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Same end by different means: Google, Amazon, Microsoft and Facebook's strategies to dominate artificial intelligence.

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Abstract

I analyse US Big Tech strategies to dominate frontier artificial intelligence (AI) by quantitatively and qualitatively comparing how they manage knowledge in their respective AI corporate innovation system (CIS). I propose "frenemies" 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 to profit from AI. Facebook, with the narrowest AI CIS, exhibits an "application-centred" strategy.

Keywords: Big Tech; Artificial Intelligence; knowledge management; corporate innovation systems; Digital Capitalism.

1. Introduction

Soon after OpenAI released ChatGPT, it became integrated into several Microsoft products. Google hastily reacted by launching its own large language model "Bard", which made a factual mistake in its first demo. By February 2023, Meta presented its own alternative, LLaMA (Large Language Model Meta AI).[1] Amazon entered the race expanding its support to Hugging Face -a start-up whose artificial intelligence (AI) chatbot is offered as a service on Amazon Web Services- and offering Amazon Bedrock, a cloud service for building and scaling generative AI applications.[2]

The generative AI race illustrates Big Tech technological convergence (Jacobides et al., 2021; Kenney & Zysman, 2020; Rikap & Lundvall, 2021). AI, notably machine learning and big data technologies that underpin generative AI models, have been conceived by many as a potential general-purpose technology and even a general-purpose method of invention (Bianchini et al., 2022; Cockburn et al., 2018; Goldfarb et al., 2023; Rikap & Lundvall, 2021).

This paper compares Alphabet (hereon Google), Amazon, Microsoft and Meta (hereon Facebook) strategies to dominate this cutting-edge technology by quantitatively and qualitatively examining an array of practices in their respective AI corporate innovation systems (CISs). To that end, I combine the literature on knowledge management practices (Coombs & Hull, 1998) in open innovation environments (see for instance Chesbrough & Bogers, 2014; Natalicchio et al., 2017) with the CISs concept. CISs were defined as innovation systems constituted by several organizations but controlled by a dominant firm, thus, distinguishing the co-production of knowledge and innovation from how the dominant firm appropriates successful outcomes (Lundvall & Rikap, 2022).

[1] https://gizmodo.com/facebook-chatgpt-google-ai-chatbot-google-bard-1850155514

[2] https://www.latimes.com/business/story/2023-02-21/amazons-aws-hugging-face-ai-deals-chatgpt and https://www.aboutamazon.com/news/aws/aws-amazon-bedrock-generative-ai-service?utm_source=amazonnewsletter&utm_medium=email&utm_campaign=041523&utm_term=generativeai

Hence, I analysed both Big Tech co-production of AI with other organizations and their capacity to appropriate resulting knowledge. I also examined AI talent indicators seen as a bridge between the co-production and appropriation of AI. Results were validated with 16 semi-structured in-depth interviews that also enabled me to inquire about the AI strategies of each company and their different AI management practices. I interviewed senior managers, AI scientists and AI engineers working for the chosen Big Tech and other dominant firms developing AI.

My findings point to four different strategies to dominate frontier AI by managing knowledge in CISs. I describe Microsoft's as a "frenemies" strategy because it has successfully integrated into its AI CIS a great deal of Chinese organizations and even rival companies. In comparison, Google's strategy seems to emulate a leading university that privileges the development of fundamental knowledge and whose appropriation mechanisms are not so clearly translating into business advantages. At the other end in terms of openness, Amazon has privileged a "secrecy" strategy in which AI development is put at the service of its multiple and expanding businesses. Likewise, Facebook mostly develops AI connected to its businesses, but -unlike Amazon's- these are mainly a few platforms and AI is developed more openly, similar to Google and Microsoft yet with a narrower capacity to influence other organizations. Thus, I characterize Facebook's AI strategy as "application-centred".

The rest of this paper is organized as follows. Section 2 mobilizes the concept of knowledge management practices to identify the concrete ways in which a dominant firm organizes and captures knowledge from its CIS. The section also shows that Big Tech AI practices have been studied without considering simultaneously knowledge co-production and appropriation and without distinguishing among Big Tech. This paper's methodology and results are presented in sections 3 and 4, respectively. Section 5 comparatively proposes a specific AI strategy for each Big Tech and section 6 concludes.

2. Managing AI practices in Big Tech corporate innovation systems

2.1. Knowledge management practices within corporate innovation systems

Knowledge management is a polysemic term (for a list of definitions see Girard & Girard, 2015) that broadly refers to how firms' strategies (should) evidence that knowledge is a key resource to be managed. According to Prusak (2001), what the firm knows, who knows what and what the firm should know became managers' unavoidable questions in the 1990s. For Leonard (1997), knowledge management entailed creating a virtuous system of generation, integration and leverage of knowledge. By managing knowledge in such ways, managers could steer knowledge and information flows with an economic profits' goal (Leonard, 1997).

Integrating this approach with insights from the evolutionary theory, Coombs and Hull (1998) studied firms' practices to manage knowledge, defined as routines for generating, processing, transferring and using knowledge. As routines in general (Nelson & Winter, 1982), Coombs and Hull (1998) argued that knowledge management routines are company specific and path dependent, thus we can expect to find a different AI strategy for each Big Tech based on their respective AI routines.

Although some initial contributions mostly focused on the intra-firm knowledge management practices (see for instance Davenport & Prusak, 1998; Prusak, 2001), for Coombs and Hull (1998), they also included how the firm learns from information and knowledge from and jointly created with its environment. In this respect, in the last decade, research on knowledge management was integrated into the open innovation framework, so that Chesbrough and Bogers (2014, p. 3) redefined open innovation as "a distributed innovation process based on purposively managed knowledge flows across organizational boundaries, using pecuniary and non-pecuniary mechanisms in line with the organization's business model." A more recent publication of these and other authors goes even further suggesting that open innovation management is crucial for enhancing and exploring new business models (Bogers et al., 2019).

This synthesis took off as open innovation became not only feasible but also regular and even to some extent necessary (Al-Aali & Teece, 2013). Indeed, Jiang and Li (2009) found that the complementary use of internal and external sources of knowledge had positive effects on firms' innovation even without necessarily exhibiting direct effects on their economic performance.

In the context of open innovation, knowledge management practices either draw upon external knowledge, which requires sufficient absorptive capacities (Cohen & Levinthal, 1990), or share -by disclosing and commercializing- internal knowledge (Natalicchio et al., 2017). Additionally, Natalicchio et al. (2017) refer to coupled open innovation processes to describe the disappearance of the boundaries between the firm and its environment engendering knowledge networks with their specific management practices.

An open question concerns who manages these networks. In such a network, a firm could centrally manage what knowledge it shares with others -which would be at the expense of other firms' capacity to integrate and manage knowledge- while strategically capturing external knowledge and information flows. Moreover, other firms could lack capacity to strategically manage knowledge, allowing predatory practices where some firms appropriate the innovation efforts of the whole network. Although Chesbrough (2006) mentions this possibility, follow up literature on managing knowledge in open innovation settings tends to present inter-organizational interaction as equally advantageous for all.

A similar positive view, Rikap and Lundvall (2020) explained, populates the global innovation networks approach (see for instance Liu et al., 2013) overlooking the potentially unequal distribution of profits of co-produced innovation. Accounting for this possibility, they suggested that leading firms in contemporary capitalism organize corporate innovation systems (CISs) (Lundvall & Rikap, 2022; Rikap & Lundvall, 2020). Building on Granstrand (2000), they argued that each CIS is controlled by a dominant firm that decides the system's general orientations and desired results. Just like in other types of innovation systems, innovation is co-produced by many (firms, universities, public research organizations, public sector dependencies, etc.). However, the CIS's dominant firm disproportionately appropriates resulting knowledge and keeps most of the economic benefits accrued from innovation.

From a knowledge management perspective, this implies that knowledge co-production and associated appropriation mechanisms are managed by a dominant firm. Here, knowledge management practices could be understood as the ways or mechanisms in which a dominant firm steers science and technology (see section 4.1) and defines who does what and how inside its CIS managing the system's inbound and outbound knowledge, thus information flows (see section 4.3). In such a scenario, other organizations face the risk of selling or sharing its core knowledge which, as pointed out by Fiegenbaum et al. (2014), is crucial for the firm's core competencies and further innovation. Inside CISs, how the dominant firm manages appropriation mechanisms, in particular intellectual property, can also differ (see section 4.2).

All things considered, this paper proposes to compare how four dominant firms -Google, Amazon, Microsoft and Facebook- manage knowledge inside their respective AI CIS. This will not only contribute to identifying similarities and differences of chosen corporations' AI management practices, but can also advance our understanding of concrete ways in which CISs are managed by dominant firms.

2.2. Big tech and AI

Lundvall and Rikap (2022) mobilized the CIS concept to analyse Big Tech companies AI technological convergence, showing that they combine knowledge predatory practices with the use of IPRs to achieve and sustain dominant positions in AI. On a similar vein, Jacobides et al. (2021) studied AI division of labour and found that Google, Amazon, Microsoft, Alibaba and Tencent are vertically integrated firms. They classified them as AI Giants that produce AI for internal and external use. The paper does not distinguish among these AI Giants but classifies Facebook as a separate species, an AI-powered operator that produces but also purchases technology from the AI Giants.

Furthermore, previous research found that since 2012 Big Tech companies are increasingly participating in major AI conferences favoured by a compute divide, defined as uneven access to computing power (Ahmed & Wahed, 2020). Similar results were found by Klinger et al. (2020, p. 1) for AI research conducted by the private sector, in particular by tech giants that specialize in what the authors defined as "data-hungry and computationally intensive deep learning methods". They also found that the diversity of the AI research field has stagnated and blamed the narrow thematical and methodological interests of the US most prestigious universities, Google, Microsoft, Facebook, Amazon and OpenAI. Along similar lines and judging by AI citations, Jurowetzki et al. (2021) found that Microsoft and Google are the most influential organizations in the AI field. They thus concluded that if these companies narrow their AI research focus, this would impact on the overall field.

A common feature of these investigations is that, even when focusing only on some Big Tech companies as Jacobides et al. (2021), the resulting set of large technology companies are studied as an homogeneous bundle that is controlling the frontier AI. 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. Their publication analyses findings for all the companies together, identifying a concentration of AI labs in the San Francisco Bay Area and Seattle. Likewise, Birch and Cochrane's (2022) asserted that Big Tech have 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 their CISs like the one conducted in the rest of this paper.

3. Methodology

I selected Amazon, Facebook, Google and Microsoft because previous research highlighted their importance in AI publishing and patenting (Ahmed & Wahed, 2020; Jurowetzki et al., 2021; Klinger et al., 2020; Rikap & Lundvall, 2021; World Intellectual Property Organization, 2019). I excluded IBM, which also significantly publishes and patents in AI, because none of my interviewees mentioned it as an AI leader and the IBM researcher that I interviewed confirmed that the company is not attempting to compete with US Big Tech since IBM is not "the queen of computing it used to be" (IBM interviewee).

I followed Coombs & Hull's (1998), and compared chosen companies' practices to manage AI in their respective CISs combining quantitative research with in-depth semi-structured interviews.

At the quantitative level, I used a set of indicators, methodologies and data sources to map the role of each company in the co-production of cutting-edge AI and identify differences in terms of appropriation mechanisms (see Table 1). I also considered AI talent indicators because co-producing and appropriating AI deeply rely on skilled scientists and engineers, which 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 collaboration and will have greater capacities to absorb successful results (Cohen & Levinthal, 1990).

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 + Betweeness 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

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

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

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

Scopus offers a field with authors' addresses including affiliations. I used this field 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 CorText platform (Tancoigne et al., 2014) and the Louvain community detection algorithm was applied as 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 also calculated the betweenness centrality of each resulting node using Gephi. This 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 pass through that node.

The same procedure was used to build a network of organizations and privileged topics for the whole 9-year period. To identify 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 whose high frequency is 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 map that links organizations and terms to get a sense of the topics privileged by each Big Tech and other organizations.

Then, I retrieved from each conference website the full list of committee members and identified the presence of industry, in particular of 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 AAAI for which data was available for 2022.

Additionally, I used Crunchbase to retrieve Big Tech acquisitions between 2012 and 2022 including acquired companies' technologies/industries, which is a classification made by Crunchbase and firms themselves. I also retrieved the list of companies in which a Big Tech appeared among the 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.

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

Concerning AI talent, as identified in previous research (Gofman & Jin, 2022), 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. Since interviewees also pointed out that internal talent was a source of differentiation among Big Tech, I also considered job posts' information obtained from company websites. Previous research has already used hiring data for labour market studies (Abis & Veldkamp, 2020).

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 developing AI. I interviewed nine employees from the four chosen giants working in the US, the United Kingdom and Germany. Interestingly, four had worked for at least another Big Tech company before, providing in total 14 company-employee answers (4 for Amazon, 4 for Facebook, 3 for Google and 3 for Microsoft). I also interviewed five researchers and engineers from Bosch, Globant, IBM Research and Mercado Libre (2 interviews one of them as part of another project) and two Alibaba managers, one from human resources. On top of asking questions related to quantitative results, interviews inquired about Big Tech AI strategies more in general and the differences among them and with other companies. Interviews lasted between 30 and 70 minutes and were conducted between August-2022 and May-2023. All the interviewees required to remain anonymous. Thus, I identify them with the name of the company experience they are referring to and numbers.

These interviews are not a representative sample because most of them were secured by indirect connections. I also emailed all the Big Tech employees listed as members of AI Conferences committees and contacted people that was anonymously recommended by my interviewees. I only received three responses and only one agreed to be interviewed. Nevertheless, the consistency of the replies and their correspondence with my quantitative results justify their inclusion.

4. Results

4.1. The co-production of AI

These section focuses on Amazon, Facebook, Google and Microsoft's production of frontier AI with other organizations, their current participation in top AI conferences' committees and briefly discuss the main content of their AI conferences' presentations.

4.1.1. Big Tech positioning in the AI research field

Over time, the position of the four companies in the AI top conferences' network becomes more central (Figures A.1, A.2 and A.3 in Appendix). Yet, there are meaningful differences in terms of their places in the network and type of privileged collaborations, especially when looking at the most recent period (Figure A.3).

Microsoft, Google and Facebook were already in the network between 2012 and 2014 (Figure A.1). Microsoft had the highest number of AI conferences' presentations and Google ranked fifth. However, the latter occupied a marginal position, only directly connected to one institution and ranking 116 in betweenness centrality (the lists of betweenness centrality and publication frequencies are available in the online appendix). Although Microsoft was more connected, it was connected to only 5 organizations from two clusters and ranked 39th in betweennesses centrality. Facebook's position was marginal, ranked 65 in frequency of presentations and last in betweennesses centrality.

By the last period (Figure A.3), Google and Microsoft, in that order, became the two organizations with the highest betweenness centrality. They were also second and third in number of presentations. The Chinese Academy of Science, which had the highest frequency of presentations in this period, ranked twelve in betweenness centrality, pointing to China's relative detachment from the rest of the world.

Precisely concerning the latter, Microsoft occupies the crucial bridging position connecting China and the West in this network (see Figure A.3). Microsoft is part of a cluster mostly integrated by Chinese organizations (firms and universities) and is directly connected to four additional clusters populated by Western organizations. In total, Microsoft is directly linked to eleven 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 what Burt's (1995) defines as a network's structural hole. In other words, the globalization of AI cutting-edge research and the overall structure of this network relies crucially on Microsoft.

This result is in line with Microsoft's strategy in China, where it conducts R&D since 1998. In 2010, Microsoft inaugurated it first major R&D campus outside the US, a high-tech industrial park in Shanghai. Two interviewees with work experience at Microsoft confirmed that, even if being in China is complicated because Microsoft will always be seen as a US corporation, the company is at the forefront of developing research and business there. According to one of them, Microsoft succeeded in China, among others, because it compromised the necessary level of collaborative investments, and mentioned a project with Xiaomi on mix-reality.

Google's position also contributes to structuring the network even though it is not geopolitically as relevant as Microsoft. Google has the highest betweenness centrality and is directly linked to 19 organizations from four clusters, including IBM, universities and public research organizations, all from the global north. All the interviewees with work experience at Google agreed that presenting at conferences entailed a quite simple internal approval process.

Facebook's evolution in the network is also impressive. However, it is not as central as the other two giants. In the last period, it jumped to the 8th position in betweenness centrality and ranks eleventh in frequency of AI papers' presentations.

Amazon joined the network in the second period. 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. 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 (Figure A.3). Interviewees stressed that the delay in developing a significant presence and the relatively non-central place in comparison to the other giants 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 metrics for selling products. A good metrics 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", are constantly emphasized and do not include sharing information publicly.

Summing up, the four companies seem to have engaged differently with the frontier AI network. While Microsoft and Google have a large capacity to steer the field beyond direct collaborations, with the former bridging, thus gatekeeping, between the West and China, Facebook's place became predominant but is not as crucial. Interestingly, Amazon's management decision has been not to promote and even to discourage its employees' participation in academic convenings.

4.1.2. The content of Big Tech research presented at leading AI conferences

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

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

Google	Amazon	Microsoft	Facebook
Neural Networks	natural language	reinforcement learning	language model
reinforcement learning	natural language processing systems	natural language	machine translation
machine learning	transfer learning	language model	action recognition
language model	knowledge graphs	machine translation	
learning algorithms	word embeddings	data mining	
generative model	time series	neural machine translation	
machine translation	text classification	large amounts	
transfer learning	context information speech recognition		
gradient methods			
sample complexity			
data augmentation			
monte carlo methods			

Source: Author's analysis based on Scopus

Google's research includes mostly general AI multi-terms not linked to any specific functional application. Intelligence chatbots, like ChatGPT and Google's Bard, are based on a "generative model" and trained with "reinforcement learning", which are terms directly connected to Google. Reinforcement learning is a deep neural network technique originally developed by Google's DeepMind that does not require a pre-set of labelled classifications to train the model (Alom et al., 2018). An interviewee defined it as "agentic" because the intelligent agent -the computer program- interacts with the environment and learns to act within it. It is a powerful tool because the AI model improves the more it is used, thus to some extent outsourcing the improvement of the model -hence part of the R&D- to the users or customers.

Amazon follows in number of direct connections to multi-terms with five of its eight terms denoting AI for language applications, including the frontier "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 data to train the model. 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 term "time series" speaks of how Amazon approaches new technologies and R&D. Amazon uses time series for long-term forecasting of demand and other aggregated variables for the countries or regions where it operates. According to an interviewee, moving too much to AI constrains the insights they can provide. Therefore, they prefer traditional statistical methods for long-term predictions. Meanwhile, frontier AI models are applied for item demand forecasting and price setting. Overall, the prevalent content of Amazon's AI conferences presentations speaks of the company's approach to technology, as explained by another interviewee.

> "I think that the good thing about Amazon's approach to AI is that it is 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. My impression is that that is the selection criteria in other companies, just a simple random forest[3] can be useful and other big companies will less likely fund it rather than a state-of-the-art algorithm. (…) Other companies will go for the more expensive things. ChatGPT is an example." (Amazon interview 1).

Microsoft, like Google, is connected to the multi-term "reinforcement learning". The rest of its 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 fundamental 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 further reinforcing the impression of this company as more focused on AI applied to its platforms.

4.1.3. 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). Hence, one may conclude that 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 field, as identified by an interviewee:

> "Most of the people leading the conference boards are in Big Tech, not all but at DeepMind we have a lot of those people. (…). 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 interviewee 1)

[3] Random Forest is a classification algorithm consisting of many decisions trees.

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.

Google stands out with 22 members distributed in 9 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.[4] The other Big Tech companies have one or two committee members in this conference.

With half the total committee members of Google, Amazon follows in both committees in which it has at least one representative and total number of committee members. Conferences with Amazon employees in their committees range from broad AI conferences to more specific convenings, 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. Its relatively low representation in NeurIPS, unlike Google, resonates with the overall company mindset. Amazon participates and thus gets access to internal discussions, thus expands its information and knowledge inflows without fully engaging in these events since it rather keeps most of its internal developments secret.

[4] See https://github.com/sanagno/neurips_2022_statistics Affiliations appear as Google, Google Research, Google Brain and DeepMind.

Facebook participates in only five committees, with more members in those on computer vision, in line with the focus of its AI presentations (Table 3). Like Facebook, Microsoft participates in only five committees and with a total of 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 OpenAI partnership, to which I refer later (see section 4.2) and with the most frequent multi-terms of its AI conferences' presentations (Table 3).

4.2. 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.

4.2.1. Acquisitions and investments in other companies

Acquiring and investing in AI companies provide privileged access to technologies and skilled workforce. According to WIPO (2019), Google ranked first in AI-related acquisitions (18 firms) between 2009 and May 2018. Microsoft was third (9 acquisitions), Amazon was fifth (6) and Facebook eight (5). Different AI management practices can be inferred by comparing not only their updated number of acquisitions and the industries/technologies of acquired companies but also by considering the relevance of investing in -without acquiring- AI firms (Table 5).

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	Machine Learning	Machine Learning	Machine Learning
	Software	Developer APIs	Analytics	Software
	Mobile	Apps	Software	Computer
	Developper Tools		Computer Vision	Mobile
	Natural Language Processing		Image Recognition	Computer Vision
	Information Technology		Natural Language Processing	Image Recognition
	iOS		Big Data	Developer APIs
	Developer Platform		Internet	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

Google keeps leading in AI-related acquisitions, which are also the most diversified in terms of represented industries/technologies, including machine learning applied to images, language and analytics (Table 5). Google is also among the top five investors of many AI start-ups. However, it is widely outpaced by Microsoft. The latter acquires less but privileging sectors where it does not have a strong business (Mobile and iOS) and strengthening its role as 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 their different practices. Google acquired the former in 2014 but until recently it remained mostly independent even if aiming to generate valuable AI for Google. This progressively changed, as an interviewee explained, when DeepMind moved away from developing AI that played games. The new strategy was to do things that people cared about, thus closer to Google’s overall business strategy, such as Alphafold, an AI model that predicts protein structures, but the business model for these solutions remained unclear.

In the meantime, in 2019 Microsoft invested USD 1 billion in OpenAI[5] 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 supercomputers, and Microsoft provided them in its cloud. The latter pushed OpenAI to move from research to applications.[6] ChatGPT is a result of this shift. Since its release, Microsoft committed an additional USD 10 billion investment in OpenAI.[7] Investing instead of acquiring was a strategic move to assure that OpenAI applications are 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[8] 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 interviewee 1).

Microsoft took the lead at a time when Google management was simultaneously communicating a slow-down in hiring and pushing its employees to be more “entrepreneurial”, as a leaked internal memo from its CEO Sundar Pichai stated.[9]

In comparison, Amazon acquires and invests less in AI start-ups, but its acquired companies tend to operate in very spread and multiple industries since there are only three industries represented in more than one acquisition but there are 21 industries associated with all its acquisitions (Table 5). This reinforces the impression of Amazon diversifying the most within AI applications.

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 in comparison to the other giants. Also, a major decentralization of Facebook’s AI research took place by mid-2022 creating AI Innovation Centers associated with each of its business units. Facebook AI Research (FAIR) team became integrated into the company’s Reality Labs Research.[10] Both this internal restructuring and its AI acquisitions seem to be further targeting AI to applications for Facebook’s existing businesses.

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[5] https://thenextweb.com/artificial-intelligence/2019/07/23/openai-microsoft-azure-ai/
[6] 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
[7] https://blogs.microsoft.com/blog/2023/01/23/microsoftandopenaiextendpartnership/
[8] Refers to Microsoft’s CEO, Satya Nadella.
[9] https://www.theverge.com/2022/7/12/23206113/google-ceo-sundar-pichai-memo-hiring-slowdown-2022
[10] https://ai.facebook.com/blog/building-with-ai-across-all-of-meta/

4.2.2. AI Patents and secrecy: complementary rather than opposites

In 2019, WIPO (2019) published a "Technological Trends in AI" report. It included the ranking of the top 30 patent applicants between 2013 and 2016, led by IBM (8,290) and Microsoft (5,930). 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) and compared it with WIPO's (2019) findings. 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.

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

Compared to WIPO's (2019) findings, Microsoft seems not as focused on AI patents as before, not only judging by its place in the ranking (22nd) but also by the distance in number of granted patents with those at the top. This change is in line with Microsoft's turn to open source. Besides reputational gains, by putting in open-source only pieces of larger projects whose key parts are kept secret, Microsoft does not risk losing its edge while benefiting from developers' free work (Rikap & Lundvall, 2020). Regarding the content of its patent portfolio, besides generic multi-terms referring to machine learning, which are 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 appendix).

Another novelty in comparison to WIPO (2019) is that Amazon integrates the top 30 ranking, with a similar number of granted patents than Microsoft and an AI portfolio that seems to be the most diverse of the four in AI functional applications, including image, audio, video and text. Like in the AI conferences' content, the multi-term "time series" pops up (Table A1 in appendix).

Facebook remains out of the ranking, occupying the 50th position. An interviewee explained that the company lacks a clear patenting culture and the process is not as formalized as it was during the interviewee's previous experience in Microsoft. Facebook patents are connected to its existing platforms, with a focus on image and video and with multi-terms that can be easily associated with the Metaverse, such as "artificial reality environment". Unlike the other Big Tech, 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 appendix). Among the four, it seems to be the most focused on patenting AI. It jumped from the tenth to the third position in the ranking. Interviewees from Google and Amazon agreed that scientific publications usually have an associated patent filled in advance. A Google interviewee stated that patenting was mostly a defensive strategy to keep others from filling patents with otherwise published knowledge and then charging Google from using its own developments. Moreover, the coupling of AI publications and patents may contribute to explaining why Amazon is now among the top 30 patent grantees, since it is also publishing more (see section 4.1.1).

Overall, patents may not be the most relevant appropriation mechanism of frontier AI. Interviewees agreed that secrecy and the speed of innovation are crucial for leading the AI field and that they are even complementary to publishing and patenting. In very simple terms, what makes a company be at the edge -nowadays the algorithmic core of massive models- is kept secret, whereas complementary or not so cutting-edge developments are often published and/or patented. Often, publications only refer to achieved results without disclosing the code, which was observed as the most common practice in the field (Benaich & Hogarth, 2020). According to Bican et al. (2017), this form of intellectual property modularity in which firms keep core knowledge secret while patenting less sensitive information is a success driver of open innovation.

Internal data is the paradigmatic example of secretly kept intangible. A trade-off arises for researchers wanting to publish papers that present the results of AI models trained with large datasets. A Google interviewee explained that using internal data sources is complicated due to compliance and privacy issues. Massive experiments, such as those underpinning Big Tech chatbots and other large language models, require massive scale data that are only available internally. These models are the frontier in AI, thus the requirement to use internal datasets contributes to explaining why the field seems to be moving towards even more secrecy.

Secrecy is also an internal practice used to protect technological leadership. Interviewees doing AI research agreed that, since all the Big Tech are developing large models, the edge in AI are small changes in configurations that most of the employees do not know about. Only the group that is programming those configurations will know. In general, the fast pace of change in these companies makes non-compete agreements less relevant. Sometimes, there is a period of paid leave between the time a scientist or engineer moves from one Big Tech to the other that is expected to assure that what the person leaving knows, does not represent a major threat.

A final point to be made is that three Google interviewees predicted a further move towards secrecy. One of them stated:

> "I see in the field a general push, led by OpenAI, to close down research, make it less open access, and offer the final product. (…) the focus of research is on massive multi-model and research on this side is going to be sparser, kept more secret and I see that companies like mine will publish more reports with 80 pages and details of the model but written on the company terms and not complying with reviewers asking for more information to publish a paper." (Google interviewee 2)

As the previous quote underlies, limiting this form of public disclosure raises employees' concerns, particularly for those that work part-time in academia, as I explore next.

4.3. 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 by Big Tech. As stated by one Amazon interviewee, having the most talented people and wanting them to stay is what matters the most to lead in the field. 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 they hire the most talented people preventing rivals from accessing talent. Likewise, my Alibaba HR interviewee pointed out that most of the international talent works for Amazon, Microsoft and Google.

Often, AI talent is drained from academia. Interviewees from different companies mentioned that engaging in AI conferences serves Big Tech to identify and capture talent. A Google employee even described conferences as hiring forums. 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. Gofman and Jin (2022) went deeper and found high and exponentially growing levels of brain drain of AI professors from US and Canadian universities into industry. The firms that hired the largest number of AI faculty were Google, Amazon and Microsoft. 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 (Table 7).

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 South California			

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

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 researchers also based at Google are US universities. Nonetheless, Google has researchers affiliated to organizations in other eight countries, which is three times more countries 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. This 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 Amazon scholars or senior academics hired as short-term consultants present what they are doing at their university or, after signing strict non-disclosure agreements, advice full-time employees.

"They (Amazon scholars) are interested in publishing their research and this is why we sometimes go to conferences without sharing confidential data but yes part of the methodology. (…) 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. (…) we have internal conferences that are larger than public conferences. Presenting sometimes takes the same work than public conferences. 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 interviewee 2)

In line with my previous findings for Amazon, this can be interpreted as part of a strategy to privilege secrecy (limit knowledge outbounds) while maximizing inflows of knowledge and information for the development of AI linked to business needs. Another example that fits into this interpretation is the AWS Cloud Credit for Research program, which offers free credits to purchase Amazon's cloud services.[11] In 2018, last year with public data, it provided 387 credit grants to 216 different organizations, of which 49 went to the University of California and 32 to Harvard.[12] This extremely cheap initiative enables Amazon to early identify, thus purchase, invest in or copy, successful projects. All the latter, without compromising or having to disclose knowledge or data since cloud services are sold as black boxes (Rikap & Lundvall, 2021, Chapter 4).

Finally, there are differences in the AI talent hired as full-time employees by Big Tech. Table 8 presents figures and simple indicators of job postings. I retrieved the number of searches that included the keywords "artificial intelligence", "machine learning" and "cloud" and compared them to the total number of job posts.

Table 8. Big Tech job postings referring to AI and related technologies

	Google	Microsoft	Amazon	Facebook
Jobs with AI or Machine Learning in the job description	251	120	321	105
Jobs with "cloud" in the job description	468	440	731	11
Total jobs posted	1044	627	3839	300
Share AI and/or ML in total jobs	24%	19%	8%	35%
Share of Cloud jobs in total jobs	45%	70%	19%	4%

Source: Author's analysis based on data extracted from Big Tech careers' websites on April 4th 2023.
* To make figures more comparable among Big Tech, I did not count the following categories for calculating Amazon's total job posts: "fulfilment & operation management", "supply chain/transportation management", "business & merchant development" and "fulfilment associate".

In terms of absolute figures, it is quite telling that Amazon was hiring more AI talent. Amazon was the 2nd company poaching AI professors to fully transition from academia (Gofman & Jin, 2022). This is also the Big Tech with the fewest double affiliations (Table 7). Hiring more AI talent is expected for a Big Tech company that does not rely as much as the others in building an open CIS.

Facebook ranks last in number of job posts, somehow expected considering its recent weaker financial performance. Nonetheless, it had a high share of AI-related open positions. An interviewee

[11] https://aws.amazon.com/awscredits/
[12] https://aws.amazon.com/government-education/research-and-technical-computing/cloud-credit-for-research/previous-recipients/

confirmed that Facebook keeps hiring machine learning talent because it is the company's most crucial technology. Finally, Table 8 also provides further evidence on the difference between Google, Microsoft and Amazon, on the one hand, and Facebook, on the other, in relation to the relevance of the cloud, which is aligned to Jacobides et al. (2021) observation of Facebook positioned differently in the AI division of labour.

5. Four strategies to dominate an AI corporate innovation system

Table 9 summarizes my findings and proposes four different strategies to organize and appropriate knowledge by a leading firm from its AI CIS. In one word, they could be summarized as: "frenemies" for Microsoft, "university" for Google, "secrecy" for Amazon and "application-centred" for Facebook.

Table 9. Four strategies to build a leading AI CIS

	Microsoft	Google	Amazon	Facebook
AI CIS strategy	**Frenemies**	**University**	**Secrecy**	**Application-centered**
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)	+	+
Job posts	++	++	+++	+
AI CIS space	Central and global positionining, geopolitically strategic: connecting China with the West	Central and widely globalized but mainly outside Asia (China)	Core: limited to the leading AI organizations among those already doing frontier research	Narrow: 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.

"Frenemies" describes Microsoft's frontier AI strategy; an AI CIS even opened to rivals but driven by Microsoft. It has successfully integrated into its CIS the least expected actors, from Chinese companies and academic institutions, including scholars with double affiliations with Chinese universities, to rival Western firms. Microsoft is the gatekeeper that connects AI research between the Global North and China. Also, by privileging investing in AI start-ups way more than other Big Tech, it enables formally separated companies to sell services to competitors, with the paradigmatic case of OpenAI. In Microsoft's AI CIS, the development of generic AI is more inclined towards language applications, which is aligned to its investments in OpenAI.

Microsoft's lower levels of AI patenting while it has the third-largest number of AI presentations between 2018 and 2020, and its decision to put in open source non-sensitive developments further explain its open AI CIS strategy. Openness does not endanger appropriation because of the speed of AI innovation and because the cutting-edge developments remain secret. Overall, Microsoft has broadened its chances of having developers from other organizations, even rivals, using its developments. Flipping the coin, it expands its chances to integrate external solutions to its private businesses, as it happened with the most advanced versions of ChatGPT and when it introduced a Linux kernel in Windows. Since then, it became compatible to use solutions that run on Linux to improve Windows.

The idea of frenemies was proposed by a Microsoft interviewee when I asked about the public Cloud, but I found that it also describes the company's AI management practices.

> "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 interviewee 1).

Among the four, Google excels in every indicator but, unlike Microsoft, it remains detached from China, building a CIS with top academic institutions mostly from developed countries. Google's strategy for its AI CIS resembles a leading university. It has the largest presence in AI conferences, both presenting papers and at their committees, has more employees with double affiliations, has acquired more and still gives particular importance to AI patenting. Nonetheless, it also relies on the management of internal and external knowledge flows, privileging secrecy for the edge developments, just like the other giants. The content of its AI presentations points to privileging more fundamental AI than functional applications in comparison with the other Big Tech, thus further away from business and closer to the type of knowledge traditionally associated with universities.

Google also has internal university-like features partly because of double affiliations.

> "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, interviewee 1. The name of the university was removed to protect the anonymity of the interviewee)

In addition, like leading universities these days, Google offers internal competitive grants for frontier AI projects that require more processing power. To get the grant, the employee must show that the project is aligned with the goals of the company.

It is not straightforward how this "university" strategy turns into higher economic benefits from AI for Google. In fact, it seems that Google's appropriation mechanisms are not translating into a clear AI business advantage. One of Google interviewees told me how after winning an AI best paper award, there was barely any recognition at Google and the authors thus attempted -unsuccessfully- to gain attention by applying the model to a company product. This case resembles academics' failed attempts to commercialize results pushed by their institution to garner intellectual rents from their research. Universities barely benefit from their patents (Popp Berman, 2011) and could be the case of Google given that it does not have a clear lead in comparison to Microsoft and Amazon, which patented way less in 2022.

According to interviewees, the release of ChatGPT was perceived at Google as the crystallization of choosing the wrong strategy, too much skewed towards more fundamental AI research without sufficiently connecting it to business applications. The company is changing its focus to make AI more profitable. This materialized in February 2023 when Google imitated Microsoft's strategy and decided to invest heavily in Anthropic, an AI start-up founded by former OpenAI employees that left when Microsoft became its main founder.[13] Next, by April 2023, DeepMind was merged with Google Brain, putting under the same organizational structure Google's more fundamental and applied AI.

On the other end, Amazon also dominates a frontier AI CIS, but by privileging secrecy and highly connected to its businesses. Amazon's AI research is the most diverse in terms of functional

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[13] https://www.theverge.com/2023/3/14/23640056/anthropic-ai-chatbot-claude-google-launch

applications, which makes sense given its business diversification and the fact that it leads the cloud market where the most diverse AI applications are sold as services (Jacobides et al., 2021; Kenney et al., 2021).

Amazon's AI CIS is characterized by non-disclosure agreements and an expansion of knowledge inflows from academia while discouraging outflows, such as AI conference presentations and patents. Nonetheless, it still developed a relatively prominent position in AI conferences' committees. Having such a panoptic view -which is also the case of Google- provides access to the latest AI and a space from which it can influence the field's agenda even if it barely publishes in those conferences in comparison with other Big Tech. Secrecy is at the service of Amazon's goal to produce and apply AI only when it provides a clear benefit for customers, which translates into more revenues and data, which would be riskier if rivals got access to its AI applications.

A Google interviewee that had worked at Amazon acknowledged a difference in terms of secrecy and a clearer business mindset in Amazon in comparison to Google. According to this interviewee, the former is more oriented to deliverables that should be measured in money and giving space to theoretical work only if the researcher proves that that can make money. As the company recently stated in response to the ChatGPT hype, for the last 25 years Amazon has been "infusing these capabilities into every business unit", it is just that Amazon develops these technologies in a closer environment, even if with hundreds of collaborators, thus its position at the AI frontier is not so apparent.[14]

Finally, Facebook's AI CIS is the narrowest and, like Amazon, it is connected to business applications. The difference is that Facebook's businesses are ultimately a few platforms with similar technology requirements. Facebook is mostly on computer vision conferences' committees and the content of its AI patents and publications further reinforce this AI focus on visual applications. Facebook does not participate in the cloud services market, which presents strong complementarities with AI and drives the other three giants to develop and offer as a service the most diverse and also fundamental AI services. When asked about the Cloud, one of Facebook's interviewees working in a strategic management position claimed that this is a market with defined leaders, hence too late for Facebook. Moreover, this and another interviewee identified Facebook's processes as too specific to its internal infrastructure, thus not suitable to be offered as cloud services.

The Metaverse could be interpreted as an attempt to diversify not only Facebook's businesses but also its AI CIS, expanding it to virtual and augmented reality. However, this attempt remains too close to Facebook's existing focus on visual solutions when compared to the other giants' AI CIS. Also, as two interviewees pointed out, the Metaverse is a quite niche business.

6. Final Remarks

The main contribution of this article has been to provide the first study of Amazon, Facebook, Google and Microsoft's different AI management practices used to organize and appropriate knowledge from their respective AI CIS. My main findings point to Microsoft, Google and Amazon leading fundamental AI, while Facebook has a narrower focus on AI for its platforms. Within the former three, I also found multiple differences. Google has opted for a sort of academic strategy. It has developed a cutting-edge AI CIS to expands to have an extremely central place in the world's frontier AI network -except China-

[14] https://www.aboutamazon.com/news/aws/aws-amazon-bedrock-generative-ai-service?utm_source=amazonnewsletter&utm_medium=email&utm_campaign=041523&utm_term=generativeai

and its focus on more fundamental research -nowadays primarily generative AI- is not combined with equal efforts to develop AI functional applications. It also remains unclear how Google will translate its AI CIS success into profitable initiatives.

Amazon and Microsoft differ in their strategies, but both seem to have better sorted out this question. I suggested the term "Frenemies" to describe the latter's strategy. It has successfully integrated rivals from around the world into its CIS. In the AI frontier research network, it is the gatekeeping organization between China and the rest of the world. Microsoft controls not only by acquiring but is also the Big Tech that has invested the most in AI companies, building a CIS with dozens of organizations that are *de jure* independent but *de facto* dependent on Microsoft. OpenAI is a case in point. In turn, Amazon has developed what looks like the most diverse AI CIS combining fundamental AI with multiple functional applications, privileging secrecy and highly connected to its businesses. Secrecy is at the service of Amazon's goal to produce and apply frontier AI as long as it provides a clear benefit for its businesses.

Summing up, my study of dominant firms' knowledge management practices to organize and appropriate knowledge from their AI CIS not only points to these companies' use of diverse mechanisms in distinct ways but also highlights aspects to keep developing in further investigations. One refers to the role of IPRs' management in AI. While more IPRs do not seem to be associated with more economic benefits, patenting is anyway used as a barrier for others' knowledge creation. The future of AI publishing should also be further investigated. Since routines are path-dependent, is still to be seen to what extent companies like Google can accomplish what interviewees foresee as an attempt to move away from academic publishing. Also, throughout this investigation, Amazon, Microsoft and Google clouds popped up as interconnected with their AI CIS. This open area of research could shed more light on Big Tech common and different knowledge management practices. Moreover, Microsoft's geopolitical role should be studied closely.

Overall, given the centrality of the analysed companies in the AI field, it could be said that this cutting-edge technology evolves as a network where Big Tech occupy the central, prominent position in shaping, gatekeeping and controlling what is developed and how. This raises several concerns given the implications of AI for every dimension of life, from war and sovereignty to economic concentration and human rights. Policy and agency should simultaneously address this general finding of this article as well as its specific findings regarding how each Big Tech is managing AI.

In terms of specific policies, less stringent IPRs and limits to AI acquisitions would impact Google more than the other Big Tech companies. Moreover, the case of Microsoft invites to reflect on ownership structures. Corporate law should be rediscussed, and antitrust offices should also investigate major investments and preferential agreements between giants and other (clearly less powerful) companies.

More generally, the International Labour Organization could be the arena for discussing policies and regulating the global AI (skilled) labour market. For instance, regulations should prevent publicly funded academics from simultaneously working for a tech giant given the latter's larger capacity to exclusively profit from achieved results. At least, regulations should prevent these academics from signing non-disclosure agreements, so that knowledge flows can go back freely to their academic institution. Also, academic institutions need to be equipped with the latest digital infrastructure so that talented AI scholars can stay or be attracted to return, which requires coordinated public sector investments. 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 publicly redefine the purpose of AI and more evenly distribute its gains.

Public funding for AI conferences could include clauses that limit -or forbid- industry researchers in their committees. Industry researchers may present their work in these events, but their participation in decision making spaces risks turning a public academic convening into a space controlled by privates and driven by for-profit motives.

Finally, much of the policy discussion since the release of ChatGPT revolves around the agency of generic AI models and even Big Tech and OpenAI top management has advocated for regulating AI uses, diverting attention from regulating the production of AI. An extreme focus on the agency of generative AI risks overlooking the role of AI agents, i.e., Big Tech companies as the main AI producers. There is still time to discuss in democratic spaces whether we need such AI models and, if yes, what type of AI should be developed, by whom and for what. However, the clock is ticking and the more people and organizations adopt ChatGPT and the like, the harder it will be to reshape routines for a production and use of AI that privileges what Acemoglu and Johnson (2023) dubbed machines usefulness. We need machines that work with humans to solve major global challenges not machines that replace labour, foster inequalities and ultimately worsen the critical times we live in.

7. References

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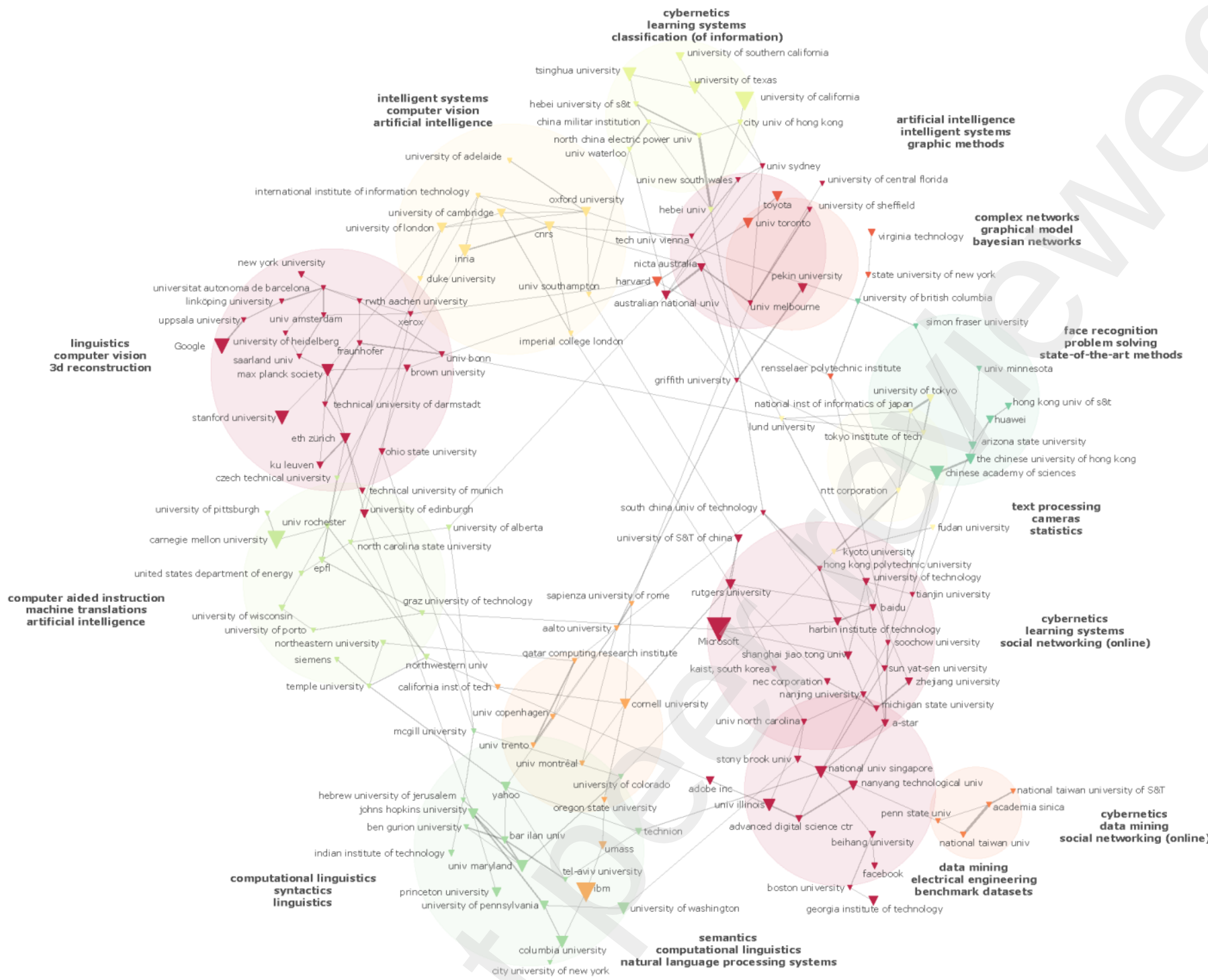
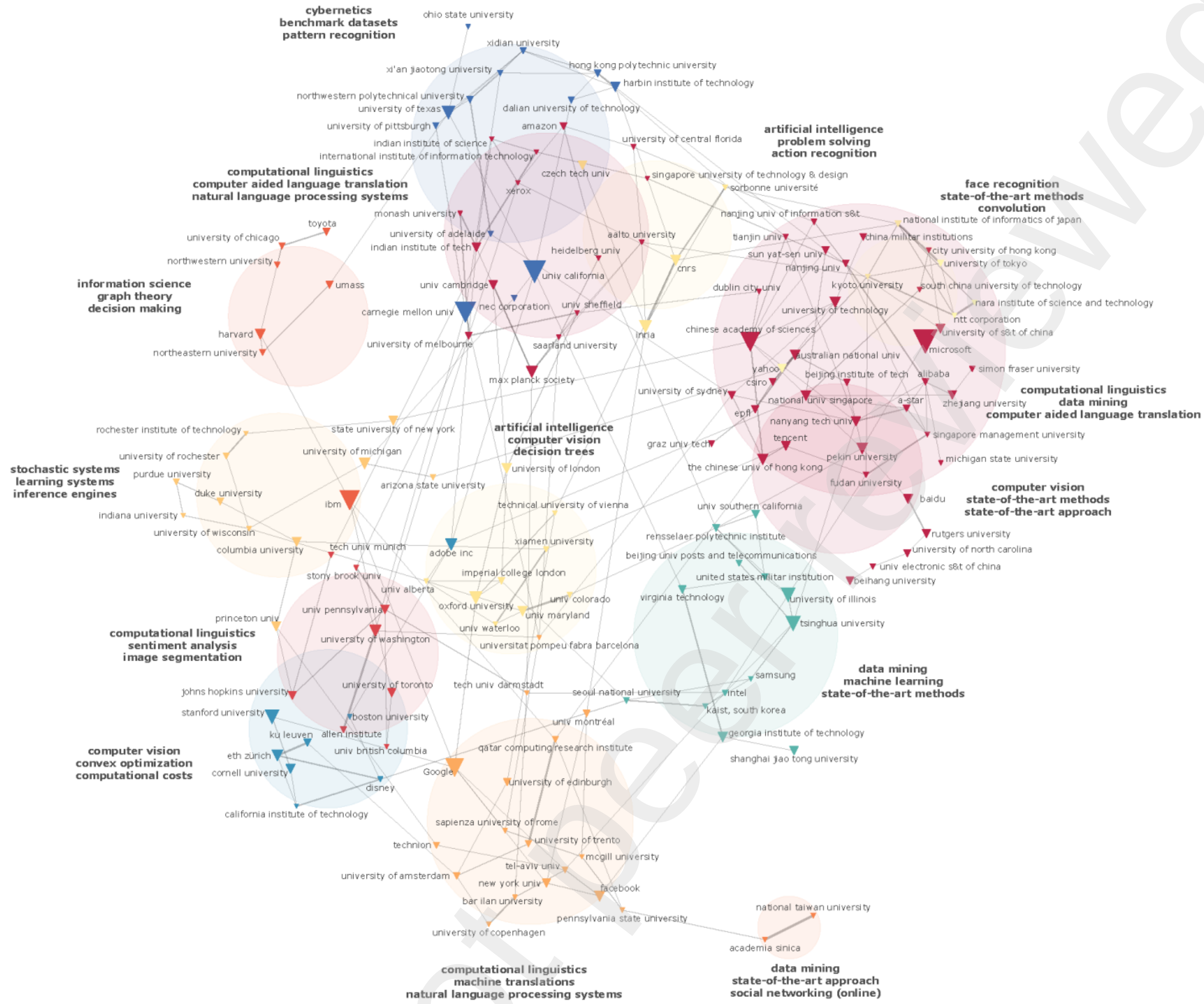
Appendix

Figure A.1. AI leading research network (2012-2014). Source: Scopus.



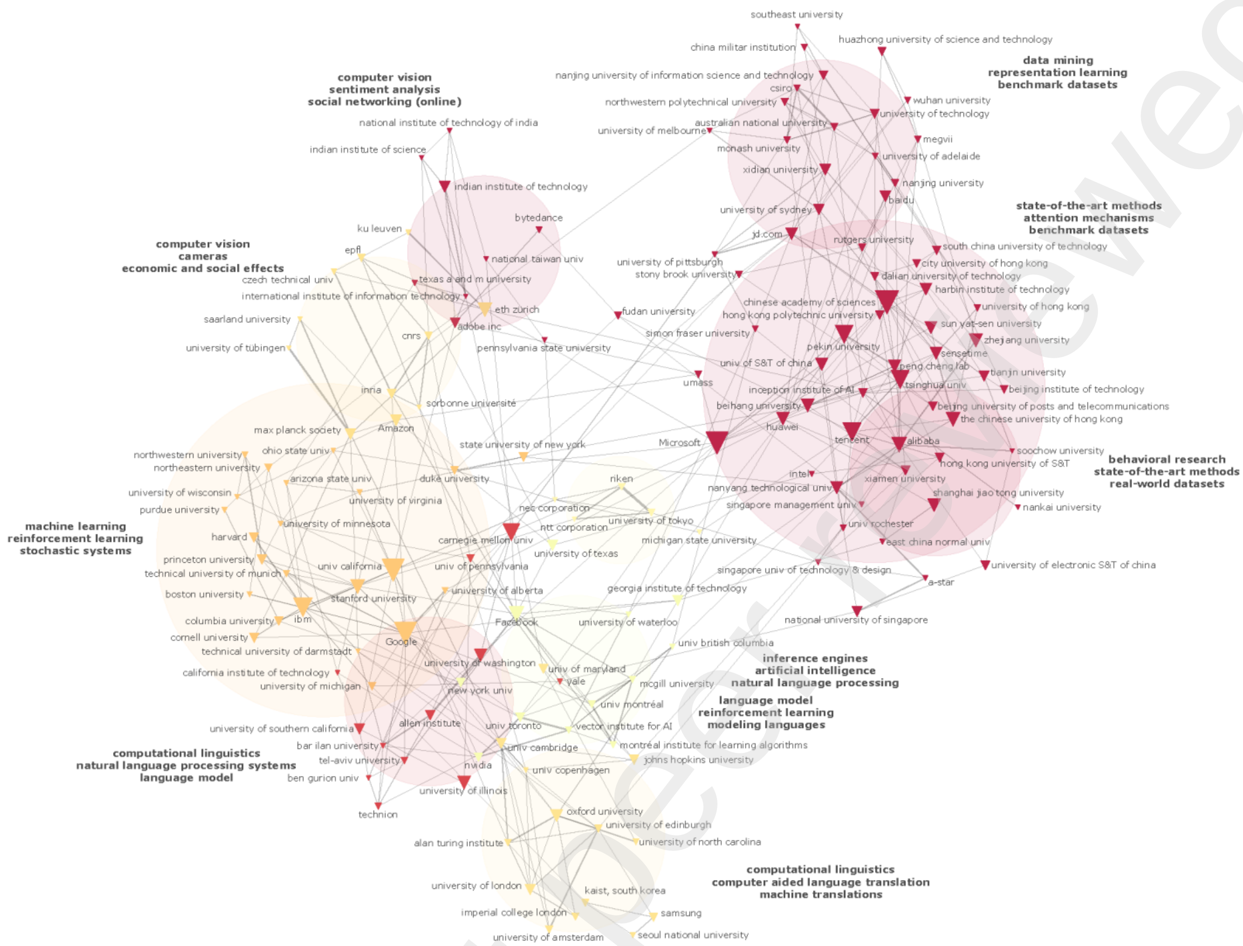
Source: Author’s analysis based on a Scopus dataset

Figure A.2. AI leading research network (2015-2017). Source: Scopus.



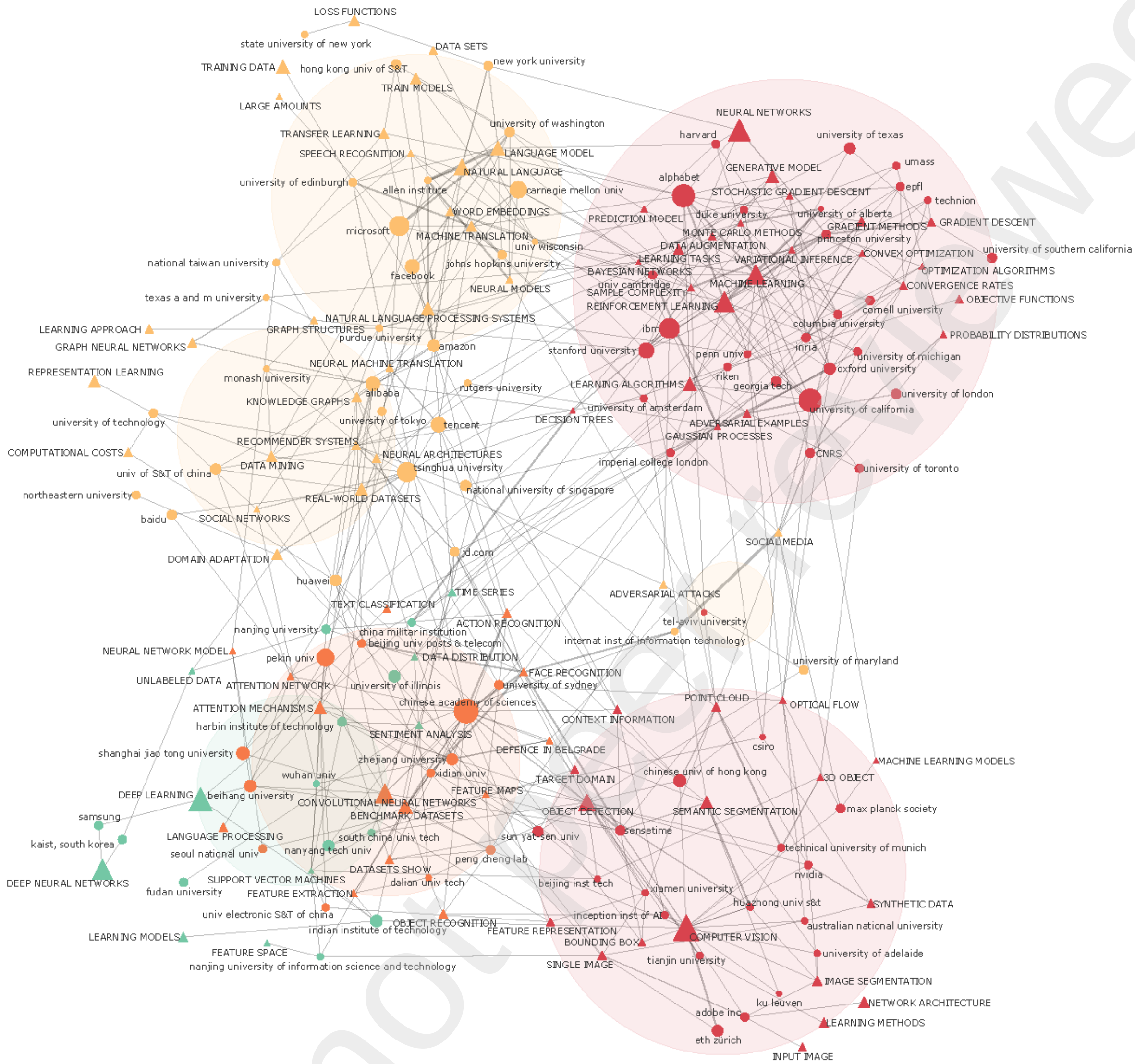
Source: Author's analysis based on a Scopus dataset

Figure A.3. AI leading research network (2018-2020). Source: Scopus.



Source: Author's analysis based on a Scopus dataset

Figure A.4. AI leading research network (2018-2020) and topics. Source: Scopus.



Source: Author’s analysis based on a Scopus dataset

Table A.1 Content of Big Tech AI patents in 2022

Microsoft	Google	Amazon	Facebook
computing system	including computer programs	image data	neural network
computer program product	computer storage medium	audio data	machine learning model
computing device	computer storage media	machine learning model	assistant systems
neural network	autonomous driving mode	neural network	computer-readable media
machine learning model	sensor data	autonomous mobile device	client system
machine learning	computing device	machine learning	processor system
clinical documentation	more processors	data representative	client system of a first user
training data	computer programs	input data	online system
user interface	computing system	video content	content item
input data	machine learning	other data	dot product
patient encounter	machine learning model	input image	matrix processor unit
sensor data	map information	physical space	computing system
encounter information	client computing device	motile device	artificial reality system
image data	autonomous mode	computer-readable media	result matrix
user input	data bus	using data	data matrix
object detection	computing unit	systolic array	video frames
user experience	input activation	time series	output image
machine train	plurality of cells	service provider	sending instructions
video game	process the image	communication devices	disclosed computer-implemented method
data samples	more computers	output data	multiplication results
conversation prints	encoder neural network	provider network	Mapping convolution
physical environment	cause the vehicle	Natural language	artificial reality environment
audio encounter information	processing unit	voice commands	hardware channel convolution processor unit
vision system	input activation value	automatic speech recognition	sensor data
context information	Example implementations	user device	head-mounted display
virtual assistant	perception system	various embodiments	calculation units
storage device	vehicle occupancy	process images	neural network model
more sensors	MAC operator	weight changes	corresponding channel convolution result matrix
computer program	first memory bank	items on the shelf	more computing systems
obtaining encounter information of a patient encounter	matrix multiplication	processing element	convolution weight matrices

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