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Formation Drivers and Evolutionary Dynamics of Industry-University-Research Collaborative Networks in China's Clean Energy Industry

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Abstract: Robust industry-university-research (I-U-R) collaborative networks are essential for accelerating innovation in the clean energy industry (CEI). This study employs the exponential random graph model to investigate how the network structural, node, and edge attributes drive the formation of I-U-R collaborative networks in China's CEI, using a dataset of 5276 I-U-R collaborative patents. Key findings reveal the following: (1) convergence structures and transitive closure differentially drive network formation across the growth and maturity phases; (2) the nodes with strong R&D capabilities consistently drive network formation, though enterprises increasingly exert a negative effect and universities show a weakening positive effect; (3) multi-dimensional proximity displays temporal dynamics—geographic proximity follows an inverted U-curve, social proximity is U-shaped, and technological proximity gradually weakens; (4) node types exhibit heterogeneous moderating effects. Enterprises negatively moderate R&D capability during growth and maturity periods, weakening the technological proximity across all periods, and social and geographic proximity in maturity. Universities positively moderate the R&D capability but show period-specific effects on proximity: weakening social proximity in the sprouting stage, geographic proximity in the growth stage, and shifting their moderation of technological proximity from positive (growth) to negative (maturity). These findings deepen the understanding of how the I-U-R collaborative networks in China's CEI format, contributing to the collaborative innovation theory through insights into the dynamic roles of node types.

Keywords: clean energy industry; industry-university-research; collaborative network; node type; heterogeneity

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1. Introduction

Advancing clean energy technologies and expediting their commercialization are pivotal to achieving net-zero emissions by mid-century [1,2]. To meet this target by 2050, clean energy must constitute over 90% of the global energy consumption, whereas China's clean energy consumption accounted for only 26.4% in 2023 [3]. This disparity highlights the urgent need for China to accelerate technological innovation in the clean energy industry (CEI) and promote its large-scale application.

Collaborative networks are instrumental in driving innovation and promoting cooperation among different entities [4]. Industry-university-research (I-U-R) collaborative networks, which leverage complementary resource endowments from enterprises, uni-

versities, and research institutes, in particular have demonstrated unique advantages in accelerating technological progress and advancing industry innovation [5].

Given their importance, investigating the mechanisms underlying the I-U-R collaborative network formation in China's CEI is crucial. However, the current understanding of their formation mechanisms remains fragmented. While prior studies have identified network structural, node, and edge attributes influencing network evolution [6–8], three critical gaps persist.

Firstly, the existing research predominantly examines how the structural, node, and edge attributes affect China's CEI I-U-R collaborative network formation in isolation, lacking integrated frameworks to capture their dynamic interplay. Secondly, the dynamic evolution of these attributes across the developmental stages of network development remains underexplored. Thirdly, empirical validation of the nodes' heterogeneous roles in networks is notably scarce. These limitations hinder the development of evidence-based strategies for optimizing the I-U-R collaborative networks in China's CEI.

To address these gaps, this paper (1) proposes twelve hypotheses based on the complex network theory, proximity theory and collaborative innovation theory, (2) employs the exponential random graph model (ERGM) to analyze the dynamic influence of network structural attributes (e.g., convergent structure), node attributes (e.g., R&D capabilities), and edge attributes (e.g., geographic proximity) on the formation of I-U-R collaborative networks in the CEI, and (3) explores the heterogeneous roles of node types—enterprises, universities, and research institutes—in shaping these networks across different stages. The overview of the theoretical model proposed in this study is depicted in Figure 1.

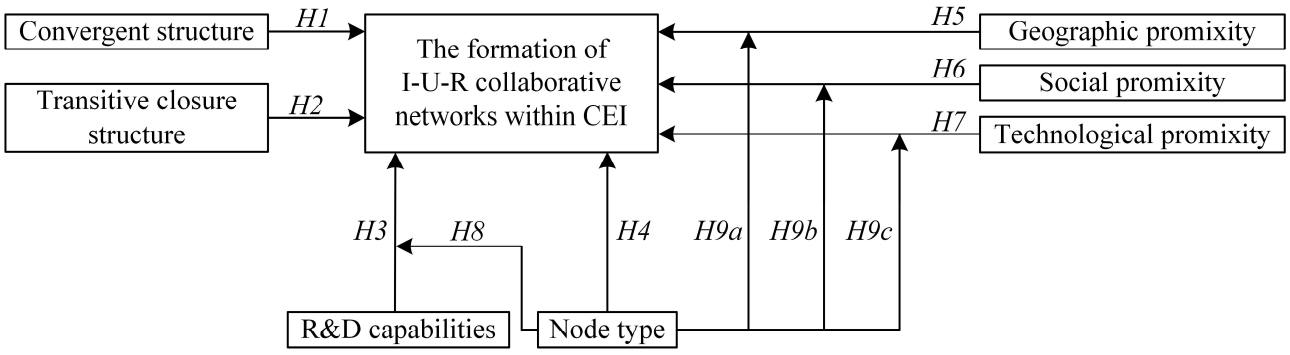


Figure 1. Conceptual model.

The main contributions of this study are threefold. First, it clarifies how structural, node, and edge attributes jointly affect the formation of I-U-R collaborative networks in the CEI, highlighting both the dynamic interplay of these factors and the resulting complexity. Second, it contributes to the collaborative innovation theory by empirically confirming the direct and moderating roles of enterprises and universities, relative to research institutes, providing valuable insights into optimizing multi-actor collaborations. Third, the findings offer scientific guidance for promoting the orderly and positive evolution of I-U-R collaborative networks in the CEI, potentially guiding other the countries' efforts toward clean energy transitions.

This article is structured as follows. In Section 2, we systematically examine how the network structural, node, and edge attributes shape the formation of I-U-R collaborative networks in the CEI, explore the moderating impact of node types, and propose research hypotheses. Section 3 outlines the data sources, research methods, variable operationalizations, and the construction of the regression models. Section 4 presents the empirical findings, including network topology analyses, model outcomes, moderating effect test, and robustness checks. Finally, Section 5 discusses the implications of these results and

offers recommendations for fostering the positive evolution of I-U-R collaborative networks in the CEI.

2. Theoretical Analysis

The innovation process is inherently complex and involves significant risks [9]. Collaborative networks, particularly I-U-R networks, which integrate heterogeneous partners and knowledge, are recognized as an effective approach to structuring relationships among participants, mitigating R&D risks, and achieving collective innovation goals [10,11]. The collaborative innovation theory underpinning the I-U-R collaborative networks posits that collaborations bridging basic and applied research are instrumental in expediting industry innovation [12].

In terms of the factors influencing network formation, research suggests that both structural attributes, including convergence and transitive closure structures, and node attributes, such as R&D capabilities and organizational types, drive the evolution of these networks [6,7]. Furthermore, drawing on the proximity theory, studies have identified multidimensional proximity factors—such as geographic, social, and technological proximity—as critical influences on the formation of I-U-R networks [13–15]. Proximity-based edge attributes, therefore, emerge as another key determinant in network development.

However, while substantial research has examined the I-U-R collaborative network in China's CEI, focusing on technological domains such as wind energy [16], lithium-ion batteries [17], and photovoltaics [18], there remains a lack of comprehensive studies on how the network attributes—structural, node, and edge—dynamically interact across different stages of network evolution. Therefore, this paper draws studies on the role of structural, node, and edge attributes in the formation of an I-U-R collaborative network in China's CEI.

2.1. Hypothesis on the Role of Network Structural Attributes in Network Formation

Network structural attributes represent the specific patterns of connections between nodes within a network, encompassing forms such as convergence structures and transitive closure structures. To avoid model degradation in ERGM, this study focuses on the effects of convergence and transitive closure structures on the formation of I-U-R collaborative networks in the CEI [19].

A convergence structure refers to a network configuration in which multiple nodes are connected to a central node. This central node often attracts additional connections due to its higher visibility and preferential attachment, a phenomenon well-documented in network theory [20]. Prior studies confirm that preferential attachment facilitates the development of collaborative networks across organizations and regions [21]. In the context of the CEI, the preference attachment effect enables highly connected nodes to attract more attention from other nodes, fostering new collaborative relationships. This dynamic contributes to network expansion, eventually forming a core-periphery structure [5]. Based on this analysis, the following hypothesis is proposed:

H1: *Convergence structures positively influence network formation as the network evolves.*

Transitive closure is another common structural form in networks. It occurs when two nodes, each collaborating with a third node, are more likely to establish a direct connection, forming a "ternary closure" [22,23]. This structure enhances both the efficiency and stability of the collaborations within the network [24,25]. For example, Baum et al. [26] and Bianconi et al. [27] highlight that the transitive closure effect fosters the emergence of collaborative ties among nodes with shared partners, reinforcing relational stability and improving the diffusion of technological innovations through redundant connections. In the context of China's CEI, these dynamics are crucial for the growth of I-U-R collabora-

tive networks, where such redundant connections support the stability and expansion of innovation-driven partnerships. This ultimately drives the formation of robust collaborative networks. Accordingly, the following hypothesis is proposed:

H2: *Transitive closure structures positively influence network formation as the network evolves.*

2.2. Hypothesis on the Role of Node Attributes in Network Formation

At the node attribute level, the R&D capability is a critical characteristic influencing network formation [8]. Additionally, the I-U-R collaborative network in the CEI consists of nodes from enterprises, universities, and research institutes, each possessing distinct innovation capabilities that generate heterogeneous effects on network formation [28]. Based on this premise, this study investigates the impacts of the nodes' R&D capabilities and types on network formation.

During network evolution, some core nodes emerge as opinion leaders, playing pivotal roles in attracting connections and driving network expansion. This phenomenon, known as the Matthew Effect, underscores the principle that "the strong get stronger" [29]. Core nodes possess a higher probability of establishing collaborations and attract more partners through a priority connection mechanism [30].

The CEI, as a strategic emerging industry, depends heavily on the integration of multidisciplinary innovation resources. Nodes with strong R&D capabilities are better equipped to mobilize these resources, accelerate knowledge absorption and transformation, and enhance the efficiency of technological innovation. Consequently, such nodes attract more collaborators, driving the expansion of I-U-R networks in the CEI. Based on this analysis, the following hypothesis is proposed:

H3: *Nodes with higher R&D capabilities positively contribute to network formation at all stages of evolution.*

Research institutes tend to form stable, in-depth collaborations with fixed partners rather than broad partnerships, resulting in limited breadth of cooperation compared to enterprises and universities [28]. Thus, this study uses the effect of research institutes on network formation as a baseline for analyzing the heterogeneous impacts of enterprises and universities.

Enterprises occupy central roles in innovation networks and are key drivers of network formation and evolution [5]. Studies on clean energy-related industries suggest that, over time, firms tend to shift their collaborative preferences from expanding external partnerships to consolidating existing ones or pursuing internal R&D, which may reduce network size [28].

Universities, on the other hand, act as primary knowledge providers in the early stages of network development and evolve into knowledge brokers in later stages [31,32]. They integrate innovative resources and achieve breakthroughs in cutting-edge technologies, thereby facilitating collaboration among network participants and supporting network expansion [33,34]. Based on these dynamics, the following hypotheses are proposed:

H4a: *As the network evolves, enterprises negatively influence network formation compared to research institutes.*

H4b: *As the network evolves, universities positively influence network formation compared to research institutes.*

2.3. Hypothesis on the Role of Edge Attributes in Network Formation

Proximity is widely recognized as a measure of similarity among nodes based on specific attributes [13]. Higher proximity is generally believed to facilitate the formation of collaborative innovation, as nodes that are closer in these dimensions are more likely to engage in partnerships. Koschatzky [35] and D'Este et al. [36] underscore the multifaceted nature of proximity, noting that no single dimension alone can fully support robust partnerships. Rather, the combination of different proximity dimensions plays a critical role in shaping collaboration patterns across various contexts [37]. Given the overlap among these dimensions, researchers often tailor their selections to align with particular study objectives, as discussed by Liu et al. [15].

In the CEI context, geographic distance, social ties, and technological structures have been identified as essential factors for network development [8]. This aligns with Guan and Yan [38], who emphasize that these factors are particularly important in driving network emergence. Consequently, this study investigates how geographic, social, and technological proximity contributes to the formation of the I-U-R collaborative networks in the CEI.

Geographic proximity, defined as the physical closeness of nodes, reduces collaboration costs and improves efficiency [39]. Paci et al. [40] found that the nodes located closer to one another are more likely to collaborate, particularly during the early stages of network formation. However, as noted by Sempsey [41], the influence of geographic proximity tends to weaken over time with advancements in communication and transportation technologies, which reduce the significance of geographic distance in promoting collaboration.

During the sprouting phase of the I-U-R networks in the CEI, geographic proximity is crucial for cost minimization. In the growth phase, the demand for rapid technological development amplifies its importance, accelerating network formation. However, in the maturity phase, reduced collaboration costs from technological advancements weaken its role. Based on these dynamics the following hypothesis is proposed:

H5: *The positive effect of geographic proximity on network formation increases and then decreases as the network evolves.*

Social proximity captures the strength of relational ties between nodes, often rooted in trust, prior collaborations, friendships, or family connections [13]. Trust-based relationships facilitate informal knowledge sharing, reduce opportunistic behavior, and increase the likelihood of collaboration [42–44].

In the sprouting phase, nodes prioritize trusted partners, making social proximity significant. During growth, increased funding and government support reduce reliance on prior ties. In the maturity phase, with stable technologies and heightened competition, nodes deepen trusted relationships to mitigate risks, restoring social proximity's importance. Accordingly, the following hypothesis is proposed:

H6: *The positive effect of social proximity on network formation decreases and then increases as the network evolves.*

Technological proximity reflects the similarity in technological capabilities or structures between nodes [45]. Studies show that technological distance is a significant barrier to collaboration and often outweighs other forms of proximity [46]. While similar technological structures facilitate resource sharing and knowledge exchange [38], excessive similarity may limit diversity and the potential for breakthrough innovations [47].

In the sprouting phase, similar technologies enable resource integration and first-mover advantages. As networks mature, increasing competition drives nodes to seek

technologically diverse partners for complementarity, reducing the influence of technological proximity. Thus, the following hypothesis is proposed:

H7: *The positive effect of technological proximity on network formation diminishes as the network evolves.*

2.4. Hypothesis on the Moderating Role of Node Types

At the early stages of network evolution, the enterprises with strong R&D capabilities prioritize external collaboration to acquire advanced technologies, foster innovation, and secure market share [48]. As technologies mature and competition intensifies, core enterprises shift focus to internal R&D to reduce costs, improve efficiency, and mitigate risks, thereby leading to technology lock-in and network contraction [8].

In contrast, universities join innovation networks to secure R&D funding and disseminate knowledge. During the early stages, universities with strong R&D capabilities act as core nodes, supplying knowledge and fostering collaborations [33]. As networks evolve, they transition to knowledge brokers, integrating resources and enhancing collaboration, thus promoting advanced technological development [49,50]. Based on this analysis the following hypothesis is proposed:

H8: *The moderating effects of different node types on R&D capability vary significantly across different stages of network evolution.*

Enterprises play a crucial role in driving joint R&D efforts and the overall growth of network scale within CEI [15]. In the early stages, they prioritize partnerships with geographically or socially close nodes to reduce costs and expand rapidly [40,43]. As networks mature, enterprises reduce regional competition and R&D risks by narrowing collaborations, favoring cross-regional partnerships and internal R&D with affiliates [28]. Across all stages, enterprises also exhibit a preference for collaborating with nodes possessing greater technological distance, as this allows them to access interdisciplinary knowledge resources and achieve technological breakthroughs [47].

Universities, as knowledge providers and brokers, facilitate collaboration among both similar and diverse nodes [49]. Sohn et al. [31] have shown that in early stages, universities act as hubs and knowledge providers, focusing on collaborating with geographically, socially, and technologically similar nodes to accelerate knowledge diffusion and network expansion. As networks mature, Kindt et al. [32] highlighted that universities' role shifts toward brokers, bridging gaps caused by geographic distance, weak social ties, and technological divergence, thereby supporting advanced technological breakthroughs. This shift in universities' role in networks aligns with findings of Yuan and Chen [28]. Based on this analysis the following hypotheses are proposed:

H9a: *The moderating effects of different node types on geographic proximity vary significantly across different stages of network evolution.*

H9b: *The moderating effects of different node types on social proximity vary significantly across different stages of network evolution.*

H9c: *The moderating effects of different node types on technological proximity vary significantly across different stages of network evolution.*

3. Methodology

3.1. Data Source and Collation

Patents are valuable documents containing critical technical and commercial information. They serve as a key metric for measuring innovation output and objectively reflect the technological achievements of innovators [51]. Information embedded in patent data, such as co-applicants, is frequently used to analyze the I-U-R collaborative relationships [8,34]. A network of patentees and their collaborative ties forms the basis of a collaborative network [52].

The patent data used in this study, sourced from PATSNAP [5], focuses on China's CEI. Relevant searches were carried out in accordance with the CEI's cooperative patent classification framework, as stipulated by the China National Intellectual Property Administration [12]. The data were collected and organized through the following steps. First, we searched for Chinese CEI patents with at least two applicants, using the CPC classification system from 1 January 1993 to 31 December 2022, yielding 12,092 authorized patents. Next, because this study focuses on the I-U-R collaboration, we selected only the patents involving partnerships among enterprises, universities, and research institutes, excluding collaborations of the same type (e.g., enterprise–enterprise). This process resulted in a final dataset of 5276 patents reflecting the I-U-R collaboration within the CEI.

3.2. Measurement of Variables

The dependent variable in this study is the I-U-R collaborative network in the CEI. We began by selecting the nodes with a degree greater than 4 to simplify the dataset. Next, consistent with common practices in research on collaborative networks, a five-year interval was used to construct each network [14,53]. We constructed adjacency matrices for three five-year periods—sprouting (2008–2012), growth (2013–2017), and maturity (2018–2022). Furthermore, we applied a thresholding method to convert these matrices into a binary form, using the average collaboration count in the initial adjacency matrix as the cutoff: values above this threshold were set to 1, and those below to 0 [5]. The resulting binary matrices accurately represent the I-U-R collaborative networks in the CEI during each phase.

The explanatory variables in this study encompass network structural, node, and edge attributes, which include seven key variables: convergence structure (*gwd*), transitive closure structure (*gwesp*), R&D capability (*RC*), node type (*Type*), geographic proximity (*GP*), social proximity (*SP*), and technological proximity (*TP*).

Convergence structure captures the aggregation characteristics of nodes, while transitive closure structure reflects the concentration of triadic closures within networks. These two structural attributes are quantified using the geometric weighted degree distribution (*gwd*) and geometrically weighted edgewise shared partners (*gwesp*) metrics within the exponential random graph model [54].

R&D capability is measured by the number of I-U-R collaborative patents associated with each node in the CEI. Node type is determined by the organization category: enterprise nodes are labeled as "1", university nodes as "2", and research institute nodes as "3".

Geographic proximity is calculated as the inverse spherical distance between the nodes based on their provincial locations [40]. Social proximity is assessed by the extent of overlap in collaborative partners between nodes [55]. Technological proximity, on the other hand, is derived by computing the cosine similarity of patent distribution vectors across various technological domains between two nodes [56].

Detailed definitions and descriptions of these variables are provided in Table 1.

Table 1. Description of ERGM variables.

Variable	Measurement	Type
I-U-R collaborative network	Cooperation matrix (0–1)	Explained variable
Convergent structure (*gwd*)	Aggregation characteristics of nodes	Explanatory variable
Transitive closure structure (*gwesp*)	Concentration of triadic closures	Explanatory variable
R&D capability (*RC*)	Number of I-U-R cooperation patents	Explanatory variable
Node type (*Type*)	Organization category	Explanatory variable
Geographic proximity (*GP*)	Inverse of geographic distance	Explanatory variable
Social proximity (*SP*)	The overlap in partnerships	Explanatory variable
Technological proximity (*TP*)	Technological similarity	Explanatory variable

3.3. Research Method

Conventional linear regression assumes variable independence [57]. However, the interconnected nature of network structural and edge attributes in this study, along with observed correlations, makes linear methods unsuitable. The ERGM, by contrast, offers a robust approach to examining and predicting relationships in complex networks [6]. One of ERGM's core strengths is its capacity to handle interdependent variables. Unlike linear regression, it incorporates structural, node, and edge attributes within a unified statistical framework—similar to logistic regression—allowing for an analysis of the multiple, interdependent factors shaping network formation [58].

This study applies the ERGM to investigate the formation mechanisms of I-U-R collaborative networks in the CEI. The general expression of ERGM is as follows:

$$P(Y = y) = \frac{1}{c(\theta)} \exp(\theta^T g(y)) \tag{1}$$

$P(Y = y)$ is the realization probability, where Y represents the observed network, and y denotes the network generated through model simulation. To ensure that the probability falls within the range of 0 to 1, a normalization constant $c(\theta)$ is introduced. Additionally, the model includes a vector of explanatory variables $g(y)$ and a vector of parameters to be estimated (θ), where T denotes the transpose operation.

As described by Hunter et al. [54], the general expression for the ERGM can be further specified as follows:

$$\log_{it}[Y_{ij} = 1 | Y_{ij}^c = y_{ij}^c] = \theta^T \delta_g(y) \tag{2}$$

Y_{ij} represents the connection between nodes i and j, where $Y_{ij} = 1$ indicates the presence of an edge, and $Y_{ij} = 0$ indicates its absence. $\delta_g(y)$ captures the change in network variables when the rest of y remain constant, and Y_{ij} transitions from 0 to 1.

The ERGM generates random networks based on the input network statistics and compares them to the observed network. A higher similarity between the simulated and observed networks indicates a better model fit, suggesting that the included statistics effectively represent the real network's structural features [59]. Following ERGM principles, independent variables are incrementally introduced into the model as described below.

First, a zero model is constructed as the baseline for analysis. Model 1 introduces only the effects of the edge on network formation, serving as a reference point for subsequent multivariate models.

$$\log_{it}[Y_{ij} = 1 | Y_{ij}^c = y_{ij}^c] = \theta_{\text{edges}} \delta_{edges}(y) \tag{3}$$

Building on the zero model, explanatory variables—including geometrically weighted degree distribution (*gwd*), geometrically weighted edgewise shared partners (*gwesp*), R&D capability (*RC*), node type (*Type*), geographic proximity (*GP*), social proximity (*SP*), and

technological proximity (*TP*)—are sequentially incorporated. These additions allow for an in-depth examination of how network structural, node, and edge attributes influence the formation of I-U-R collaborative networks in the CEI. This process produces Models 2, 3, and 4.

$$\log_{it}[Y_{ij} = 1|Y_{ij}^c = y_{ij}^c] = \left[\theta_{edges}\delta_{edges}(y) + \theta_{gwd}\delta_{gwd}(y) + \theta_{gwesp}\delta_{gwesp}(y)\right] \quad (4)$$

$$\log_{it}[Y_{ij} = 1|Y_{ij}^c = y_{ij}^c] = \begin{bmatrix} \theta_{edges}\delta_{edges}(y) + \theta_{RC}\delta_{RC}(y) + \theta_{Type}\delta_{Type}(y) \\ +\theta_{GP}\delta_{GP}(y) + \theta_{SP}\delta_{SP}(y) + \theta_{TP}\delta_{TP}(y) \end{bmatrix} \quad (5)$$

$$\log_{it}[Y_{ij} = 1|Y_{ij}^c = y_{ij}^c] = \begin{bmatrix} \theta_{edges}\delta_{edges}(y) + \theta_{gwd}\delta_{gwd}(y) + \theta_{gwesp}\delta_{gwesp}(y) \\ +\theta_{RC}\delta_{RC}(y) + \theta_{Type}\delta_{Type}(y) \\ +\theta_{GP}\delta_{GP}(y) + \theta_{SP}\delta_{SP}(y) + \theta_{TP}\delta_{TP}(y) \end{bmatrix} \quad (6)$$

Finally, based on Model 4, the interaction between node types (*Type*) and R&D capability (*RC*), as well as between node type (*Type*) and multidimensional proximity are introduced separately to examine the heterogeneous moderating effects of node types on these variables. Model 5 and Model 6 are obtained.

$$\log_{it}[Y_{ij} = 1|Y_{ij}^c = y_{ij}^c] = \begin{bmatrix} \theta_{edges}\delta_{edges}(y) + \theta_{gwd}\delta_{gwd}(y) + \theta_{gwesp}\delta_{gwesp}(y) \\ +\theta_{RC}\delta_{RC}(y) + \theta_{Type}\delta_{Type}(y) \\ +\theta_{RC*Type}\delta_{RC}(y) \times \delta_{Type}(y) \\ +\theta_{GP}\delta_{GP}(y) + \theta_{SP}\delta_{SP}(y) + \theta_{TP}\delta_{TP}(y) \end{bmatrix} \quad (7)$$

$$\log_{it}[Y_{ij} = 1|Y_{ij}^c = y_{ij}^c] = \begin{bmatrix} \theta_{edges}\delta_{edges}(y) + \theta_{gwd}\delta_{gwd}(y) + \theta_{gwesp}\delta_{gwesp}(y) \\ +\theta_{RC}\delta_{RC}(y) + \theta_{Type}\delta_{Type}(y) \\ +\theta_{GP}\delta_{GP}(y) + \theta_{SP}\delta_{SP}(y) + \theta_{TP}\delta_{TP}(y) \\ +\theta_{GP*Type}\delta_{GP}(y) \times \delta_{Type}(y) + \theta_{SP*Type}\delta_{SP}(y) \times \delta_{Type}(y) \\ +\theta_{TP*Type}\delta_{TP}(y) \times \delta_{Type}(y) \end{bmatrix} \quad (8)$$

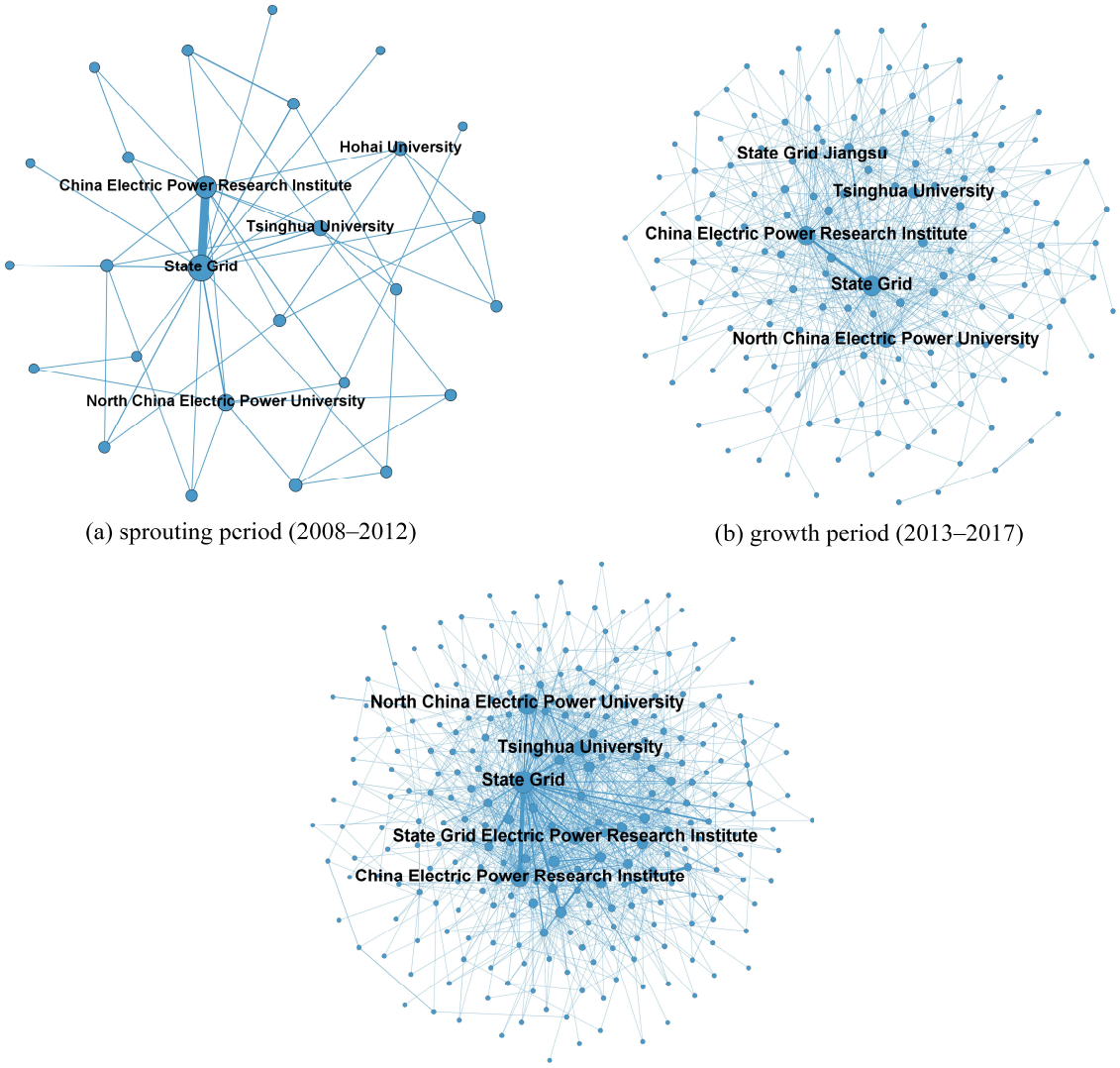
4. Empirical Results

4.1. Network Topology Analysis

Using degree-screened patent data on I-U-R cooperation in the CEI, this study constructs network maps for three periods with Gephi 0.9.7 software (see Figure 2). Descriptive statistics for the network's topology indexes are provided in Table 2.

Table 2. A descriptive analysis of the network's topology structural indicators.

Network Indicators	Sprouting Period	Growth Period	Maturity Period
Number of nodes	27	156	260
Number of edges	50	552	1162
Connecting times	182	2104	4301
Network density	0.1425	0.0457	0.0345
Average clustering coefficient	0.0054	0.0024	0.0034
Average path length	3.2621	3.4680	3.6999
Average degree	3.7037	7.0769	8.9385
Standard deviation of degree	3.0528	8.8958	11.5327
Average edge partner sharing	0.9000	1.8967	2.3520



(a) sprouting period (2008–2012)

(b) growth period (2013–2017)

(c) maturity period (2018–2022)

Figure 2. The I-U-R collaborative network maps of China's CEI. Note: The node size represents degree centrality, while the displayed institutions correspond to the top five ranked by centrality. Additionally, the thickness of the edges represents collaborative frequency.

As Figure 2 illustrates, hubs, represented by State Grid, China Electric Power Research Institute and Tsinghua University, occupy the core position of the I-U-R collaborative networks, indicating the networks' obvious core-periphery structure.

As shown in Table 2, from the sprouting period onward, the number of network nodes and connected edges exhibits steady growth. The average clustering coefficient follows a "U"-shaped trend, while the average path length increases over time. The average degree steadily rises, indicating that the connections between nodes become increasingly dense at each stage. Simultaneously, the standard deviation of the degree increases, reflecting greater differences in node connectivity and the emergence of a few highly connected hub nodes. Additionally, the average number of edge-sharing partners improves progressively, suggesting that the local network structure becomes more cohesive. This enhanced grouping and community formation strengthens the network's robustness and redundancy, showing clear small-world characteristics.

4.2. Model Results

The Statnet package in R was used to estimate the parameters of the ERGM [60]. Network structural variables were analyzed using the Markov Chain Monte Carlo algorithm, and the significance of model parameters was assessed via t-statistics. A variable's parameter estimate was deemed significant only when its standard deviation was less than 50% of the parameter value. Model goodness-of-fit was evaluated using the AIC and BIC, with smaller values indicating better fit [61]. The ERGM estimation results for factors influencing the formation of I-U-R collaborative networks in the CEI are presented in Tables 3–5.

Table 3. The estimation results of the ERGM (sprouting period).

	Model 1	**Model 2**	**Model 3**	**Model 4**
edges	−1.7951 ***	−2.3901 ***	−5.3467 ***	−5.9266 ***
gwd		0.8142		2.3781
gwesp		0.4149 *		−0.3559
RC			0.0216 ***	0.0258 ***
Type.E			−0.3549	−0.4620
Type.U			0.0436	−0.0021
GP			2.1163 *	2.7546 **
SP			7.2637 ***	8.5460 ***
TP			6.2296 **	7.3351 ***
AIC	289.3892	288.6122	209.3106	207.1029
BIC	293.2500	300.1945	236.3361	241.8500

Note: *, **, and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% levels

Table 4. The estimation results of the ERGM (growth period).

	Model 1	**Model 2**	**Model 3**	**Model 4**
edges	−3.0399 ***	−4.1672 ***	−6.3585 ***	−6.4027 ***
gwd		−0.2540		0.2596
gwesp		1.0084 ***		0.1950 **
RC			0.0058 ***	0.0051 ***
Type.E			−0.6979 ***	−0.6520 ***
Type.U			0.4624 ***	0.4289 ***
GP			3.3075 ***	3.1538 ***
SP			5.0182 ***	4.8202 ***
TP			3.7572 ***	3.7067 ***
AIC	4487.9953	4208.1887	3549.2936	3546.3119
BIC	4495.3954	4230.3891	3601.0946	3612.9131

Note: **, and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% levels

In the estimation results, the coefficient for edges is consistently negative and significant, reflecting the sparsity of the observed network. The integrated model exhibits minimal AIC and BIC values across different periods, indicating superior simulation and fit compared to other models. Furthermore, the integrated model's results closely align with those of other models, demonstrating the robustness of the estimations.

From Tables 3–5, the coefficient for *gwd* is insignificant during the sprouting and growth phases but becomes significantly positive in the maturity stage, indicating a preference attachment effect and underscoring the importance of convergent structures for network formation, validating H1. The coefficient for *gwesp* is insignificant in the sprouting period but turns significantly positive in both the growth and maturity stages, suggesting that transitive closure strengthens over time and plays an increasingly crucial role in promoting network formation, supporting H2.

Table 5. The estimation results of the ERGM (maturity period).

	Model 1	Model 2	Model 3	Model 4
edges	−3.3313 ***	−4.7598 ***	−6.1549 ***	−6.4450 ***
gwd		−0.4628		1.2096 *
gwesp		1.2606 ***		0.5013 ***
RC			0.0045 ***	0.0030 ***
Type.E			−0.9583 ***	−0.8179 ***
Type.U			0.2646 ***	0.2282 ***
GP			2.9482 ***	2.6891 ***
SP			9.3924 ***	8.5873 ***
TP			3.8345 ***	3.6170 ***
AIC	10,109.0919	9298.0998	7974.0660	7897.1555
BIC	10,117.5163	9323.3729	8033.0365	7972.9748

Note: * and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% levels

Regarding the node attributes, R&D capability shows a significantly positive effect in every phase, confirming H3. For node type, enterprise (*Type.E*) is insignificant in the sprouting phase but becomes significantly negative during the growth and maturity periods, with the negative effect intensifying over time, supporting H4a. In contrast, university (*Type.U*) is insignificant in the sprouting phase but significantly positive in the growth and maturity periods, though this positive effect diminishes over time, validating H4b.

Turning to edge attributes, geographic proximity is significantly positive across all phases and follows an inverted "U" pattern, indicating that while closer nodes collaborate more initially, this effect eventually declines, confirming H5. Social proximity is also significantly positive in every stage but exhibits a "U" trend, reflecting an initial decrease followed by a later increase, supporting H6. Finally, technological proximity remains significantly positive throughout but shows a downward trend, suggesting its influence weakens over time, confirming H7.

4.3. Moderating Effect Test

This study incorporates interaction terms between node type and R&D capability into the ERGM, using research institutes as the reference category, to examine how enterprises and universities moderate the influence of R&D capability on network formation. The results of this analysis are presented in Table 6.

Table 6. Heterogeneity analysis based on node type and R&D capacity.

	Sprouting Period	Growth Period	Maturity Period
edges	−6.3104 ***	−7.1117 ***	−6.9325 ***
gwd	2.7973	0.1329	1.0444 *
gwesp	−0.3195	0.1925 **	0.4968 ***
RC	0.0260 ***	0.0117 ***	0.0078 ***
Type.E	0.0055	−0.1211	−0.3559 ***
Type.U	−0.3700	0.4132 ***	−0.0046
*RC*Type.E*	−0.0067	−0.0049 ***	−0.0036 ***
*RC*Type.U*	0.0131 *	0.0035 ***	0.0038 ***
GP	2.7789 **	3.2512 ***	2.7546 ***
SP	8.4959 ***	5.1455 ***	7.9364 ***
TP	8.4978 **	3.5670 ***	3.7858 ***
AIC	199.2447	3376.2745	7587.1585
BIC	241.7133	3457.6759	7679.8265

Note: *, **, and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% levels

In Table 6, the interaction between enterprises and R&D capability is negative during the growth and maturity phases, indicating that enterprises diminish the positive impact of R&D capability on network formation. By contrast, the interaction between universities and R&D capability is significantly positive across all three stages, implying that universities strengthen R&D's role in driving network development. These findings support H8, underscoring the contrasting moderating effects of enterprises and universities at different points in network evolution.

To examine the varying moderating effects of node type on multidimensional proximity, we introduced interaction terms between node type and geographic, social, and technological proximity, using research institutes as the reference category. The results of this analysis are presented in Table 7.

Table 7. Heterogeneity analysis based on node type and proximity.

	Sprouting Period	Growth Period	Maturity Period
edges	−7.4800 ***	−7.4477 ***	−7.7509 ***
gwd	2.6855	0.3712	1.1968 *
gwesp	−0.3224	0.1914 **	0.4772 ***
RC	0.0273 ***	0.0053 ***	0.0031 ***
Type.E	0.5879	−0.2093	0.2098
Type.U	0.1057	1.3989 ***	0.8715 ***
GP	1.9613	4.2670 ***	3.6930 ***
SP	15.8282 ***	4.1497 ***	12.0282 ***
TP	26.0720 ***	8.0221 ***	9.1163 ***
*GP*Type.E*	0.3071	−0.4288	−0.7464 **
*GP*Type.U*	1.4432	−1.3837 **	−0.6005
*SP*Type.E*	−3.6864	0.9521	−2.4780 ***
*SP*Type.U*	−7.3550 **	0.9801	−0.6257
*TP*Type.E*	−16.1911 **	−4.1988 ***	−4.4788 ***
*TP*Type.U*	−2.0528	6.5232 ***	−1.1822 *
AIC	203.9535	3474.4416	7795.8302
BIC	261.8653	3585.4436	7922.1957

Note: *, **, and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% levels

As shown in Table 7, enterprises exert a significant negative moderating effect on geographic proximity in the maturity stage, while universities exhibit a negative effect in the growth phase. In other periods, neither node type shows a significant moderating influence on geographic proximity, aligning with H9a and highlighting the distinct strategies employed by enterprises and universities over time.

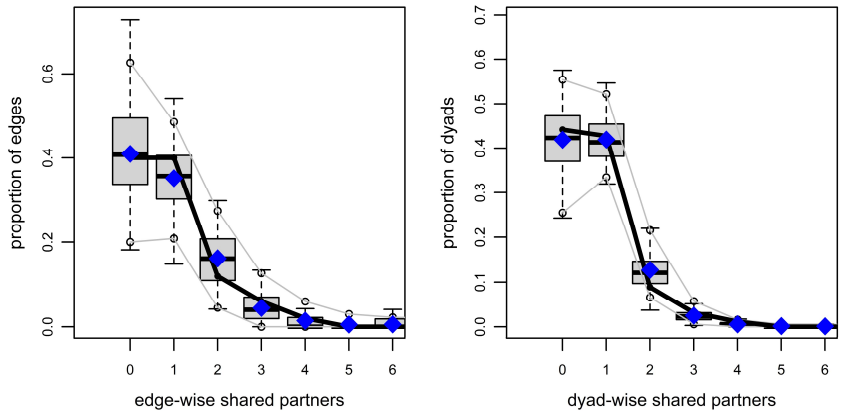
For social proximity, enterprises demonstrate a significant negative moderating effect in the maturity stage, whereas universities do so in the sprouting stage, indicating that each actor type plays a dynamic role in shaping social proximity across network evolution, supporting H9b.

Finally, enterprises consistently impose a significant negative moderating influence on technological proximity across all stages. Universities, however, enhance technological proximity in the growth phase but shift to a negative effect in the maturity stage, revealing a clear divergence between enterprises and universities in how they moderate technological proximity over time, thereby validating H9c.

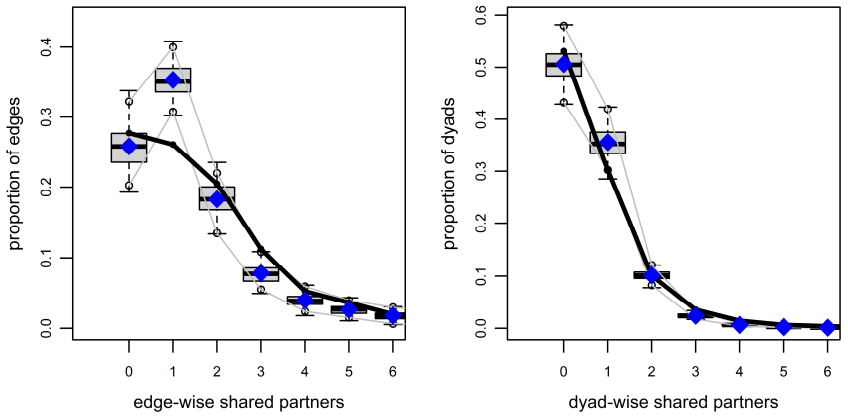
4.4. Robustness Test

To ensure model robustness, this study employs a goodness-of-fit diagnostic to assess its performance. Two indicators, edge-wise shared partners and dyad-wise shared partners, evaluate the alignment between the simulated and actual networks [62]. The

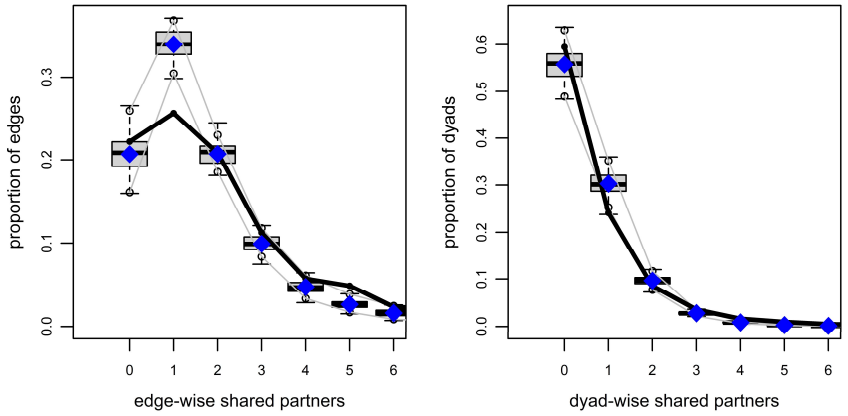
analysis focuses on Model 4 of the I-U-R collaborative network in the CEI, with results presented in Figure 3.



(**a**) Sprouting period



(**b**) Growth period



(**c**) Maturity period

Figure 3. Diagnostic plot of goodness-of-fit. Note: the black line depicts the statistical outcomes of the observed network, whereas the gray line with the box plot illustrates the simulated network estimates within a 95% confidence interval. The wide range of gray lines reflects the variability in simulated network outcomes, suggesting that the model is flexible and can capture diverse potential network structures.

In Figure 3, the wide range of gray lines indicates significant variability in the simulated network outcomes. This variability highlights the model's capacity to accommodate various network configurations, particularly in terms of edge-wise and dyad-wise shared partners. Despite this flexibility, the observed network's outcomes (represented by the black line) predominantly lie within the range of the gray lines, indicating that the model

provides a robust fit, effectively capturing the structural characteristics of the observed data. The strong consistency between black lines and gray lines in all stages of network evolution supports the model's goodness-of-fit and the robustness of the ERGM estimation results.

5. Discussion

This study provides empirical evidence on the formation and evolution of China's I-U-R collaborative network in the CEI. The results reveal several key insights into the structural dynamics and driving forces of network formation.

First, the findings demonstrate that China's I-U-R collaborative network exhibits steady growth, forming a distinct core-periphery structure dominated by few hub nodes. This pattern aligns with prior studies on wind and hydrogen energy industries [16,63], suggesting a common evolutionary pattern in clean energy innovation networks. Expanding on static network research by Cao et al. [5], this study leverages I-U-R collaboration patent data and applies the methodology of excluding same-type collaboration patents [28] to model network dynamics, revealing increasing structural cohesion, more pronounced community formation, and stronger small-world characteristics over time.

Second, network structural attributes play different roles at various network development stages. The convergence structure facilitates network formation during the maturity period, while the transfer closure structure significantly contributes throughout the growth and maturity periods. These result are consistent with the findings of Ma et al. [8], supporting the notion that R&D resource aggregation attracts external innovation inputs, promoting the diffusion of complex technologies [21]. The increasing effect of transitive closure indicates the strengthening of redundant collaborative ties, enhancing network connectivity and stability [26].

Third, the nodes' R&D capability remains a key driver of network formation, particularly in the sprouting and growth phases. This finding supports the preferential attachment mechanism of network formation [29,30]. In addition, enterprise nodes exhibit a growing negative effect over time, supporting the argument of Yuan and Chen [28] that firms restrict new external collaborations to maintain competitive advantages. As market competition intensifies, enterprises reduce collaborative efforts to mitigate financial risks, as noted by Wei et al. [64]. This trend may also be influenced by the tightening of intellectual property protection policies in China. Firms, motivated by the desire to avoid potential legal conflicts, become more reluctant to engage in collaborations due to concerns over intellectual property infringement [64]. External shocks, such as COVID-19, further amplify the firms' financial risk aversion toward collaborative R&D [65]. In contrast, university nodes positively contribute to network expansion, aligning with Kirkels and Duysters [33] and Cao et al. [34], highlighting the critical role of universities in network formation. This positive trend may be driven by subsidies and other financial incentives, as Zan et al. [66] demonstrate, which encourage universities to engage in collaborative efforts. Additionally, as Decter et al. [67] claimed, the need to commercialize research outcomes and secure gap funding continually motivates universities to strengthen I-U-R collaborations.

Fourth, proximity factors exhibit distinct temporal patterns. The influence of geographic proximity initially increases but later decreases. This is consistent with the findings of Sempsey [41], which suggest that advancements in communication and transportation technologies reduce the constraints imposed by geographic distance, leading to a weaker impact of spatial proximity over time. And the effect of social proximity exhibits a U-shaped trend, with its role strengthening in later network stages, as the nodes increasingly rely on existing social ties for collaboration [63]. Past collaboration experiences enhance the effectiveness of future partnerships, as Bellini et al. [68] note, promoting the expansion of I-U-R networks. Meanwhile, the impact of technological proximity declines over time, sug-

gesting that as technologies mature, the demand for heterogeneous innovation resources grows, reducing the reliance on technological similarity [47]. This supports the findings of Xu et al. [69], who discovered that the degree of technological complementarity positively influences collaborative behaviors.

Fifth, node heterogeneity influences collaboration dynamics. Enterprises negatively moderate the effect of R&D capability on network formation during the growth and maturity periods. This suggests that as firms develop greater R&D capabilities, they tend to reduce their willingness to engage in I-U-R collaborative networks. Su and Yan [70] highlight this tendency, showing that enterprises with high R&D capacity are more inclined to focus on internal innovation efforts to minimize investment risks. Universities, by contrast, consistently exhibit positive moderating effects, fostering interdisciplinary collaboration and promoting knowledge diffusion [71,72]. This suggests that as universities enhance their R&D capabilities, they are more likely to engage in I-U-R collaborative networks, potentially influenced by government policies such as the collaborative R&D subsidies. Zeng et al. [73] found that China's I-U-R policies have strengthened and consolidated the dominant role of universities, thereby driving the expansion of network scale.

Sixth, enterprises display varying moderation effects on proximity dimensions. They negatively moderate technological proximity throughout all periods, extending the conclusions of Yuan and Chen [28] that core enterprises prefer collaborating with highly proximate nodes. Our findings indicate that while core enterprises favor technologically proximate partners, most peripheral firms seek technologically distant collaborators to access diverse innovation resources. This distinction underscores the contrasting collaboration strategies between core and peripheral enterprises.

Additionally, enterprises selectively suppress social and geographic proximity in the maturity stage. As market competition intensifies, they tend to reduce cooperation with geographically proximate nodes to maintain regional competitiveness [45,70]. Moreover, as Bellini et al. [68] suggest, firms must carefully select partners that align with their long-term strategic goals and avoid financial risks, as relying solely on past relationships is insufficient to fully benefit from I-U-R collaborations.

Finally, the universities' moderation of proximity effects shifts over time, reflecting their evolving role. Their negative moderation of social proximity in the sprouting stage and geographic proximity in the growth stage highlights their function as knowledge brokers, mitigating the risks of closed innovation systems and fostering knowledge diffusion [50]. Their moderation of technological proximity transitions from positive in the growth stage, where they promote knowledge exchange with similar partners, to negative in the maturity stage, where they link diverse innovation agents to navigate increasing technological competition [31,32].

6. Conclusions and Implications

In this paper, the ERGM method was applied to test the influence mechanism of network structure attributes, node attributes and edge attributes on the formation of I-U-R collaborative network in China's CEI and verify the heterogeneous moderating effect of nodes of different organizational types on node R&D capability and multidimensional proximity. After the robustness test, the following conclusions are obtained:

First, the I-U-R collaborative networks in the CEI exhibit steady growth, forming a core-periphery structure with increasing cohesion and stronger small-world properties.

Second, convergence structures play a crucial role in network expansion during the maturity phase, while transitive closure drives network formation throughout the growth and maturity periods.

Third, R&D capability consistently facilitates network formation, with its strongest impact occurring during the sprouting and growth phases. Enterprise nodes exhibit a growing negative effect on network formation over time. Universities, in contrast, consistently foster network expansion.

Fourth, geographic, social, and technological proximity all contribute to network formation, but follow distinct trends, with geographic proximity showing an inverted U-shaped effect, social proximity exhibiting a U-shaped pattern, and technological proximity weakening as networks mature.

Fifth, enterprises negatively moderate the impact of R&D capability on network formation during both the growth and maturity stages, whereas universities consistently exert a positive moderating effect.

Sixth, enterprises persistently exhibit a negative moderation effect on technological proximity and only restrict social and geographic proximity in the maturity stage. In contrast, universities negatively moderate social proximity during the sprouting stage and geographic proximity during the growth stage. Their moderation of technological proximity evolves over time, shifting from a positive influence in the growth stage to a negative effect in the maturity stage.

These findings provide valuable insights for advancing I-U-R collaborative networks in China's CEI. To mitigate network unipolarization, entities with strong R&D capabilities should establish innovation platforms that attract small and medium-sized peripheral nodes. This would foster industrial innovation clusters and promote convergence and transfer closure structures, facilitating a more balanced, efficient, and stable collaboration system.

Government intervention is essential to enhance the role of multidimensional proximity in network formation. Efforts should focus on developing regional innovation clusters and leveraging digital tools to strengthen geographically proximate collaborations. Simultaneously, improving legal and regulatory frameworks is crucial for protecting participants' rights, fostering stable relationships among socially connected entities. Additionally, establishing technical standards would facilitate seamless integration of innovation resources among technologically similar actors, further strengthening network cohesion.

Recognizing the heterogeneous roles of enterprises and universities in shaping I-U-R collaborative networks, targeted government policies are needed to strengthen the nodes' participation in networks: tax incentives for enterprises, and subsidy programs for universities and research institutes to foster collaboration [74]. Additionally, enterprises, particularly peripheral ones, should actively seek diverse partners to access heterogeneous knowledge resources and sustain long-term competitiveness. Encouraging balanced collaboration strategies can help mitigate excessive internalization and promote knowledge exchange.

Additionally, prioritizing university-led I-U-R innovation alliances could amplify the impact of academic resources. Universities should reinforce their role as knowledge brokers by establishing structured interdisciplinary collaboration mechanisms. Improving mechanisms for valuing university innovation contributions and strengthening intellectual property protection would enable the universities to act as both knowledge providers and brokers. Institutional reforms aimed at overcoming geographic, social, and technological barriers would foster synergy across innovation, talent, and industry chains, driving technological advancement and ensuring the CEI's long-term prosperity.

This study has certain limitations. The 18-month invisibility period in patent data excluded the most recent CEI patents from analysis. Moreover, while widely used in innovation research, patent data cannot fully capture tacit knowledge, a crucial factor in innovation [65]. Future studies could address these gaps by incorporating alternative data sources, such as journal articles or project records, to construct I-U-R collaborative network

models. Additionally, conducting comparative research on cross-country variations in the factors shaping I-U-R networks in the context of CEI could further enhance the robustness and generalizability of the findings. Lastly, the empirical validation of the effect of external factors, such as the COVID-19 pandemic and policy, on networks formation remains an important area for future research.

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Abbreviations

The following abbreviations are used in this manuscript:

I-U-R	Industry-university-research
CEI	Clean energy industry
ERGM	Exponential random graph model

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