Rethinking Economic Embeddedness and Technological Dominance in AI Development

Introduction

The rapid growth of artificial intelligence (AI) technologies is fundamentally reshaping global industries, particularly through the paradigm of Industry 4.0, which emphasizes smart manufacturing, process optimization, and automation via machine learning, the Internet of Things (IoT), and big data (Rashid and Kausik, 2024; Sony and Naik, 2019). Driven by compound annual growth rates projected to expand the market significantly by 2031, the global demand for computational power, data centers, and advanced hardware infrastructure has intensified at an unprecedented pace (Statista, 2025; McKinsey & Company, 2024; Wasi et al., 2025). This evolution fosters a deep interdependence between the AI ecosystem and the semiconductor industry, which provides the critical hardware foundation for AI development while continuously benefiting from AI applications in manufacturing efficiency (Capgemini, 2024; Vaswani et al., 2017; IBM Research, 2024).

According to data from the U.S. Patent and Trademark Office (USPTO), a premier global database for technological innovation tracking (Érdi et al., 2013; Fleming and Sorenson, 2001), recent AI patent trends reveal the U.S., Japan, China, South Korea, and Germany (closely followed by Taiwan) as the top global manufacturing powers. However, comparing AI and semiconductor patent trends reveals a striking strategic divergence. While the U.S. and Japan continue to dominate advanced AI applications and foundational algorithms, they increasingly rely on external markets for critical semiconductor supply and foundational innovation. Notably, Taiwan surpassed Japan in 2021 and became the largest global producer of semiconductor patents in 2023. This dynamic highlights a deeply coupled structural relationship among key nations, emphasizing that AI technological advancement is no longer an isolated domestic endeavor but relies heavily on cross-border collaboration, complementary resources, and transnational knowledge networks (AlShebli et al., 2024; Olcott et al., 2025; Sullivan, 2025).

Historically, cross-national technology collaboration has been primarily analyzed through gravity models and revealed technological advantage (RTA) frameworks. However, as AI operates as a general-purpose technology (GPT) requiring the complementary integration of diverse subfields—from deep learning and attention mechanisms to hardware execution—existing frameworks encounter significant limitations (Elahi et al., 2023; Krizhevsky et al., 2012; Rashid and Kausik, 2024; Vaswani et al., 2017). Gravity models often struggle to explain the non-linear AI interdependencies, while RTA frequently overlooks the rapid shifts driven by cross-disciplinary integration and institutional bandwagon pressures (Anderson, 2011; Peri, 2005; Cockburn et al., 2018; DiMaggio and Powell, 1983; Swanson and Ramiller, 2004). Furthermore, traditional Global Value Chain (GVC) frameworks, while useful for mapping sequential production networks, are less equipped to characterize the multi-directional, emergent, and structurally locked-in interdependencies unique to AI technologies (Feenstra, 1998; Gereffi et al., 2005). To bridge these critical research gaps, this ongoing study examines the complementarity between AI subfields and structural interdependencies among the five major AI manufacturing powers (U.S., China, Japan, South Korea, and Taiwan) to understand the true drivers of global AI technology co-opetition.

Theoretical Background

2.1 Structural embedding in global value chains and the formation of technological dependence

In contemporary global production systems, firms and countries increasingly specialize in specific stages of production, giving rise to extensive cross-border Global Value Chains (GVCs) and interdependent networks of technological specialization (Feenstra, 1998; Kogut, 1985). Prior research distinguishes multiple governance types within GVCs—ranging from market and modular to relational and captive—which reflect varying degrees of coordination and power asymmetry between lead firms and suppliers (Gereffi et al., 2005). In technologically complex but codifiable product domains like AI chips and data-center modules, modular and relational governance allow suppliers to undertake high-value activities but require relationship-specific investments in specific standards. This dynamic frequently leads to "structural technological lock-in," where suppliers become anchored to dominant trajectories (Sturgeon, 2002; Gereffi et al., 2005). Recent network-analytic perspectives further reinterpret GVCs, emphasizing that countries occupying central or bridging roles within these global technological systems gain structural advantages that stabilize existing dependency patterns, laying the foundation upon which economic gravity and technological advantages operate (Cingolani et al., 2017; Criscuolo and Timmis, 2018; Piccardi et al., 2024; Antràs and de Gortari, 2020; Tajoli et al., 2021).

2.2 Gravity forces and relative technological advantages in cross-national technology flows

Gravity models suggest that bilateral interactions systematically increase with the economic scale of the involved countries and decrease with geographic or cultural distance (Anderson, 2011; Frankel and Rose, 2002; Tinbergen, 1962). In the context of R&D and international technology flows, distance, borders, and cultural frictions continue to impede cross-national knowledge exchange despite global integration (Peri, 2005; Baldwin, 2006; Picci, 2010). In conjunction with interaction conditions, a country's Revealed Technological Advantage (RTA) highlights how relative specialization influences the direction of these flows, acting as a catalyst for net knowledge exports in specific domains (Dalum et al., 1998; Jaffe, 1986; Laursen, 2000; Soete, 1987).

Comparative evidence from Taiwan and South Korea well-illustrates how gravity forces and RTA jointly shape technology flows. Through active state involvement and export-oriented strategies, these economies evolved dense technological ties with advanced economies like the U.S. and Japan (Hobday, 1995; Wang, 2007). These flows co-evolved with local absorptive capacity, strengthening technological proximity and value-chain ties (Hu and Jaffe, 2003). Thus, gravity-based perspectives, combined with RTA, theoretically demonstrate how field-specific capabilities and interaction conditions co-determine the direction and intensity of technology diffusion (Le Bas and Sierra, 2002; Patel and Pavitt, 1991; Peri, 2005).

2.3 Technological complementarity and the co-evolution of technical clusters

From a social network theory perspective, technological complementarity arises from locally dense clusters connected by limited bridging ties, which reduce path lengths, accelerate knowledge diffusion, and mitigate creative stagnation (Almeida and Kogut, 1999; Singh, 2005; Cowan and Jonard, 2004). When technologies share similar knowledge bases or capability requirements, organizations tend to expand from related to adjacent domains rather than leaping to distant technological islands. This repetitive mobilization progressively stabilizes complementary combinations into long-term specialization paths (Boschma and Frenken, 2011; Kogler et al., 2014; Rigby, 2015). Furthermore, knowledge spillovers exhibit strong technological proximity (Jaffe, 1986). When R&D, manufacturing, and distribution assets are aligned with core AI technologies, related technologies are jointly embedded both spatially and relationally, significantly enhancing the durability and self-reinforcement of clusters (Teece, 1986).

2.4 Isomorphic diffusion under competitive pressure

Despite the structural models, the diffusion of AI is highly complicated by its characteristics as a general-purpose technology (GPT), showing broad applicability and strong cross-sectoral complementarities (Bresnahan and Trajtenberg, 1995; Cockburn et al., 2018). Combined with platformization, participation in AI is perceived as a critical prerequisite for future competitive survival (Kenney and Zysman, 2016). Consequently, AI adoption increasingly takes the form of competitive diffusion. Firms and nations may invest heavily, regardless of clear cost-benefit evaluations, driven by "institutional bandwagons" (legitimacy concerns) or "competitive bandwagons" (fear of marginalization) (Abrahamson and Rosenkopf, 1993; DiMaggio and Powell, 1983; Swanson and Ramiller, 2004). In this hyper-competitive environment, cross-national technology flows may deviate significantly from traditional gravity or RTA predictions, representing a critical open question this research seeks to systematically address.

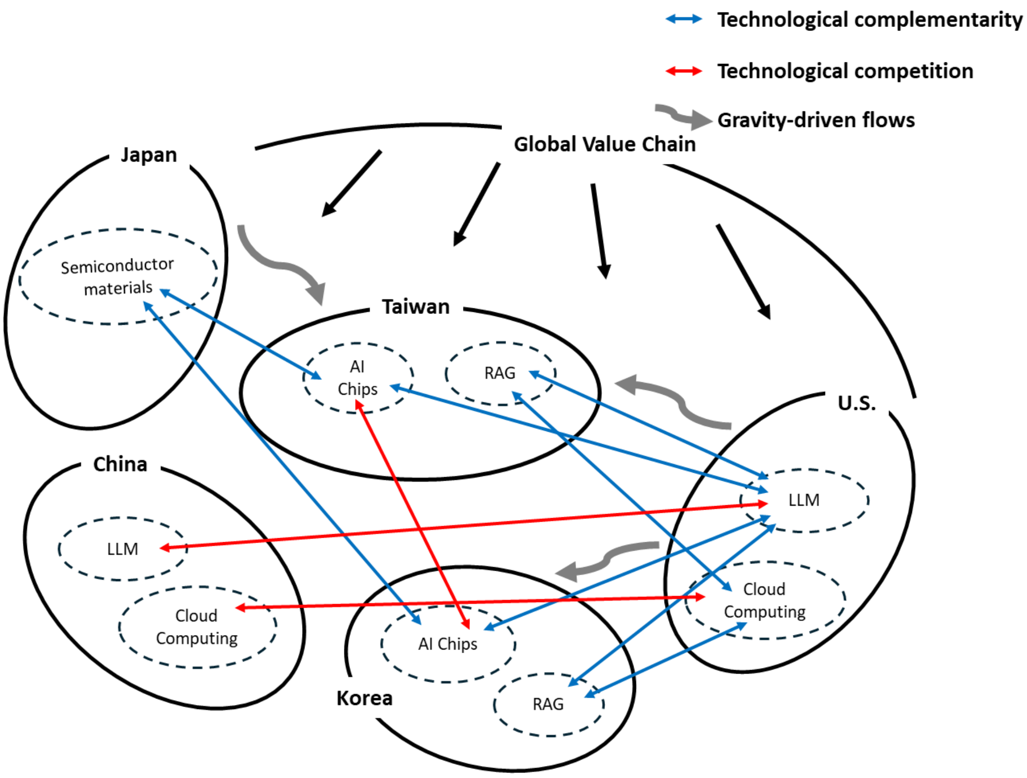

Figure 1. Schematic representation of GVCs, gravity effects, and technical clusters; adapted and extended from prior frameworks (Bakhuis et al., 2024; Markard and Truffer, 2008).

Methodology

3.1 Data Source and Sample

This study employs patent data as a robust proxy for measuring innovative outputs, technological trajectories, and cross-border knowledge interactions. The USPTO database is utilized due to its comprehensive data completeness and broad industry coverage, making it highly reliable for capturing global technological dynamics (Callaert et al., 2006; Érdi et al., 2013; Hall et al., 2005; Pezzoni et al., 2022). To strictly isolate AI-related technological diffusion, focal patents are identified using the Artificial Intelligence Patent Dataset (AIPD). A stringent 93% confidence threshold is adopted to restrict the analytical sample to inventions with highly probable AI-related core technologies (e.g., machine learning, natural language processing, computer vision) (Pairolero et al., 2025).

To mitigate truncation bias in forward citations—a common issue where recent patents lack sufficient time to accumulate citations—the focal sample encompasses patents granted between 1976 and 2019, while their forward citations are continuously tracked through 2024. This design ensures a robust minimum 5-year observation window post-grant for each focal patent (Dechezleprêtre et al., 2014; Hall et al., 2001).

3.2 Mapping cross-national technology flows and structural variables

To analyze cross-national diffusion trajectories, we construct directed technology flow networks at the country-pair level, meaning each observation represents a directed technological flow from a cited country (origin) to a citing country (destination) (Kim, 2021). The analysis narrows specifically to the top five AI powers (US, CN, KR, JP, TW), isolating bilateral intra-core exchanges and excluding domestic citations to focus purely on international diffusion. Technology classifications are operationalized at the IPC main group level (typically 5 to 7 characters) to achieve fine-grained precision within AI subfields (WIPO, 2024, 2022).

The dependent variable in this framework is Technology Citation Counts (CitedCNT), representing the intensity of directional technology diffusion. Explanatory variables are constructed as follows:

- **Gravity-based index:** Quantifies bilateral economic embeddedness based on the economic scale (GDP) and geographic distance between country pairs, sourced from the widely recognized CEPII database. Variables are log-transformed to standardize scales and reduce skewness (Anderson, 2011; Bergstrand and Egger, 2013; Conte et al., 2022).
- **Revealed Technological Advantage (RTA):** Measures a country's relative technological dominance by calculating the ratio of a country's citation share within a specific IPC main group compared to the global share of that same domain (Dalum et al., 1998; IEA, 2024).
- **Technology Distance:** Computes the cognitive gap between cited and citing technological domains based on four hierarchical levels (IPC1, IPC3, WIPO5, and WIPO35). The distance score is computed as a weighted sum of binary indicators, assigning higher weights to broader classifications to reflect larger cognitive separation (Caviggioli, 2016; Trajtenberg et al., 1997).

To examine conditional amplification effects, an interaction term between gravity and RTA is introduced. To mitigate non-essential multicollinearity, continuous variables are mean-centered prior to forming the interaction (Aiken et al., 1991; Wooldridge, 2010).

3.3 Analytical Models

The empirical strategy combines network visualization and statistical inference. First, directed weighted network graphs are employed to visualize cross-national AI flows. Node sizes reflect the weighted out-degree within specific country-IPC main groups, and edge widths correspond to the unidirectional citation counts between nodes, capturing flow intensity (Lee et al., 2023; Molnár et al., 2024; Newman, 2018; Wasserman and Faust, 1994).

Second, to provide rigorous statistical inference aligned with the dyadic structure, this study utilizes a Negative Binomial Generalized Linear Model (NB-GLM). Given that patent citation distributions are highly skewed and over-dispersed, violating standard Poisson assumptions, the NB-GLM is optimally suited for this paired observation data. The model estimates separate directional effects while controlling for patent issue year and citation year, preserving the inherent asymmetry of international technology flows (Griliches, 1990).

Table 1. Measurement of key variables.

Variables	Measurement and descriptions	Reference
Explanatory variables		
Gravity-based index (gravity)	A measure of bilateral economic embeddedness constructed from the economic mass (GDP) of two countries and the geographical distance between them, reflecting the structural intensity of international economic interaction.	(Anderson, 2011; Anderson and van Wincoop, 2004; Bergstrand and Egger, 2013; Conte et al., 2022)
Revealed technology advantage (RTA)	An index capturing a country's relative technological dominance within a specific technological subfield.	(Dalum et al., 1998; IEA, 2024; Jaffe, 1986; Laursen, 2000; Soete, 1987)
Technology distance (Tech_Dist)	A measure of technological dissimilarity between two technologies, capturing the cognitive distance separating distinct technological domains.	(Caviggioli, 2016; Jaffe, 1986; Trajtenberg et al., 1997; WIPO, 2022)
IPC main group	Patent technology categories defined at the IPC main group level, which provides a finer-grained classification and enables more precise delineation of technological subfields.	(WIPO, 2024, 2022)
Gravity mean-centered (gravity_c) RTA mean-centered (RTA_c)	Gravity and RTA are mean-centered before forming interaction terms, allowing main-effect coefficients to be interpreted at average levels of the moderator.	(Aiken et al., 1991; Wooldridge, 2010)
Dependent variables		
Technology citation counts (CitedCNT)	The number of times a focal patent is cited by subsequent patents, capturing the intensity of technology diffusion. To mitigate truncation bias, the observation window for forward citations is restricted to a minimum of five years for each focal patent.	(Dechezleprêtre et al., 2014; Hall et al., 2001)
Control Variables		
Cited patent issued year (IssuedYear) Citing year (CitingYear)	Control variables capturing the grant year of the cited patent (IssuedYear) and the citing patent (CitingYear), included to account for time-specific effects and temporal heterogeneity in patenting and citation behavior.	(Griliches, 1990)
Interaction Terms		
Gravity × Revealed technology advantage (gravity_RTA)	To capture whether the effect of technological advantage on cross-national technology flows varies with the degree of bilateral economic embeddedness.	(Anderson, 2011; Anderson and van Wincoop, 2004; Bergstrand and Egger, 2013; Conte et al., 2022; Dalum et al., 1998; IEA, 2024; Jaffe, 1986; Laursen, 2000; Soete, 1987)

Preliminary Results and Discussion

As this research is currently in progress, our initial empirical analyses and network mappings have yielded several compelling patterns that challenge conventional frameworks regarding how economic embeddedness and technological advantage influence global AI knowledge flows.

4.1 Descriptive Network Architectures

Preliminary visualizations of the network structures highlight that bilateral AI flows are sharply uneven and architecturally heterogeneous across country pairs, indicating that AI value chains are organized differently depending on the nations involved. For instance, the US-JP network demonstrates dense, reciprocal co-specialization anchored firmly in core computational infrastructures (e.g., G06K9, G06F9, G06F15). In contrast, the US-CN network reveals a highly stratified and asymmetric structure; high-intensity knowledge predominantly flows outward from US computational cores toward Chinese signal-processing and media domains, with limited reciprocal feedback. Most notably, the US-TW network exhibits pronounced cross-domain integration, featuring thick bidirectional linkages that bridge algorithmic-oriented AI with hardware, signal-processing, and semiconductor layers (H01L, G11), validating Taiwan's vital structural role at the hardware-software nexus of the AI ecosystem.

4.2 Preliminary Estimations of Embeddedness and Dominance

Initial NB-GLM estimations provide critical evidence that technological dominance and economic embeddedness do not collapse into a single mechanism of "technological leadership." While aggregate baseline models (including global destinations) indicate positive complementary effects for both gravity and RTA, estimations strictly restricted to the intra-core five-country network reveal that these effects often attenuate or behave inconsistently.

Specifically, evaluations of the top bidirectional dyads indicate that RTA does not mechanically scale citation intensity. In the US-JP dyad, RTA positively interacts with gravity primarily in specific asymmetric directions (JP→US) within core computational domains, implying that capability advantages translate into knowledge flows only when aligned with a partner's active absorptive capacity. In other pairs, such as US-KR and US-CN, high citation volumes coexist with weak, neutral, or insignificant marginal effects of RTA and gravity.

These preliminary findings strongly suggest that in the era of general-purpose AI and intense competitive bandwagon pressures, traditional gravity and RTA mechanisms are often decoupled. The structural capacity to drive cross-national knowledge exchange depends heavily on a country's specific position along the AI value chain and whether its technological trajectories are reciprocally coupled or subject to one-way extensions and jurisdictional frictions. Further refinement of these dyadic models is actively ongoing to precisely define the boundary conditions of traditional diffusion theories within the modern AI paradigm.

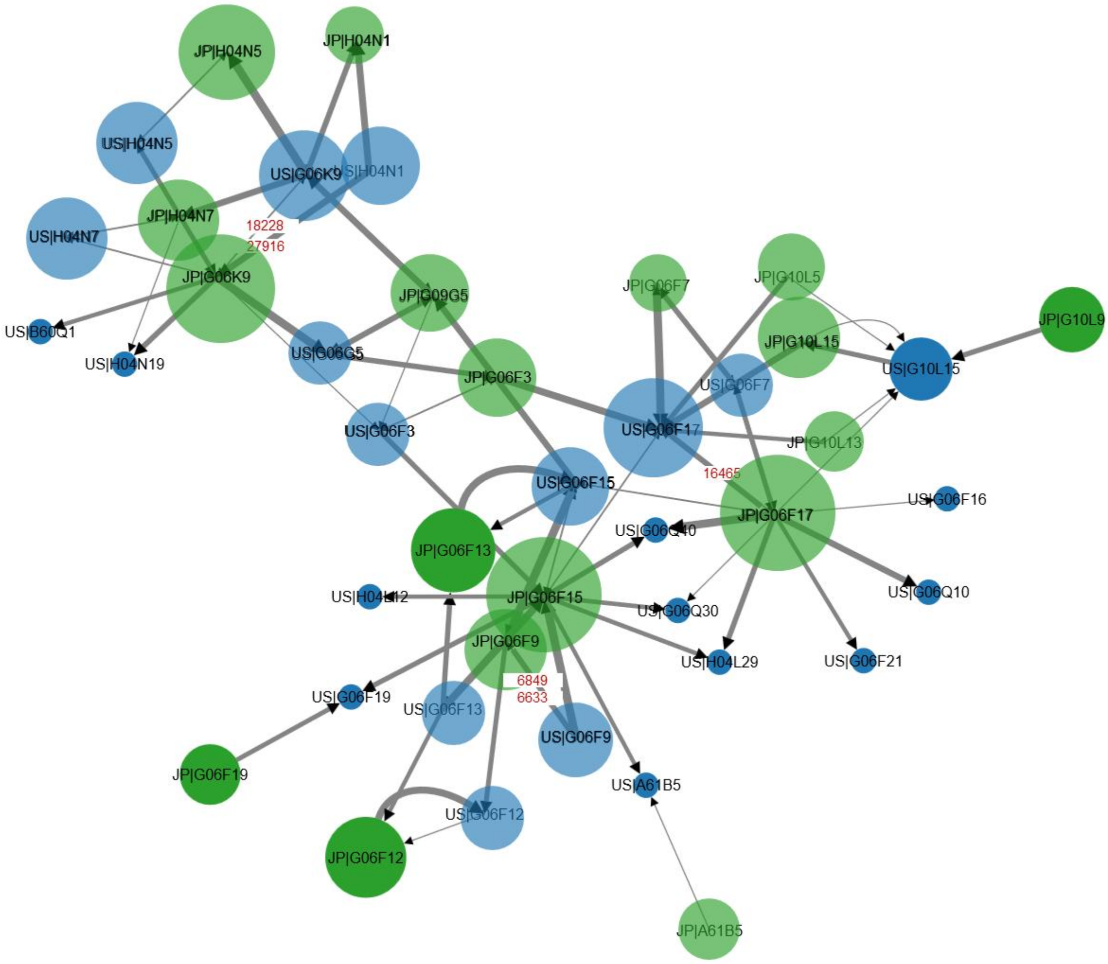

Figure 2. US-JP bilateral AI flow network.

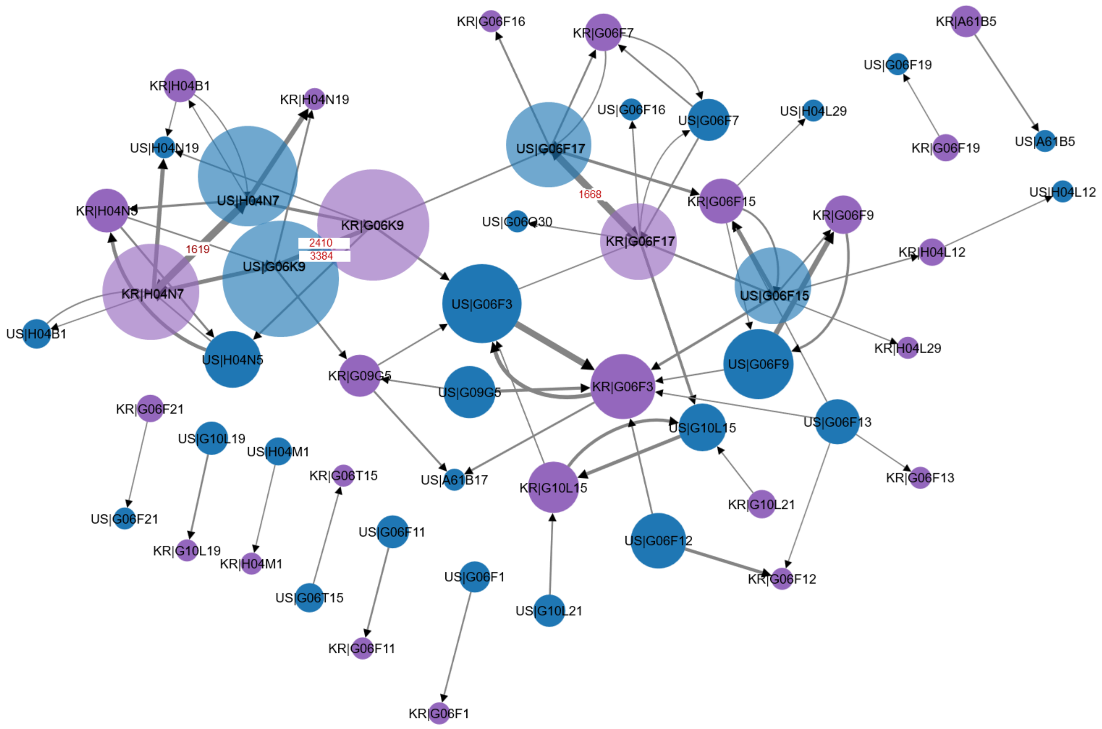

Figure 3. US-KR bilateral AI flow network.

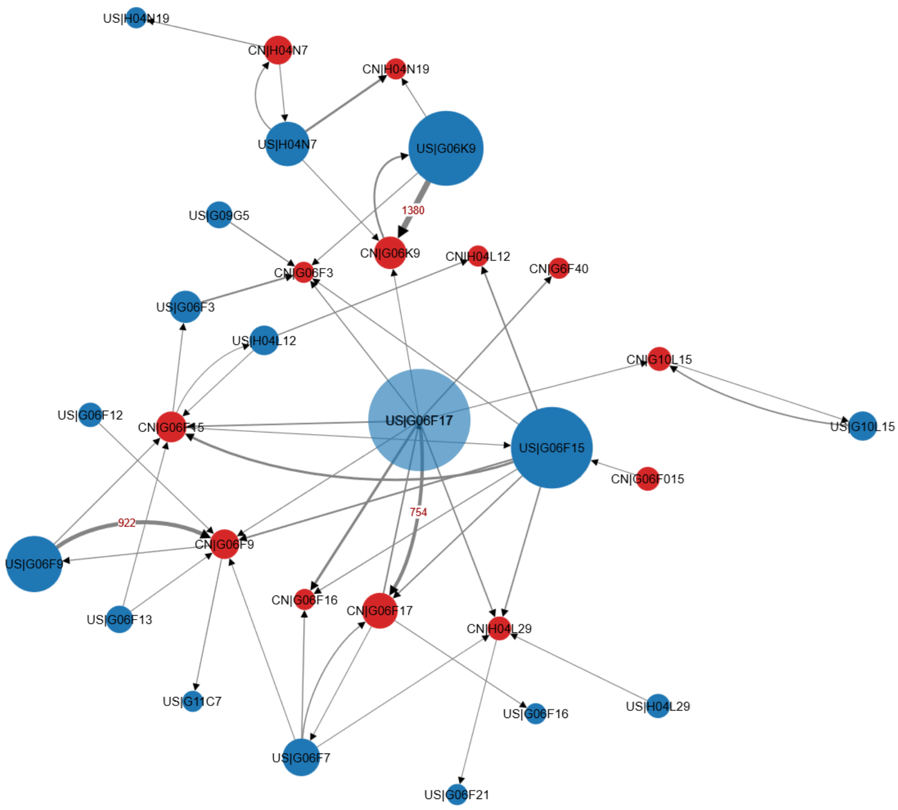

Figure 4. US-CN bilateral AI flow network.

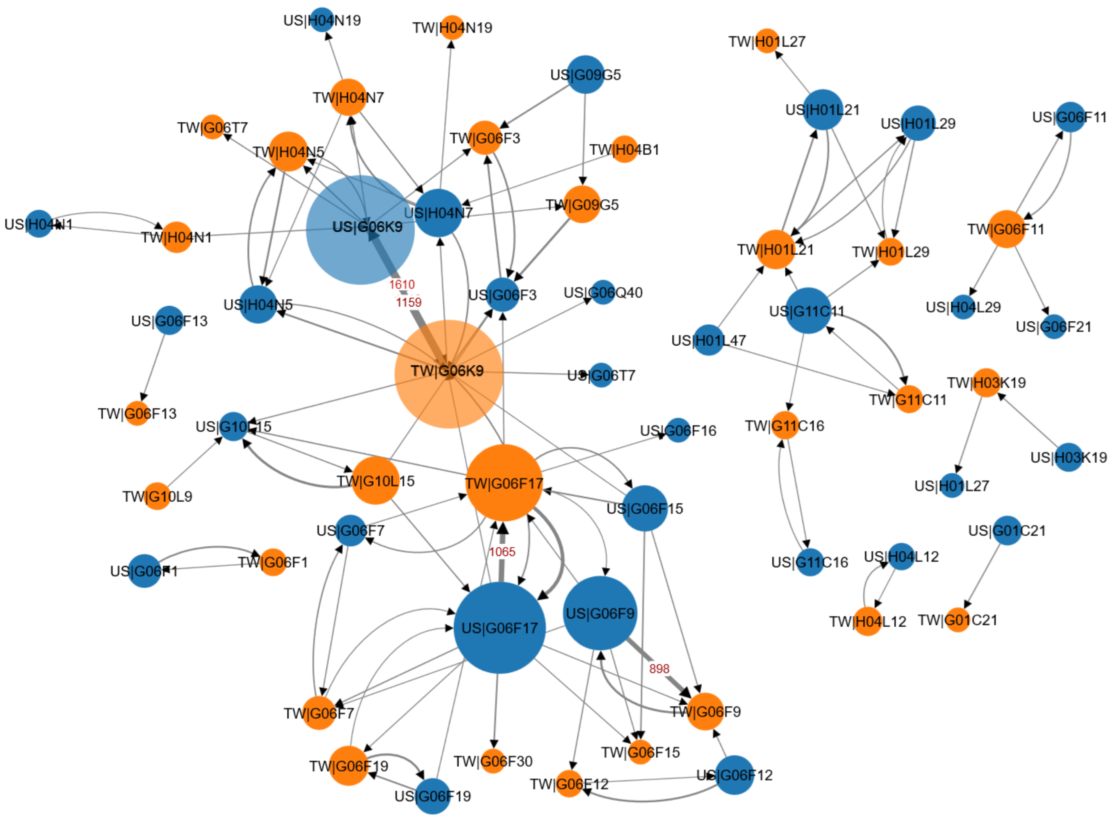

Figure 5. US-TW bilateral AI flow network.

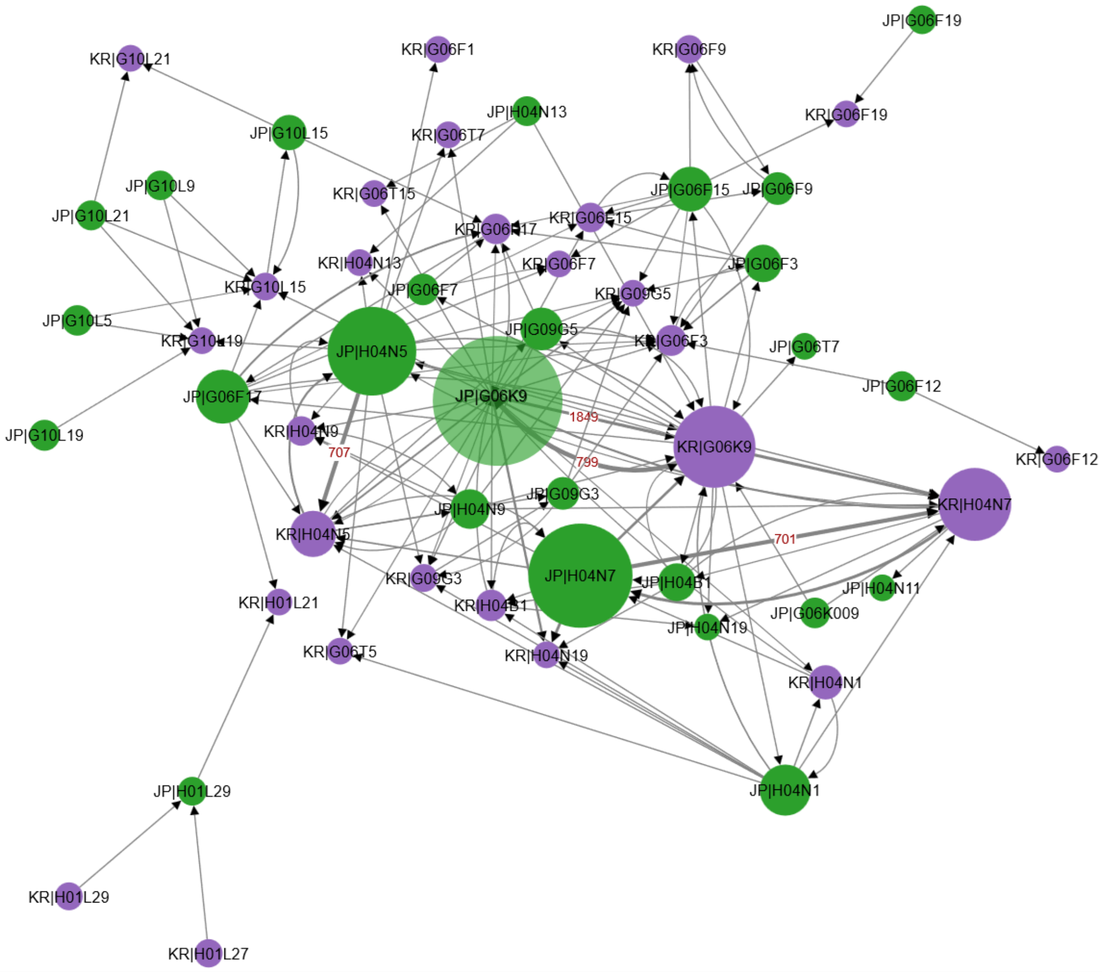

Figure 6. JP-KR bilateral AI flow network.

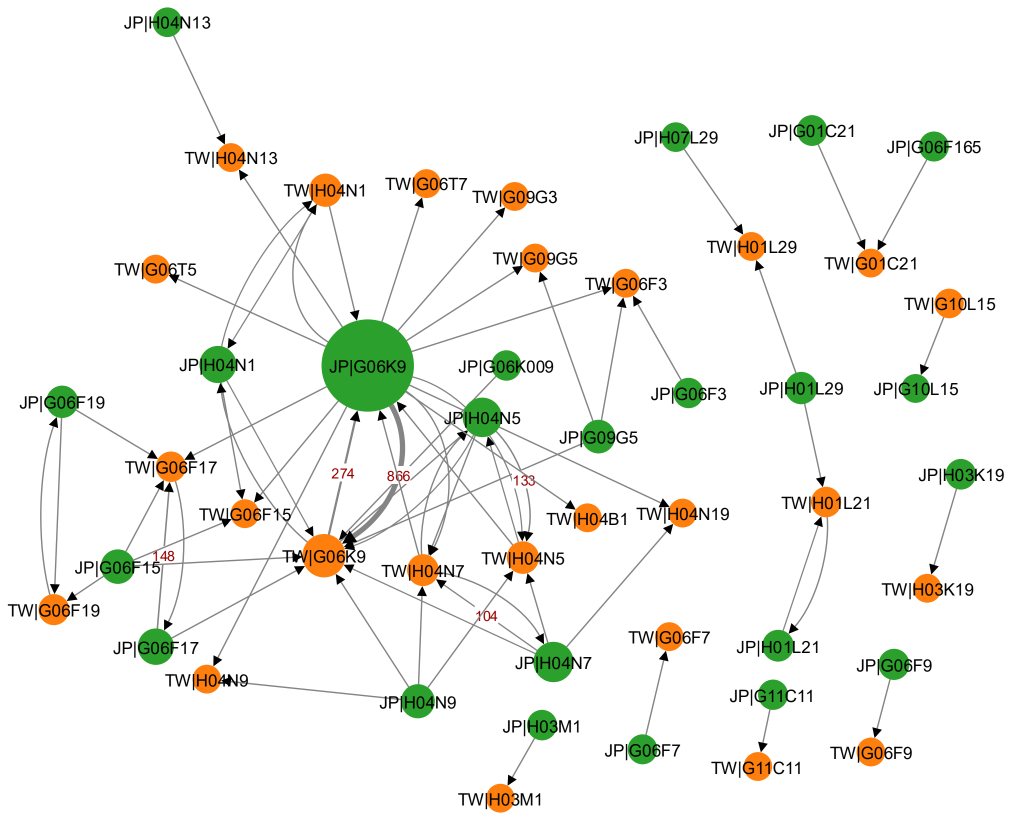

Figure 7. JP-TW bilateral AI flow network.

Areas for feedback and development

Reference

Abrahamson, E., Rosenkopf, L., 1993. Institutional and competitive bandwagons: using mathematical modeling as a tool to explore innovation diffusion. AMR 18, 487–517. https://doi.org/10.5465/amr.1993.9309035148

Aiken, L.S., West, S.G., Reno, R.R., 1991. Multiple Regression: Testing and Interpreting Interactions. SAGE.

Almeida, P., Kogut, B., 1999. Localization of Knowledge and the Mobility of Engineers in Regional Networks. Management Science 45, 905–917. https://doi.org/10.1287/mnsc.45.7.905

AlShebli, B., Memon, S.A., Evans, J.A., Rahwan, T., 2024. China and the U.S. produce more impactful AI research when collaborating together. Sci Rep 14, 28576. https://doi.org/10.1038/s41598-024-79863-5

Anderson, J.E., 2011. The Gravity Model. Annual Review of Economics 3, 133–160. https://doi.org/10.1146/annurev-economics-111809-125114

Anderson, J.E., van Wincoop, E., 2004. Trade Costs. Journal of Economic Literature 42, 691–751. https://doi.org/10.1257/0022051042177649

Antràs, P., de Gortari, A., 2020. On the Geography of Global Value Chains. Econometrica 88, 1553–1598. https://doi.org/10.3982/ECTA15362

Arndt, S.W., Kierzkowski, H., 2001. Fragmentation: New Production Patterns in the World Economy. OUP Oxford.

Bakhuis, J., Kamp, L.M., Barbour, N., Chappin, É.J.L., 2024. Frameworks for multi-system innovation analysis from a sociotechnical perspective: A systematic literature review. Technological Forecasting and Social Change 201, 123266. https://doi.org/10.1016/j.techfore.2024.123266

Baldwin, R., 2006. Globalisation: the great unbundling(s). Presented at the Globalisation Challenges for Europe and Finland, Geneva.

Bergstrand, J.H., Egger, P., 2013. Gravity Equations and Economic Frictions in the World Economy, in: Bernhofen, D., Falvey, R., Greenaway, D., Kreickemeier, U. (Eds.), Palgrave Handbook of International Trade. Palgrave Macmillan UK, London, pp. 532–570. https://doi.org/10.1007/978-0-230-30531-1_17

Boschma, R., Frenken, K., 2011. The emerging empirics of evolutionary economic geography. J Econ Geogr 11, 295–307. https://doi.org/10.1093/jeg/lbq053

Bresnahan, T.F., Trajtenberg, M., 1995. General purpose technologies 'Engines of growth'? Journal of Econometrics 65, 83–108. https://doi.org/10.1016/0304-4076(94)01598-T

Callaert, J., Looy, B.V., Verbeek, A., Debackere, K., Thijs, B., 2006. Traces of Prior Art: An analysis of non-patent references found in patent documents. Scientometrics 69, 3–20. https://doi.org/10.1007/s11192-006-0135-8

Cantwell, J., 2009. Location and the multinational enterprise. J Int Bus Stud 40, 35–41. https://doi.org/10.1057/jibs.2008.82

Capgemini, 2024. The semiconductor industry in the AI era. URL https://www.capgemini.com/insights/research-library/semi-conductors/ (accessed 8.7.25).

Caviggioli, F., 2016. Technology fusion: Identification and analysis of the drivers of technology convergence using patent data. Technovation 55, 22–32.

Chandra, P., Dong, A., 2018. The relation between knowledge accumulation and technical value in interdisciplinary technologies. Technological Forecasting and Social Change 128, 235–244. https://doi.org/10.1016/j.techfore.2017.12.006

Chesbrough, H., 2003. The logic of open innovation: managing intellectual property. California Management Review 45, 33–58.

Cingolani, I., Panzarasa, P., Tajoli, L., 2017. Countries' positions in the international global value networks: Centrality and economic performance. Appl Netw Sci 2, 21. https://doi.org/10.1007/s41109-017-0041-4

Cockburn, I.M., Henderson, R., Stern, S., 2018. The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis, in: The Economics of Artificial Intelligence: An Agenda. University of Chicago Press, pp. 115–146.

Cohen, W.M., Levinthal, D.A., 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. Administrative Science Quarterly 35, 128–152. https://doi.org/10.2307/2393553

Conte, M., Cotterlaz, P., Mayer, T., 2022. The CEPII Gravity Database. CEPII, Paris.

Cowan, R., Jonard, N., 2004. Network structure and the diffusion of knowledge. Journal of Economic Dynamics and Control 28, 1557–1575. https://doi.org/10.1016/j.jedc.2003.04.002

Criscuolo, C., Timmis, J., 2018. GVC centrality and productivity: Are hubs key to firm performance? OECD Productivity Working Papers, OECD Productivity Working Papers.

Dalum, B., Laursen, K., Villumsen, G., 1998. Structural Change in OECD Export Specialisation Patterns: de-specialisation and 'stickiness.' International Review of Applied Economics 12, 423–443. https://doi.org/10.1080/02692179800000017

Deardorff, A.V., 2001. Fragmentation in simple trade models. The North American Journal of Economics and Finance 12, 121–137. https://doi.org/10.1016/S1062-9408(01)00043-2

Dechezleprêtre, A., Märtin, R.P., Mohnen, M., 2014. Knowledge spillovers from clean and dirty technologies. Centre for Economic Performance, London, UK.

DiMaggio, P.J., Powell, W.W., 1983. The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields. American Sociological Review 48, 147–160. https://doi.org/10.2307/2095101

Elahi, M., Afolaranmi, S.O., Martinez Lastra, J.L., Perez Garcia, J.A., 2023. A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment. Discov Artif Intell 3, 43. https://doi.org/10.1007/s44163-023-00089-x

Érdi, P., Makovi, K., Somogyvári, Z., Strandburg, K., Tobochnik, J., Volf, P., Zalányi, L., 2013. Prediction of emerging technologies based on analysis of the US patent citation network. Scientometrics 95, 225–242.

Feenstra, R.C., 1998. Integration of Trade and Disintegration of Production in the Global Economy. Journal of Economic Perspectives 12, 31–50. https://doi.org/10.1257/jep.12.4.31

Fleming, L., Sorenson, O., 2001. Technology as a complex adaptive system: evidence from patent data. Research Policy 30, 1019–1039.

Frank, A.G., Ribeiro, J.L.D., 2014. An integrative model for knowledge transfer between new product development project teams. Knowledge Management Research & Practice 12, 215–225. https://doi.org/10.1057/kmrp.2012.57

Frankel, J., Rose, A., 2002. An Estimate of the Effect of Common Currencies on Trade and Income*. Q J Econ 117, 437–466. https://doi.org/10.1162/003355302753650292

Freeman, L.C., 1978. Centrality in social networks conceptual clarification. Social Networks 1, 215–239. https://doi.org/10.1016/0378-8733(78)90021-7

Gereffi, G., 1999. A Commodity Chains Framework for Analyzing Global Industries. Institute of Development Studies.

Gereffi, G., Humphrey, J., Sturgeon, T., 2005. The governance of global value chains. Review of International Political Economy 12, 78–104. https://doi.org/10.1080/09692290500049805

Goldfarb, A., Trefler, D., 2018. AI and International Trade. Working Paper Series. https://doi.org/10.3386/w24254

Griliches, Z., 1990. Patent Statistics as Economic Indicators: A Survey. Journal of Economic Literature 28, 1661–1707.

Guiso, L., Sapienza, P., Zingales, L., 2009. Cultural Biases in Economic Exchange?*. Q J Econ 124, 1095–1131. https://doi.org/10.1162/qjec.2009.124.3.1095

Hall, B.H., Jaffe, A., Trajtenberg, M., 2005. Market Value and Patent Citations. The RAND Journal of Economics 36, 16–38. https://doi.org/10.2307/1593752

Hall, B.H., Jaffe, A.B., Trajtenberg, M., 2001. The NBER patent citations data file: lessons, insights and methodological tools. NBER working paper.

Harrigan, K.R., Guardo, M.C.D., Marku, E., Velez, B.N., 2017. Using a distance measure to operationalise patent originality. Technology Analysis & Strategic Management 29, 988–1001. https://doi.org/10.1080/09537325.2016.1260106

Hidalgo, C.A., Klinger, B., Barabasi, A.-L., Hausmann, R., 2007. The Product Space Conditions the Development of Nations. Science 317, 482–487. https://doi.org/10.1126/science.1144581

Hobday, M., 1995. East Asian latecomer firms: Learning the technology of electronics. World Development 23, 1171–1193. https://doi.org/10.1016/0305-750X(95)00035-B

Hoekman, J., Frenken, K., van Oort, F., 2009. The geography of collaborative knowledge production in Europe. Ann Reg Sci 43, 721–738. https://doi.org/10.1007/s00168-008-0252-9

Hu, A.G.Z., Jaffe, A.B., 2003. Patent citations and international knowledge flow: the cases of Korea and Taiwan. International Journal of Industrial Organization 21, 849–880. https://doi.org/10.1016/S0167-7187(03)00035-3

IBM Research, 2024. The Transformative Impact of Advanced AI Technologies on the Electronics and Semiconductor Industry [WWW Document]. ResearchGate. URL https://www.researchgate.net/publication/382939387_The_Transformative_Impact_of_Advanced_AI_Technologies_on_the_Electronics_and_Semiconductor_Industry (accessed 8.7.25).

IEA, 2024. A Global Review of Patent Data for Smart Grid Technologies – Analysis [WWW Document]. IEA. URL https://www.iea.org/reports/a-global-review-of-patent-data-for-smart-grid-technologies (accessed 8.23.25).

IEEE IRDS, 2023. Semiconductors and Artificial Intelligence - IEEE IRDS™ [WWW Document]. URL https://irds.ieee.org/topics/semiconductors-and-artificial-intelligence (accessed 8.7.25).

Jaffe, A.B., 1986. Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value. American Economic Review 76, 984–1001.

Jaffe, A.B., Trajtenberg, M., 1999. International Knowledge Flows: Evidence From Patent Citations. Economics of Innovation and New Technology 8, 105–136. https://doi.org/10.1080/10438599900000006

Jones, L., Krulikowski, S., Lotze, N., Schreiber, S., 2023. US exposure to the Taiwanese semiconductor industry. US International Trade Commission.

Kenney, M., Zysman, J., 2016. The rise of the platform economy. Issues in science and technology 32, 61.

Kim, J.E., 2021. Patent Analytics: Transforming IP Strategy into Intelligence. Springer.

Kogler, D.F., Rigby, D.L., Tucker, I., 2014. Mapping Knowledge Space and Technological Relatedness in US Cities, in: Global and Regional Dynamics in Knowledge Flows and Innovation. Routledge.

Kogut B., 1985. Designing Global Strategies: Comparative and Competitive Value-Added Chains - ProQuest. Sloan Management Review 26.

Krizhevsky, A., Sutskever, I., Hinton, G.E., 2012. ImageNet Classification with Deep Convolutional Neural Networks, in: Advances in Neural Information Processing Systems. Curran Associates, Inc.

Lai, I.-C., Su, H.-N., 2024. Initiating Technology Convergence Through Knowledge Integration: The Critical Role of Dynamic Capabilities. IEEE Transactions on Engineering Management 71, 11533–11550. https://doi.org/10.1109/TEM.2024.3425656

Laursen, K., 2000. Do export and technological specialisation patterns co-evolve in terms of convergence or divergence? Evidence from 19 OECD countries, 1971–1991. J Evol Econ 10, 415–436. https://doi.org/10.1007/s001910000044

Le Bas, C., Sierra, C., 2002. "Location versus home country advantages" in R&D activities: some further results on multinationals' locational strategies. Res. Policy 31, 589–609.

Lee, Juhyun, Park, S., Lee, Junseok, 2023. Citationwalk: Network representation learning with scientific documents. Expert Systems with Applications 227, 120372. https://doi.org/10.1016/j.eswa.2023.120372

Lee, P.-C., 2021. Investigating Long-Term Technological Competitiveness: Originality, Generality, and Longevity. IEEE Transactions on Engineering Management.

Liaw, Y.-C., Chan, T.-Y., Fan, C.-Y., Chiang, C.-H., 2014. Can the technological impact of academic journals be evaluated? The practice of non-patent reference (NPR) analysis. Scientometrics 101, 17–37. https://doi.org/10.1007/s11192-014-1337-0

Major, E., Cordey-Hayes, M., 2000. Knowledge translation: a new perspective on knowledge transfer and foresight. Foresight 2, 411–423. https://doi.org/10.1108/14636680010802762

Markard, J., Truffer, B., 2008. Technological innovation systems and the multi-level perspective: Towards an integrated framework. Research policy 37, 596–615.

McKinsey & Company, 2024. AI data center growth: Meeting the demand | McKinsey [WWW Document]. URL https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/ai-power-expanding-data-center-capacity-to-meet-growing-demand (accessed 8.5.25).

McKinsey & Company, 2021. Applying artificial intelligence at scale in semiconductor manufacturing | McKinsey [WWW Document]. URL https://www.mckinsey.com/industries/semiconductors/our-insights/scaling-ai-in-the-sector-that-enables-it-lessons-for-semiconductor-device-makers (accessed 8.7.25).

Molnár, B., Márton, I.-B., Horvát, S., Ercsey-Ravasz, M., 2024. Community detection in directed weighted networks using Voronoi partitioning. Sci Rep 14, 8124. https://doi.org/10.1038/s41598-024-58624-4

Newman, M., 2018. Networks. Oxford University Press.

No, H.J., Park, Y., 2010. Trajectory patterns of technology fusion: Trend analysis and taxonomical grouping in nanobiotechnology. Technol. Forecast. Soc. Chang. 77, 63–75. https://doi.org/10.1016/j.techfore.2009.06.006

Olcott, E., Yu, Y., Li, L., Zhou, C., Ko, H., Ting-Fang, C., 2025. TSMC’s trade secrets and Trump’s chip tariffs [WWW Document]. Financial Times. URL https://www.ft.com/content/d82687e2-703e-4507-9a10-1c70ef00955d (accessed 8.7.25).

Pairolero, N.A., Giczy, A.V., Torres, G., Islam Erana, T., Finlayson, M.A., Toole, A.A., 2025. The artificial intelligence patent dataset (AIPD) 2023 update. J Technol Transf 50, 2587–2610. https://doi.org/10.1007/s10961-025-10189-8

Patel, P., Pavitt, K., 1991. Large firms in the production of the world’s technology: an important case of “non-globalisation.” Journal of international business studies 22, 1–21.

Peri, G., 2005. Determinants of Knowledge Flows and Their Effect on Innovation. Review of Economics and Statistics 87, 308–322. https://doi.org/10.1162/0034653053970258

Pezzoni, M., Veugelers, R., Visentin, F., 2022. How fast is this novel technology going to be a hit? Antecedents predicting follow-on inventions. Research Policy 51, 104454. https://doi.org/10.1016/j.respol.2021.104454

Piccardi, C., Tajoli, L., Vitali, R., 2024. Patterns of variability in the structure of global value chains: a network analysis. Rev World Econ 160, 1009–1036. https://doi.org/10.1007/s10290-023-00521-5

Picci, L., 2010. The internationalization of inventive activity: A gravity model using patent data. Research Policy 39, 1070–1081. https://doi.org/10.1016/j.respol.2010.05.007

Rashid, A.B., Kausik, M.A.K., 2024. AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications. Hybrid Advances 7, 100277. https://doi.org/10.1016/j.hybadv.2024.100277

Ravenstein, E.G., 1889. The Laws of Migration. Journal of the Royal Statistical Society 52, 241–305. https://doi.org/10.2307/2979333

Rigby, D.L., 2015. Technological Relatedness and Knowledge Space: Entry and Exit of US Cities from Patent Classes. Regional Studies 49, 1922–1937. https://doi.org/10.1080/00343404.2013.854878

Rose, A.K., 2000. One money, one market: the effect of common currencies on trade. Econ Policy 15, 08–45. https://doi.org/10.1111/1468-0327.00056

Sacks, D., Huang, S., 2024. Onshoring Semiconductor Production: National Security Versus Economic Efficiency | Council on Foreign Relations [WWW Document]. URL https://www.cfr.org/article/onshoring-semiconductor-production-national-security-versus-economic-efficiency (accessed 8.7.25).

Salmerón, R., García, C.B., García, J., 2018. Variance Inflation Factor and Condition Number in multiple linear regression. Journal of Statistical Computation and Simulation 88, 2365–2384. https://doi.org/10.1080/00949655.2018.1463376

Salmerón, R., Rodríguez Sánchez, A., García, C.G., García Pérez, J., 2020. The VIF and MSE in Raise Regression. Mathematics 8, 605. https://doi.org/10.3390/math8040605

Singh, J., 2005. Collaborative Networks as Determinants of Knowledge Diffusion Patterns. Management Science 51, 756–770. https://doi.org/10.1287/mnsc.1040.0349

Soete, L., 1987. The impact of technological innovation on international trade patterns: The evidence reconsidered. Research Policy 16, 101–130. https://doi.org/10.1016/0048-7333(87)90026-6

Sony, M., Naik, S., 2019. Key ingredients for evaluating Industry 4.0 readiness for organizations: a literature review. Benchmarking: An International Journal 27, 2213–2232. https://doi.org/10.1108/BIJ-09-2018-0284

Statista, 2025. Autonomous & Sensor Technology - Worldwide | Forecast [WWW Document]. Statista. URL http://frontend.xmo.prod.aws.statista.com/outlook/tmo/artificial-intelligence/autonomous-sensor-technology/worldwide (accessed 8.5.25).

Sturgeon, T.J., 2002. Modular production networks: a new American model of industrial organization. ICC 11, 451–496. https://doi.org/10.1093/icc/11.3.451

Sullivan, H., 2025. A journey through the hyper-political world of microchips [WWW Document]. The Guardian. URL https://www.theguardian.com/technology/2025/feb/28/inside-the-mind-bending-tin-blasting-and-hyper-political-world-of-microchips (accessed 8.7.25).

Swanson, E.B., Ramiller, N.C., 2004. Innovating Mindfully with Information Technology. MIS Quarterly 28, 553–583. https://doi.org/10.2307/25148655

Tajoli, L., Airoldi, F., Piccardi, C., 2021. The network of international trade in services. Appl Netw Sci 6, 68. https://doi.org/10.1007/s41109-021-00407-1

Teece, D.J., 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. Research policy 15, 285–305.

Tinbergen, J., 1962. Shaping the World Economy; Suggestions for an International Economic Policy.

Trajtenberg, M., Henderson, R., Jaffe, A., 1997. University Versus Corporate Patents: A Window On The Basicness Of Invention. Economics of Innovation and New Technology 5, 19–50. https://doi.org/10.1080/10438599700000006

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł. ukasz, Polosukhin, I., 2017. Attention is All you Need, in: Advances in Neural Information Processing Systems. Curran Associates, Inc.

Vázquez Rojo, J., Visintin, S., 2024. The US-China race for technological centrality: A network perspective. Structural Change and Economic Dynamics 71, 68–83. https://doi.org/10.1016/j.strueco.2024.06.008

Wang, J.-H., 2007. From technological catch-up to innovation-based economic growth: South Korea and Taiwan compared. The Journal of Development Studies 43, 1084–1104. https://doi.org/10.1080/00220380701466609

Wasi, A.T., Eram, E.H., Mitu, S.A., Ahsan, M.M., 2025. Generative AI as a Geopolitical Factor in Industry 5.0: Sovereignty, Access, and Control. https://doi.org/10.48550/arXiv.2508.00973

Wasserman, S., Faust, K., 1994. Social network analysis: Methods and applications. Cambridge university press.

Watts, D.J., 1999. Networks, Dynamics, and the Small-World Phenomenon. American Journal of Sociology 105, 493–527.

Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of ‘small-world’networks. Nature 393, 440–442.

WIPO, 2024. WIPO IPC e-forum [WWW Document]. URL https://www3.wipo.int/classifications/ipc/ipcef/public/en (accessed 8.23.25).

WIPO, 2022. Guide to the International Patent Classification (2022).

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data, second edition. MIT Press.

Zhang, M., Wei, L., Yi, Z., 2025. The impact of embedded global innovation networks on manufacturing value chains. Sci Rep 15, 28275. https://doi.org/10.1038/s41598-025-13395-4