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Collaborative Mechanism and Value Co-creation Model of Enterprise Innovation Ecosystems Embedded with Artificial Intelligence

Yikun Zhang

College of Business, City University of Hong Kong, Hong Kong, China
rara481846778@gmail.com

Abstract. Artificial intelligence is increasingly embedded in enterprise R&D, production, management, and platform operations. This process shifts collaboration in enterprise innovation ecosystems from experience driven interaction to data identification, algorithmic matching, and intelligent feedback. Focusing on core firms, partners, supply chain actors, and technological cooperation relationships, an analytical framework is developed to examine AI embeddedness, collaborative mechanisms, and value co creation performance. The sample includes 480 Chinese A share listed enterprises from 2020 to 2025. Annual reports, ESG reports, announcement texts, joint patents, and public patent data are used as data sources. Python based text mining, BERT semantic identification, NetworkX analysis, panel regression, XGBoost, and SHAP interpretation are applied. The results show that enterprises with higher AI embeddedness have higher network density, stronger degree centrality, and a higher joint patent ratio. Collaborative mechanisms play a key role in the effect of AI embeddedness on value co creation performance. The findings indicate that AI does not improve innovation output in isolation. It promotes value co creation by optimizing cooperation structures, knowledge connections, and resource allocation in enterprise innovation ecosystems.

Keywords: artificial intelligence, enterprise innovation ecosystem, collaborative mechanism, value co-creation, social network analysis

1. Introduction

Digital transformation has moved enterprise innovation from closed internal R&D toward cross-organizational collaboration, where core firms, suppliers, customers, research institutions, and platform actors jointly form dynamic innovation ecosystems. The embeddedness of artificial intelligence further changes opportunity recognition, resource allocation, and partner matching, enabling firms to improve innovation decision-making through text recognition, algorithmic recommendation, and data-based feedback [1]. Existing studies have examined the influence of AI adoption on firm performance, product innovation, and managerial decision-making, while also discussing the importance of complementary actors and resource integration in innovation ecosystems [2]. In enterprise management, AI functions not merely as a technical tool but as a

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mechanism that affects collaborative order through data flows, knowledge flows, and cooperation networks [3]. Following this logic, the analysis focuses on the relationships among AI embeddedness, collaborative innovation mechanisms, and value co-creation performance, using public annual report texts, joint patent data, and cooperation announcements to build a testable analytical framework.

2. Literature review

2.1. Enterprise innovation ecosystem research

Enterprise innovation ecosystem research emphasizes structural interdependence among multiple actors, in which core firms form ecosystem centers through strategic guidance and resource integration, while suppliers, users, research institutions, and complementary firms participate through knowledge contribution, technical support, and market feedback [4]. This perspective understands innovation performance through network structure and ecosystem collaboration, extending enterprise boundaries from internal R&D departments to cross-organizational cooperation relationships. As digital platforms and industrial-chain collaboration continue to deepen, innovation activities show stronger openness and embeddedness, requiring firms to acquire external knowledge, coordinate complementary resources, and reduce technological uncertainty within ecosystems [5]. The analytical focus of innovation ecosystems therefore shifts from the capability of a single firm to the linkage among actor position, cooperation intensity, resource complementarity, and governance rules.

2.2. Collaborative innovation under AI embeddedness

After AI becomes embedded in collaborative innovation mechanisms, firms can use natural language processing to identify market demand, machine learning to predict technological trends, and recommendation algorithms to screen potential partners [6]. This technological embeddedness improves information-processing capability in cross-organizational cooperation, shifting collaboration from experience-based judgment toward data identification and algorithmic matching. The efficiency of collaborative innovation depends not only on the predictive capability of AI models but also on the degree of inter-firm data openness, willingness to share knowledge, and clarity of governance responsibilities [7]. When AI participates in resource allocation and technology-route judgment, central firms in cooperation networks are more likely to develop information advantages, while resource dependence, trust structures, and negotiation rules among ecosystem members are also reshaped.

2.3. Value co-creation model extension

Value co-creation theory focuses on how firms, users, and partners generate value through resource integration, interactive participation, and joint decision-making, making it suitable for explaining how multiple actors in innovation ecosystems jointly create technological and market outcomes [8]. After AI is embedded, value co-creation is no longer driven only by human communication and experience-based negotiation; data flows, algorithmic explanation, platform connection, and feedback optimization jointly shape the path of value generation. Value outputs in enterprise innovation ecosystems can appear as joint patent quality, new product revenue, knowledge diffusion, cooperation continuity, and customer participation [9]. In this process, AI enhances value co-

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creation efficiency by improving opportunity recognition, cooperation matching, and knowledge recombination, while also making value distribution, data control, and algorithmic transparency important variables in ecosystem governance.

3. Experimental methods

3.1. Public data source design

Data cover Chinese A-share listed enterprises from 2020 to 2025, focusing on manufacturing, information technology services, and high-end services. From an initial sample of about 720 firms, ST firms, financial firms, firms listed for fewer than three years, and observations with substantial missing reports, unmatched patent data, or unidentifiable cooperation announcements are excluded, leaving about 480 firms and 2,880 firm-year observations. AI embeddedness is identified from annual reports, ESG reports, and CNINFO announcements using AI-related textual indicators. Collaborative innovation data include joint patents, strategic and R&D cooperation announcements, and supply-chain cooperation disclosures. Value co-creation is measured by invention patents, joint patent ratios, patent citations, new product revenue, and innovation-related textual intensity. All data are matched by firm name, stock code, and year to construct the panel dataset.

3.2. Variable measurement scheme

Variable measurement focuses on AI embeddedness, collaborative mechanisms, and value co creation performance. AI embeddedness is constructed from the semantic intensity of AI related expressions in annual reports, ESG reports, and announcement texts. Python is first used for text cleaning, word segmentation, stop word removal, and keyword expansion. BERT semantic classification is then applied to determine whether the relevant sentences truly refer to AI applications in enterprise R&D, production, management, or platform operation [10]. To avoid the bias caused by simple word frequency in longer texts, the AI embeddedness index combines TF IDF weight, BERT semantic probability, and text length correction, as shown in Formula (1).

$$\mathrm{AI}_{\mathrm{it}}=\frac{\sum_{\mathrm{k=1}}^{\mathrm{K}}\mathrm{TFIDF}_{\mathrm{kit}}\times\mathrm{P}_{\mathrm{kit}}^{\mathrm{BERT}}}{\ln(1+\mathrm{Words}_{\mathrm{it}})} \tag{1}$$

In Formula (1), $\mathrm{AI}_{\mathrm{it}}$ refers to the AI embeddedness of enterprise i in year t. $\mathrm{TFIDF}_{\mathrm{kit}}$ refers to the text weight of the k_{th} AI keyword. $\mathrm{P}_{\mathrm{kit}}^{\mathrm{BERT}}$ refers to the probability that the sentence is classified as a real AI application meaning. $\mathrm{Words}_{\mathrm{it}}$ refers to the total number of words in the text.

The collaborative mechanism index is measured through joint patent relationships and cooperation announcement relationships. NetworkX is used to calculate network density, degree centrality, and betweenness centrality. Annual cooperation frequency is also included in the composite index, as shown in Formula (2).

$$\mathrm{CM}_{\mathrm{it}}=0.30\mathrm{Density}_{\mathrm{it}}+0.30\mathrm{DegreeC}_{\mathrm{it}}+0.25\mathrm{BetweenC}_{\mathrm{it}}+0.15\mathrm{CoopFreq}_{\mathrm{it}} \tag{2}$$

In Formula (2), $\mathrm{CM}_{\mathrm{it}}$ refers to the strength of the collaborative mechanism. $\mathrm{Density}_{\mathrm{it}}$ refers to cooperation network density. $\mathrm{DegreeC}_{\mathrm{it}}$ refers to degree centrality. $\mathrm{DegreeC}_{\mathrm{it}}$ refers to betweenness centrality. $\mathrm{CoopFreq}_{\mathrm{it}}$ refers to the annual frequency of cooperation announcements and joint patent cooperation.

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3.3. Variable measurement scheme

Model testing uses the AI embeddedness index and collaborative mechanism index constructed in Section 3.2 as the core explanatory variables. Value co creation performance is used as the explained variable. Value co creation performance is formed by standardizing and weighting invention patent counts, joint patent ratios, patent citation counts, and textual intensity of new product revenue. Before regression, continuous variables are winsorized at the 1% and 99% levels. Enterprise size, leverage ratio, R&D intensity, enterprise age, and industry differences are controlled [11]. The core path is tested through an enterprise and year two way fixed effects panel model, as shown in Formula (3).

$$VCC_{it}=\beta_0+\beta_1 AI_{it}+\beta_2 CM_{it}+\beta_3 AI_{it}\times CM_{it}+\gamma X_{it}+\mu_i+\lambda_t+\varepsilon_{it} \tag{3}$$

In Formula (3), VCC_{it} refers to value co creation performance. AI_{it} refers to AI embeddedness. CM_{it} refers to the strength of the collaborative mechanism. X_{it} refers to control variables. μ_i and λ_t refer to enterprise fixed effects and year fixed effects. ε_{it} refers to the random error term.

To further identify the nonlinear contribution of variables, XGBoost is used to build a prediction model for value co creation performance. SHAP is then used to decompose the marginal contribution of each variable to the prediction result, as shown in Formula (4).

$$\hat{f}(x_i)=\phi_0+\sum_{j=1}^{m}\phi_j(x_{ij}) \tag{4}$$

In Formula (4), $\hat{f}(x_i)$ refers to the predicted value of value co creation for enterprise i. ϕ_0 refers to the baseline prediction value. $\phi_j(x_{ij})$ refers to the SHAP contribution of the j_{th} variable to the prediction result. m refers to the number of explanatory variables included in the model.

4. Results

4.1. Variable measurement scheme

Based on the illustrative statistical results of 480 enterprises and 2,880 enterprise year observations, enterprises with higher AI embeddedness show stronger connection capability in collaborative innovation networks. After grouping the sample by terciles of the AI embeddedness index, the network density of the high AI embeddedness group reaches 0.068. It is higher than 0.041 in the medium AI embeddedness group and 0.026 in the low AI embeddedness group. The mean degree centrality of the high AI embeddedness group is 0.104, which indicates that these enterprises are more likely to occupy central connection positions in joint patent and cooperation announcement networks. The joint patent ratio also shows clear differences. It is 12.9% in the high AI embeddedness group, 7.6% in the medium AI embeddedness group, and 4.8% in the low AI embeddedness group. As shown in Table 1, enterprises with higher AI embeddedness present stronger external knowledge connections, partner aggregation, and cross actor collaboration features in public cooperation networks. This provides a descriptive basis for the subsequent test of the value co creation model.

Table 1. Differences in collaborative innovation networks under different levels of AI embeddedness

AI embeddedness level	Enterprise year observations	Mean AI embeddedness index	Network density	Mean degree centrality	Mean betweenness centrality	Joint patent ratio
Low AI embeddedness group	960	0.118	0.026	0.043	0.011	4.8%
Medium AI embeddedness group	960	0.286	0.041	0.067	0.019	7.6%
High AI embeddedness group	960	0.512	0.068	0.104	0.032	12.9%

4.2. Value co-creation model validation

The illustrative test results of the value co creation model show that AI embeddedness, the collaborative mechanism index, and their interaction term all maintain positive relationships with value co creation performance. In the panel regression, the coefficient of the AI embeddedness index is 0.083. The coefficient of the collaborative mechanism index is 0.126, while the coefficient of the interaction term is 0.041. These results indicate that AI embeddedness does not affect innovation output in isolation. It works through the structure of collaborative networks. Further XGBoost and SHAP interpretation results show that network centrality, AI textual intensity, cooperation announcement frequency, and network density have relatively high mean SHAP values, reaching 0.186, 0.159, 0.142, and 0.126, respectively. As shown in Figure 1, the explanatory contribution of network structure variables is generally higher than that of control variables such as firm size. This indicates that value co creation is shaped by the joint effect of AI capability and ecosystem collaboration position, rather than by firm size advantages alone.

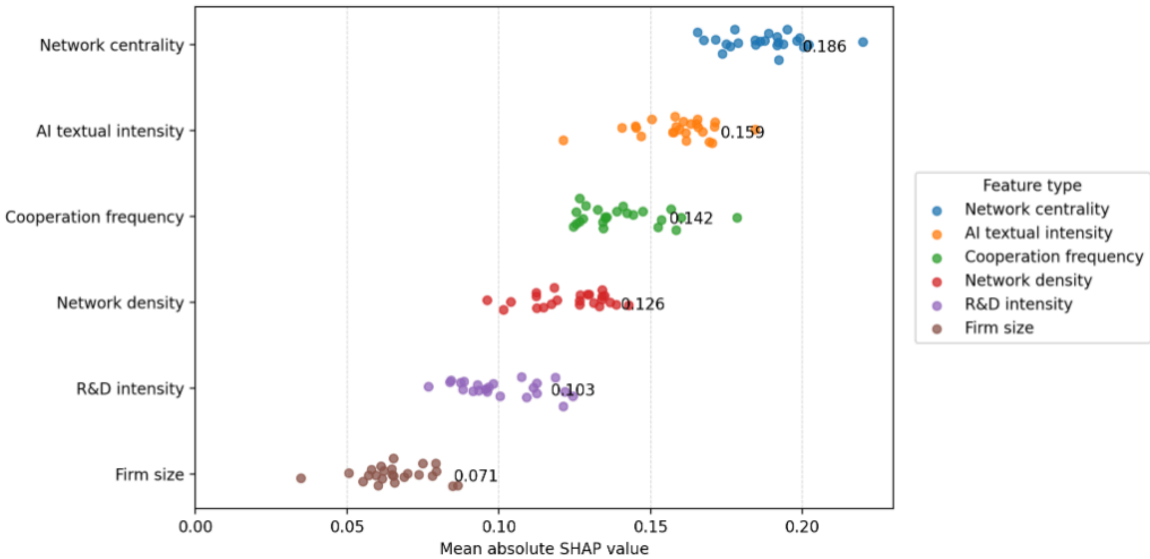

Figure 1. SHAP feature contribution distribution

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5. Discussion

The results show that enterprises with higher AI embeddedness have stronger connection capability in cooperation networks. Their network density, degree centrality, and joint patent ratio are higher than those of enterprises with medium or low AI embeddedness. This indicates that the role of AI is not limited to internal process automation. It extends to external knowledge search, partner identification, and cross actor resource integration. The positive results of the collaborative mechanism index and the interaction term further show that the effect of AI on value co creation performance depends on the structure of cooperation networks. In the SHAP results, network centrality has the highest explanatory contribution. This means that the position of an enterprise in the innovation ecosystem affects the degree to which AI capability is transformed into innovation value. Therefore, the managerial challenge created by AI embeddedness is not only a problem of technology deployment. It is also an ecosystem coordination issue shaped by data sharing, network governance, knowledge collaboration, and benefit distribution.

6. Conclusion

The analysis examines collaborative mechanisms and value co-creation after AI is embedded in enterprise innovation ecosystems. Using Chinese A-share listed firms from 2020 to 2025, it integrates annual reports, ESG reports, cooperation announcements, joint patents, and patent quality indicators. Text mining, social network analysis, panel regression, and explainable machine learning are applied. The results show that greater AI embeddedness promotes denser cooperation networks and stronger network centrality, while collaboration further enhances value co-creation. AI creates ecosystem value mainly through intelligent identification, cooperation matching, knowledge flow, and network coordination, providing implications for digital transformation, open innovation, and ecosystem governance.

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