes providing a prototype platform, exchanging needs, and sharing technology. Such collaboration creates knowledge spillover [62], which reduces β in the transformation cost for OEs. Consequently, the transformation cost becomes $(1-\beta)C_s$. After the DT of its upstream and downstream OEs, the supply chain collaboration cost between the CE and these partners decreases [63]. When all upstream and downstream enterprises of the CE complete DT, its collaboration benefit gains an increase γ, i.e., $(1+\gamma)R_f$. Consequently, if the CE has y_a ordinary enterprises across its upstream and downstream supply chain, and y_t of them have completed DT, the collaboration benefit obtained by the CE is $(y_a + y_t\gamma)R_f$.

(5) Assumption 5: Within the IIP, enterprises share information regarding demand, production, and logistics. Meanwhile, the PHE leverages this information to optimize plat-

form service levels. The addition of more members increases the information and resources accessible within the platform, enhancing benefits for all parties and thereby generating network effects [64]. A single OE joining the platform generates a benefit K_s for other platform members. The CE joining the platform generates a benefit K_u for other platform members. However, as the CE places greater importance on its proprietary information, joining the platform entails a certain information leakage risk C_{u1}. Furthermore, if the CE attempts to join a potential platform while it is not built, it incurs an opportunity cost C_{u2}.

(6) Assumption 6: The government provides incentive subsidies for DT to encourage enterprises to adopt or support DT. An OE receives an incentive subsidy I_s upon adopting DT, while the CE receives an incentive subsidy I_f for building an IIP.

3.4. Payoff Matrix

In summary, within a single hyperlink of the multi-platform hypergraph, two types of game relationships exist: the game between the PHE and OEs, and the game between the PHE and its upstream/downstream CEs. All enterprise nodes within the hyperlink engage in a multiplayer game, where their strategies and payoffs mutually influence each other. The payoff matrix for the game relationship between the PHE and OEs is shown in Table 1. The payoff matrix for the game relationship between the PHE and its upstream/downstream CEs is shown in Table 2.

Table 1. Payoff matrix: PHE vs. OE.

PHE f	**OE** s	
	Transform y	**Not Transform** $1-y$
Build x	$(1+\alpha)R_s-(1-\beta)C_s+(y_t-1)K_s+zK_u+I_s$	R_s
	$(y_a+y_t\gamma)R_f-C_f+yK_s+z_jK_u+I_f$	$(y_a+y_t\gamma)R_f-C_f+yK_s+z_jK_u+I_f$
Not Build $1-x$	$(1+\alpha)R_s-C_s+I_s$	R_s
	$(y_a+y_t\gamma)R_f$	$(y_a+y_t\gamma)R_f$

Table 2. Payoff matrix: PHE vs. upstream/downstream CE.

PHE f	**Upstream/Downstream CE** u	
	Join z	**Not Join** $1-z$
Build x	$y_tK_s+\left(z_j-1\right)K_u-C_{u1}$	0
	$(y_a+y_t\gamma)R_f-C_f+yK_s+z_jK_u+I_f$	$(y_a+y_t\gamma)R_f-C_f+yK_s+zK_u+I_f$
Not Build $1-x$	$-C_{u2}$	0
	$(y_a+y_t\gamma)R_f$	$(y_a+y_t\gamma)R_f$

It is important to note that although the payoff matrices only explicitly outline the game relationships between the "PHE–OE" and the "PHE–Upstream/Downstream CE," OEs and upstream/downstream CE within the same potential platform hyperlink can also influence each other's payoffs through network effects.

3.5. Decision-Making Mechanisms

The introduction of structural relationships among players makes it difficult to derive the replicator dynamics equation for evolutionary games on complex networks or hypergraphs, unlike in traditional evolutionary game theory. Existing studies often use agent-based simulation methods to model evolutionary processes, which involve defining strategy-learning and updating rules for each node.

Common strategy update methods include unconditional imitation, Moran rule, and Fermi rule [65]: (1) Unconditional imitation: Nodes directly adopt the strategy of their highest-payoff neighbor. Although simple in principle, this rule ignores the bounded rationality that may occur in real decision-making. (2) Individuals are selected for reproduction proportionally to their payoffs, and then replace a random neighbor's current strategy with their own [66]. This rule introduces stochasticity, but its updating mechanism lacks a clear practical interpretation in the context of enterprise decision-making. (3) Fermi rule: a node randomly selects a neighbor and updates its strategy with a probability determined by the payoff difference and system noise [67]. This rule not only closely mimics human learning and imitation in decision-making but also incorporates stochasticity to reflect the bounded rationality of agents.

Therefore, this study employs the Fermi rule to simulate the bounded rationality of enterprise decision-makers. The strategy update rule is defined as Equation (1):

$$P_{S_i \to S_j} = \frac{1}{1 + e^{(U_i - U_j)/k}} \tag{1}$$

Here, $P_{S_i \to S_j}$ denotes the probability that a node updates its strategy from S_i to S_j, where S_i and S_j represent the node's current strategy and the strategy of the reference node (i.e., the learning object), respectively. U_i and U_j refer to the payoffs of the node itself and the reference node. The parameter k represents the noise intensity $(k > 0)$.

Figure 3 illustrates how the strategy update probability varies with the payoff difference under different values of k. It can be observed that within a certain range of payoff differences, nodes have a small probability of updating to a strategy with a lower payoff. When k is small, the strategy update tends toward unconditional imitation. When k is large, the strategy update approaches complete randomness. Under this rule, nodes may adopt suboptimal strategies due to the influence of system noise, thus capturing the bounded rationality of decision-makers.

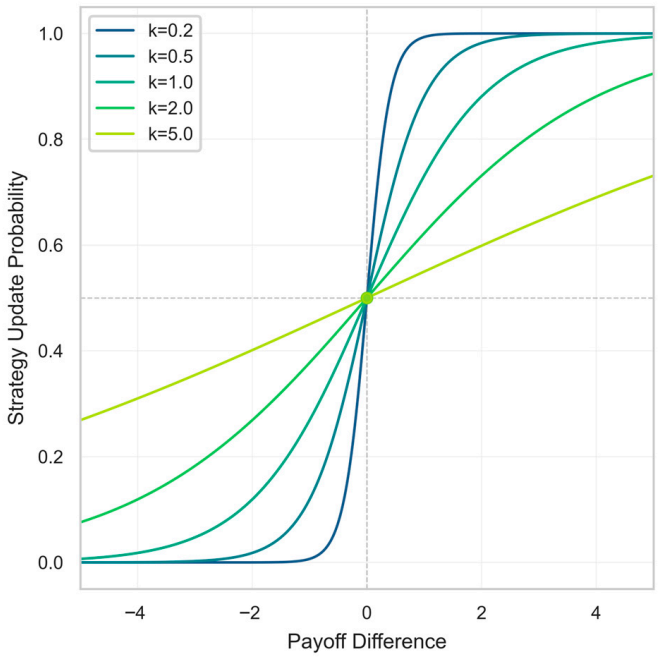


Figure 3. The effect of varying noise intensity k on the strategy update probability.

3.6. Model Solving Algorithm

The stepwise solution method for the model is presented in Algorithm 2. It takes supply chain network data, payoff matrices, and parameter settings as inputs. Through multiple iterations, the final strategy proportions of the hypergraph evolutionary game model can be obtained.

Algorithm 2 Hypergraph Evolutionary Game Model Solving Algorithm

Input: Supply chain network, payoff matrix, parameter settings, maximum number of iterations

Output: Final strategy proportion of "Build", "Transform" and "Join"

Initialization: Assign an initial strategy to each node according to the initial strategy proportions x_0, y_0 and z_0.
Divide nodes in the supply chain network into "CE" and "OE" based on the CE node degree threshold θ.
Construct a hypergraph from the supply chain network data using Algorithm 1.
for each node $i \in$ hypergraph, **do**
  if node $i \in$ CE **then:**
    Calculate node i's payoff relating to strategy "Build" using the payoff matrix in Tables 1 and 2
    Calculate node i's payoff relating to strategy "Join" using the payoff matrix in Table 2
    Use Equation (1) to update the "Build" and "Join" strategies, treating the opposite of its current strategy as the reference strategy.
  if node $i \in$ OE **then:**
    Calculate node i's payoff relating to strategy "Transform" using the payoff matrix in Table 1
    Randomly select another node within the same hyperlink and use Equation (1) to update the "Transform" strategy.
Repeat Steps 4 to 11 until the maximum number of iterations is reached
Calculate the final strategy proportion of "Build", "Transform" and "Join"

4. Simulation

This section analyzes the evolutionary dynamics of DT based on IIPs using a hypergraph evolutionary game model, applied to real supply chain data from China's automotive manufacturing sector obtained from S&P Global. To further investigate the influence of various factors, the DT process was simulated under multiple scenarios. Sensitivity analyses were also conducted on several key model parameters, thus establishing robust conclusions for this study.

This study constructs the supply chain network data set referring to the method by Li et al. [68]. Six major Chinese automakers—BYD, SAIC, Geely, FAW, Changan, and Chery—were selected as focal enterprises. Their upstream two-tier supplier data was acquired from S&P Global to form the supply chain network, and the multi-platform hypergraph was built using Algorithm 1. To simplify the research problem and ensure network connectivity, all subsidiaries appearing in the network are treated as suppliers of their respective parent companies. The resulting network comprises 1151 nodes, and its degree distribution is shown in Figure 4.

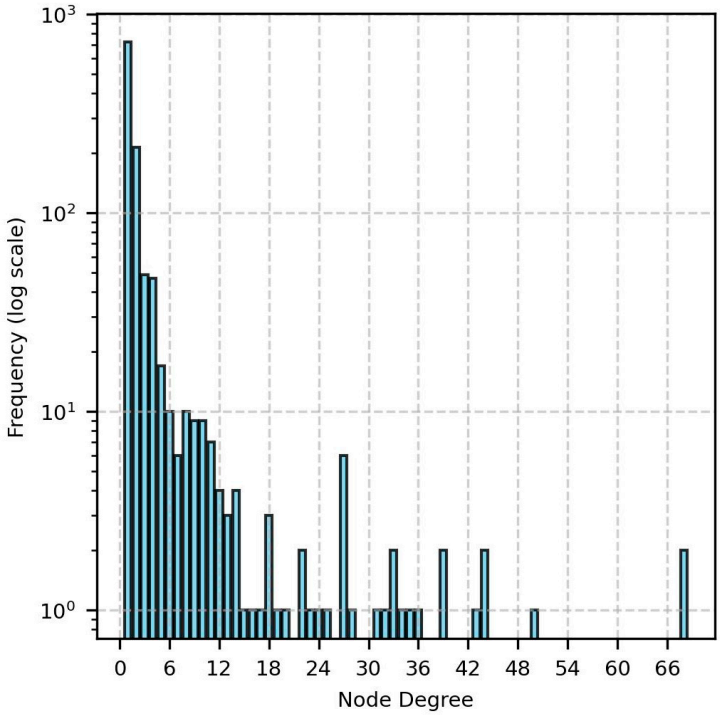


Figure 4. The degree distribution of China's automotive supply chain network.

According to the "Several Policies of Changsha City in Support of the National Pilot Program for Digital Transformation of Small and Medium-Sized Enterprises" issued by the Changsha City Government in 2025: "General pilot enterprises receive a subsidy equivalent to 30% of their total digital transformation procurement, with a maximum subsidy of CNY 300,000 per enterprise. Industrial Internet platforms included in the pilot demonstration list of the Ministry of Industry and Information Technology are eligible for a subsidy of 20% of their total investment, capped at CNY 2 million per project." Based on this policy, the incentive for DT of OEs, denoted as I_s, is set at CNY 300,000, while the cost of DT for OEs, C_s, is set at CNY 1 million. The incentive for a IIP built by CEs, I_f, is set at CNY 2 million, and the IIP building cost for CEs, C_f, is set at CNY 10 million.

Based on DT cases in Guangdong Province: "after Foshan Xinwei Knitting accessed the cloud platform developed by ZhiJing Technology, its overall production efficiency increased by 30%; Midea Group, through its MeiQing Industrial Internet Platform, helped improve R&D and design efficiency by 40% for related supply chain enterprises." Accordingly, the benefit gain coefficient for DT of OEs, α, is set to 0.3, and the cost reduction coefficient β for DT of enterprises supported by the IIP is set to 0.4.

According to the "2024 Collection of Exemplary Cases in Manufacturing Digital Transformation" published by the China Academy of Information and Communications Technology, Chery Motors shortened its delivery cycle time by 23% through improved coordination efficiency with component manufacturers via the HiGOPlat platform. Based on this case, the benefit gain coefficient of upstream and downstream OEs' DT for the CE was set to 0.2.

Based on relevant research and market survey, other parameters were configured accordingly. The initial parameters for the simulation experiments are shown in Table 3. The evolution time, i.e., the number of iterations, was set to 50. Each set of simulation experiments was repeated 50 times, with the average values taken as the final results.

Table 3. The initial parameters for the simulation experiments.

Parameter Notation	Description	Value
x_0	Initial "Build" strategy proportion	0.5
y_0	Initial "Transform" strategy proportion	0.5
z_0	Initial "Join" strategy proportion	0.5
Rs	OE collaboration benefits	200 ten thousand CNY
Rf	CE collaboration benefits	200 ten thousand CNY
C_s	DT cost	100 ten thousand CNY
C_f	IIP building cost	1000 ten thousand CNY
Is	DT incentive subsidy	30 ten thousand CNY
If	IIP building incentive subsidy	200 ten thousand CNY
Ks	Network effect benefits attributed to the OE's joining	20 ten thousand CNY
Ku	Network effect benefits attributed to the CE's joining	200 ten thousand CNY
C_{u1}	Information leakage risk	200 ten thousand CNY
C_{u2}	Opportunity cost of failing to join the IIP	200 ten thousand CNY
α	Benefits gain coefficient for DT of OEs	0.3
β	Cost reduction coefficient for DT supported by the IIP	0.4
γ	Benefits gain coefficient for CEs after DT of supply chain patterners	0.2
θ	CE node degree threshold	5
k	Noise intensity in bounded rational strategy updating	0.1

4.1. Evolutionary Dynamics Under Initial Parameter Settings (Scenario 1)

Figure 5 illustrates the evolutionary dynamics of strategy adoption proportions among enterprises within the hypergraph—specifically regarding "Build", "Transform", and "Join"—under the initial parameter settings. The light shaded area surrounding the curve represents the stochastic dispersion resulting from the random assignment of initial strategies and the application of the Fermi rule.

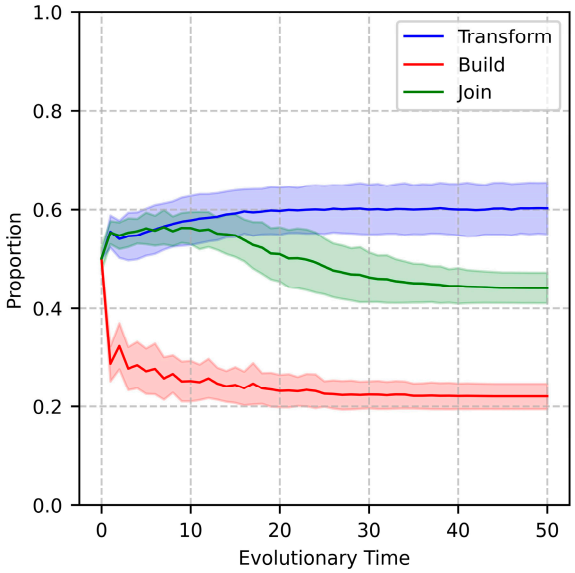


Figure 5. Evolutionary dynamics under initial parameter settings.

Under the initial conditions, the rate of IIP building experiences a sharp initial decline, followed by a brief rebound before continuing to decrease and eventually stabilizing at around 20%. This trend occurs because a 50% DT rate among OEs is insufficient to generate the necessary benefits and network effects to justify the costs of platform building for most CEs. As a result, only a few large CEs can build platforms that attract enough participants to achieve positive returns.

The DT rate rises rapidly in the early stages, supported by the numerous IIPs initially built by CEs. However, as the number of IIPs declines, the DT rate fluctuates downward

before recovering and eventually stabilizing at approximately 60%. Meanwhile, the reduction in available IIPs leads to a decrease in opportunities for CEs to join other IIPs, which is reflected in the declining proportion of the "Join" strategy.

4.2. Evolutionary Dynamics Under Different Scenarios

To test the model's robustness, this section analyzes the evolution of IIP-driven DT across different scenarios using the proposed hypergraph evolutionary game model. Based on the initial parameter settings in Scenario 1 as the baseline, the following scenarios are designed with reference to different country environments outside China.

(1) Scenario 2: This scenario refers to the development trends of IIPs and DT in manufacturing in the United States. In terms of technological foundation, the U.S. has a more advanced digital infrastructure and a stronger environment for cutting-edge technology R&D compared to China [69]. Regarding policy support, although the U.S. government does not provide direct subsidies for IIP construction or enterprise DT actions, it supports advanced basic technology R&D by enterprises and institutions through policies such as the National Strategic Plan for Advanced Manufacturing and the Small Business Innovation Research (SBIR) program. This indirectly reduces the costs for establishing IIPs and conducting DT, while also improving the efficiency with which enterprises utilize IIPs and digital technologies. Therefore, in this scenario, policy subsidies for establishing IIPs and undertaking DT are removed. However, the costs and related benefits of establishing IIPs or performing DT are increased to reflect its stronger technological foundation.

(2) Scenario 3: This scenario draws on the development trends of IIPs and DT in manufacturing in developing countries such as Brazil and Vietnam. Technologically, these countries have limited IT infrastructure [70] and a shortage of sufficient professional talent [71]. In terms of policy support, some developing countries also offer national-level subsidies for enterprise DT. For example, Brazil's government invested approximately USD 32 billion (of which USD 8 billion was borne by the public sector) in 2024 to promote DT in the industrial sector. Vietnam's government plans to allocate USD 3.6 billion by 2026 to foster enterprise innovation and DT. However, these countries lack clear subsidy policies specifically targeting IIPs. Thus, in this scenario, policy subsidies for establishing IIPs are removed, while the related benefits from establishing IIPs or undertaking DT are reduced to reflect their relatively weaker technological foundation.

Table 4 presents a comparison of model parameter settings across different scenarios. For clarity, the table only includes parameter values that differ between scenarios, and units of measurement have been omitted. The evolutionary dynamics of the system under the parameter settings for Scenario 2 and Scenario 3 are illustrated in Figure 5.

Table 4. The comparison of parameters for different scenarios.

Parameter Notation	Scenario 1	Scenario 2	Scenario 3
C_s	100	90	100
C_f	1000	900	1000
Is	30	0	30
If	200	0	0
Ks	20	30	10
Ku	200	300	100
α	0.3	0.4	0.2
β	0.4	0.5	0.3
γ	0.2	0.3	0.1

Figure 6a shows that, despite the absence of direct government subsidies for IIP construction and DT, the overall rate of DT adoption within the supply chain and the rate of IIP establishment remain relatively high. Furthermore, compared to Scenario 1, more

CEs are willing to join IIPs established by CEs in the upstream and downstream supply chain. This is because, even without direct subsidies, a stronger technological foundation enhances enterprises' efficiency in utilizing platforms and digital technologies, thereby indirectly boosting their motivation to either establish IIPs or undergo DT.

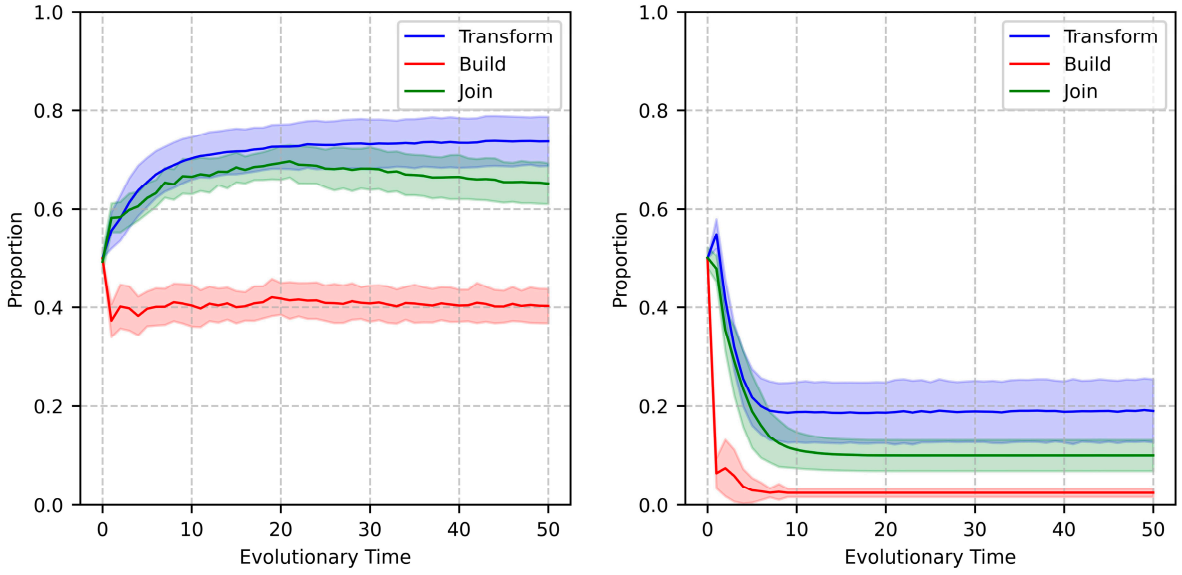


Figure 6. Evolutionary dynamics under different scenarios: (**a**) Evolutionary dynamics under scenario 2; (**b**) Evolutionary dynamics under scenario 3.

Figure 6b shows that in regions with weaker foundational infrastructure and lower adoption of digital technologies, government subsidies for the DT of ordinary enterprises (OEs) are ineffective at significantly increasing the overall DT rate across the supply chain. Moreover, the lower rate of enterprise DT means IIPs lack a sufficient operational base, preventing them from fulfilling their role in assisting and driving DT among upstream and downstream enterprises.

These results indicate that direct subsidies for IIPs and DT are neither sufficient nor necessary for improving DT in manufacturing supply chains. Governments must also prioritize the R&D of foundational technologies to provide a solid base for enterprise DT and the operation of IIPs.

4.3. The Sensitivity Analyses of IIP-Related Factors

Based on the parameter settings of Scenario 1, this section conducts a sensitivity analysis on parameters related to IIP factors. The aim is to investigate how variations in different technology-related factors affect the evolutionary dynamics of supply chain DT driven by IIPs.

4.3.1. The Sensitivity Analysis of OE Benefits Gain

By adjusting the benefits gain coefficient α of DT for OEs as shown in Figure 7, it can be observed that changes in α lead to a discontinuous jump in its impact on the DT. When α ranges from 0.1 to 0.3, variations in the gain have an insignificant influence on the final "Transform" proportion. However, once α reaches or exceeds 0.5, the DT rate of OEs rapidly increases to 100% during the initial evolutionary phase and remains stable. This also moderately boost CEs' willingness to build IIPs and enhances their opportunities to join platforms hosted by their supply chain partners.

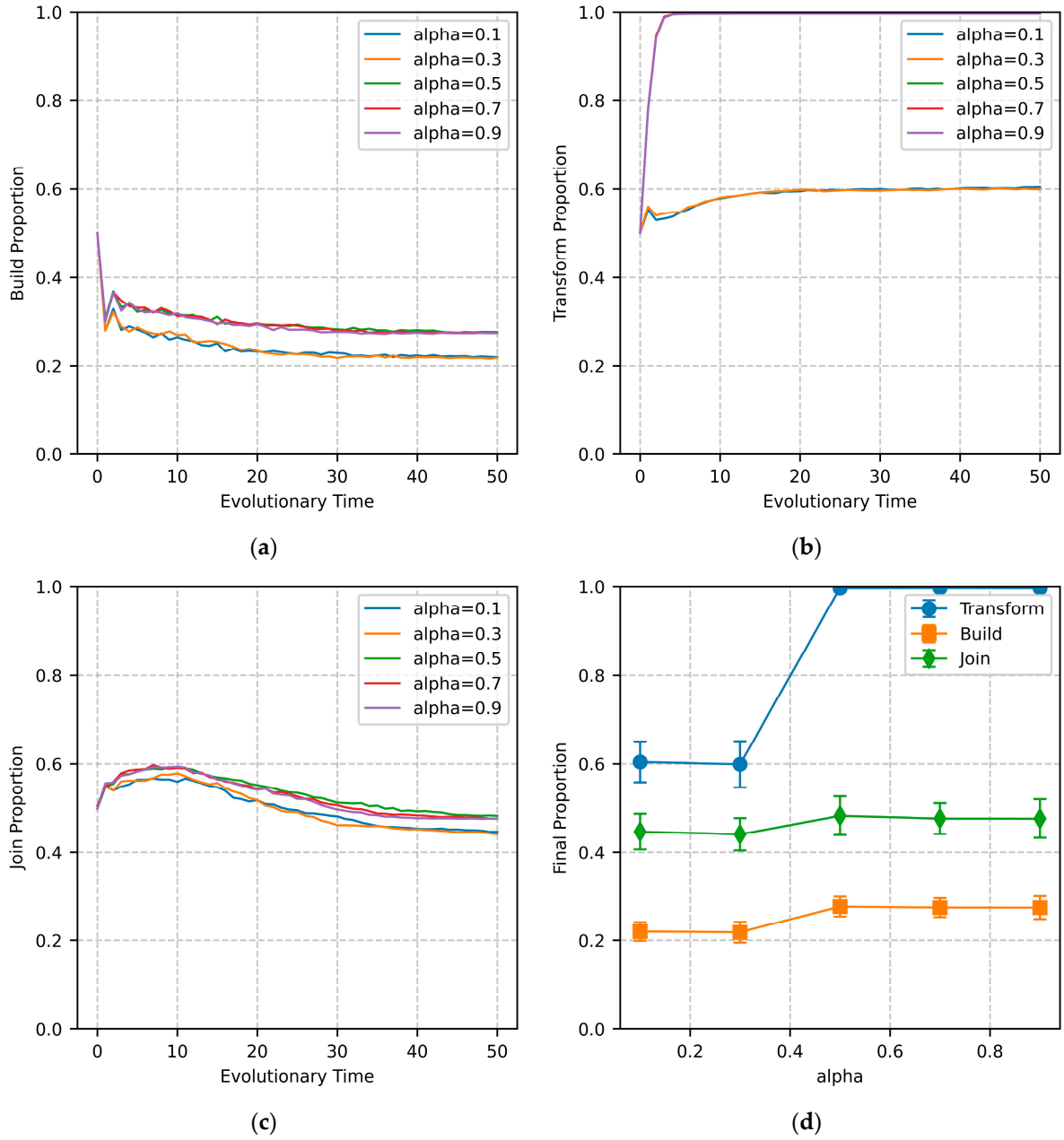


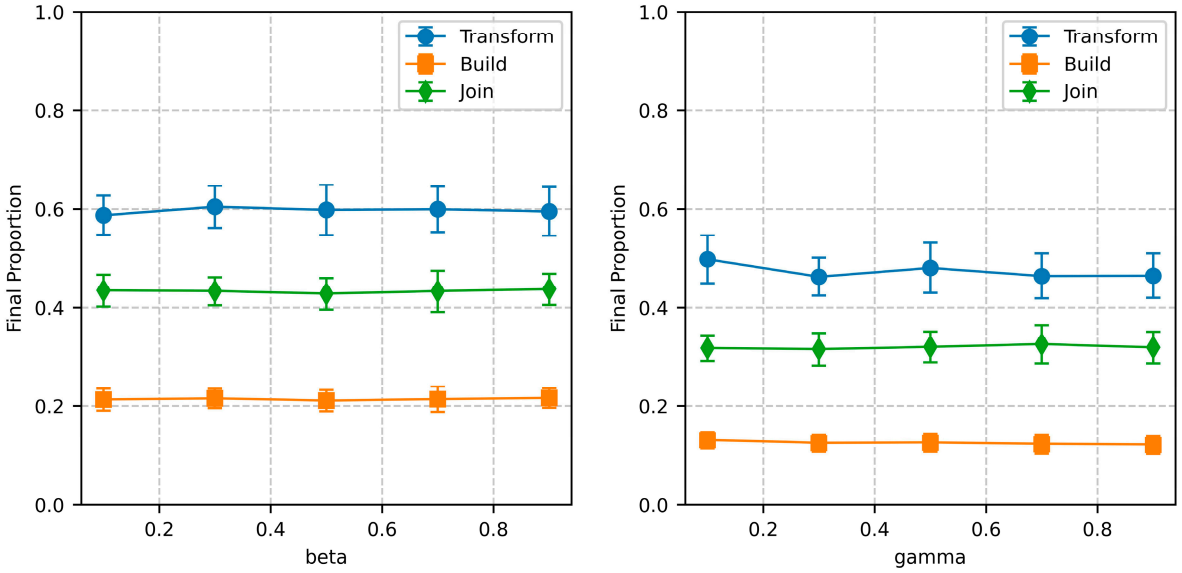
Figure 7. Evolutionary dynamics under the variation in the OE benefits gain coefficient α: (**a**) The impact of α on the "Build" strategy evolutionary dynamic; (**b**) The impact of α on the "Transform" strategy evolutionary dynamic; (**c**) The impact of α on the "Transform" strategy evolutionary dynamic; (**d**) The impact of α on the final strategy proportion.

The reason for this phenomenon lies in the fact that when α is low, the increase in benefits brought by DT only partially motivates OEs to adopt the "Transform" strategy. The network effects generated after joining a platform also serve as a major driver for DT among ordinary enterprises. In contrast, when $\alpha = 0.5$, the DT benefits fully offset the costs. As a result, the choice of "Transformation" strategy by OEs becomes independent of the IIP building efforts of CEs, making "Transform" a strictly dominant strategy.

4.3.2. The Sensitivity Analysis of DT Cost Reduction

As shown in Figure 8a, varying the DT cost reduction coefficient β for OEs supported by the IIP has no significant impact on the final strategies proportion of all players within the hypergraph. The IIP's role in facilitating DT by reducing implementation costs proves

to be limited. This is because such cost reductions do not improve the benefits that CEs gain from building platforms. Smaller CEs, which have fewer upstream and downstream partners, still find that the returns from IIP building cannot offset the associated costs. As a result, they do not adopt the "Build" strategy. Consequently, their connected enterprises cannot benefit from IIP-supported cost reductions and thus continue to stick to their "Not Transform" strategy.



(**a**) (**b**)

Figure 8. Final strategy proportion under the variation in DT cost reduction β and CE benefits gain γ (**a**) The impact of β on the final strategy proportion; (**b**) The impact of γ on the final strategy proportion.

4.3.3. The Sensitivity Analysis of CE Benefits Gain

As shown in Figure 8b, varying the benefit gain coefficient γ, which represents the impact of upstream and downstream enterprises' DT on the benefits of CEs, has no significant effect on the adoption of the "Transform" or "Build" strategies. The reason is similar to that of β: it does not fundamentally alter the IIP building payoff for CEs. Even when the benefits from DT among connected enterprises are relatively low, large CEs can still attract upstream and downstream partners to DT and join their IIPs. The resulting network effects provide sufficient benefits to sustain IIP. On the other hand, smaller CEs find that the gains and network effects generated through supporting DT are still inadequate to cover the costs of IIP building.

4.3.4. The Sensitivity Analysis of Network Effect Benefits Attributed to the OE's Joining

As shown in Figure 9, varying the network effect benefit Ks attributed to the OE's joining shows that an increase in K_s significantly enhances the DT rate of OEs. On one hand, a higher K_s increases the benefits for all participants within built IIPs, attracting more OEs to pursue DT. On the other hand, it makes IIP building more appealing to CEs that had not previously built IIPs, as they can leverage network effects to improve returns. This, in turn, encourages more of their upstream and downstream OEs to adopt the "Transform" strategy.

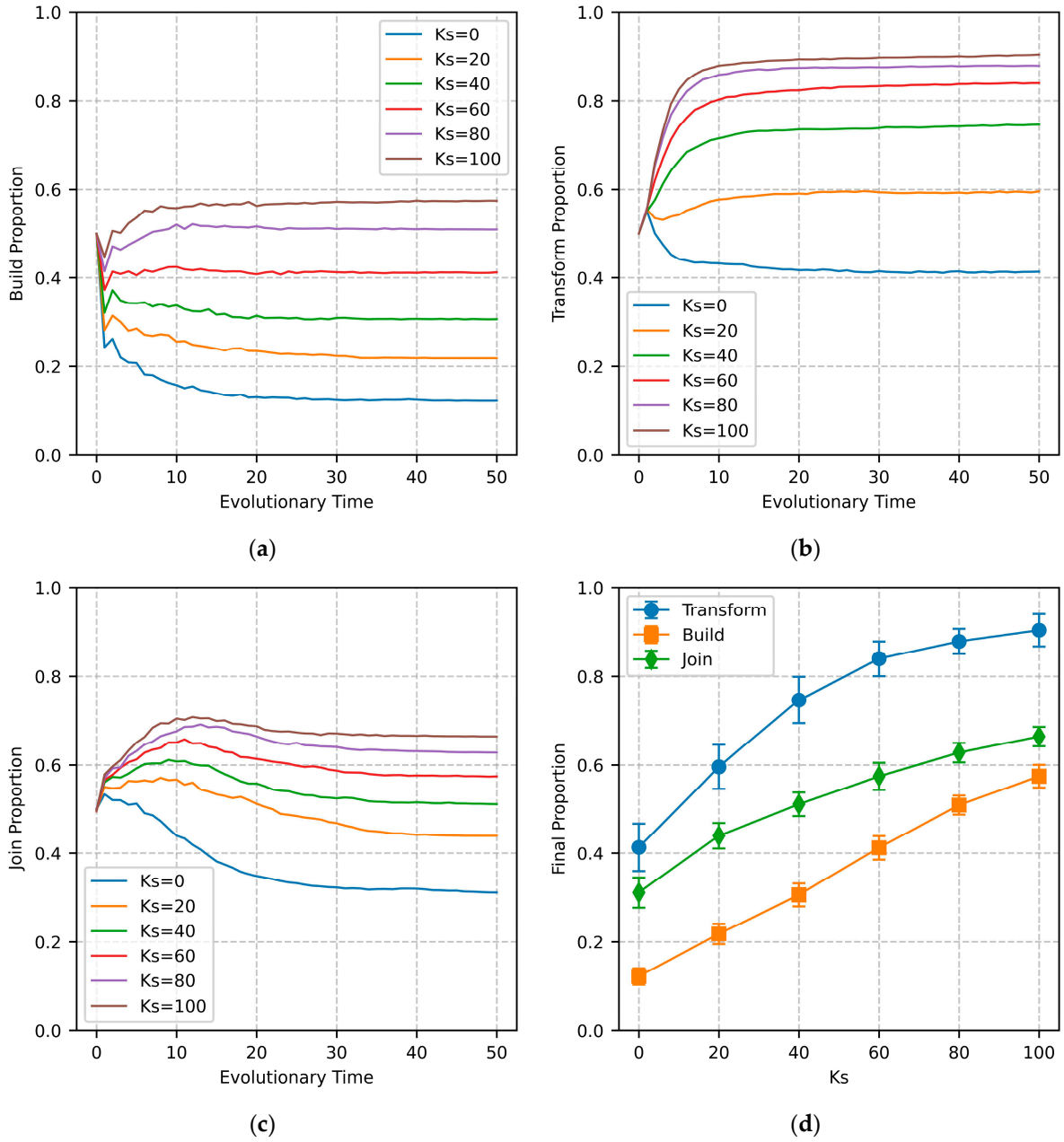


Figure 9. Evolutionary dynamics under the variation in network effect benefits K_s attributed to the OE's joining: (**a**) The impact of K_s on the "Build" strategy evolutionary dynamic; (**b**) The impact of K_s on the "Transform" strategy evolutionary dynamic; (**c**) The impact of K_s on the "Transform" strategy evolutionary dynamic; (**d**) The impact of K_s on the final strategy proportion.

It is also noteworthy that even when $K_s = 0$, both the IIP building rate and the DT rate remain non-zero, indicating that network effects are not the only motivation for CEs to build IIPs or for OEs to DT. Furthermore, as K_s increases from 0 to 40, its effect on promoting DT shows a trend of linear growth. Beyond Ks = 40, further increases result in a diminishing marginal effect on the promotion of the DT rate.

4.3.5. The Sensitivity Analysis of Network Effect Benefits Attributed to the CE's Joining

As shown in Figure 10, varying the network effect benefit K_u gained by platform members after CEs join the platform indicates that an increase in K_u also significantly enhances the DT rate. When $K_u = 0$, both the IIP building rate and the DT rate remain close to 0, suggesting that the joining of upstream and downstream CEs plays a crucial role in the

initial IIP development and user attraction. It should also be noted that beyond $K_u = 200$, further increases exhibit a diminishing marginal effect on both the IIP building rate and the DT rate, which is consistent with the impact of changes in K_s on strategy evolution.

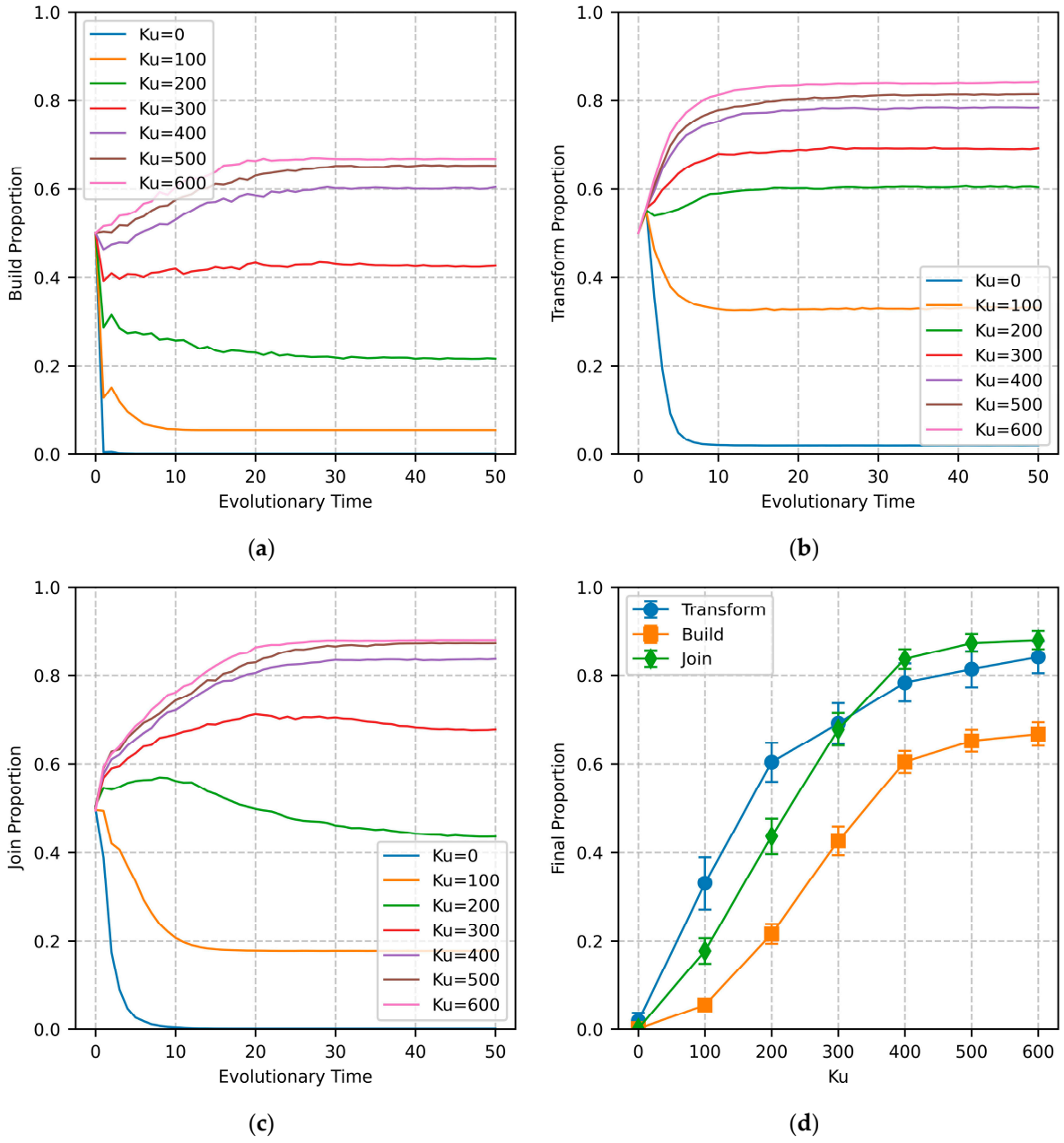


Figure 10. Evolutionary dynamics under the variation in network effect benefits K_u attributed to the CE's joining: (**a**) The impact of K_u on the "Build" strategy evolutionary dynamic; (**b**) The impact of K_u on the "Transform" strategy evolutionary dynamic; (**c**) The impact of K_u on the "Transform" strategy evolutionary dynamic; (d) The impact of K_u on the final strategy proportion.

From the impact of the above platform-related factors on the strategy evolution of players within the multi-platform hypergraph, it can be observed that platforms primarily attract enterprises to join through the network effects generated by multi-party participation, thereby increasing the overall DT rate across the supply chain. However, the enhancement in benefits due to network effects shows diminishing marginal effect on the overall DT rate.

4.4. The Sensitivity Analyses of Government Incentive Subsidy

This section employs the parameter settings of Scenario 1 as the baseline to conduct a sensitivity analysis on variations in incentive and subsidy parameters. This approach enables an in-depth exploration of the impact of governmental support on IIP-driven DT.

4.4.1. The Sensitivity Analysis of IIP Building Incentive Subsidy

As shown in Figure 11, increasing the government subsidy I_f for core enterprises to build industrial Internet platforms—from 0 to 500, covering 0% to 50% of the building cost—effectively encourages core enterprises to support digital transformation among upstream and downstream partners. When the subsidy reaches 50% of the building cost, it is expected to drive nearly 80% of ordinary enterprises to adopt digital transformation.

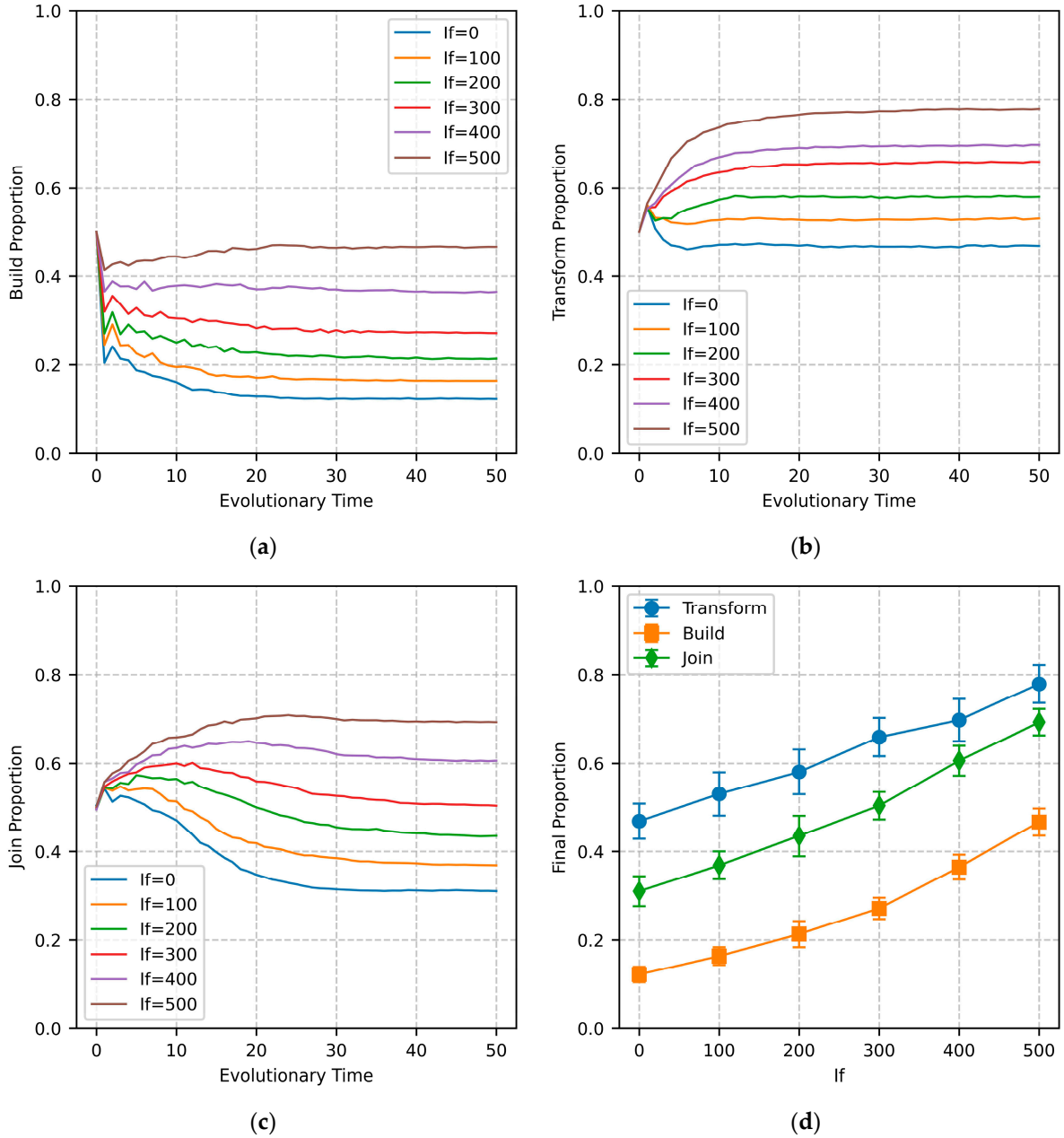


Figure 11. Evolutionary dynamics under the variation in IIP building incentive subsidy I_f: (**a**) The impact of I_f on the "Build" strategy evolutionary dynamic; (**b**) The impact of I_f on the "Transform" strategy evolutionary dynamic; (**c**) The impact of I_f on the "Transform" strategy evolutionary dynamic; (**d**) The impact of I_f on the final strategy proportion.

4.4.2. The Sensitivity Analysis of DT Incentive Subsidy

As shown in Figure 12, the government subsidy I_s for supporting DT is varied from 0 to 50, covering 0% to 50% of the DT cost. It can be observed that when I_s is less than 30% of the DT cost, its impact on the decisions of both CEs and OEs is not significant. However, when I_s reaches 40, the subsidy policy substantially increases the motivation of OEs to pursue DT. A further increase in the subsidy amount leads all OEs within the multi-platform hypergraph to undergo DT.

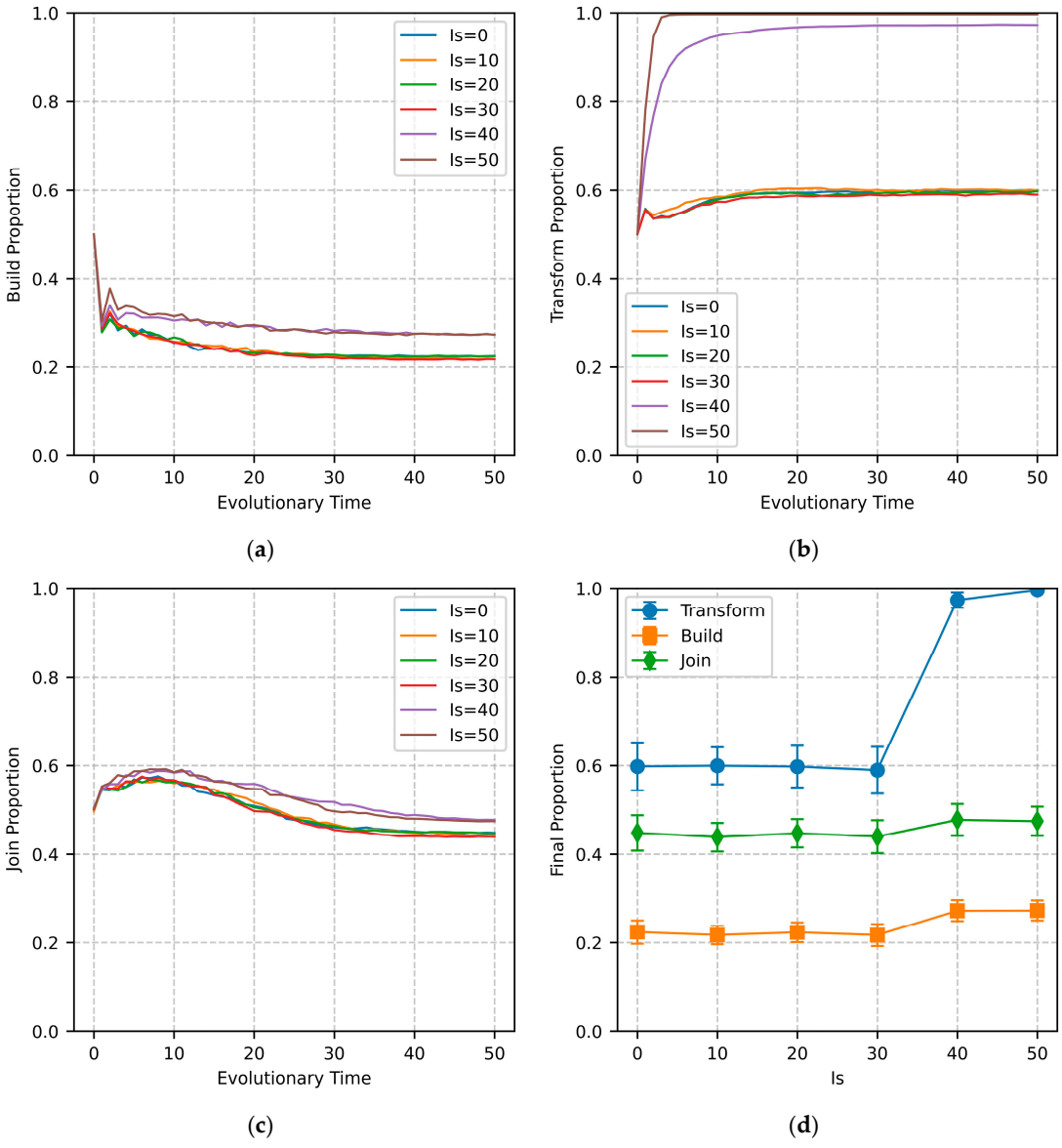


Figure 12. Evolutionary dynamics under the variation in DT incentive subsidy I_s: (**a**) The impact of I_s on the "Build" strategy evolutionary dynamic; (**b**) The impact of I_s on the "Transform" strategy evolutionary dynamic; (**c**) The impact of I_s on the "Transform" strategy evolutionary dynamic; (**d**) The impact of I_s on the final strategy proportion.

This occurs because when $I_s = 40$, the government subsidy and the DT benefits gain offset the cost of DT. Under this incentive level, DT enterprises are bound to join the IIPs built by upstream and downstream core enterprises to generate benefits from their "Transform" strategy. The few enterprises that do not DT may lack support from CEs along the chain or exhibit non-rational decision-making behavior.

When $I_s = 50$, DT yields consistently positive returns for OEs, making "Transform" a strictly dominant strategy. As a result, the DT rate among OEs reaches 100%.

4.4.3. Interactive Effect Between Incentive Subsidies for IIP Building and DT

In practice, governments often provide financial subsidies not only to OEs to support DT, but also to CEs for the building of IIPs. Therefore, this study investigates the interactive effect between these two types of subsidies by simultaneously varying the values of I_s and I_f. As shown in Figure 13, as I_s increases from 0 to 50 yuan and I_f from 0 to 500, the final strategy proportion of both CEs and OEs within the hypergraph changes accordingly. It can be observed that when I_s is less than 40, the interactive effect between the two subsidies is not significant. A change in the value of one type of subsidy does not alter the promoting effect of the other subsidy on either DT or IIP building.

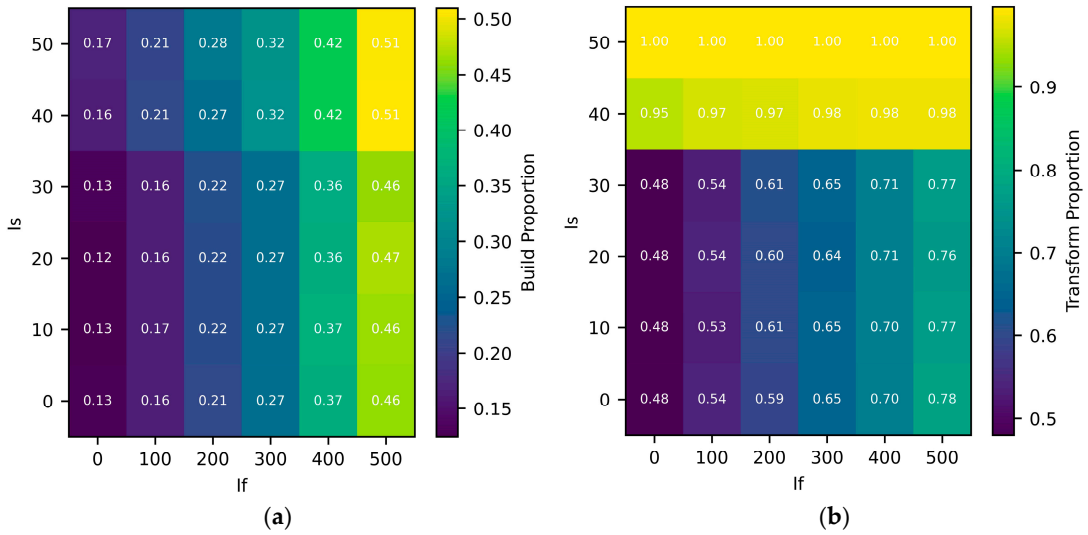


Figure 13. The interactive effect between incentive subsidies for IIP building and DT on final strategy proportion: (**a**) The interactive effect between different subsidies on the final "Build" strategy proportion; (**b**) The interactive effect between different subsidies on the final "Transform" strategy proportion.

Although increasing I_s can significantly boost the DT rate, it requires the government to cover the entire actual cost of DT for enterprises. Moreover, given that the number of OEs far exceeds that of CEs, subsidizing DT for all enterprises would impose a substantial financial burden on the government. Therefore, promoting DT through subsidies targeted solely at OEs is not a feasible approach. In contrast, subsidies directed at CEs not only reduce the fiscal pressure on the government but also enhance the income of CEs while motivating OEs to undergo DT. This approach proves to be a more effective means of increasing the DT rate across the supply chain.

4.5. The Sensitivity Analyses of Initial Strategy Proportions Without Incentive Subsidies

While government subsidies for enterprises have often produced positive results, the precedent of gradually reduced support for the photovoltaic and electrical vehicles suggests a similar path for DT and IIP subsidies. Once manufacturing DT can sustain itself, such subsidies should also be phased out. This approach aims to prevent enterprises from developing overdependence on government subsidies and making rash investments. Therefore, in this section, the incentive subsidy I_s and I_f is set to 0 to examine whether the DT rate can be maintained after the withdrawal of subsidies, and under what conditions

such policy withdrawal would be feasible. The study involves adjusting the initial strategy proportions in the evolutionary game to simulate scenarios without subsidies.

4.5.1. The Sensitivity Analysis of Initial "Transform" Proportion

By varying the initial proportion of OEs choosing the "Transform" strategy—ranging from 0 to 1—the impact on the evolutionary dynamics and equilibrium state of all players is illustrated in Figure 14. It can be observed that when the initial DT rate is 0, although the join of CEs sustains the development of some IIPs, OEs fail to perceive the potential benefits of DT due to the absence of prior successful cases. Consequently, they do not adopt the "Transform" strategy, a behavior shaped by their tendency to learn and imitate each other's decisions. As the initial DT rate increases from 20% to 80%, the final proportion of OEs adopting the "Transform" strategy rises from approximately 40% to 60%. Notably, within a certain range of initial DT rates, the final proportion of "Transform" tends to converge around 50%. This convergence elevates the ultimate DT rate in scenarios with initial rates of 20% and 40%, while reducing the final DT proportion in cases with initial rates of 60% and 80%. However, whether this convergent final proportion is related to the initial IIP building rate warrants further investigation.

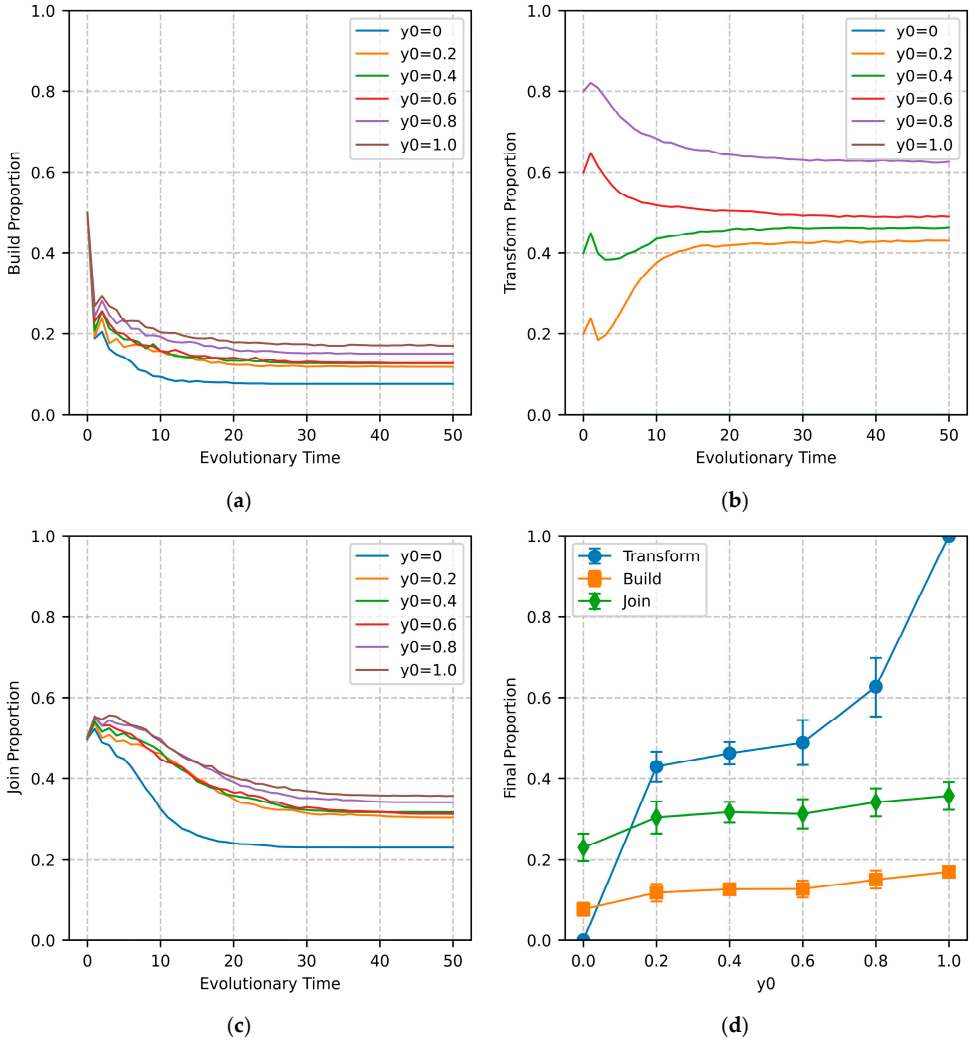


Figure 14. Evolutionary dynamics under the variation in the initial "Transform" proportion y_0: (**a**) The impact of y_0 on the "Build" strategy evolutionary dynamic; (**b**) The impact of y_0 on the "Transform" strategy evolutionary dynamic; (**c**) The impact of y_0 on the "Transform" strategy evolutionary dynamic; (**d**) The impact of y_0 on the final strategy proportion.

4.5.2. The Sensitivity Analysis of Initial "Build" Proportion

As shown in Figure 15, although varying the initial proportion of CEs adopting the "Build" strategy has a limited impact on the final IIP building rate at the evolutionary equilibrium state, the initial level of IIP building significantly enhances or diminishes the DT willingness of ordinary enterprises. This, in turn, affects their final DT rate. These results imply that, even with a constant initial transformation rate, modifying the initial IIP building rate can alter the convergence outcome of OEs' transform. This interactive effect will be further explored in the following section.

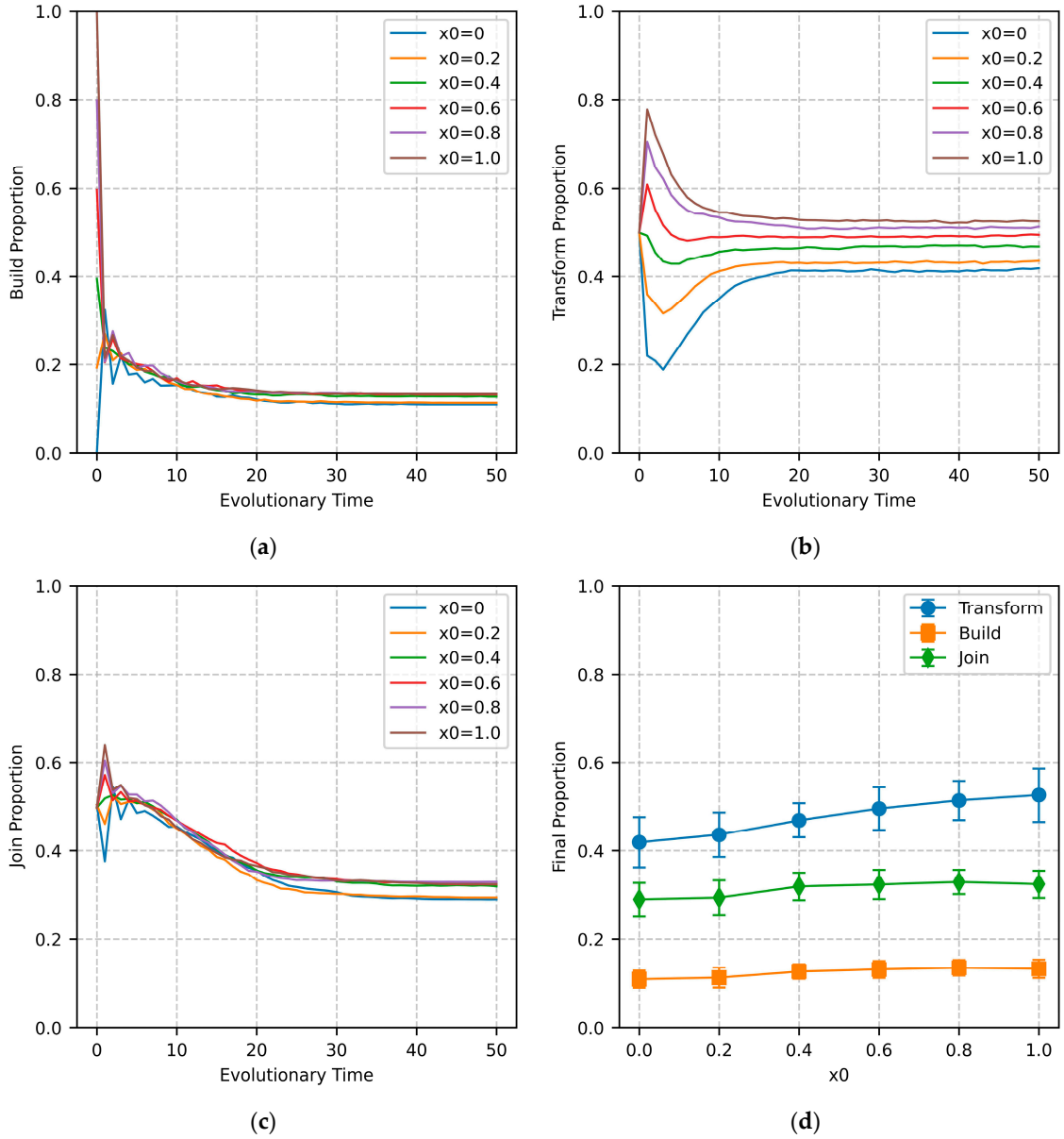


Figure 15. Evolutionary dynamics under the variation in the initial "Transform" proportion x_0: (**a**) The impact of x_0 on the "Build" strategy evolutionary dynamic; (**b**) The impact of x_0 on the "Transform" strategy evolutionary dynamic; (**c**) The impact of x_0 on the "Transform" strategy evolutionary dynamic; (**d**) The impact of x_0 on the final strategy proportion.

4.5.3. Interactive Effect Between the Initial "Build" and "Transform" Proportion

As shown in Figure 16, the initial "Join" proportion does not significantly affect the final evolutionary equilibrium. Therefore, only the interactive effect between the initial proportions of the "Transform" and "Build" strategies is considered.

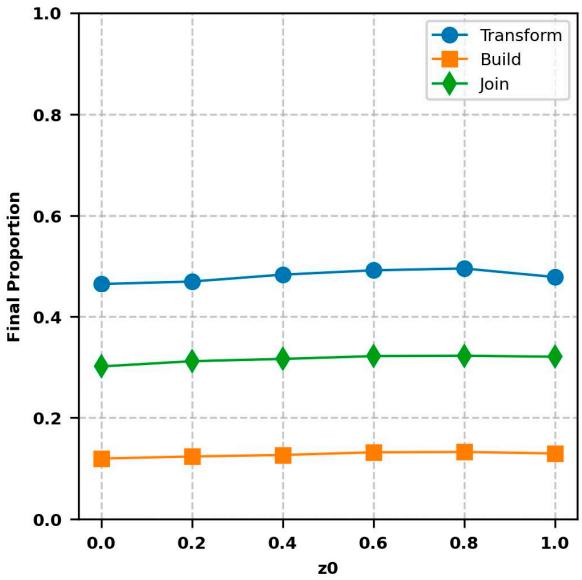


Figure 16. Final strategy proportion under the variation in the initial "Join" proportion z_0..

From Figure 17, it can be observed that, excluding the extreme cases where the initial DT rate is 0% or 100%, an increase in the initial proportion of the "Transform" strategy improves both the survival rate of the IIP and its role in promoting the DT of OEs. For instance, when the initial "Transform" proportion is 20%, increasing the initial "Build" proportion from 0% to 100% only raises the final "Transform" proportion from 36% to 43% at the equilibrium state. In contrast, when the initial "Transform" proportion is 80%, increasing the initial "Build" proportion from 0% to 100% elevates the final "Transform" proportion from 51% to 79%. This further underscore the critical role of IIPs in promoting the DT of OEs.

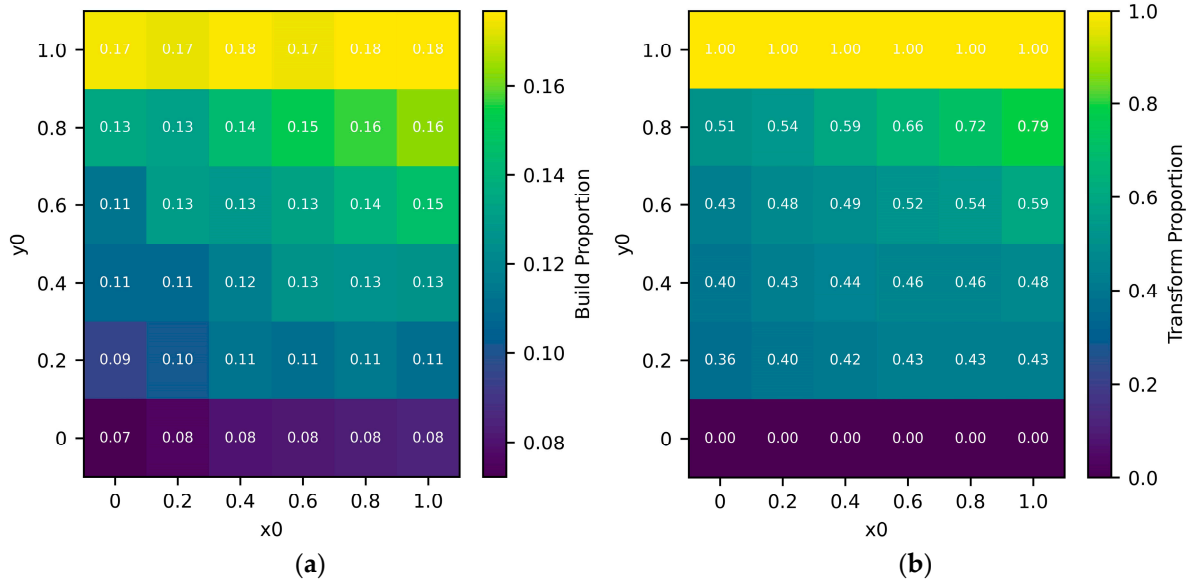


Figure 17. The interactive effect between the initial "Build" and "Transform" proportion on final strategy proportion: (**a**) The interactive effect between different initial strategy proportion on the final "Build" strategy proportion; (**b**) The interactive effect between different initial strategy proportion on the final "Transform" strategy proportion.

4.6. The Sensitivity Analyses of CE Node Degree Threshold

This section conducts a sensitivity analysis on the CE node degree threshold θ (hereinafter referred to as the CE threshold) based on the parameter settings of Scenario 1, aiming to explore the impact of CE scale and hypergraph concentration on the system's evolutionary dynamics. Figure 18 illustrates the final strategy proportions of the evolutionary game under different CE node degree thresholds.

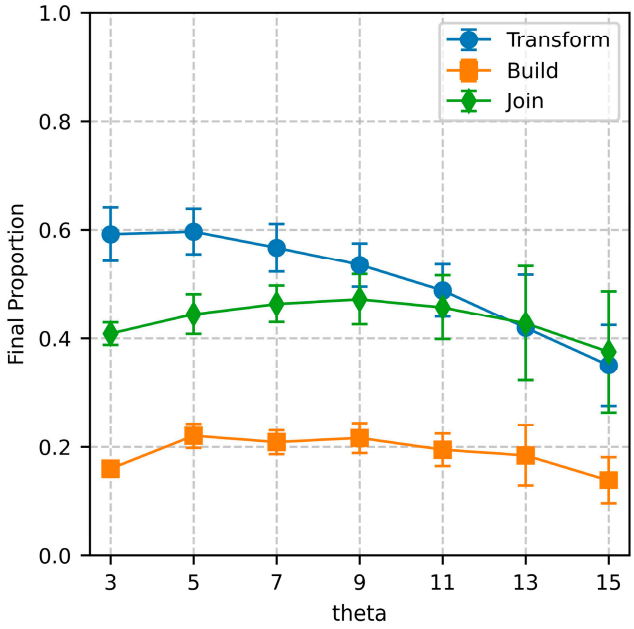


Figure 18. Final strategy proportion under the variation in the CE node degree threshold θ..

An increase in the CE threshold changes the criteria for identifying CEs within the supply network. This leads to a reduction in the number of hyperlinks in the hypergraph and an increase in OE nodes within each hyperlink. Simulation results show that as the CE threshold rises from 3 to 15, the proportion of the "Transform" strategy in the system continuously declines. In contrast, the proportions of the "Join" and "Build" strategies first increase and then decrease, peaking when the CE threshold is 9.

This phenomenon occurs for the following reasons. When the CE threshold is low, there are potentially more CE enterprises both upstream and downstream from a single OE node. Consequently, OEs have greater access to DT assistance provided by CEs via IIPs. After undergoing DT, these OEs also have more potential IIPs to join, enabling them to gain additional benefits. For CEs, a moderate increase in the CE threshold raises the number of upstream and downstream OEs. This allows a CE, after building an IIP, to attract more users and stimulate network effects.

However, when the CE threshold becomes too high, the "Transform" proportion drops significantly. Although there may be a sufficient pool of potential users for IIPs, many OEs have not completed DT. Meanwhile, the OEs that have already completed DT meet the CE's needs for digital collaboration. This reduces the CE's motivation to build an IIP, leading to the decline in the "Build" proportion.

This result indicates that an appropriate number of coexisting IIPs can improve their survival rate. Beyond focusing on IIP development led by large CEs, it is also important to encourage relatively smaller CEs to establish IIPs. This can promote the platformization of the entire supply chain and enhance the overall DT adoption rate in manufacturing.

5. Empirical Case Study

This section will present practical cases of IIP development and enterprise DT, and analyze phenomena observed in these cases using conclusions drawn from the hypergraph evolutionary game model simulations. This aims to demonstrate the explanatory power of this study in the context of IIP-driven DT.

COSMOPlat is an IIP under the home appliance manufacturer Haier. It initially focused on serving Haier's internal digitalization needs. After accumulating substantial experience in the industrial internet field, the platform expanded externally and was spun off as an independent company, COSMOPlat [72]. It primarily uses digital technologies to deliver DT solutions for OEs while collaborating with other CEs to build industry-specific sub-platforms. For instance, the RV industry sub-platform developed by COSMOPlat for Comparks RV not only assisted in its DT to enhance production efficiency but also enabled Comparks RV and its upstream and downstream partners to collaborate online via the IIP in areas like production planning and quality traceability. They could also make timely adjustments based on feedback from the platform. Furthermore, based on COSMOPlat, Comparks RV collaborated with upstream suppliers, such as auto parts manufacturers and RV refrigerator producers, to deliver customized designs and production, thereby increasing product value-added and benefits for all parties involved [14]. This validates the model's assumption that CEs interact with upstream and downstream enterprises based on the IIP. It also proves the importance of network effects stimulated by multi-party participation in the IIP ecosystem, which aligns with the simulation results.

Conversely, focusing solely on the DT services provided by an IIP while neglecting the added value from network effects driven by large-scale user adoption can lead to operational failure. ADAMOS was an IIP jointly established in 2017 by several German manufacturers, including DMG MORI and Zeiss. The platform aimed to achieve DT for OEs through cross-industry digital services and data sharing. However, despite substantial funding and rich technical resources from several CEs, ADAMOS ultimately failed and ceased operations in 2023. While the reasons for its failure were multifaceted, a key factor was the ambiguity of data-sharing agreements. These raised doubts among OEs about whether the benefits of data sharing were mutual, leading them to only superficially engage with platform applications and information sharing. Furthermore, the CEs' hidden agendas made it difficult for them to achieve strategic alignment on platform-related matters [73]. This shows that although ADAMOS had participation from some CEs and OEs, the increase in participants failed to enhance the overall benefits for all parties within the platform through network effects, ultimately leading to its failure. This phenomenon also closely matches the simulation results.

6. Conclusions and Implications

6.1. Conclusions

Based on a hypergraph evolutionary game model, this study investigates how CEs, driven by IIPs, promote the DT of upstream and downstream OEs through platform building, thereby enhancing collaboration benefits for all parties and improving the overall efficiency of the manufacturing supply chain. Using hypergraphs and evolutionary game theory, the research simulates the strategic evolution mechanism among boundedly rational players across multiple IIPs within the supply chain network. By adjusting the payoff parameters in the game model, the effects of IIP-related factors—such as digital collaboration benefits, platform support for DT, and network effects—on decision-making are analyzed. The study also simulates the impact of varying levels of government subsidies and examines evolutionary dynamics in the DT of manufacturing following subsidy withdrawal under different conditions. The main findings are as follows:

(1) The establishment of IIPs by core enterprises significantly advances the DT of both upstream and downstream enterprises, as well as the supply chain overall. While DT enhances supply chain collaboration, and IIPs reduce DT costs, the network effects generated by the IIPs emerge as the primary driver of DT. However, the marginal benefits of network effects diminish in attracting both CEs to establish IIPs and OEs to pursue DT. This result contrasts with previous research, which suggests that network effects must reach a specific threshold to attract enterprises to join IIPs [50].

(2) Government incentive subsidies play a crucial role in promoting DT, although their effectiveness differs between CEs and OEs. Subsidies targeting CEs can effectively motivate them to build IIPs, thereby driving DT across supply chain partners. However, under limited subsidy intensity (no more than 50% of the IIP building cost), such support can only increase the DT rate to around 80%. Subsidies for OEs produce noticeable effects only when reaching a certain threshold—i.e., when enterprises can achieve positive returns from DT even without joining the IIP—yet this approach entails higher fiscal burdens. Furthermore, the two subsidy types did not show a significant interactive effect on enhancing the DT rate.

(3) The impact of withdrawing subsidy policies on the DT rate exhibits a convergence effect, which varies with the initial DT rate. In the scenario of this study, without subsidies, the DT rate of OEs consistently converges to a range of 40% to 60%. Although the withdrawal of subsidies for CEs leads to a significant reduction in the number of IIPs, the platform adoption rate at the time of subsidy withdrawal can, to some extent, elevate the final convergence level of the DT rate. Furthermore, a noticeable interactive effect exists between the DT rate and the IIP building rate. Maintaining a higher number of IIPs before the policy withdrawal can effectively help OEs sustain their willingness to pursue DT even in the absence of subsidies.

6.2. Managerial Implications

This study provides the following managerial insights for various stakeholders involved in digital transformation, which are concisely summarized in Table 5.

Table 5. Managerial implications for stakeholders.

Stakeholder	Managerial Implications	Potential Risks
Core Enterprises	1. Assess subsidy reliance; ensure post-subsidy profitability. 2. Boost user resource sharing to leverage network effects. 3. Offer free basic features early; provide clear data terms & easy integration tools.	Platform failure if overly subsidy-dependent; inability to sustain growth without network effects.
Ordinary Enterprises	1. Join if subsidies cover DT costs. 2. Prefer large, established IIPs. 3. Be cautious with small/emerging platforms.	Losses from choosing unstable platforms; over-reliance on a single IIP.
Governments	1. Subsidize CEs to build IIPs and drive chain-wide DT. 2. Subsidies can be withdrawn after sufficient platform buildup. 3. Mitigate fallout from potential mass platform closures.	Unstable IIP growth after subsidy cuts; economic & employment impacts from shutdowns.

(1) Regarding CEs: A reduction or withdrawal of government subsidies may lead to the shutdown of numerous IIPs, so CEs must carefully assess the risks when establishing such platforms with subsidy support. They should consider not only the short-term benefits and subsidies generated by the IIP, but also evaluate their own capabilities to ensure the platform achieves sustainable profitability while operating independently. For CEs that have already established an IIP, efforts should be made to encourage platform users to share their resources. By aggregating and optimizing these resources, the platform can improve service quality, thereby enabling it to fully leverage network effects. This will attract more users to join and retain their engagement.

Specifically, in the early stages of IIP development, CEs can offer free access to some basic features. This helps quickly attract upstream and downstream users to join and stimulate network effects. Secondly, designing clearer data security terms is important. These terms should help users understand how their shared data will be used and the benefits that greater data sharing can bring them. Furthermore, building open and user-friendly technical integration solutions is key. Examples include standardized API interfaces, lightweight SaaS tools, and pre-integrated hardware kits. These solutions make it easier for users to connect their systems and share data, thereby encouraging their active participation.

(2) Regarding OEs: When government subsidies can cover the costs of DT, OEs should respond proactively. When deciding whether to join an IIP, they are advised to choose large-scale, well-established platforms to access their services and internal resources, thereby leveraging network effects to their advantage. When considering emerging or small-to-medium IIPs, however, enterprises should exercise caution in joining to avoid potential losses arising from unstable platform operations.

(3) Regarding governments: This paper concludes by recommending that governments prioritize subsidizing core enterprises to establish IIPs, thereby driving the DT of OEs. This approach ensures a relatively high DT rate without imposing excessive fiscal burdens. However, a potential issue is that the high rate of IIP building achieved through subsidies may not be sustainable once funding is reduced or withdrawn. Even with a high DT rate, cutting IIP subsidies could lead to many platforms ceasing operations. Therefore, while governments can withdraw subsidies once a sufficient level of platform building is achieved—and still benefit from enhanced DT across supply chains—they must also address the economic and employment losses resulting from widespread platform shutdowns.

7. Contextual Boundaries, Limitations and Future Research

7.1. Contextual Boundaries

This study primarily investigates the role of OEs in the manufacturing supply chain DT under the influence of IIPs. The research context is the recent trend in China where some manufacturing OEs utilize IIPs to facilitate DT for other OEs. The Chinese manufacturing supply chain is characterized by a large number of sizable OEs, resulting in a highly centralized supply network structure. Additionally, the Chinese government plays a relatively strong role in market intervention. These contextual features have profoundly influenced this study's model construction, data sources, and parameter settings, consequently defining the boundaries of its findings. While the analysis of simulation results across various scenarios has been presented earlier, a more detailed discussion of the potential variability of these findings across contexts is necessary.

(1) Less centralized economies: A less centralized economy implies that the average size of enterprises in the supply network is smaller, with no overwhelmingly large dominant CEs. In such an environment, the potential for platform network effects may weaken. At the same time, because CEs have fewer upstream and downstream OEs than the cases examined in this study, the independent DT of these OEs may not meet CEs' digital collaboration requirements. Therefore, CEs may still turn to IIPs to enhance their own performance ceilings. A reasonable inference is that, in less centralized economies, there may be a threshold. Moderate centralization could foster more vibrant development of IIPs and enterprise DT, whereas excessively low centralization might prevent IIPs from being established or operating effectively.

(2) Service industry: Service industry platforms differ from manufacturing platforms in several key aspects. First, supply chains in the service sector are more dynamic and flatter. This often leads service platforms to involve more participants than IIPs, making network effects even more critical for their development. For example, retail, food delivery,

and ride-hailing platforms rely almost entirely on network effects generated by the number of users and merchants. Second, the flat and dynamic structure of service supply chains may render the static network models used in this study less applicable. Third, service platforms are often established by pure platform companies and have already achieved high profitability (e.g., Amazon, Uber, Taobao). In such cases, government subsidies may no longer be crucial for platform development.

7.2. Limitations and Future Research

Despite substantial efforts and significant findings, this study is not without limitations. This section will address how some important limitations may have influenced the results and discuss potential extensions arising from them:

(1) Hyperlink Definition: This study defines hyperlinks solely based on interactions between CEs and their direct upstream and downstream enterprises within the platform. In real-world settings, enterprises may engage in cross-tier supply chain interactions—for example, directly communicating with secondary suppliers. Additionally, platforms may include third parties not directly part of the manufacturing supply chain, such as technology providers or end customers. Expanding the definition of hyperlinks would introduce more participants into the platform. On one hand, this could enhance the potential for network effects and broaden the scope of possible government subsidies. On the other hand, it would also introduce more diverse interests among participants, requiring a corresponding redefinition of game relationships and payoff matrices.

(2) Enterprise Heterogeneity: Although this study distinguishes between CEs and OEs based on node degree, real-world enterprises exhibit richer heterogeneity in terms of firm size, digital maturity, and strategic orientation. Future research could better simulate this heterogeneity by adjusting payoff matrix parameters for different nodes and incorporating more varied game-theoretic interactions.

(3) Platform-to-Platform Interactions: While this study examines interactions among enterprises via platforms, it does not consider interactions between platforms themselves. Introducing platform-level dynamics would mainly bring the following implications: First, platforms may compete with each other—for instance, over users or standard-setting authority. Future work could develop a multi-layer network model, adding a separate network layer to represent platform relationships and simulate such competition. Second, a single enterprise might participate in multiple platforms, gaining different functionalities from each. Future models could allow nodes to adopt differentiated strategies across platforms and incorporate heterogeneity in platform design to simulate varied effects of platform participation. Third, platforms may exhibit spillover effects similar to those among enterprises, such as imitation of influence strategies or technology standards. Subsequent studies could introduce strategy-learning mechanisms and free-riding behaviors at the platform level to simulate inter-platform spillovers.

(4) National Context Limitations: The primary research background, data sources, and parameter settings of this study are all based on the context of China's manufacturing industry. This, to some extent, limits the validity of the findings when applied to the manufacturing development of other countries. Future research will consider incorporating the heterogeneity of enterprises and platforms. It will further examine the impact of different national policies and technological contexts on the development of DT and IIPs within global supply chains.

Additionally, the conclusions of this study are not supported by quantitative verification through real-world cases. Future research will seek to expand upon micro- or macroeconomic cases and data that allow for such quantitative validation.

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