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Varieties of corporate innovation systems and their interplay with global and national systems: Amazon, Facebook, Google and Microsoft's strategies to produce and appropriate artificial intelligence

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ABSTRACT

The widely accepted globalization of innovation entails two interrelated undertheorized aspects: (1) the capacity of certain firms to orchestrate transnational innovation systems appropriating successful results, which some have explained with the concept of corporate innovation systems (CIS), and (2) the co-existence of such globalization with those CIS and national innovation systems. I address these matters analysing US Big Tech artificial intelligence (AI) CIS showing that they combine multiple mechanisms to co-produce and appropriate AI. I propose 'frenemy' to describe Microsoft's strategy because many Chinese organizations and even direct competitors integrate its CIS. 'University' symbolises Google's strategy, given its focus on fundamental AI, its central place in the AI research field and appropriation mechanisms that are not translating into clear business advantages. 'Secrecy' defines Amazon's strategy, maximizing knowledge inflows while minimizing outflows. Facebook, with the narrowest AI CIS, exhibits an 'application-centred' strategy. Ultimately, this paper contributes to understanding the multiple mechanisms used by leading corporations for controlling and shaping frontier transnational knowledge production and appropriation. By doing so, it advances our knowledge of the interplay between different innovation spheres (national, global and corporate) and highlights the dangers of CIS's encroachment of national and global systems.

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KEYWORDS
Global innovation networks; Corporate Innovation Systems; weaponized networks; Big Tech; artificial intelligence; corporate-state diplomacy

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Introduction

Soon after OpenAI released ChatGPT, it was integrated into several Microsoft products. Google, Amazon and Meta reacted fast with their own generative AI services. Although artificial intelligence (AI) models are proliferating since then, there is an agreement that the whole AI field orbits around these four giants. This points to the relevance of further examining the processes of production and appropriation of frontier knowledge as well as its geopolitical implications, since AI has been at the eye of the US-China storm (Rikap & Lundvall, 2021).

Albeit the apparent benefits that Big Tech are deriving from AI, this technology is produced globally in what could be seen as a combined global knowledge and innovation network or system (Binz & Truffer, 2017; Chaminade et al., 2016). This paper advances our knowledge of this network by addressing two undertheorized aspects of particular relevance to the case of AI and Big Tech: (1) the capacity of certain firms to orchestrate such a network appropriating and turning into assets successful results, and (2) the co-existence of global knowledge and innovation networks with corporate-dominated innovation systems and national innovation systems (NIS). I draw on the intellectual monopoly framework to elaborate on the former and, to address the latter, I integrate Strange's (1992) concept of corporate-state diplomacy into the literature on weaponized interdependence across networks.

At the empirical level, this paper compares the AI strategies of Alphabet (hereon Google), Amazon, Microsoft and Meta (hereon Facebook) showing, by means of a mixed-methods analysis, that they combine different tactics to co-produce AI with thousands of organizations with diverse yet complementary appropriation mechanisms. The paper also argues that they use AI scientists and engineers as a bridge between the co-production and appropriation of AI. By identifying these concrete mechanisms, I contribute to our understanding of the role of leading corporations and their home states, in this case Big Tech and the US, in shaping, controlling and weaponizing global innovation networks.

My empirical findings point to four different strategies to manage the production and appropriation of frontier AI resulting in Corporate Innovation Systems (CIS) that occupy prominent positions within the global AI network, with Google and Microsoft virtually controlling it. Big Tech companies profit at the expense of the US—and other core countries'—NIS. Simultaneously, it is strategic for the US state to build diplomatic relations with Big Tech to weaponize the global AI network.

Both Google and Microsoft's CIS are widely glocalized—global but concentrated in hubs—but only the latter integrates Chinese actors. I describe Microsoft's AI CIS strategy as 'frenemies' precisely because it has successfully integrated into its AI CIS Chinese organizations and even rival companies. Despite decoupling pressures, Microsoft's AI research remains anchored in China, thus contributing to its catching-up, which can be seen as a source of tensions with the US state.

Google's strategy seems to emulate a leading university that shapes the global knowledge and innovation system by privileging the development of fundamental knowledge whose appropriation mechanisms are not so clearly translating into business advantages. At the other end in terms of openness and with a more limited geographical scope, Amazon has privileged a 'secrecy' strategy, offering no leeway to the US state to use Amazon's CIS to weaponize the whole AI network. At Amazon's CIS, AI development is put at the service of its multiple and expanding international businesses. Likewise, Facebook mostly develops AI connected to its businesses, but—unlike Amazon's—these are mainly a few platforms. I characterize Facebook's AI strategy as 'application-centred'. Facebook's AI CIS is as open as those of Google and Microsoft, but its more limited knowledge scope translates into a more circumscribed and less central CIS within AI's global knowledge and innovation network. This gives the US state fewer chances to weaponize the global AI network by negotiating with Facebook.

The rest of this paper is organized as follows. Section 'Leading corporations controlling and states weaponizing innovation networks' draws on seminal and contemporary international political economy (IPE) contributions to conceptualize the interplay between leading corporations and their home countries' states amid different -global, corporate and national- innovation networks or systems. The section also shows that Big Tech AI practices have been narrowly studied lacking a distinction of each companies' strategy and a comprehensive analysis of the different mechanisms of knowledge co-production and appropriation used to build their CIS. This paper's methodology and results are presented in Sections 'Methodology' and 'Results', respectively. Section 'Four strategies to dominate an AI corporate innovation system leading to different spaces for weaponizing the global AI network' discusses achieved results and Section 'Final remarks' concludes.

Leading corporations controlling and states weaponizing innovation networks

By the end of the twentieth century, advancements in science and technology, as well as specific innovations in computational capabilities and the instruments used to perform, analyse and record experiments, enabled the modularization of knowledge, so that different steps of the same research and development (R&D) project could be performed separately (Arora & Gambardella, 1994). The globalization of knowledge and innovation sprang from expanding this de-verticalization beyond borders coupled with the surge of start-ups specialized in the production of science and technology (Antonelli, 1999). Many described this process as the emergence of global innovation networks or systems in which organizations co-produce innovation modules in distant geographies (Chaminade et al., 2016; Ernst, 2008, 2009; Liu et al., 2013; Parrilli et al., 2013).

The question about power asymmetries inside these networks remained undertheorized until recently, leading Binz and Truffer (2017) to call for connecting the innovation systems' approach with the global value chain (GVC) and global production network frameworks. This is precisely where Rikap and Lundvall (2020) found inspiration to propose the idea of CIS defined as global systems in which the overall R&D orientation is set by a leading firm that disproportionately captures the bulk of associated profits—intellectual rents—even if innovation is co-produced with many others, such as universities, public (research) organizations and start-ups (Lundvall & Rikap, 2022; Rikap & Lundvall, 2020). In fact, many had already observed that outsourcing R&D offsets related risks without losing the chance to predominantly profit from successful results (Dolgin, 2010; Lazonick et al., 2017; Rikap, 2019).

Such behaviours were specially documented for pharmaceuticals and information technologies. It was found that Roche, Novartis and Pfizer systematically turned into their exclusively owned patents discoveries whose related publications were co-authored with hundreds of other organizations (Rikap, 2019). Likewise, Google, Amazon, Microsoft, Alibaba and Tencent only shared ownership of up to 0.3% of their patents with other organisations despite establishing hundreds of research collaborations (Rikap, 2020; Rikap & Lundvall, 2020). These leading firms controlling CIS were conceived as intellectual monopolies, a concept also mobilized to understand firm-level power dynamics in GVCs (Durand & Milberg, 2020; Rikap, 2018).

A close examination of these contributions reveals that the intellectual monopoly definition is still on the making. Boldrin and Levine (2004, p. 328) had defined it as 'the power of producers of ideas to control how their products are used'. However, the CIS concept stresses that global corporations capture knowledge co-produced with other organizations. Hence, intellectual monopolies are not necessarily the producers of the ideas, but those that systematically capture and turn knowledge and information into rent bearing assets. Innovation is produced systemically but stratified and reducing the economic risks for the intellectual monopoly without risking its innovation lead.

Summing up, the CIS concept offers a different angle to study the globalization of innovation. Along the lines of GVC's distinction between value production and capture, it differentiates between the coproduction and appropriation of knowledge. However, most of the empirical research has looked at this distinction either providing indicators of intellectual monopolization (Baines & Hager, 2023) without exploring the CIS dynamics or comparing co-publications with patent co-ownership, as in the examples above. Although contributions usually argue that other knowledge co-production and appropriation mechanisms matter (Rikap, 2021; Rikap & Lundvall, 2021), we still know little about how companies use them to control innovation and reinforce their intellectual monopolies.

I address this blind spot by suggesting that the intellectual monopoly has the exclusive capacity to combine knowledge modules within its CIS. It is expected that each module will be produced by or with experts in specific domains, probably unaware of how other pieces are produced, by whom or even what is being produced in the rest of the system. Experts will certainly ignore how modules are recombined. In such a process, the intellectual monopoly mobilizes diverse—potentially complementary—knowledge co-production and appropriation mechanisms to maximize success rates without sacrificing its disproportionate monetization of co-produced knowledge.

In such a scenario, other organizations end up selling or sharing their core knowledge which, as pointed out by Fiegenbaum et al. (2014), is crucial for the firm's core competencies and further innovation. At the organization level, the other side of intellectual monopolization are a myriad of firms that lost innovation autonomy. This has resulted in industries with a stable core of intellectual monopolies surrounded by a turbulent periphery of firms and other satellite organizations (Rikap, 2023b).

Interplay between intellectual monopolies, states and the global knowledge and innovation network

Another blind spot concerns the spatiality of CIS and their interplay with geographically determined innovation spheres, such as NIS and the global knowledge and innovation network. Intellectual monopolies organize CIS beyond borders, which challenges the idea that states are the main architects of innovation articulating NIS. Recent work has addressed this by arguing that the global digital innovation race shall be seen as the co-evolution of Big Tech CIS with the US and Chinese NIS (Rikap & Lundvall, 2021). Yet, the borders and overlaps of CIS with NIS and their interplay with the overall global innovation network remain undertheorized.

Building on Farrell and Newman (2019), this gap could be filled by explaining that if a global knowledge and innovation network is controlled by such an intellectual monopoly, this company's home state could leverage on the former's hub position. Whether the central position creates a chokepoint or provides a panopticon view, the state could use it to weaponize the network, coercing other states. For instance, Beaumier and Cartwright (2024) analysed the semiconductors' supply chain as an assembly of four networks. The US has a chokepoint in one of them, the design network, and the US state has used this hub position to restrict access to Chinese companies in the four networks, what the authors defined as cross-network weaponization.

In these studies of weaponized interdependence there is a somewhat passive role on the side of the corporation. Yet, since the early 1990s, Strange (1992) noted that governments had to bargain with multinational corporations as much as with other governments. Corporate-state diplomacy is crucial because, as she continued explaining, transnational corporations command 'an arsenal of economic weapons that are badly needed by any state wishing to win world market shares', among which technology looms large (Strange, 1992, p. 7). Against this backdrop, Babić et al. (2017) suggest that states and corporations are not subordinated to each other, but juxtaposed and intertwined; they use each other to increase their respective power positions. Weaponized interdependence, thus, relies on core states' diplomatic relations with multinational corporations, as noted by Gjesvik (2022) for the case of submarine internet cables.

Also, drawing on Beaumier and Cartwright's (2024) idea of cross-networks and how they can be weaponized, the global knowledge and innovation network of a certain technology can be seen as a network of cross-networks, the latter being a set of CIS and NIS. If a certain NIS or part of it—such as a regional innovation cluster—is a hub, that state could weaponize the global network quite straightforwardly. Meanwhile, if a CIS—thus a leading corporation with its satellite co-innovators—sits at the centre, corporate-state diplomacy will mediate the chances of the corresponding state to weaponize the network.

Big tech as intellectual monopolies and the development of AI

Amazon, Google, Facebook and Microsoft offer a privileged scenario for studying all the above. In his study of the world's submarine internet cables, Gjesvik (2022) identified that over half of them are owned by these four giants, so the US state would need to bargain with Big Tech if it wants to use this network to coerce other states. The same could be happening with AI's global knowledge and innovation network since US Big Tech have already been described as intellectual monopolies controlling CIS focused on frontier AI (Rikap & Lundvall, 2020, 2021), and Google, Amazon, Microsoft, Alibaba and Tencent were found to be vertically integrated firms in the AI division of labour (Jacobides et al., 2021).

Since 2012, previous research found that Big Tech is increasingly participating in major AI conferences favoured by the uneven access to computing power (Ahmed & Wahed, 2020). Mateos-Garcia and Klinger (2023, p. 1) arrived at similar results. They noted that the effect of the narrow topic interest of Big Tech was driving the field towards 'data-hungry and computationally intensive deep learning methods'. In the same vein and judging by citations, for Jurowetzki et al. (2021), Microsoft and Google are the most influential organizations in the AI research field.

A common feature of these investigations is that Big Tech companies are studied as a homogeneous bundle. An exception is Heston and Zwetsloot (2020), who geolocalized Facebook, Google, IBM and Microsoft AI R&D and identified differences in the share of AI staff and AI labs across companies. However, they did not explore what these differences mean or why they take place. They analysed findings for all the companies together, identifying a concentration of AI labs in the San Francisco Bay Area and Seattle. Likewise, Birch and Cochrane (2022) asserted that Big Tech has heterogeneous techno-economic practices but did not explore them. To the best of my knowledge, there is still no comprehensive analysis of the different ways in which these companies are developing, shaping and capturing AI by managing knowledge in CIS, addressing resulting impacts on state-corporate diplomacy and the global AI knowledge and innovation network, like the one conducted in the rest of this paper.

Methodology

I compared Amazon, Facebook, Google and Microsoft. At the quantitative level, I used a set of indicators, methodologies and datasets to map the role of each company in the co-production and appropriation of cutting-edge AI (see Table 1). I also considered AI talent indicators. Skilled scientists and engineers can be considered a bridge between knowledge co-production and appropriation. In a nutshell, a firm with more AI talent will not only have more resources for developing AI internally, but will also be able to have more diverse and larger numbers of collaborations—thus a larger CIS—and will have greater capacities to absorb successful results (Cohen & Levinthal, 1990).

I proxied the frontier AI research network with a bibliometric sample of all the presentations at the top 14 AI conferences between 2012 and 2020 extracted from Scopus because previous research has shown that the most influential AI research is presented there (Ahmed & Wahed, 2020). I followed Ahmed and Wahed (2020) to choose the AI conferences listed in the Computer Science Rankings (www.csranking.org). I validated the list with an AI computing scientist who suggested to include two smaller AI conferences (the 'European Conference on Artificial Intelligence' and 'Uncertainty in AI'). The final list is presented in Table 2. My resulting dataset contained 71,264 presentations.

My sample starts in 2012, the year when the AlexNet convolutional neural network architecture won the ImageNet Large Scale Visual Recognition Challenge, which is identified as a breaking point in AI (Ahmed & Wahed, 2020; Jurowetzki et al., 2021). 2020 is the end date because building this network was the first step

Table 1. Summary of the quantitative methodological strategy.

Dimensions of analysis		Proxy	Data source	Period of analysis
Co-production of AI	Positioning in the AI research field	Network analysis + Betweenness centrality	Top 14 AI Conferences' bibliometric data extracted from Scopus	2012–2020
		Participation in conference committees	Conference websites	2023 (except for AAAI Conference that only had data for 2022)
	Content of AI research	Text mining and network analysis	Top 14 AI Conferences (Scopus)	2012–2020
Appropriation mechanism	AI-firms' acquisitions	Number and industries of AI acquisitions	Crunchbase	2012–2022
	Funding AI start-ups	Number of AI start-up firms' in which a Big Tech appears among the start-up's top 5 investors	Crunchbase	2021 (except for Facebook, data for 2023)
	AI granted patents	Ranking of top 30 AI granted patents assignees in 2022, comparison with WIPO's (2019) report for a previous period	Derwent Innovation	2022
	Content of AI patents	Text mining of the 30 most frequent multi-terms in abstracts and titles of each Big Tech AI patents	Derwent Innovation	2022
Bridge between co-production and appropriation	AI talent	Academic institutions with scholars that also work for a Big Tech (double affiliations)	Top 14 AI Conferences (Scopus)	2012–2020
		Open job posts in AI (absoute terms and in relation to total job posts)	Company career websites	April 2023

Table 2. List of leading AI conferences.

Acronym	Conference Name
AAAI	Association for the Advancement of Artificial Intelligence
IJCAI	International Joint Conference on Artificial Intelligence
CVPR	Conference on Computer Vision and Pattern Recognition
ECCV	European Conference on Computer Vision
ICCV	International Conference on Computer Vision
ICML	International Conference on Machine Learning
KDD	Conference on Knowledge Discovery and Data Mining
NeurIPS	Conference on Neural Information Processing Systems
ACL	Association for Computational Linguistics
EMNLP	Empirical Methods in Natural Language Processing
NAACL	North American Chapter of the Association for Computational Linguistics
SIGIR	Annual International ACM SIGIR Conference on Research and Development in Information Retrieval
ECAI	European Conference on Artificial Intelligence
UAI	Uncertainty in AI

of the investigation. At the time of retrieval, late 2021, it was the last year with complete information. Since I wanted to have a sense of its evolution, I split the sample into three sub-periods (2012–2014, 2015–2017 and 2018–2020).

For each sub-period, I combined network analysis with clustering to map the network of most frequent co-authoring organizations. Previous studies used this technique for mapping relations within a knowledge or innovation network (Cooke, 2006; Testoni et al., 2021; Trujillo & Long, 2018; Wasserman & Faust, 1994).

Scopus offers a field with authors' addresses, including affiliations. I used it to proxy the overall frontier AI network of organizations. From a total of 59,907 addresses, an in-depth cleaning process was conducted to identify affiliations resulting in a final list of 13,637 organizations. The data were processed using the network mapping algorithm provided by CorText Manager (Tancoigne et al., 2014), which is an online open access platform for large text analysis methods, including network analysis and text mining.[1] The Louvain community detection algorithm was applied as the cluster detection method (Blondel et al., 2008). To focus on the most influential actors, I prioritized the 150 organizations with the highest co-occurrence frequency for each period.

I used the chi-square proximity measure to determine nodes and edges. This is a direct local measure, meaning that it computes actual co-occurrences (co-authorships). To define the direct ties (edges), chi-square normalization prioritises links towards higher degree nodes; these are the most frequent co-authorships for each network. It thus privileges the strongest links for each organization. I calculated the betweenness, closeness and degree centrality of each node using Gephi (lists available in the online appendix). The former is a standard measure for considering the intermediating role of each node in a network, defined as the sum of the ratio of the shortest paths between any two nodes in the network that passes through that node. Closeness centrality refers to how far a node is from all the other nodes. The higher the closeness centrality, the shorter the distances to all the other nodes. The degree centrality (in-degree and out-degree centrality in the online appendix) informs of direct connections of a node with other nodes but, unlike the other two measures, misses the indirect influence that a node can exercise on the whole network, thus on those that are not directly connected. Indirect influences are particularly relevant for identifying if Big Tech's CIS are encroaching the global network and impacting the US state weaponized interdependence possibilities.

The same procedure was used to build a network of organizations and privileged topics for the whole nine-year period. To detect the privileged topics within my sample, I text mined the 500 most frequent multi-terms appearing in the titles, abstracts and keywords. The output list was cleaned to exclude words with a high frequency explained by either their grammatical function (such as 'and' and 'or') or the level of grammaticalization within the scientific genre ('previous research', 'proposed method', etc.). The final list consisted of 416 terms. I built a network that links organizations and terms to get a sense of the topics privileged by each Big Tech and the other most active organizations.

Then, I retrieved from each conference website the full list of committee members and identified the presence of industry, particularly Big Tech. Since this was suggested by one of the interviewees and previous years' data was not always available, I retrieved information for 2023, except for the Association for the Advancement of Artificial Intelligence Learned Society (AAAI) for which data was available for 2022.

Additionally, I used Crunchbase for Big Tech acquisitions between 2012 and 2022 including acquired companies' technologies/industries, which is a Crunchbase classification. I also retrieved the lists of companies with a Big Tech among their top five investors by the end of 2021, choosing that moment to avoid the effects of more recent global macroeconomic and tech sector distress. This information was not available for Facebook; thus, its data corresponds to 2023.

Moreover, I analysed AI granted patents in 2022 extracted from Derwent Innovation. I applied the same methodology used by the World Intellectual Property Organization (WIPO) (2019) and compared my results with those of this report. Furthermore, I used text mining to extract the 30 most frequent terms in each Big Tech AI patents' portfolio for 2022.

Concerning AI talent, I included an indicator of double affiliations at the institution level by retrieving from my AI top conferences' dataset all the academic institutions with scholars that, for the same article, also declared a Big Tech as their affiliation. Double affiliations are a living tie between Big Tech and other organizations integrating AI's global knowledge network.

Finally, I conducted semi-structured in-depth interviews with senior managers, AI researchers and AI engineers working for the chosen Big Tech and other leading corporations. I interviewed ten employees from the four giants working in the US, the United Kingdom and Germany. Interestingly, five had worked for at least another US Big Tech, providing in total 18 company-employee answers (five for Amazon, four for Facebook, five for Google, and four for Microsoft). I interviewed 15 other AI researchers, engineers and managers from Alibaba (four), Bosch (one), Globant (one), IBM Research (four, including two former lead scientists, Ted Selker and Randy Isaac, who were the only interviewees that agreed to be mentioned by their names), Mercado Libre (three), PayPal (one) and Samsung (one). The main goal of the interviews was to clarify and validate the quantitative results of this investigation. Interviews lasted between 30 and 120 min and were conducted between August, 2022 and August, 2023. These interviews are not a stand-alone representative sample because 19 out of 25 were secured by indirect connections. Nevertheless, the consistency of the replies and their correspondence with my quantitative findings justify including them.

Results

The co-production of AI

Big Tech positioning in the global AI research network

Over time, the four companies occupy a more central position in the AI top conferences' network, which proxies the leading AI global knowledge network (Figures A.1–A.3 in the supplemental Appendix). Yet, there are meaningful differences in terms of their places in the network and type of privileged collaborations depicted in the global network that integrate their CIS.

Microsoft, Google and Facebook were already in the AI top conferences' network between 2012 and 2014 (supplemental Figure A.1). Microsoft ranked first in the number of AI conferences' presentations and Google tenth. However, the latter occupied a marginal position, only directly connected to one institution and ranking 116 in betweenness centrality. Although Microsoft was more connected, it was linked to only five organizations from two clusters and ranked 39th in betweenness centrality. Facebook's position was even more marginal, ranked 134 in frequency of presentations and last in betweenness centrality. Other centrality measures exhibited similar results. This reflects more limited CIS and an overall marginal place in the global network.

By the last period (supplemental Figure A.3), from a total of 6471 organizations from 65 different countries presenting at these convenings, Google and Microsoft had the highest betweenness and closeness centrality. They were also second and fourth in the number of presentations.

Microsoft's positioning stands out. It is the crucial bridge connecting China and the West. Microsoft integrates a cluster of mostly Chinese organizations (firms and universities) and is directly connected to four additional clusters mainly populated by Western organizations. In total, Microsoft is directly linked to 11 universities from China, the US, Switzerland and the UK. By being both deeply related to several US and European universities and widely established in China, Microsoft unifies the frontier AI field, connecting what would otherwise be a structural hole (Burt, 1995). In other words, there is a global cutting-edge AI research network because of Microsoft.

This result is in line with Microsoft's strategy in China, where it has conducted R&D since 1998. As a result, between 2012 and 2021, 24% of Microsoft's total publications—not only those presented at the top AI conferences—had at least one author based in China. From the 120 countries represented in these publications, only the US appeared more than China. Almost half of its publications have at least one author from Redmond, the location of Microsoft's headquarters. Beijing (20.49%), Cambridge (17.4%) and Seattle (6.21%) follow.

Given its betweenness centrality, Google is also central in structuring the global network while not geopolitically as relevant. Judging by their place and connections in the AI top conferences' network between 2018 and 2020 (supplemental Figure A.3), the spatial dimension of both companies' CIS is transnational yet simultaneously concentrated in a few cities. Google has the largest degree centrality, directly tied to 19 organizations from four clusters, including IBM, universities and public research organizations, all from the Global North. Meanwhile, Microsoft ranks 27th in degree centrality. This is indicative of their different strategies to build CIS. Both significantly encroach the global AI network, but interviewees confirmed that Google prioritized expanding the size of DeepMind—its AI heart—and establishing as many collaborations as possible to control the global network like a bulldozer. Instead, Microsoft meticulously chose the organizations that it wanted to have closer to maximize its global influence.

Facebook's evolution in the AI top conferences' network is also impressive. However, it is not as central. In the last period, it jumped to the 8th position in betweenness centrality, 5th in closeness centrality and ranks eleventh in frequency of AI papers' presentations. It is directly linked to organizations from the US, Canada, France and Israel.

Amazon joined the network in the second period because in the first one it ranked 326th. Although it progressively won centrality (from 105th by the second period to 48th by the third period in betweenness centrality), it remains far from the other Big Tech companies. In the last period, it was directly linked to six organizations from three clusters, all of them from the US except for the Max Planck (supplemental Figure A.3). It seems that Amazon is the least globalized of the four, though this will be challenged when looking at other indicators. Interviewees stressed that the delay in developing a significant presence at conferences and the relatively non-central place given to publications are not a sign of technological laggardness, but a top-down decision.

> The founder of Amazon never really wanted publications to be a big thing because science is only useful for him if it is for customer benefits. It was done to be a more attractive employer and to validate what we do (…). The number of good publications is the wrong metric for selling products. A good metric for Amazon would be how much of the customer retention and engagement is affected by science. (Amazon interview 1)

Publications, the interviewee continued explaining, are not the best output because they are not written in an easy jargon for engineers. Another interviewee also pointed out that Amazon is behind in terms of the culture of working towards external publications because its principles, such as 'learn and be curious', do not include sharing information publicly. Interviewees from other companies also stressed that Amazon was the least open among the four, while still recognizing its AI leadership.

Summing up, the four companies seem to have engaged differently with the global AI research network. While Microsoft and Google have a large capacity to steer the field beyond direct collaborations, with the former connecting the West and China, Facebook's place became predominant but is not as determinant. Interestingly, according to my interviewees, Amazon's less prominent place was a management decision and does not reflect a smaller CIS.

The content of Big Tech research presented at leading AI conferences

Figure A.4 in the supplemental Appendix presents a network that connects the most frequent topics in AI conference presentations with more frequently presenting organizations. Table 3 lists the multi-terms directly connected to each Big Tech company in supplemental Figure A.4. Besides their common focus on deep neural networks, there are differences.

Google's research includes mostly general AI multi-terms not linked to any specific functional application. Intelligence chatbots, like ChatGPT, are based on a 'generative model' and trained with 'reinforcement learning', which are terms directly connected to Google years before the release of ChatGPT. Amazon follows in number of direct ties to multi-terms with five of its eight terms denoting AI for language applications, including 'natural language processing systems'. Also, Amazon and Google are directly linked to the term transfer learning. This is a technique in which algorithms transfer what they have learned from one or several datasets to another problem with insufficient training data. This approach has been used for improving classifications in object recognition and text categorization databases using Amazon data (Zhuang et al., 2020).

According to two employees, the direct link to the term 'time series', used for long-term forecasting of national demand and other aggregated variables, speaks to how Amazon approaches new technologies. Frontier AI models are applied for item demand forecasting and price setting. Overall, the prevalent content of Amazon's AI conference presentations speaks of the company's approach to AI as

Table 3. Topics directly linked to Big Tech in Figure 3.

Google	Amazon	Microsoft	Meta
Data augmentation	Context information speech recognition	Data mining	Action recognition
Generative model	Knowledge graphs	Language model	Language model
Gradient methods	Natural language	Large amounts	Machine translation
Language model	Natural language processing systems	Machine translation	
Learning algorithms	Text classification	Natural language	
Machine learning	Time series	Neural machine translation	
Machine translation	Transfer learning	Reinforcement learning	
Monte carlo methods	Word embeddings		
Neural networks			
Reinforcement learning			
Sample complexity			
Transfer learning			

Source: Author's analysis based on Scopus.

> Agnostic and application focus. It doesn't matter to keep using an old method, it doesn't become a selection criterion for a project how new the proposed method is. (…) Just a simple random forest can be useful and other big companies will less likely fund it rather than a state-of-the-art algorithm. (Amazon interview 1)

Microsoft, like Google, is connected to the multi-term 'reinforcement learning'. Its other directly linked terms refer to common aspects of Big Tech research, in particular AI functional applications for language, like Amazon. So, we may say that Google and Microsoft are more focused on frontier foundational AI while Amazon develops more applied frontier AI together with other forecasting techniques. In comparison, Facebook only exhibits one exclusive multi-term, 'action recognition', which is a specific computer vision task used for recognizing and classifying human actions in videos or images, cementing the impression of AI applied to its platforms.

AI conferences' committees

AI top conferences exhibit a significant presence of industry representatives in their committees (22%), mostly driven by US and, to a lesser extent, Chinese Big Tech (57 committee members) (Table 4). Thus, the private sector has a strong foothold in defining what papers will be accepted or win prizes, which is a sign of power to shape the global knowledge network:

> Most of the people leading the conference boards are in Big Tech (…). They will say that they are independent and do it for the research but, are they? (…) Are they trying to steer the research and who gets the best paper? (…) I don't know if it is significantly skewed, but do the members of the industry leave when they need to decide on papers from these companies? Someone told me that he tried to raise the alarm of conflict of interest (…) but they still stayed in the decisions. (Google interview 1)

Google stands out with 22 members distributed in nine of the 14 committees. It has nine of the 39 committee members of NeurIPS, the main machine learning annual conference. In 2022, it had the largest number of accepted papers.[2] The other Big Tech companies have one or two committee members in this conference.

Table 4. Composition of leading AI Conferences' committees.

Name of AI conference	Number of members in committee	From industry	Big Tech (US and Chinese)	Amazon	Google	Microsoft	Facebook	Share of industry participation
Association for the Advancement of Artificial Intelligence (AAAI)	45	3	1	0	1	0	0	7%
The International Joint Conference on Artificial Intelligence (IJCAI)	12	0	0	0	0	0	0	0%
Conference on Neural Information Processing Systems (NeurIPS)	39	20	13	1	9	1	2	33%
International Conference on Machine Learning (ICML)	25	6	2	0	1	0	0	24%
Conference on Knowledge Discovery and Data Mining (KDD)	58	15	8	1	3	2	0	26%
Association for Computational Linguistics (ACL)	42	10	7	2	2	1	1	24%
Empirical Methods in Natural Language Processing (EMNLP)	44	9	7	0	2	2	1	20%
Conference on Computer Vision and Pattern Recognition (CVPR)	38	8	3	1	2	0	0	21%
European Conference on Computer Vision (ECCV)	34	11	6	3	0	0	3	32%
International Conference on Computer Vision (ICCV)	34	11	5	1	1	0	3	32%
North American Chapter of the Association for Computational Linguistics	9	2	2	0	1	0	0	22%
International ACM SIGIR Conference on Research and Development in Information Retrieval	41	5	3	2	0	1	0	12%
Uncertainty in AI	25	1 (2)	(1)	0	0	0	0	4%
European Conference on Artificial Intelligence	20	3	0	0	0	0	0	5%
Totals	466	103	57	11	22	7	10	22%
Number of conferences with private presence				7	9	5	5	

Source: Author's analysis from AI conferences websites.

Amazon follows in both the number of committees with at least one representative and the total number of committee members. These range from broad to more specific AI conferences, including the Conference on Computer Vision and Pattern Recognition and the Association for Computational Linguistics. The latter's committee is chaired by Dr. Yang Liu, affiliated to the University of Texas and Amazon.

Facebook participates in only five committees, with more members in those on computer vision, in line with its AI presentations (Table 3). Like Facebook, Microsoft integrates only five committees and with seven members. Unlike the other companies, it does not participate in computer vision conferences' committees. Instead, on top of having a representative in NeurIPS and in another broad AI conference, it participates in committees of conferences on AI applied to language, which is certainly more aligned with its—back then already existing—relation with OpenAI (see section 'AI appropriation mechanisms') and with the most frequent multi-terms of its AI conferences' presentations (Table 3).

AI appropriation mechanisms

Big Tech companies' capacity to capture—and therefore eventually benefit from—AI is explored here by analysing their AI-related acquisitions and top investments, AI patents and where they stand in relation to secrecy.

Microsoft's AI CIS not simply co-evolves with China's NIS, but to some degree overlaps and subordinates it. This displacement is also observed for Microsoft and Google's CIS and core Western countries' NIS because both companies widely co-create knowledge modules with these economies' leading universities and public research organizations while retaining most of the associated intellectual rents by recombining those modules.

Acquiring and investing in AI companies provide privileged access to technologies and a skilled workforce. According to WIPO (2019), Google ranked first in AI-related acquisitions (18 firms) between 2009 and May 2018. Microsoft was third, Amazon fifth and Facebook eight (nine, six and five acquisitions respectively). Investments in AI firms (Table 5) further expand Big Tech CIS. The relations between AI start-ups and their investors inform about a portion of AI's global innovation network, thus complementing the global knowledge network analysed in Section 'The co-production of AI'. AI knowledge and innovation networks are interconnected not only by the fact that innovation in AI is based on scientific advancements, but also because Big Tech companies, as we will see, actually control the whole process that goes from data harvesting and inception of the model until its application. In this process, AI start-ups usually develop specific models partly based on technologies offered by Big Tech on their clouds or modules within larger developments.

Google continued leading in AI-related acquisitions, which are also the most diversified, including machine learning applied to images, language and analytics (Table 5). By 2021, Google was also among the top five investors of many AI start-ups coming from 14 countries. Only one was Chinese. However, it was widely outpaced in the number of investments by Microsoft. The latter's corporate venture capital included firms from 13 countries, 18 were Chinese. Microsoft acquired less, but privileged sectors where it did not have a strong business (Mobile and iOS) and strengthened its role as a provider of tools and platforms for developers. This is reflected by the acquisition of companies working on 'Developer Tools' and 'Developer Platforms'.

The stories of DeepMind and OpenAI give testament of different approaches towards organizing AI innovation. Google acquired the former in 2014. In 2019, Microsoft made its first investment in OpenAI[3] granting Microsoft an exclusive license to GPT-3, back then the most advanced language model (Benaich & Hogarth, 2020). To train AI models, OpenAI needed previously never seen super-computers, and Microsoft's cloud provided them. The latter pushed OpenAI to move from research to applications.[4] ChatGPT results from this shift. Since its release, Microsoft committed an additional USD 10 billion in OpenAI.[5] According to my interviewees, investing instead of acquiring was a strategic move to assure that OpenAI applications were purchased even by Microsoft rivals.

> 'We have 49% of this company and the agreement has certain stipulations, privileged access to developments. OpenAI, for example, also works with Salesforce, which is one of our biggest competitors, but that is not a problem because if Salesforce uses OpenAI we still win because we earn revenue there. (…) Satya[6] saw it coming and said, "let's do partnership with Open AI" and that mindset about how we can grow, be better all the time, brought us here' (Microsoft interview 1).

In comparison, Amazon acquired and was investing less in AI start-ups, which were also geographically more concentrated (seven countries including a firm from Egypt and one from India). Its acquired companies operated in very broad and multiple fields since acquisitions came from 21 industries, with only three industries represented in more than one acquisition (Table 5). This reinforces the impression of Amazon diversifying the most within AI applications. Instead of corporate venture capital investments, Amazon prioritizes free credits to purchase AWS cloud

Table 5. Big Tech AI acquisitions and investments in AI start-ups.

	Microsoft	Amazon	Google	Meta
Industries appearing in more than one acquisition	Machine Learning Software Mobile Developer Tools Natural Language Processing Information Technology iOS Developer Platform	Machine Learning Developer APIs Apps	Machine Learning Analytics Software Computer Vision Image Recognition Natural Language Processing Big Data Internet	Machine Learning Software Computer Mobile Computer Vision Image Recognition Developer APIs Photography
Total number of industries	21	21	35	29
Total AI acquisitions since 2012	10	5	17	11
Cloud related acquisitions	1	1	0	2
Number of AI start-ups for which top 5 investors in 2021 (Meta info for 2023)	80	19	35	0

Source: Author's analysis from Crunchbase.

services, a practice that Microsoft and Google have emulated. Credits represent an extremely low additional cost and are an effective mechanism for inducing organizations, particularly start-ups, to build their solutions inside the cloud (Rikap, 2023b). This generates what interviewees described as high stickiness, in other words, a lock-in effect. Along the lines of captive GVCs, Amazon not only captures value from selling again and again the same lines of code, but also, since AWS is a marketplace, it sets the terms in which each service is sold, from a 30% fee charged to third parties to services' prices.[7] All these services are examples of knowledge modules with AWS operating as their recombinator.

Since the release of ChatGPT, both Google and Amazon joined Microsoft by making sizeable investments in AI start-ups. The three invested two-thirds of the USD 27 billion raised by AI start-ups in 2023.[8] This points to an expansion of their control over the AI global innovation network by expanding their CIS. This time, Google leads among the three in number of funded AI companies.

Finally, and in line with the previous section's findings, Facebook acquired firms working on image and visual AI applications, which are more related to its relatively narrower business. Relatedly, a major decentralization of Facebook's AI research took place by mid-2022 creating AI Innovation Centers associated with each business unit. Facebook AI Research (FAIR) team became integrated into the company's Reality Labs Research.[9] Both this restructuring and its AI acquisitions seem to be further targeting AI to applications for Facebook's businesses.

Complementarities between AI patents and secrecy

In 2019, WIPO (2019) published the ranking of the top 30 patent applicants between 2013 and 2016, led by IBM (8290) and Microsoft (5930). Google ranked tenth and Amazon and Facebook were not listed. Using WIPO's (2019) definition of AI patents, I analysed AI granted patents in 2022 (Table 6). Large companies sometimes use patents to create artificial barriers for rivals and usually do not profit from their whole portfolio. Since these practices are shared among top patenting organizations in high-tech (Hall et al., 2013), the indicator remains relevant for comparing knowledge management routines as long as it is not assumed that patents imply innovation rents.

Compared to WIPO's (2019) findings, Microsoft seems less focused on AI patents judging by its place in the ranking (22nd) and the distance in number of granted patents with those at the top. This is in line with its turn to promote open source, a global network in itself that intersects with the AI global innovation network. Besides reputational gains, putting in open-source pieces of larger projects whose key parts are kept secret does not risk losing the edge while benefiting from developers' free work (Rikap & Lundvall, 2020). Future research shall use the cross-network approach to delve into the open-source community in connection to the AI knowledge and innovation networks studied in this paper.

Regarding the content of Microsoft's patent portfolio, besides generic multi-terms referring to machine learning, shared by the four Big Tech companies, the 30 most frequent multi-terms in Microsoft AI patents' titles and abstracts refer to virtual assistants and healthcare (Table A1 in supplemental appendix). It was already observed that Big Tech were particularly interested in the latter (Rikap, 2022). Their expansion into other sectors is not surprising given AI ubiquity. We see here signs of Microsoft's CIS overlapping with the healthcare and pharmaceutical global innovation network, thus, also potentially with Big Pharmaceuticals' CIS. This stresses avenues of conflict among leading corporations in global knowledge and production networks that require further analysis.

Another novelty is that Amazon integrates the top 30 ranking, with a similar number of granted patents than Microsoft and an AI portfolio that looks like the most diverse of the four in AI functional applications, including image, audio, video and text. Like in the AI conferences' presentations, the multi-term 'time series' pops up (Table A1 in supplemental appendix).

Facebook remains out of the ranking (50th position). An interviewee explained that it lacks a clear patenting culture. The patenting process is not as formalized as it was during the interviewee's previous experience in Microsoft. Facebook's patents are connected to its platforms, with a focus on image and video and multi-terms that can be easily associated with the Metaverse, such as 'artificial reality environment'. Unlike the other Big Tech companies, terms referring to the cloud, natural language or AI for text are absent.

Google's patent portfolio includes inventions dealing with computer storage (possibly related to the cloud) and autonomous vehicles (Table A.1 in supplemental appendix). Among the four, it seems to be the most interested in patenting AI. It jumped from the tenth to the third position. Interviewees from Google and Amazon agreed that scientific publications usually have an associated patent filed in advance.

Table 6. Top 30 AI patent grantees in 2022.

Organization	AI granted patents in 2022
Toyota	673
Samsung	538
Alphabet	452
Baidu	443
Honda Motor Co. Ltd.	367
IBM	295
Hyundai	280
Tencent	278
LG	254
Sensetime	211
Renault	206
Siemens AG	203
Sony Corporation	202
Ford	199
Bosch	175
Intel Corporation	172
University of Electronic Science and Technology of China	170
Huawei	168
HITACHI	164
General Motors LLC	160
Zhejiang University	158
Microsoft	149
NEC Corporation	147
Amazon	140
Mitsubishi	138
State Grid Corporation of China	137
Chinese Academy of Sciences	137
Canon Inc.	136
Tsinghua University	131
Fujifilm	122

Source. Author's analysis based on data extracted from Derwent Innovation.

A Google interviewee stated that this was mostly a defensive move to keep others from filing patents with published knowledge and then charging Google from using it. The coupling of AI publications and patents may explain why Amazon is now among the top 30 patent grantees since it is also publishing more (see section 'Big Tech positioning in the global AI research network').

Overall, patents are not Big Tech's most relevant appropriation mechanism of frontier AI. Interviewees agreed that secrecy and the speed of innovation are crucial for leading the field. The edge is kept secret, whereas complementary or not so cutting-edge developments are frequently published, put in open source and/or patented. Often, publications refer to achieved results without disclosing the code, which was observed as the most common practice in the field (Benaich & Hogarth, 2020). Big data are another paradigmatic example of secretly kept intangibles. A Google interviewee referred to the limitations of publishing results using internal big data due to compliance and privacy issues. Massive experiments, such as large language models, require massive scale data that are only available internally. While who knows what is decided by management, the actual development of each piece of this frontier technology is in the hands of the most expert AI scientists and engineers both coming from the company and hired from academia, which generally do not know what other internal teams are doing.

AI talent: the bridge between co-production and appropriation

AI scientists and engineers working for Big Tech can be seen as a bridge between AI co-production and appropriation, as they knit together the global AI knowledge and innovation network. As stated by an Amazon interviewee, having the most talented people and wanting them to stay is what matters the most to lead in AI. Big Tech statements and industry reports overviewed by Heston and Zwetsloot (2020) also mentioned access to talent as the main reason for setting up AI R&D laboratories outside the US. According to a BOSCH AI scientist, Big Tech companies are the AI forerunners precisely because of their employees, preventing rivals from accessing talent. Likewise, an Alibaba interviewee pointed out that most of the international talent works for Amazon, Microsoft and Google.

AI talent is drained from academia. Different interviewees mentioned that Big Tech uses AI conferences to identify and capture talent. By reconstructing the affiliation history of over 60,000 AI researchers, Jurowetzki et al. (2021) found that 8% had transitioned from academia to industry, with a sharp increase in the last decade. Similarly, Gofman and Jin (2022) found high and exponentially growing levels of brain drain of AI professors from US and Canadian universities into industry with Google, Amazon and Microsoft hiring the largest number of AI faculty. Facebook shared the 4th position with Uber and NVIDIA.

Sometimes, leading scholars are hired part-time, keeping their academic positions. In my sample of AI conference papers, I found around 100 double affiliations between a Big Tech and a university or public research organization. The list of institutions employing scholars with such double affiliations in my sample is presented in Table 7.

In line with their higher presence in AI conferences, Google and Microsoft have developed more of these collaborations. Microsoft's double affiliations are in ten countries. They are less concentrated in the US, mainly due to double affiliations with eight Chinese institutions. Meanwhile, 20 of the 36 organizations with scholars also based at Google are US universities. Nonetheless, Google has researchers affiliated with organizations in eight other countries, which is three times more than Amazon. When inquired about the rationale for these double affiliations, an interviewee referred to Google's small office at the University of Alberta, one of the best institutions in reinforcement learning, and added that 'a scholar from there is one of the fathers of the topic and he is at least part time in DeepMind' (Google interviewee 1).

Different interviewees mentioned that researchers with double affiliations typically push Big Tech companies to publish and present at AI conferences and often propose collaborations with other universities. While Google, Microsoft and Meta embrace these practices, presenting at conferences is an area of struggle at Amazon, unsurprisingly the least engaged in double affiliations (Table 7). Amazon never shares confidential information when presenting to externals. Interviewees agreed that it privileges internal presentations where senior academics with double affiliations or hired as short-term consultants present their university research or, after signing strict non-disclosure agreements, advise full-time employees.

> We also have meetings where we present papers and get feedback specially on the science part. Amazon scholars give advice on methodologies or suggest papers we should rely on (…). And obviously in external conferences you pass by a legal team (to assure you are not sharing confidential information) that can take a couple of months. It is a bit unpredictable and not that smooth, how many follow up questions they will have and how many things you will need to remove may require more work and these are complicating factors. (Amazon interview 2)

In line with my previous findings for Amazon, this can be interpreted as part of a strategy to privilege secrecy while maximizing inflows of knowledge and information.

Four strategies to dominate an AI corporate innovation system leading to different spaces for weaponizing the global AI network

Table 8 summarizes my findings and proposes four different CIS strategies to co-produce and appropriate knowledge. They can be summarized as: 'frenemy' for Microsoft, 'university' for Google, 'secrecy' for Amazon and 'application-centred' for Facebook.

'Frenemy' describes Microsoft's frontier AI strategy; a CIS even opened to rivals but driven by Microsoft. By privileging investing in AI start-ups, it enables formally separated companies to sell services to competitors, with the paradigmatic case of OpenAI. In accordance with this relation, Microsoft's development of foundational AI is more inclined towards language applications.

Microsoft's lower levels of AI patenting vis-à-vis publications and its decision to open-source non-sensitive developments further explain its AI CIS strategy. It expands its chances to combine external with internal knowledge, as it happened in the past with a Linux Kernel. This attracts developers from other organizations, even rivals, to use its solutions, further expanding Microsoft's CIS. Openness does not seem to endanger appropriation because some pieces are always kept secret and given the speed of AI innovation.

Table 7. Institutions with AI scientists also working for Big Tech.

Google	Microsoft	Facebook	Amazon
ASIT Japan	Aalto University	Georgia Tech	Caltech
Australian National University	Alan Turing Institute	Harvard	Carnegie Mellon University
Bar Ilan University	Carnegie Mellon University	ICREA	Heidelberg University
Brown University	China Sun Yat-Sen University	INRIA	Imperial College
Caltech	Chinese Academy of Sciences	Johns Hopkins University	Ohio State University
Carnegie Mellon University	ETH Zurich	McGill University	Rutgers University
CMU	Harbin Institute of Technology	New York University	University College London
Columbia University	Hebrew University	Sorbonne Universite	University of California
Cornell University	Hefei University of Technology Beijing	Stanford University	University of Edinburgh
ETH Zurich	Hong Kong Polytechnic University	Tel Aviv University	University of Southern California
Harvard	Indian Institute of Science	Texas A&M University	University of Texas
Hebrew University	MILA	Universite Le Mans	University of Washington
INRIA	MIT	University College London	University of Wisconsin-Madison
INSEE	Polytechnique Montreal	University of California	
Mila	Princeton University	University of Michigan	
Mines ParisTech	Shanghai Jiao Tong Unviersity	University of Texas	
MIT	South China University of Technology	University of Washington	
New York University	Stanford University		
Princeton University	Technion-Israel Institute of Technology		
Rutgers University	Tel Aviv University		
Stanford University	Tsinghua University		
Technion-Israel Institute of Technology	Universite de Montreal		
Tel Aviv University	University College London		
TTS Research	University of California		
University College London	University of Cambridge		
University of Alberta	University of Illinois		
University of California	University of Maryland		
University of Colorado	University of Massachusetts		
University of Edinburgh	University of Münster		
University of Michigan	University of Science and Technology of China		
University of Minnesota	University of Trento		
University of Oxford	University of Washington		
University of Texas	Weizmann Institute		
University of Warsaw			
University of Washington			
University of Southern California			

Source: Author's analysis based on the dataset of top 14 AI Conference presentations between 2012 and 2020.

One of my interviewees worked closely in the technical team that ran the relation with OpenAI and confirmed that, albeit with frictions regarding information sharing, the two organizations met once a week, sharing from large datasets to the progress of model training and technical stacks. Anyway, theirs is not a relation among equals. While Microsoft's cloud offers other large language models, OpenAI can only run on Microsoft's cloud. The idea of frenemies was proposed by another Microsoft interviewee when I asked about the public cloud, but I found that it also describes the company's AI CIS as a whole.

> There is the question of the frenemies; and this happens a lot at Microsoft. It is a cultural shift that was brought by Satya. When we moved from on premise to cloud, we had to adapt how we thought about partnerships. (Microsoft interview 1)

Also, Microsoft has successfully integrated into its CIS the least expected actors from around the world, from Chinese organizations to rival Western firms. Microsoft profits from knowledge co-produced with Chinese institutions and underpinned by the Chinese state's digital infrastructure and promotion of the sector. Results resonate with Lundvall and Rikap's (2022) analysis of the co-evolution between CIN and NIS in China. However, they were looking at Chinese Big Tech and their potential contribution and threat to the Chinese state goals. Microsoft's frenemy strategy could hijack the latter's aim to make China the AI leader by 2030 as China's NIS may end up disproportionately favouring a US giant.

Microsoft's AI CIS not simply co-evolves with China's NIS but to some degree overlaps and subordinates it. This displacement is also observed for Microsoft and Google's CIS and core Western countries' NIS because both companies widely co-create knowledge modules with these economies' leading universities and public research organizations while retaining most of the associated intellectual rents by recombining those modules.

At the same time, Microsoft's strong foothold in China can spark US state concerns. Microsoft research in China and with Chinese organizations enhances the country's AI capabilities even if Microsoft captures most of the associated profits. Among its co-authors, Microsoft conducted research with the National University of Defense Technology, an institution controlled by the Central Military Commission of the People's Republic of China, for AI research (Rikap, 2023a).

Google excels in every indicator, building a CIS with top academic institutions mostly from developed countries and AI start-ups coming both from core and peripheral countries. Overall, its CIS is the most internationalized and, given that it ranks first in every network centrality indicator, its CIS overlaps the most with the AI global knowledge network, yet with the caveat of remaining mostly detached from China.

Although Google manages internal and external knowledge flows privileging secrecy for edge developments just like the other giants, its AI strategy resembles a leading university. It has the largest presence in AI conferences, more employees with double affiliations and gives particular attention to AI patenting, just like leading universities these days pushing scholars to patent. The content of its AI presentations points to favouring more foundational AI, thus closer to the type of knowledge traditionally associated with universities. Google also has internal university-like features partly because of double affiliations.

Table 9. Four strategies to build a leading AI CIS.

	Microsoft	Google	Amazon	Facebook
AI CIS strategy	Frenemies	University	Secrecy	Application-cantered
AI Conference Presentations	+++	+++	+	+
Participation in AI conference committees	+	+++	++	++
Content of AI research	General topics with a focus on AI functional applications for language. Includes reinforcement learning	Maximum diversity with general and specific AI, including reinforcement learning	Highly diversified but skewed towards AI for language. Specific focus on time series and transfer learning	Very few direct links. Among them, 'action recognition' is a specific computer vision task
Acquisitions	++	+++	+	++
Top investor	+++	++	+	–
AI patents (count)	+ (less important than in the past)	+++	+	–
AI patents (content)	Besides terms referring to more general machine learning, focus on virtual assistants and healthcare	Besides terms referring to more general machine learning, computer storage (possibly related to the cloud) and autonomous vehicles	The most diverse of the four in terms of AI functional applications	Connected to its existing platforms, with multi-terms that can be associated with the Metaverse
Double affiliations	+++ (less concentrated in the US - importance of China)	+++ (highly concentrated in the US)	+	+
AI CIS space	Central and glocal positionining, geopolitically strategic: connecting China with the West	Central and widely glocalized but mainly outside Asia (China)	Core: limited to the leading AI organizations among those already doing frontier research, limited internationalization, concentrated in a few US hubs	Narrow but internationalized: it is the smallest of the four, driven by Facebook's narrower focus on AI connected to its applications/ platforms
AI CIS scope	General, including research on generative AI and reinforcement learning. In terms of application fields, exhibits more focus than Amazon	General, including research on generative AI and reinforcement learning. In terms of application fields, exhibits more focus than Amazon	The most diverse in functional applications but without explicit indications of research on generative models or reinforced learning. Frontier AI is developed but only applied when there is a clear economic benefit	Focus on developing AI for its applications/ platforms

Source: Author's analysis.

> The management style of my team is super academic, my manager is at the University of *XXX* half of the time, he is the big leader of the team and sees us as an army of postdocs. (Google interview 1. The name of the university was removed to protect the anonymity of the interviewee)

For Google interviewees, ChatGPT was perceived as the crystallization of this being the wrong strategy. They all agreed that Google changed its focus to make AI more application and business oriented. This materialized in February 2023 when it imitated Microsoft's strategy and decided to invest heavily in Anthropic, an AI start-up founded by former OpenAI employees.[10] By April 2023, DeepMind was merged with Google Brain, putting under the same organizational structure Google's fundamental and applied AI.

From the lens of Farrell and Newman (2019), it could be argued that Google and Microsoft's CIS are positioned in the AI global knowledge and innovation network in places that could be weaponized as chokepoints and panopticons. Google's CIS offers a more extensive panopticon considering that it has both more direct ties in the global knowledge network (supplemental Figure A.3) and double affiliations. However, this panopticon excludes China. Google is also the Big Tech with the largest number of members in conferences' committees, which could also play a chokepoint role rejecting, for instance, papers from Chinese organizations, dictating to what degree each organization and country's research will feature in the leading AI global network. Amazon also developed a relatively prominent position in AI conferences' committees. Having such a panoptic view provides access to the latest AI and a space from which they can steer the field's agenda.

Although Microsoft has fewer direct ties in the frontier AI research network, it is positioned to exercise a global chokepoint between China and the rest of the world. This chokepoint is partly knit by scholars with Chinese affiliations simultaneously working at Microsoft Research. This positioning also grants Microsoft more information about the whole network, thus a more comprehensive panopticon view, even if more indirect or relying more on the mediation of (fewer) direct ties when compared to Google. Its oversight is extended to the AI global innovation network through investments in AI start-ups, a strategy that, as I mentioned before, is these days also prioritized by Google and Amazon.

Summing up, just like US Big Tech control of digital infrastructure (Gjesvik, 2022), given in particular Microsoft and Google's centrality in the overall network, the US state would need to bargain with them to exercise weaponizing interdependence. If successful, it could use these giants' chokepoints and panopticon positions to coerce other states and cut adversaries—China—off from the network.

The fact that Amazon does not enjoy a similar hub position in the global network is not at the expense of its dominance of a frontier AI CIS even if it renders its CIS less prone to offer the US state a chance to negotiate weaponization. Amazon's CIS is highly connected to its businesses, thus, greatly centred around secrecy and privileging knowledge absorption from US universities yet internationalized when it comes to controlling AI start-ups. Amazon's AI CIS is especially characterized by non-disclosure agreements that limit knowledge outflows. A Google interviewee that had worked at Amazon acknowledged a difference in terms of secrecy and added that Amazon had a clearer business mindset. The latter was more oriented to deliverables measured in money and gave space to theoretical work only if the researcher proves that it can make money. Amazon develops its major AI projects in a sealed environment with mostly US-based collaborators that cannot disclose what is developed. This probably makes its position at the AI frontier not so apparent.

Amazon's AI research is the most diverse in terms of functional applications, which makes sense given its business diversification and that it leads the cloud market where AI applications are sold as services (Jacobides et al., 2021; Kenney et al., 2021). Cloud credits as a form of venture capital further reinforces this lead. Even more importantly, it is a specific way to finance AI start-ups that will eventually integrate their AI CIS since the cloud is the main AI adoption channel. Once their solutions are built on AWS, it is too costly to migrate. Cloud credits are similar to GVC leaders' strategy for developing suppliers. For instance, it is widely known that Apple financed part of Foxconn's acquisition of equipment to manufacture iPhones. Likewise, Apple dedicated specific investments to develop new premium iPhone assemblers, like Luxshare Precision.[11] Amazon seems to be at the forefront in developing diverse AI value chains following the captive GVC governance mode.

The cloud is also a global network. Judging by market shares, AWS can be considered the central hub of the largest cloud network. Big Tech clouds could also be weaponized. However, in this case, decoupling has already happened, and Chinese organizations prominently use Alibaba Cloud or other Chinese Big Tech clouds. In all, for advancing the US state aim to prevent China's catching up, weaponizing Big Tech clouds is certainly not a right move, unlike the weaponization of the AI global knowledge and innovation network as described above.

Finally, Facebook tried to both control the AI global knowledge and innovation network and focus on business applications. Its AI CIS exhibits internationalization and has a strong foothold in the overall field. However, it is overshadowed by Microsoft and Google's omniscient positions. Also, since its businesses are a few platforms with similar technological requirements, its AI CIS is narrower when compared to Amazon's. My interviewees identified Facebook's technologies as too specific to its internal infrastructure. The Metaverse could be interpreted as an attempt to diversify not only Facebook's businesses but also its AI CIS, towards virtual and augmented reality. However, it remains too close to Facebook's existing core technologies when compared to the other giants. And, as two interviewees pointed out, the Metaverse is a quite niche business. The US state could weaponize Facebook's CIS, but the effect in the AI global network will not be as neat as if it weaponizes those of Google or Microsoft.

Seen together, Big Tech's CIS and not the US or other core countries' NIS are at the heart of AI's global knowledge and innovation network. US Big Tech companies certainly rely on the US's strong NIS, judging by the importance of US universities in terms of co-authorships and double affiliations and the nationality of their funded AI start-ups. However, this does not automatically grant the US state the chance to weaponize AI networks since Big Tech companies build their CIS internationally and can redirect R&D efforts accordingly. Needless to say that universities are—at least in principle—autonomous, and there are no policies in place preventing, for instance, double affiliations with Big Tech.

Another common insight is that albeit Big Tech's tendency to diversify and enter multiple sectors (Rikap, 2022), results point to their AI CIS as ultimately linked to their cores. The fact that Amazon, Microsoft and Google are increasingly centred on their clouds, with Google also sustaining an interest in managing global information, contribute to explaining their broad attempt to control AI globally, either focusing on AI foundations (Google and Microsoft) or directly starting from business applications (Amazon). Meanwhile, Facebook's limited business correlates with the narrower scope of its AI CIS. While the specific differences among Big Tech shall not be taken for granted, since AI is a fast-moving field in which the interplay among leading actors—including core states—and with all the other organizations may lead each Big Tech company to revise its strategy, these giants' central position in the AI global knowledge and innovation network is unquestionable, and there are no signs of this changing in the near future.

Final remarks

This article has provided a deeper understanding of the diverse mechanisms mobilized by intellectual monopolies to control and shape knowledge production and appropriation. This was accomplished by comparing Big Tech ways of building their CIS to control the frontier AI global knowledge and innovation network. Enjoying a hub position in AI's global network provides panopticon insights that can be seen as knowledge modules that Big Tech companies, particularly Microsoft and Google, recombine and monetize.

This paper also suggested a way to conceptualize the entanglements between CIS, NIS and global innovation networks. I proposed to think of the latter as a network composed of CIS and NIS and these as intertwined spheres of knowledge and innovation co-production. The US state's NIS has previously occupied the main hub position in global knowledge and innovation networks, particularly but not exclusively through its innovation hubs and under the leadership of what Weiss (2014) dubbed the US national security state. This balance of power has been disrupted not only by the growing relevance of China's NIS, but also, as this paper shows for the case of AI, by the influence of intellectual monopolies controlling *glocal* CIS that can potentially control global innovation networks, as in the case of Big Tech. They steer and profit from AI's global knowledge and innovation network.

One could argue that, as long as there is a gain to be made by local actors, particularly if accomplishing state goals, there will be space for accepting Big Tech's—or other intellectual monopolies'—strong foothold in an economy's NIS even at the expense of unequal relations. Concretely, if Microsoft's research in China with local organizations contributes to developing China's NIS, then the asymmetric profiting of results could be seen as a necessary hardship. However, this would expand tensions with the US state that may also expect to use Big Tech's CIS to weaponize the AI global knowledge and innovation network. For that end, it would need to bargain, especially with Microsoft and Google. In fact, the US state decision to regulate the uses of AI but not its production, which directly favours US Big Tech and is what they had advocated for, can be seen as a state-corporate diplomatic move along the lines described by Strange (1992). As the US vice-president Kamala Harris stated when the US Executive AI Order 'Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence' was introduced:

> Let us be clear: when it comes to AI, America is a global leader. It is American companies that lead the world in AI innovation. It is America that can catalyse global action and build global consensus in a way that no other country can.

Getting the chance to politically weaponize the global AI network would strengthen the US state power and influence amid global turbulence. Speaking of turbulence, the Chinese state does not seem to have the same opportunity to weaponize this network. Chinese Big Tech and other Chinese institutions partake in the AI global knowledge network (see supplementa Figure A.3) but they do not enjoy a hub position and are mainly tied to Chinese universities. Thus, the Chinese state cannot borrow from them a weaponized network power.

This overall scenario raises several concerns given AI implications for every dimension of life, from war and sovereignty, to economic concentration and human rights, that call for more policy and agency. Moreover, corporate venture capital calls for investigations on ownership structures. Corporate law should be rediscussed, and antitrust offices should scrutinize major investments and preferential agreements between giants and other companies.

More generally, the International Labour Organization could be the arena for discussing policies and regulating the global AI (skilled) labour market. Regulations should prevent publicly funded academics from signing non-disclosure agreements. Also, academic institutions must access the latest digital infrastructure, which requires public investments in truly public clouds. A survey published by Nature (2021) found that scientists in industry are more satisfied and better remunerated than those in academia. This must be revised if the aim is to democratically redefine the purpose of AI and more evenly distribute its gains. On a more specific level, public funding for AI conferences could include clauses that limit—or forbid—industry researchers in their committees. Their participation in decision making spaces risks turning a public academic convening into a space driven by for-profit motives.

Finally, much of the policy debate revolves around the agency of generic AI models. This narrow focus risks overlooking the role of AI agents, i.e., Big Tech. It urges us to discuss in democratic spaces whether we want such AI models and, if yes, what type of AI should be developed, by whom and for what. We need technologies that empower humans to solve global challenges, not machines that control labour, foster inequalities and worsen the critical times we live in.

Notes

1. More information on Cortext and access to the platform are available here: https://www.cortext.net/projects/cortext-manager/.
2. See https://github.com/sanagno/neurips_2022_statistics Affiliations appear as Google, Google Research, Google Brain and DeepMind.
3. https://thenextweb.com/artificial-intelligence/2019/07/23/openai-microsoft-azure-ai/.
4. https://news.microsoft.com/source/features/ai/how-microsofts-bet-on-azure-unlocked-an-ai-revolution/?ocid=eml_pg394041_gdc_comm_mw&mkt_tok=MTU3LUdRRS0zODIAAAGKwmbrwlHO5mYvwKCSRwk2rcEO-79_q_J-nzO8jDiYkLCqxQDI3WXezvp1v-R1XS1chmfOLULFh7NnuL1mIejIT2WWNnZHWf1mc2zzg39WJ2aT7z8ppJQFXEi5
5. https://blogs.microsoft.com/blog/2023/01/23/microsoftandopenaiextendpartnership/.
6. Refers to Microsoft's CEO, Satya Nadella.
7. https://docs.aws.amazon.com/marketplace/latest/userguide/pricing.html and https://docs.aws.amazon.com/marketplace/latest/userguide/saas-contracts.html.
8. https://www.ft.com/content/c6b47d24-b435-4f41-b197-2d826cce9532.

9. https://ai.facebook.com/blog/building-with-ai-across-all-of-meta/.
10. https://www.theverge.com/2023/3/14/23640056/anthropic-ai-chatbot-claude-google-launch.
11. Retrieved from https://www.ft.com/content/975f0979-5d09-4e36-944d-44901477d762.

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