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Research on the Formation Mechanism of Enterprises' AI Technology Collaborative Innovation Network

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Abstract. Based on the invention patent data in the AI field jointly applied by enterprises in Chinese mainland from 2015 to 2024, this paper constructs a dynamic collaborative innovation network and employs the Temporal Exponential Random Graph Model (TERGM) to explore the formation mechanism of enterprises' AI innovation collaborative relationships. Considering both endogenous and exogenous factors affecting network construction, it incorporates structural dependence, temporal dependence, node characteristics, and exogenous network covariates into the model framework. The results show that the formation of enterprises' AI collaborative innovation relationships is influenced by the peer effect, and network evolution presents characteristics of structural self-organization and path dependence. This study helps to understand the evolution of AI innovation collaborative networks and provides theoretical support for the allocation of innovation resources and the formulation of relevant policies.

Keywords: AI collaborative innovation network; Temporal Exponential Random Graph Model (TERGM); network evolution mechanism; peer effect.

1. Introduction

Against the backdrop of the accelerated digital economy, AI is reshaping industrial structures and making inter-organizational collaborative innovation increasingly complex. Enterprises can hardly address the knowledge challenges in innovation relying solely on internal capabilities, so they have successively leveraged external resources to establish cross-industry and cross-regional collaborative networks.

Essentially, such cooperation reflects enterprises' tendency to collaborate with "similar others" in an environment of uncertainty and information asymmetry (Leary et al., 2014)—a phenomenon known in academia as the "peer effect." It is widely present in corporate innovation networks and profoundly influences the formation of cooperation. However, existing studies lack a clear framework to explain its mechanism of action on the construction of collaborative relationships and the dynamic evolution of networks.

To address this, this paper focuses on the peer effect in collaborative networks in the AI field and analyzes its underlying logic regarding the formation of cooperation and network evolution.

2. Research Hypotheses and Research Methods

2.1. Formulation of Research Hypotheses

The formation and evolution of firms' AI collaborative innovation networks are driven by four core factors, which can be incorporated into the TERGM to accurately depict their dynamic logic: first, network structural dependence (e.g., star nodes, triangular closure); second, temporal path continuity (cooperative memory mechanism); third, firms' own attributes (scale, technology, age); fourth, exogenous network variables (regional, industrial, and technological relevance). Combining relevant theories, this paper proposes the following hypotheses:

Network structural characteristics exhibit self-organization and continuity. Although core node firms serve as cooperation hubs (Wang et al., 2014), they will restrict network expansion to control redundancy and information spillover (H1a). In an uncertain environment, firms tend to establish new cooperation through sharing third parties (transitivity, H1b) or form triangular structures within existing groups to enhance stability (H1c) (Guo et al., 2021).

H1a: Core node firms tend to maintain existing cooperation and restrict network expansion.

H1b: Firms are more likely to establish new cooperation through indirect paths (shared partners) to reduce uncertainty.

H1c: Firms tend to form closed triangular structures within original cooperative groups to strengthen cooperation stability.

Path Dependence Theory indicates that past cooperation experience will reinforce future choices, which is particularly evident in the AI field. "Deep path dependence" accumulated through repeated cooperation has a stronger impact on relationship continuity than single cooperation (H2).

H2: The continuity of AI collaborative relationships is mainly driven by intertemporal accumulated cooperation experience rather than single-period cooperation status.

As firms age, they are prone to organizational inertia (Demirkan et al., 2013). Older firms are more willing to maintain old cooperation and reduce new explorations (H3). Meanwhile, equal strength is a key prerequisite for cooperation—firms tend to choose partners with similar scale and technological level to achieve risk-sharing and resource exchange (Vasudeva et al., 2013) (H4a/H4b).

H3: The older the firm, the lower the probability of establishing new cooperation.

H4a: Firms are more inclined to cooperate with partners of similar scale to share innovation risks equally.

H4b: Firms are more inclined to cooperate with partners with equivalent technological accumulation for fair resource exchange.

Spatial proximity is crucial. Firms in the same province share policy environments and resources, making collaboration easier (Boschma, 2005; Gao et al., 2021) (H5). The AI field has both needs for homogeneous collaboration and heterogeneous complementarity: similar technology can improve efficiency (H6a), while cross-industry cooperation can promote knowledge recombination (H6b) (Jiang et al., 2018).

H5: Firms are more inclined to cooperate with those in the same province to adapt to the institutional environment and share resources.

H6a: Firms tend to cooperate with partners with similar technological foundations to improve collaborative efficiency.

H6b: Firms will select cross-industry partners to carry out innovation through resource complementarity.

2.2. Research Methods

To explore the dynamic evolution mechanism of firms' AI collaborative innovation relationships, this paper employs the Temporal Exponential Random Graph Model (TERGM) to model and analyze the inter-firm joint patent network from 2015 to 2024. As a temporal extension of the classic Exponential Random Graph Model (ERGM), TERGM can simultaneously handle the endogenous dependence of network structure and the temporal evolution characteristics of collaborative relationships, making it suitable for dynamic modeling of multi-period network data (Block, 2018).

$$P_{\mathrm{r}}\left(N^{\mathrm{t}} \mid N^{\mathrm{t-k}},\cdots,N^{\mathrm{t-1}},\theta\right)=\frac{\exp(\theta \cdot h(N^{\mathrm{t}},N^{\mathrm{t-1}},\cdots,N^{\mathrm{t-k}}))}{K(\theta,N^{\mathrm{t-k}},\cdots,N^{\mathrm{t-1}})} \tag{1}$$

The TERGM defines that the network N_t at time t is a function of the networks N_{t-k},··, N_{t-1} over the time steps from $t\text{-}k$ to $t\text{-}1$, and the model is as shown in Equation (1).

3. Design of Research Variables and Research Results

3.1. Design of Research Variables

3.1.1. Explained Variable.

The core dependent variable is the probability of forming AI collaborative innovation relationships among enterprises, determined by whether they jointly applied for AI invention patents (network edges) in a specific year. The data is sourced from the State Intellectual Property Office (SIPO). AI-related invention patents jointly applied by enterprises in Chinese mainland from 2015 to 2024 were retrieved based on AI-related IPC classification numbers. Only invention patents are retained (excluding utility models and design patents), and the cooperation time is defined by the patent publication date. Finally, 82,495 patents are obtained, identifying 10,654 independent enterprises.

To meet the requirements of the TERGM, the k-core method is adopted to select 1,395 multi-period active enterprise nodes, constructing a 10-period dynamic collaborative innovation network that balances network representativeness and model convergence.

3.1.2. Explanatory Variables.

Endogenous structural dependence variables: gwdegree, gwdsp, gwesp; Temporal dependence terms: stability, memory. Exogenous factors include node attributes and network covariates:

Node attributes: Firm age (AGE) is measured by the number of years since registration; firm size is grouped by the number of social security participants; technological accumulation is classified by the logarithm of cumulative AI invention patents; the geographic peer variable is identified based on the registered province.

Network covariates: The industry proximity index is calculated based on the similarity of industry classification codes; the technological proximity index integrates patent semantic similarity and IPC classification similarity, with lag processing applied.

3.2. Research Results

Using ten periods of dynamic cooperative network data as samples, this paper employs the Temporal Exponential Random Graph Model (TERGM) to capture the temporal path dependence characteristics and inherent mechanisms of cooperative relationships. The model obtains parameters and confidence intervals through bootstrap pseudo-likelihood estimation ($R>200$) via the btergm package, enhancing the estimation robustness under high-dimensional networks. In the empirical part, five hierarchical models are constructed sequentially to gradually reveal the influencing factors of cooperative relationships. See Table 1 for detailed estimation results of each model.

Table 1 shows that the Edges term is significantly negative at the 0.1% significance level across Models (1) to (5), indicating that cooperation among enterprises in the AI field is not randomly formed but subject to systematic constraints from structural characteristics and behavioral preferences. This provides methodological support for the subsequent introduction of multi-dimensional variables. The following interprets the core influencing factors based on Model (5), which includes the most comprehensive set of variables:

Network Structure Dimension: The gwdegree term is significantly negative (−2.01, $p<0.001$), supporting H1a. Core node enterprises tend to maintain stable cooperative circles to control information diffusion and collaborative costs. Both gwdsp (0.02) and gwesp (2.18) are significantly positive, verifying H1b and H1c. Enterprises are more inclined to establish cooperation through indirect contacts or form triangular closure structures within acquaintance networks, highlighting trust orientation in a high-uncertainty environment.

Table 1. Benchmark Regression Results

	Model Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Endogenous Structural Variables	Edges	-7.4072*** (0.0128)	-7.14*** (0.1020)	-6.9200*** (0.3112)	-6.93*** (0.2755)	-7.13*** (0.1735)
	Gwdegree		-2.53*** (0.0740)	-2.42*** (0.0765)	-2.38*** (0.0791)	-2.01*** (0.1148)
	Gwdsp		0.02*** (0.0026)	0.02*** (0.00255)	0.02*** (0.0026)	0.02*** (0.0026)
	Gwesp		2.36*** (0.0357)	2.25*** (0.0408)	2.26*** (0.0408)	2.18*** (0.0408)
Temporal Dependence	Stability					0.05 (0.0332)
	Memory					3.73*** (0.1046)
Node Attributes	Nodecov(AGE)			-0.16*** (0.0408)	-0.16*** (0.0383)	-0.19*** (0.0408)
	Nodematch(SIZE)			0.15*** (0.0153)	0.17*** (0.0204)	0.14*** (0.0255)
	Nodematch(TECH_ACC)			0.59*** (0.0332)	0.54*** (0.0383)	0.25*** (0.0357)
	Nodematch (Province)			1.29*** (0.0637)	1.30*** (0.0587)	1.20*** (0.0689)
Network Covariates	Edgecov(Industry)				-0.29*** (0.0587)	-0.23*** (0.0587)
	Edgecov(TECH_SIM)				2.25*** (0.5153)	1.76*** (0.3776)

Note: Values in parentheses ( ) are robust standard errors. *** p<0.001, ** p<0.01, * p<0.05

Temporal Continuity Dimension: The memory variable is significantly positive (3.73, p<0.001), indicating that the higher the frequency of historical interactions, the greater the probability of future cooperation continuity. Although the stability term is positive, it is not significant, suggesting that collaborative continuity is driven by multi-period in-depth interactions rather than occasional single-period cooperation, which reinforces the logic of path dependence.

Enterprise-Specific Characteristics Dimension: Older enterprises have a lower tendency to establish new cooperation, supporting H3 (organizational inertia). Technological accumulation and scale matching significantly affect cooperation probability, verifying H4a and H4b, which reflects rational matching under the "principle of equivalence." Enterprises in the same province show a stronger cooperative tendency (supporting H5), highlighting the "spatial embedding effect" of provincial institutions and resources.

Technology and Industry Dimension: Technological path similarity significantly increases cooperation probability (supporting H6a), and cross-industry heterogeneity significantly promotes cooperation (supporting H6b). These two factors are complementary, reflecting the cooperative pattern of coexisting "convergence deepening" and "heterogeneous complementarity" in AI collaborative networks.

Overall, the evolution of AI collaborative innovation networks is influenced by multiple factors, including enterprise-specific characteristics, historical relationships, institutional environments, and technological peer effects. Cooperation is more likely to be established and deepened among enterprises with similarities in technology, scale, and region, as well as close network ties. This reflects the evolutionary trend of collaborative models under complex general-purpose technologies.

4. Summary

Based on the data of AI joint invention patents by enterprises in Chinese mainland from 2015 to 2024, this study constructed a ten-period dynamic collaborative innovation network. Via the Temporal

Exponential Random Graph Model (TERGM), it identified the key drivers of the formation and continuity of AI collaborative relationships from four aspects: network structural dependence, path memory, node attributes, and external network factors. The evolution of AI collaborative innovation networks is jointly driven by structural inertia, experience accumulation, resource equivalence, and cognitive consensus. Cooperative relationships embody both stability mechanisms and open exploration, providing important reference for understanding enterprises' cooperative behaviors and the laws of technological evolution.

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