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

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Abstract

Previous studies have shown that a collaborative ecosystem among diverse organisations is more effective for the development and application of artificial intelligence than a single organisation working alone. 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 are playing a major 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 within the network structure compared with other organisations. As an analytical method, information from recent newspaper articles was analysed using social network analysis to assess the current situation. As a result of the analysis, several characteristics of Big Tech's network structure were identified. 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 artificial intelligence (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 by their acquisitions of complementary players.

The objective of this study is to quantitatively analyse Big Tech's position 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).

Literature review

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 provided by Cusumano et al. (2024b) further suggests that platform-based Big Tech firms outperform others in growth and valuation. Their ability to orchestrate innovation platforms leads to increased value capture and network-effect-based scaling. Azoulay et al. (2025) 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) offers quantitative tools to explore the structural features of inter-organisational collaboration. While still sparse in 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 effective 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 interconnections may be constrained by competitive dynamics, potentially reducing their eigenvector scores relative to those of 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.

Newspaper articles were utilised as sources of information. Newspaper articles are primary sources that provide comprehensive coverage of 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 analysis target. Additionally, press release information was included to enhance comprehensiveness. In collecting information, the author adhered to the terms of use through Lexis+, which is contracted by the author's affiliated university. 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 published by Lexis+, Dow Jones had by far the largest number of 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 analytical method, social network analysis was used to examine the relationships among 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, the structure can be characterised 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.

Results

Descriptive 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

Comparison of Big Tech and other organizations

The 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 demonstrates a pronounced concentration of collaborative ties around a small number of Big Tech firms. Microsoft occupies by far the most central position in terms of network size, with 157 collaborating organisations, followed by Amazon Web Services with 73 and Google with 59. Even the lower-ranked firms within the Big Tech group, such as Meta Platforms and OpenAI, maintain collaboration networks that are substantially larger than the overall sample average. This pattern indicates that Big Tech firms do not participate in the generative AI ecosystem merely as ordinary actors, but rather as focal organisations around which many inter-organisational relationships form. The results, therefore, suggest a highly asymmetric collaboration structure, in which a limited number of large firms connect to disproportionately many partners and thereby shape the overall configuration of the ecosystem.

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

Table 3 shows the results of the comparison of Big Tech and other organizations. The average network size across the entire survey sample was 2.87, whereas the network sizes for each Big Tech organisation were significantly larger, suggesting that Big Tech companies have formed a massive collaborative network, known as a generative AI ecosystem.

Next, a two-group comparison using a t-test was conducted on the network indices related to the aforementioned hypotheses between Big Tech and other organisations.

Since the sample sizes of the two groups differed substantially, Welch's test, which is more robust and does not assume equal variances, was selected. All differences were statistically significant at the 5% level.t.

Table 3
Comparison between Big Tech and other organisations according to network characteristics

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.

The results in Table 3 provide strong support for the argument that Big Tech firms occupy structurally distinct positions within the generative AI collaboration network. Compared with other organisations, they have significantly larger ego networks, substantially lower constraint, much higher normalised ego betweenness, and markedly lower density. Taken together, these differences indicate that Big Tech firms are not only more extensively connected but also more likely to serve as brokers linking otherwise weakly connected actors across the ecosystem. Their network profiles, therefore, reflect openness, reach, and intermediation rather than embeddedness in tightly knit local clusters. Although the difference in eigenvector centrality is statistically significant, its substantive interpretation should be made with caution, as the absolute values are very small. Overall, the findings suggest that Big Tech firms occupy central brokerage positions, giving them disproportionate influence over the structure and coordination of inter-organisational collaboration in generative AI.

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 adoption phase of the generative AI product lifecycle, inter-organisational collaboration networks appear to be 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 attempting to develop generative AI on their own, while others are partnering with platform providers to leverage their vast resources and compete in 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 a stronger tendency for non-Big Tech companies to collaborate with central Big Tech companies than for Big Tech companies to collaborate among themselves. 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 generative AI model development and cloud server provision, with Microsoft, Google, and Amazon each vying for dominance. On the other hand, it is also imaginable that organisations outside the Big Tech companies seek to align themselves with one of the Big Tech companies, 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 open, collaborative relationships with a wide range of organisations. On the other hand, it is assumed that other organisations are collaborating with individual companies in their respective business areas.

The present findings provide quantitative support for the view that generative AI innovation is organised as an ecosystem rather than a vertically integrated industry, and that a small set of Big Tech firms occupies structurally privileged positions within that ecosystem (Jacobides, 2022; Jacobides et al., 2021). Interpreting the observed configuration through classic network lenses, Big Tech's markedly larger ego-network size is consistent with a strategy of broad boundary spanning, which can increase access to heterogeneous information and opportunities for recombination (Burt, 1992; Granovetter, 1973). At the same time, the substantially lower constraint around Big Tech ego networks indicates that these firms sit in positions rich in structural holes, enabling brokerage between otherwise disconnected actors (Burt, 1992). This is theoretically meaningful because brokerage is particularly valuable in settings characterised by technological uncertainty, modular architectures, and shifting standards—conditions that typify the early commercialisation of generative AI (Baldwin & Clark, 2000; Jacobides et al., 2021).

The large between-group differences in (normalised) ego betweenness centrality further suggest that Big Tech firms do not merely "participate" in collaboration networks but function as key intermediaries through which inter-organisational paths are routed (Freeman, 1977). In the context of platform and ecosystem theory, such betweenness is a plausible network analogue of "orchestration": ecosystem leaders define interfaces, govern access, and shape complementor incentives (Adner, 2017;

Jacobides, 2022; Jacobides et al., 2018). The results are therefore consistent with arguments that digital platform owners can appropriate value by positioning themselves as indispensable coordinators while leaving experimentation and variety generation to complementors (Gawer & Cusumano, 2002; Parker et al., 2016; Tiwana, 2014). In generative AI specifically, the platform logic is reinforced by multi-sided participation (developers, enterprise customers, end users, content/data owners) and by feedback loops that can strengthen early movers (Cusumano et al., 2024a; Eisenmann et al., 2006; Rochet & Tirole, 2003).

A further implication of the findings is that Big Tech's network advantage may be rooted in complementary assets rather than in model "ideas" alone. Classical appropriability arguments emphasise that control over complementary assets often determines who profits from innovation (Teece, 1986). Generative AI appears to amplify this mechanism: large-scale compute, model-serving capabilities, data access, evaluation infrastructure, and governance processes can operate as bottleneck assets that shape entry and value capture (Azoulay et al., 2025; Jacobides et al., 2021). This framing offers an interpretation for the observed concentration of collaborative ties around a few firms: complementors may rationally cluster around those who can provide scarce inputs (e.g., cloud capacity, distribution channels, or widely adopted APIs), creating a hub-and-spoke network that is efficient for ecosystem scaling but can also generate dependence (Azoulay et al., 2025; Teece, 1986; Tiwana, 2014).

The patterns for eigenvector centrality and density help refine this interpretation. The comparatively lower eigenvector centrality for Big Tech (relative to non–Big Tech actors) is consistent with a competitive environment in which the dominant hubs are not densely interconnected with one another, but instead draw connections primarily from peripheral organisations seeking alignment with a particular platform (Bonacich, 1972; Jacobides, 2022). In platform markets, rivalry often occurs between ecosystems rather than between standalone products, and competition can be intensified by strategies of envelopment, exclusivity, and the creation of incompatible interfaces (Eisenmann et al., 2006; Jacobides, 2022; Parker et al., 2016). Under such conditions, tight inter-hub collaboration may be strategically unattractive, while complementors are incentivised to "pick a side" or to multi-home selectively depending on costs and governance (Rochet & Tirole, 2003; Tiwana, 2014). The very low density within Big Tech ego networks is also consistent with an open, expansive collaboration style oriented towards maximising reach and optionality rather than building cohesive cliques (Coleman, 1988; Krackhardt et al., 1992). This combination—large ego networks, low constraint, high betweenness, and low density—resembles an archetypal brokerage-driven platform position, where the hub coordinates many otherwise weakly connected partners.

Substantively, these structural features suggest a trade-off: Big Tech-centred ecosystems may accelerate diffusion and experimentation, yet they may also concentrate control and potentially shape the direction of innovation. Research on general-purpose technologies emphasises that downstream productivity effects depend on complementary organisational investments and diffusion pathways (Bresnahan & Trajtenberg, 1995). If access to foundation models, compute, or distribution is mediated through a small set of platforms, then the pace and direction of downstream innovation may become contingent on platform governance, pricing, and permitted use-cases (Azoulay et al., 2025; Teece, 1986; Tiwana, 2014). This aligns with broader concerns that platform dominance can stimulate innovation at the edge while simultaneously imposing constraints on where value can be created and captured (Eisenmann et al., 2006; Gawer & Cusumano, 2002). The present network evidence, therefore, complements qualitative accounts by providing an empirical signature of ecosystem centralisation during early adoption and scale-up (Cusumano et al., 2024a; Jacobides et al., 2021).

At the same time, the results should be interpreted with caution in light of methodological limitations and the sector's evolving nature. First, collaboration ties extracted from newspaper and press-release content are likely to reflect salience and disclosure incentives rather than the full population of cooperative relationships (Wasserman & Faust, 1994). Platform leaders may be over-represented because journalists systematically cover them more intensively, whereas smaller technical collaborations (e.g., open-source contributions, informal research ties, and supplier relationships) may be under-observed (Baldwin & Clark, 2000). Second, ties are treated as unweighted, yet partnership depth varies widely—from co-marketing agreements to joint development and equity investments—which can alter the substantive meaning of centrality measures (Wasserman & Faust, 1994). Third, generative AI is a multi-layer system spanning hardware, cloud infrastructure, foundation models, tooling, and applications; a single-layer collaboration network may mask important multiplex patterns in which influence differs across layers (Cusumano et al., 2024a; Jacobides et al., 2021). Future work could therefore triangulate with alternative data sources (e.g., alliance databases, venture investment and acquisition data, open-source dependency networks, standards participation, and patent co-assignment) and adopt multiplex or temporal network models to distinguish infrastructure-centric from application-centric ecosystems (Baldwin & Clark, 2000; Wasserman & Faust, 1994).

Finally, the future trajectory of the observed concentration remains an open question. Platform theory suggests that early dominance can persist through increasing returns and network effects, especially when interoperability is limited (Eisenmann et al., 2006; Rochet & Tirole, 2003). However, modular architectures and open-innovation dynamics can also enable entry through specialised niches, new interface layers, and open-source alternatives (Baldwin & Clark, 2000; Tiwana, 2014). In generative AI, the possibility of shifting centrality from a few global hubs towards more domain-specific ecosystems depends on whether complementary assets (compute, data, distribution, and governance) become more widely accessible or remain tightly controlled (Azoulay et al., 2025; Teece, 1986). A longitudinal extension of the present approach—re-estimating network structure across multiple years and separating ties by technical layer—would help clarify whether Big Tech's brokerage position is a transient feature of early diffusion or a durable structural characteristic of the generative AI economy (Jacobides, 2022; Jacobides et al., 2021).

In this study, it was estimated that the inter-organisational network related to generative AI is highly concentrated among Big Tech firms. However, it remains unclear whether such a structure will continue 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 in which various competing models emerged, surpassing or being surpassed in technical performance, and high-performance models began to appear outside the United States as well. Furthermore, the competitive environment has expanded from competition in the development of generative AI models themselves to competition in the development of applications such as robots. In application areas, each has its own unique development elements, which may lead to domain-specific ecosystems. 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 attempted to analyse 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 in which each organisation served as a node. The analysis of the network structure quantitatively demonstrated the characteristics of the collaborative structure of U.S. big tech companies, which are considered to be at 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.

References

1. Adner, R. (2017). Ecosystem as structure: An actionable construct for strategy. *Journal of Management*, *43*(1), 39–58. https://doi.org/10.1177/0149206316678451
2. Aikins, H., & Khansa, L. (2024). Transforming healthcare with artificial intelligence: An integrated approach to patent analysis and strategic commercialization. *SSRN*. https://ssrn.com/abstract=4995376
3. Azoulay, P., Krieger, J., & Nagaraj, A. (2025). Old moats for new models: Openness, control, and competition in generative artificial intelligence. *Entrepreneurship and Innovation Policy and the Economy*, *4*(1), 7–46. https://doi.org/10.1086/732852
4. Baldwin, C. Y., & Clark, K. B. (2000). *Design rules, Volume 1: The power of modularity*. MIT Press.
5. Bonacich, P. (1972). Factoring and weighting approaches to status scores and clique identification. *Journal of Mathematical Sociology*, *2*(1), 113–120.
6. Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies "Engines of growth"?. *Journal of Econometrics*, *65*(1), 83–108.
7. Burt, R. S. (1992). *Structural holes: The social structure of competition*. Harvard University Press.
8. Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, *94*, S95–S120.
9. Cusumano, M. A., Farias, V. F., & Ramakrishnan, R. (2024a). Generative AI as a new platform for applications development. *MIT*. https://doi.org/10.21428/e4baedd9.f189351f
10. Cusumano, M. A., Gawer, A., Yoffie, D. B., von Bargen, S., & Acquay, K. (2024b). The impact of platform business models on the valuations of unicorn companies. *Information and Organization*, *34*(3), 100521. https://doi.org/10.1016/j.infoandorg.2024.100521
11. Dwivedi, R., & Elluri, L. (2024). Exploring generative artificial intelligence research: A bibliometric analysis approach. *IEEE Access*.
12. Eisenmann, T. R., Parker, G. G., & Van Alstyne, M. W. (2006). Strategies for two-sided markets. *Harvard Business Review*, *84*(10), 92–101.
13. Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, *40*(1), 35–41.
14. Gawer, A., & Cusumano, M. A. (2002). *Platform leadership: How Intel, Microsoft, and Cisco drive industry innovation*. Harvard Business School Press.
15. Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380.
16. Granovetter, M. (1995). *Getting a job: A study of contacts and careers*. University of Chicago Press.
17. Isada, F. (2024). Inter-organisational collaboration networks in the introduction phase of generative AI. *ENTRENOVA-ENTerprise REsearch InNOVAtion*, *10*(1), 481–488.
18. Jacobides, M. G. (2022). How to compete when industries digitize and collide: An ecosystem development framework. *California Management Review*, *64*(3), 99–123.
19. Jacobides, M. G., Brusoni, S., & Candelon, F. (2021). The evolutionary dynamics of the artificial intelligence ecosystem. *Strategy Science*, 6(4), 412–435.

20. Jacobides, M. G., Cennamo, C., & Gawer, A. (2018). Towards a theory of ecosystems. *Strategic Management Journal*, *39*(8), 2255–2276. https://doi.org/10.1002/smj.2904
21. Krackhardt, D., Nohria, N., & Eccles, B. (1992). The strength of strong ties: The importance of philos in organizations. In *Networks in the knowledge economy* (pp. 216–239).
22. Lantz, J. S., Lacaze, D., Braune, E., & Sahut, J. M. (2024). Innovation in the artificial intelligence sector: An exploratory study of the structure of co-inventor networks. *Management International*, *28*(6), 101–114.
23. Parker, G. G., Van Alstyne, M. W., & Choudary, S. P. (2016). *Platform revolution: How networked markets are transforming the economy and how to make them work for you*. W.W. Norton & Company.
24. Rochet, J.-C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, *1*(4), 990–1029. https://doi.org/10.1162/154247603322493212
25. Teece, D. J. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, *15*(6), 285–305. https://doi.org/10.1016/0048-7333(86)90027-2
26. Tiwana, A. (2014). *Platform ecosystems: Aligning architecture, governance, and strategy*. Morgan Kaufmann.
27. Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. Cambridge University Press.
28. Xu, G., Dong, C., & Meng, L. (2022). Research on the collaborative innovation relationship of artificial intelligence technology in Yangtze River Delta of China: A complex network perspective. *Sustainability*, *14*(21), 14002.

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