

International comparison of innovation networks in artificial intelligence

Fumihiko Isada, Kansai University, Japan
2-1-1 Ryozenji-cho, Takatsuki-shi, Osaka, 569-1095, Japan
isada@kansai-u.ac.jp

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Abstract

This study conducts an international comparison of AI innovation networks across the United States, Europe, and China using patent co-application data and social network analysis. Building on prior literature, it distinguishes core AI technologies from AI applications, focusing on the latter due to its stronger dependence on inter-organisational collaboration. Patent data from 2015 to 2024, extracted via refined classification codes and keywords, serve as indicators of innovation activity. The analysis applies network metrics such as degree centrality, betweenness, eigenvector centrality, and density. Distinct regional patterns emerge: the US and China exhibit broad, centralised collaborations, while Europe is characterised by bilateral partnerships among major firms and public research bodies. In further development, the study aims to integrate additional collaboration forms, such as joint ventures and research consortia, to capture a more comprehensive view of AI ecosystem dynamics.

Word count (excluding tables and references)

1,981 words

1. Introduction

This study conducts a quantitative international comparison of AI innovation networks using patent data. AI innovation differs from traditional technological development, as it heavily relies on modularity, cross-organisational collaboration, and ecosystem-driven structures (Jacobides et al., 2021). Unlike hardware-driven innovation, AI development requires contributions from diverse actors, including cloud providers, semiconductor firms, and research institutions. AI models improve through data-driven network effects, necessitating extensive collaboration (Iansiti & Lakhani, 2020). Furthermore, AI R&D depends on an integrated ecosystem of hardware, software, and cloud infrastructure, making inter-organisational partnerships essential (Cusumano et al., 2024). However, regional variations exist in AI innovation structures due to differences in industry environments and national innovation systems. The Triple Helix model (Jacobides et al., 2021) highlights differences in AI ecosystems across the US, Europe, and China. This study explores how network structures impact AI innovation outcomes across regions using international patent data and social network analysis, acknowledging limitations in fully capturing innovation activities.

2. Previous research

1) Differential AI innovation networks by region

Jacobides et al. (2021) highlights regional differences in AI ecosystems across the U.S., EU, and China, shaped by national policies, corporate strategies, and regulatory environments. The U.S. follows a firm-driven model dominated by Big Tech firms, which control AI infrastructure and applications. The EU's AI development is fragmented, emphasising ethical governance but struggling with scalability due to limited cross-border collaboration. China adopts a government-led model, integrating state-owned enterprises with private tech firms, facilitating rapid innovation with extensive data access but facing ethical and geopolitical concerns. Lundvall & Rikap (2021) argue that China's AI growth is supported by the co-evolution of Corporate and National Innovation Systems, while Mariani et al. (2023) emphasise differences in innovation strategies, including the U.S.'s venture capital-driven approach, Europe's regulatory constraints, and China's government-driven data policies.

2) Collaboration in the AI ecosystem

Jacobides et al. (2021) categorise AI development into enablement, production, and consumption stages, and identify distinct actor roles—AI Giants, Creators, Traders/Integrators, Powered Operators, and Takers—emphasising their complementary

contributions to innovation. They argue that AI innovation reflects a Schumpeter Mark IIa model, emerging from collaboration between large firms and complementors, rather than solely from startups (Mark I) or internal corporate innovation (Mark II). Similarly, Weber et al. (2025) assert that platform-led innovation is insufficient in AI applications; instead, innovation emerges collaboratively through diverse, distributed actors within the ecosystem.

3) Social network analysis of AI innovations

Despite limited studies on AI innovation networks using social network analysis, some notable research exists. Lantz et al. (2024) examine co-inventor networks in 30 leading AI firms, analysing the impact of network structure on patent productivity. Using centrality measures, clustering coefficients, and modularity, they identify trade-offs between centrality and diversity in knowledge flow. However, their focus on large firms excludes smaller innovators and does not fully capture regional differences. Xu et al. (2022) analyse AI collaboration in China's Yangtze River Delta using network analysis, while Aikins & Khansa (2024) study AI patent collaboration in healthcare, revealing strengthened partnerships post-COVID-19. Dwivedi & Elluri (2024) investigate generative AI research networks, highlighting increased global collaboration, particularly between Chinese and U.S. researchers post-2018.

3. Research hypotheses

Granovetter's (1973) weak-ties hypothesis suggests that weak-but-wide networks facilitate innovation by enabling diverse knowledge flow, whereas strong-but-narrow networks limit new information. Given AI's rapid expansion and technological uncertainty, collaboration with external organisations is essential for R&D and big data utilisation.

Hypothesis 1. Organisations engaging in more external collaborations will achieve higher R&D results.

Burt (2004) distinguishes Bridging Ties and Cohesive Ties, with the former fostering radical innovation. AI firms increasingly act as platforms (Gawer & Cusumano, 2002), expanding collaborations beyond industry boundaries.

Hypothesis 2. Organisations mediating external collaborations will enhance R&D results.

Bonacich (1972) introduced eigenvector centrality, reflecting strong ties between central firms. A high degree of complementarity among key AI players may boost innovation.

Hypothesis 3. Closer collaborations among central organisations improve innovation

outcomes.

Finally, network density impacts trust and knowledge exchange (Coleman, 1988).

Hypothesis 4. Organisations with denser inter-organisational collaboration achieve superior R&D outcomes.

4. Research Methods

This study utilises patent data from Google Patents to measure AI innovation, using patent registrations as an indicator of innovation activity and co-applicant information to analyse inter-organisational networks.

Drawing upon previous literature, this study distinguishes between core AI technologies and AI applications, positing that the latter requires greater inter-organisational collaboration. The application of AI often necessitates domain-specific expertise, thus increasing the need for cooperative innovation across organisations with complementary knowledge bases. Consequently, the analysis focuses on AI application patents, where joint patent filings are expected to serve as more explicit indicators of collaborative innovation arising from AI adoption.

The classification of AI application patents follows the Japan Patent Office (2024), which builds upon WIPO's (2019) foundational methodology while introducing further refinements. AI core inventions involve fundamental mathematical or statistical processing techniques underpinning AI, whereas AI application inventions pertain to the deployment of these core technologies across fields such as image and speech processing, natural language processing, robotics, diagnostics, prediction, and optimisation systems. Patent identification employs both classification codes and keywords; specifically, 52 codes (e.g., A61B1/045) and 44 keywords (e.g., machine learning) are utilised. Unlike previous approaches using OR conditions (Japan Patent Office, 2024; WIPO, 2019), which yielded numerous irrelevant patents, this study applies a stricter AND condition combining both classifications and keywords to enhance precision.

The dataset comprises patents registered between 2015 and 2024, restricted to granted patents to ensure novelty. The country of invention is determined using the two-digit country code embedded within each patent's priority number, which reflects the original filing jurisdiction, thereby avoiding distortions arising from international patent consolidations.

To test the hypotheses, social network analysis was conducted on patent co-applicants in these regions, calculating degree centrality, ego betweenness, eigenvector centrality, and ego density. Normalised betweenness was used to control for degree centrality effects. UCINET (Version 6) was employed for network calculations, while

multiple regression analysis using SPSS (Version 29) assessed the impact of network structures on patent output.

5. Analysis Results

5.1, Basic Statistics

Table 1 presents basic statistics on patent registrations and joint applications, showing the total number of organisations and co-applicant relationships per region.

Table 1: Basic statistics for patent data

	US	EU (major countries)	China
Total number of patents	72,456	2,540	42,740
Number of jointly-filed patents	3,625	211	4,763
Total number of organisations (including joint applicants)	2,409	277	4,086
Number of pairs	8,850	1,010	14,592

5.2 Analysis Results

Network indices were calculated for each organisation by region, followed by regression analyses using patent registrations as the dependent variable. Tables 2 to 4 summarise results, including single and multiple regression models, with standardised coefficients, coefficient of determination, F-values, and variance inflation factor (VIF) of the multiple regression analysis.

Table 2: Results of multiple regression analysis in the US

	model 1	model 2	model 3	model 4	model 5	VIF
Degree centrality	0.184**				0.198**	1.060
nEgoBetween		0.272**			0.088*	3.108
Eigenvector			0.141**		0.115**	1.009
Density				-0.264**	-0.203**	3.121
R2	0.034	0.074	0.020	0.070	0.132	
Adj. R2	0.034	0.074	0.019	0.069	0.130	
F value	83.931**	135.799**	48.422**	127.165**	64.593**	

(Note 1) The dependent variable is the number of registered patents

(Note 2) **: 1% significance level or less, *: 5% significance level or less

Table 3: Results of multiple regression analysis in the EU (major countries)

	model 1	model 2	model 3	model 4	model 5	VIF
Degree centrality	0.037				0.101*	1.245
nEgoBetween		0.049			-0.195	8.167
Eigenvector			0.806**		0.805**	1.003
Density				-0.078	-0.259*	8.504
R2	0.001	0.002	0.649	0.006	0.662	
Adj. R2	-0.002	-0.001	0.648	0.002	0.657	
F value	0.378	0.659	508.416**	1.658	132.423**	

(Note 1) The dependent variable is the number of registered patents

(Note 2) **: 1% significance level or less, *: 5% significance level or less

Table 4: Results of multiple regression analysis in China

	model 1	model 2	model 3	model 4	model 5	VIF
Degree centrality	0.563**				0.532**	1.299
nEgoBetween		0.118**			0.030	4.690
Eigenvector			0.302**		0.061**	1.269
Density				-0.083**	-0.057*	4.655
R2	0.317	0.014	0.091	0.007	0.326	
Adj. R2	0.317	0.014	0.091	0.007	0.326	
F value	1891.139**	54.233**	410.081**	26.812**	465.737**	

(Note 1) The dependent variable is the number of registered patents

(Note 2) **: 1% significance level or less, *: 5% significance level or less

6. Discussion

Based on the statistical analyses, the study evaluates the hypotheses across three regions. In the United States, significant positive relationships were observed for Hypothesis 1 (degree centrality), Hypothesis 2 (betweenness centrality), and Hypothesis 3 (eigenvector centrality), whereas Hypothesis 4 (density) exhibited a significant negative relationship. Although multicollinearity between betweenness centrality and density was suspected in multiple regression, the alignment with simple regression results suggests

interpretative stability. These findings indicate that both the weak ties hypothesis and structural hole theory are strongly applicable in the US context. Here, innovation appears to be driven by central organisations collaborating extensively with complementary actors, fostering one-to-one partnerships rather than dense, closed networks. Highly centralised organisations also seem to engage collaboratively, forming diverse complementary relationships. Dominant central actors include major technology firms such as Microsoft, Google, and IBM, which possess substantial patent portfolios and have vertically integrated their operations from AI model development to applications. Prominent universities (e.g., MIT) and AI user organisations (e.g., Mayo Clinic) also participate, collectively constructing an open AI application ecosystem.

In contrast, the European Union (EU) presents a distinct pattern. For Hypothesis 1 (degree centrality), multiple regression identified a significant positive relationship, while simple regression found no correlation, suggesting a suppressed effect emerging under multivariate control. Hypothesis 2 (betweenness centrality) showed no significant relationship, while Hypothesis 3 (eigenvector centrality) demonstrated a significant positive effect. The results for Hypothesis 4 (density) were inconsistent across analyses; however, given potential multicollinearity, the simple regression result indicating no correlation is prioritised. The findings imply that in the EU, central organisations promote innovation through direct collaboration with one another, rather than by accumulating numerous weak ties. Consequently, neither the weak ties hypothesis nor structural hole theory are particularly applicable. The EU appears to lack dominant platform leaders capable of bridging structural holes to stimulate innovation. Instead, key central actors include AI-using firms in automotive (e.g., Bosch), medical device companies, universities, and public research bodies such as the Centre National De La Recherche Scientifique (CNRS). Overall, the EU's AI application ecosystem seems driven by collaborations between large industrial firms and major research institutions rather than private platform companies, as seen in the US.

In China, the statistical results closely resemble those of the US. Both simple and multiple regression analyses revealed significant positive relationships for Hypotheses 1 (degree centrality) and 3 (eigenvector centrality). For Hypothesis 2 (betweenness centrality), the simple regression indicated significance, while the multiple regression did not; given multicollinearity concerns, the simple regression result is prioritised. Hypothesis 4 (density) showed a significant negative relationship across both analyses. These results suggest that the weak ties hypothesis and structural hole theory are applicable to China's AI application ecosystem. Although private firms such as Tencent, Baidu, and Huawei possess large patent portfolios, their network centrality is not

necessarily high. Instead, central positions are occupied by major public research institutes, including the Chinese Academy of Sciences and universities such as Tsinghua University, which maintain extensive collaborative networks. The structure suggests that private enterprises maintain distinct, specialised research domains with limited cross-collaboration, while public research institutions serve as platforms fostering broad, innovation-driving ecosystems.

7. Conclusion and remaining issues

This study conducted an empirical comparison of innovation ecosystems related to artificial intelligence, particularly in the application field, in the United States, Europe, and China. Network analysis of joint patent applications revealed structural characteristics of inter-organisational networks related to innovation ecosystems in each region.

However, this study focuses on co-application-based collaborations visible in patent data, other forms of inter-organisational collaboration (e.g., joint ventures, strategic alliances) are not captured. Future research should complement this analysis with case-based or qualitative data. Statistical limitations also exist, as the low determination coefficients suggest that patent numbers cannot be fully explained by joint applications alone. Other factors, including firm size, likely influence patent output, requiring additional control variables to improve the model's explanatory power.

A key limitation of this study is the timeframe of patent data, covering registrations up to 2024, which mainly reflect applications submitted by 2023. As a result, the study does not fully capture the rapid expansion of generative AI, which is expected to significantly impact inter-organisational collaboration in AI innovation. Future research should incorporate longitudinal analyses to track these evolving trends. Additionally, Japanese organisations were excluded from the analysis due to their low AI patent output and traditionally closed innovation networks. However, with the expansion of generative AI, Japanese firms are increasingly engaging in international open innovation. Future research should examine Japan's role in global AI ecosystems and its changing innovation strategies.

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