The Network Structure of Big Tech's Inter-Organizational Collaboration on Generative AI

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Abstract

Goal: Previous studies have shown that an ecosystem of collaboration among diverse organisations is more useful for the development and application of artificial intelligence than a single organisation working on its own. It has also been pointed out that, particularly in the case of generative AI, which has become popular in recent years, companies such as Big Tech play a significant role in shaping and developing ecosystems. This study aims to quantitatively analyse the network structure of cooperation relationships among organisations in generative AI and to demonstrate the characteristics of big techs' positioning in this network structure compared with other organisations.
Methodology: As an analysis method, information from recent newspaper articles was analysed using social network analysis to examine the current situation.
Conclusion: The analysis revealed several characteristics of Big Tech's network structure. As a future task, the information that cannot be obtained from newspaper articles alone should be supplemented by other research methods.

Keywords: Inter-Organizational Collaboration, Business Ecosystem, Generative AI, Big Tech, social network analysis

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Introduction

This study investigates the network structure of collaborative relationships among organisations involved in the development and application of generative AI, with a specific focus on the structural characteristics of Big Tech firms. Prior literature has highlighted the modular and distributed nature of AI innovation, which inherently necessitates cross-organisational collaboration (Jacobides et al., 2021). Unlike traditional R&D models reliant on vertical integration, AI ecosystems are shaped by diverse contributions from cloud providers, chipmakers, software developers, and research institutions. As such, innovation in generative AI arises from an interconnected ecosystem rather than isolated corporate pipelines.

Big Tech companies have emerged as dominant actors in this ecosystem. Jacobides et al. (2021) argue that a small number of such firms control both upstream infrastructure (e.g., cloud and edge computing) and downstream applications, reinforcing their strategic positions through data accumulation, open-source frameworks, and AI-driven service integration. Their ecosystem dominance is further supported by their central roles in AI research and the acquisition of complementary players.

The objective of this study is to quantitatively analyse the position of Big Tech within inter-organisational networks related to generative AI. While many prior studies have approached this topic qualitatively, especially via case studies, quantitative examinations—particularly those employing social network analysis—remain limited. This study applies social network analysis to real-world collaboration data to elucidate the structural roles played by Big Tech in the generative AI ecosystem (Wasserman & Faust, 1994).

Prior Research

Big Tech and Generative AI Ecosystems

Several studies elaborate on the structural dominance of Big Tech in generative AI. Jacobides (2022) highlights their role as ecosystem orchestrators, enabling AI-powered digital transformations across sectors. Firms such as Google, Amazon, and Microsoft operate multi-layered AI ecosystems, integrating services while leveraging vast datasets and selectively open-sourcing key tools to shape the competitive landscape. Cusumano et al. (2024a) position generative AI as a platform technology, likening it to prior digital revolutions. Big Tech companies are central at all levels: foundational models (e.g., OpenAI, Google, Meta), infrastructure (e.g., Nvidia, Microsoft Azure), and API ecosystems. These firms not only lead in innovation but also regulate access, thus acting as both enablers and gatekeepers. Empirical evidence from Cusumano et al. (2024b) further suggests that platform-based Big Tech firms outperform others in terms of growth and valuation. Their ability to orchestrate innovation platforms drives increased value capture and network-effect-based scaling. Azoulay et al. (2024) focus on competitive dynamics, arguing that Big Tech's control over complementary assets—such as computing infrastructure and proprietary data—has created substantial entry barriers. This has confined many start-ups to the application layer while centralising foundational control within a few incumbent firms.

Social Network Analysis of Generative AI

Social network analysis (SNA) provides quantitative tools for exploring the structural features of inter-organisational collaboration. While still sparse in the context of generative AI, some notable examples exist. Dwivedi & Elluri (2024) use SNA to analyse co-authorship patterns in academic research, observing increased collaboration post-2018, especially between Chinese and U.S. researchers. Isada (2024) applies SNA to media-based data, finding loosely coupled partnerships and identifying Nvidia as a central broker. Beyond generative AI, Lantz et al. (2024) explore co-inventor networks in AI patents, identifying trade-offs between centrality and diversity in relation to innovation outcomes. Xu et al. (2022) examine city- and institution-level collaboration patterns in China, revealing central hubs in the Yangtze River Delta. Aikins & Khansa (2024) focus on healthcare AI patents and observe strengthened institutional ties post-COVID.

Research Hypotheses

This study examines Big Tech's structural position in generative AI networks using SNA metrics. These include network size, structural holes, betweenness centrality, eigenvector centrality, and network density.

- Hypothesis 1 (Network Size): Building on the weak ties hypothesis (Granovetter, 1973), Big Tech firms are presumed to have broader collaborative reach than other organisations. Their engagement with diverse actors suggests a larger network size.
- Hypothesis 2 (Structural Holes): According to structural hole theory (Burt, 1992), Big Tech firms likely act as brokers connecting otherwise unlinked actors. Metrics such as constraint and adequate size help evaluate their brokerage advantage.
- Hypothesis 3 (Betweenness Centrality): Freeman (1977) introduced betweenness centrality to measure influence based on control over communication. Big Tech firms are hypothesised to exhibit high betweenness due to their intermediary role in collaborative networks.
- Hypothesis 4 (Eigenvector Centrality): Eigenvector centrality (Bonacich, 1972) reflects the influence of an entity's connections. While Big Tech firms are central, their connections with one another may be limited by competitive dynamics, potentially reducing their eigenvector scores relative to other organisations.
- Hypothesis 5 (Network Density): Finally, drawing on Krackhardt et al. (1992) and Coleman (1988), network density reflects internal cohesion. Big Tech firms are assumed to maintain sparser networks, optimising for flexibility and reach rather than tight integration.

Research Method

Data

The objective of this study is to empirically understand the network structure of inter-organisational ecosystems accompanying the spread of generative AI. Chat GPT, one of the most representative generative AI technologies, launched GPT-3.5 in autumn 2022 and GPT-4 in spring 2023, attracting widespread public attention. Following this, artificial intelligence technology, which had previously been used primarily in limited fields such as information-related scientific research, suddenly gained the potential for widespread application in general business operations of ordinary companies. In 2023, various companies conducted trials, proposed diverse use cases, expanded cloud-based infrastructure, and numerous venture companies emerged in related fields such as business reform support. Following this trial period, in

2024, the practical use of AI is rapidly expanding across a wide range of industries and occupations. This study analyses the situation among organisations in 2024, which marks the beginning of the practical application phase in the AI adoption lifecycle.

As information sources, newspaper articles were utilised. Newspaper articles are primary sources that comprehensively collect the latest information from around the world. However, there are significant differences in information collection capabilities and editorial policies depending on the newspaper company that publishes them. In this study, Dow Jones, which has strong coverage of corporate and economic information and maintains a global information collection network, was selected as the target for analysis. Additionally, press release information was included to enhance comprehensiveness. In collecting information, the author adhered to the terms of use through Lexis+, which the author's affiliated university contracts. The search criteria were newspaper articles from 1 January to 31 December 2024, and a full-text search was conducted for articles containing 'Generative AI' or 'Generative Artificial Intelligence.' Among the more than 100 newspapers in Lexis+, Dow Jones had by far the most articles.

From the searched newspaper articles, combinations of two or more organisations with some forms of cooperative relationship were extracted. For text mining, the natural language processing library spaCy was used to extract words, and the results were manually verified. While spaCy is a powerful tool for extracting organisation names, it is not always effective for non-standard writing styles or abbreviations commonly found in newspaper articles, so significant time was spent on additional revisions to improve accuracy. For organisational collaborative relationships, the search criteria were set to include any of the following terms: partnership, joint venture, collaboration, agreement, alliance, alignment, cooperation, joint business, tie-up, or link-up. The search was conducted using a Python programme, and the output results were manually reviewed to remove irrelevant data.

Network indices

As an analysis method, social network analysis techniques were used to analyse the relationships between the extracted organisations, with the organisations serving as nodes. UCINet was used as the analysis tool, and the following network indices corresponding to the aforementioned hypotheses were calculated for each organisation. For Hypothesis 1, the size of the ego network was calculated. For the structural holes in Hypothesis 2, the degree of constraint was calculated. Note that Burt (1992) proposed the concept of constraint and its calculation method, and evaluated the number of structural holes, i.e., structural autonomy, as the reciprocal (1/constraint). For Hypothesis 3, the normalised ego network betweenness centrality (nEgobetweeness) was used. This is based on the basic definition of betweenness centrality presented by Freeman (1977), but is applied only to subnetworks centred on the ego. However, the value of EgoBetweenness tends to increase with the size of the ego network. Using normalised values allows the structure's characteristics to be observed while eliminating the influence of size. For Hypothesis 4, eigenvector centrality was used, and for Hypothesis 5, the density of the ego network was used.

Analysis Results

Basic Statistics

The number of data items extracted from newspaper articles and press releases in this survey is shown in Table 1. Here, 'pairs' refers to the simple total number of cooperative relationships extracted between organisations. 'Size total' refers to the total number of other organisations with which each organisation is connected. Note that if the same combination is extracted multiple times from newspaper articles or press releases, it is counted as 1 when calculating each organisation's size. This study evaluates the number of connected organisations and does not consider weighting. The average Size is the Size count divided by the number of organisations.

Table 1
Organisations and combinations extracted from newspaper articles and press releases

Item	Count
Articles and press releases	3,239
Organisations	1,223
Pairs	22,814
Size total	3,502
Average Size	2.87

Source: Author's work

Analysis Results

The collected data was divided into two categories: big tech companies, such as the so-called Magnificent Seven in the United States, and other organisations. Network indicators based on each hypothesis were then calculated. The network size, or the number of organisations with some form of cooperative relationship, for the big tech companies is shown in Table 2. Amazon.com, which mainly provides consumer-oriented distribution services, and Amazon Web Services, which mainly provides enterprise-oriented cloud services, were calculated separately.

Table 2
Number of organisations collaborating with Big Tech companies in generative AI

Organisation Name	Network Size
Microsoft	157
Amazon Web Services	73
Google	59
Amazon.com	31
Nvidia	26
Apple	25
OpenAI	25
Meta Platforms	20

Source: Author's work

The average network size of the entire survey sample was 2.87. In contrast, the network sizes of each Big Tech organisation were significantly larger, suggesting that Big Tech companies have formed a massive collaborative network, or a generative AI ecosystem.

Next, a two-group t-test was conducted on the network indices related to the aforementioned hypotheses for Big Tech and other organisations. Since the sample sizes of the two groups were very different, Welch's test, which is more robust and does not assume equal variances, was selected. Table 3 shows the results of each analysis. All differences were statistically significant at the 5% level.

Table 3
Comparison between Big Tech and other organisations

Variable	Big Tech companies	Other organisations	Mean Diff.	t	p	95% CI
Size	M = 52.00 (SD = 46.47)	M = 2.540 (SD = 2.706)	49.46	3.01	.020	[10.61, 88.31]
Constraint	M = 0.20 (SD = 0.08)	M = 0.95 (SD = 0.24)	-0.76	-25.20	<.001	[-0.82, -0.69]
nEgoBetween	M = 84.30 (SD = 9.03)	M = 10.10 (SD = 24.45)	74.20	22.45	<.001	[66.58, 81.82]
Eigenvector	M = 0.00 (SD = 0.00)	M = 0.00 (SD = 0.03)	-0.00	-2.81	.005	[-0.00, -0.00]
Density	M = 8.06 (SD = 4.58)	M = 88.98 (SD = 25.41)	-80.91	-43.87	<.001	[-84.94, -76.89]

Note: M = Mean; SD = Standard Deviation; CI = Confidence Interval. Two-tailed t-tests were conducted.
Source: Author's work

Discussion

The results of this study suggest that the theoretical hypotheses mentioned above are all likely to be supported. Specifically, during the early stages of the generative AI product lifecycle, inter-organisational collaboration networks are concentrated among a small number of companies. This finding is generally consistent with the results of various previous studies (Jacobides et al., 2021, etc.), and this study has quantitatively confirmed this through network structure analysis.

The first hypothesis concerns the scale of collaborative networks, and it has been confirmed that Big Tech companies are overwhelmingly larger. In the development of generative AI, while there are certainly differences in the quality of software such as algorithms, the need for massive resources—particularly in data generation and hardware like GPUs and cloud servers—means that economies of scale are likely to play a significant role. For example, only a few vendors can provide high-performance GPUs suitable for generative AI development, with NVIDIA as the primary supplier. This structure inherently favours companies that can secure a limited supply of such hardware, giving them a competitive advantage in terms of scale.

The second and third hypotheses pertain to the mediating and bridging functions of networks, with quantitative analyses suggesting that Big Tech companies act as platforms connecting numerous other businesses. The practical application of generative AI is still in the experimental stage, with no standardisation, and various uses are being developed. Countless companies, both large and small, are entering the market to support such development. Some of these companies are developing generative AI in-house, while others are partnering with platform providers to leverage their vast resources and compete in specific application areas. This situation is expected to create an environment where network effects can be easily realised for platform providers.

The fourth hypothesis concerns connections with other central organisations. The analysis suggests that there is a stronger tendency for non-Big Tech companies to collaborate with central Big Tech companies than for Big Tech companies to collaborate. This suggests that Big Tech companies are incorporating many other organisations into their own ecosystems while engaging in fierce competition with other ecosystems. While companies like nVidia, which dominate a specific technology layer, are likely to collaborate extensively with other Big Tech companies, intense competition is expected in areas such as the development of generative AI models and the provision of cloud servers, with Microsoft, Google, and Amazon each vying for dominance. On the other hand, it is conceivable that organisations outside the Big Tech companies seek to align with one of them, given the resource constraints mentioned earlier.

The fifth hypothesis concerns density. The results of the analysis are consistent with the previous hypotheses, suggesting that Big Tech companies are not forming closed relationships with a limited number of organisations, but rather forming open, collaborative relationships with a wide range of organisations. On the other hand, it is imagined that other organisations are collaborating with individual companies in their own specific business areas.

In this study, it was estimated that the inter-organisational network related to generative AI is highly concentrated around Big Tech. However, it remains unclear whether this structure will persist in the future. As an example, in 2025, the generative AI model market shifted from a situation where OpenAI was the sole leader to one where various competing models emerged, surpassing or being surpassed in terms of technical performance, and high-performance models began to appear outside the United States as well. Furthermore, the competitive environment has expanded from competition over the development of generative AI models to competition over the development of applications such as robots. In application areas, each has its own unique development elements, allowing domain-specific ecosystems to form. If this happens, the current network structure, where a few companies dominate, may change. Alternatively, big tech companies could form cross-industry platforms through horizontal specialisation.

Conclusion

This study analysed the structure of the collaborative ecosystem among organisations related to generative AI, which is currently entering the adoption phase of its lifecycle, by examining the network structure with each organisation as a node. The analysis of the network structure quantitatively demonstrated the collaborative structure of U.S. big tech companies, which are considered the centre of this ecosystem.

As future challenges, the adoption of generative AI is still in its early stages, and the collaborative relationships between organisations are expected to evolve. Therefore, continued research is necessary.

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