Machine Learning Tech Giants:
What are the Current Trends in Research?

Assel Omarova, Fazliddin Shermatov & Gabriela Fuentes

Abstract

Artificial Intelligence (AI) and Machine Learning (ML) are driving a transformative revolution across industries and society. AI, simulating human intelligence, and ML, its backbone, enable machines to learn, predict, and improve. Tech giants like Google and Facebook harness AI for digital advertising, utilising vast datasets to understand and engage audiences. ML's role in pattern recognition without explicit programming enhances efficiency and innovation.

Major companies like Microsoft, Google, and Amazon, with exabytes of data, invest significantly in AI R&D. Google and Facebook's 2021 R&D budgets surpassed the R&D spending of many countries. Google and Microsoft lead in extensive R&D networks, reflecting AI's dynamic evolution. Machine Learning, particularly Deep Learning (DL) and Computer Vision, has seen remarkable growth. DL, a subset of ML, powers AI applications like Apple's Siri and Google's Assistant. Computer Vision, pivotal for image recognition, gained prominence with breakthroughs in 2012. Our research delves into these domains, providing insights beyond GAFAM (Google, Apple, Facebook, Amazon, Microsoft) and exploring contributions from other big players like NVIDIA and Intel.

Methodologically, we analyse 1,907 ML-related papers and 6,490 patents funded by seven major companies from 2008 to 2023, utilising sentiment analysis, multi-term phrase extraction, and semantic profiling to reveal relationships between related topics within and among these corporations. Technological cooperation simulations showcase the potential impact on patent production. Cooperation yields more patents than competition or oligopoly scenarios, emphasizing the benefits of collaborative innovation for the potential development of new technologies but with the detrimental consequence of more concentration of knowledge and reinforcement of intellectual monopolies. Public policy implications suggest a shift towards open science and markets, democratising knowledge access and fostering global cooperation. Our research provides a holistic view of the evolving AI and ML landscape, emphasising the importance of collaboration, technological trends, and public policies for a sustainable and inclusive future.

Introduction

Artificial Intelligence (AI) and Machine Learning (ML) are at the forefront of a technological revolution reshaping industries and enhancing various facets of our society. AI centers on building machines and programs able to execute activities that humans are naturally adept at. This comprises natural language understanding, speech comprehension, and image recognition (Raschka et al., 2020).

AI has enabled businesses to gain a competitive edge by achieving nearly perfect accuracy in forecasting customer demand; and optimising research and development processes, thereby increasing production quality while reducing costs; enhancing marketing strategies; and offering better customer experience (Dash et al., 2019). Technology's versatility and capability are evident in its widespread adoption by tech giants such as Facebook, Amazon, and Google. These companies thoroughly use AI-driven digital advertising: they analyse a substantial amount of information, including user interests, demographics, and various other parameters. This enables them to not only understand their audience but also predict the most suitable prospects for their brands (Dash et al., 2019).

While AI refers to machines simulating human-like intelligence and decision-making, Machine Learning is the backbone of AI, responsible for training systems to identify patterns, make predictions, and constantly improve (Pramod et al., 2021). Machine Learning is the nucleus of AI, focusing on replicating human learning processes in computer models and algorithms for tasks like pattern recognition without manual programming (Raschka et al., 2020). Its primary goal is to enable intelligent systems to improve through experience gained from historical data (Akinosho et al., 2020).

Big tech companies like Microsoft, Amazon, Google, YouTube, and Facebook own enormous data, often measured in Exabytes. These tech giants continuously extract useful patterns from the huge amount of data that can be used in decision-making and prediction with the use of machine learning (Jan et al., 2019). All these companies contribute significantly to ongoing research and development in AI. In 2021, Google and Facebook allocated substantial budgets for R&D, surpassing the R&D budgets of most countries, including Belgium, Spain, India, and Russia (Bajpai, 2021). Similarly, Rikap (2023b) mentions the active participation of these companies but states that Google and Microsoft are the two corporations with the most extensive research and development networks.

Artificial Intelligence and Machine Learning are revolutionising the technological landscape and reshaping industries worldwide. While AI embodies the broader concept of creating intelligent machines, ML serves as the critical driving force behind AI, allowing systems to learn, adapt, and make data-driven decisions. Our research into R&D patterns within the realm of ML will show the versatile nature of ML, further contributing to comprehending how this technology continues to evolve, impact industries, and shape the future. The literature review will offer a comprehensive overview of previous and current research trends within ML, shedding light on the strategies of key industry players, collaborative networks, and emerging trends.

Literature Review

Over the past seventy years, machine learning has seen remarkable progress. It all started in the 1950s when computer scientists began exploring ways to train machines to learn. Studies on Machine Learning have risen dramatically in the last decade, and it has also received a lot of attention as a result of the COVID-19 outbreak (Sharma et al., 2021). In a world where contactless interactions have become the norm, face recognition technology has gained substantial significance as a crucial area of study due to its high level of authenticity, leveraging the uniqueness of every individual's face. ML has moved beyond the healthcare industry and into other key sectors, such as facial recognition systems, attendance tracking, and banking for age recognition. Additionally, industry giants like Google which started actively developing its self-driving car, and Netflix and YouTube, with their recommendation systems, base their products on ML technology (Pramod et al., 2021; Sharma et al., 2021). Besides the wide variety of possible uses of Machine Learning, Dash et al. (2019) mention cases of Big Tech companies' ML algorithms surpassing human performance.

In this way, tech giants, small and medium-sized companies, universities, as well as public and private organisations - all concentrate on researching ML for several purposes: innovating, building networks, developing new products and services, and increasing forecast accuracy (Chen et al., 2020). However, tech giants not only improve their products but also control the market by regulating access and user communication on their web platforms. Moreover, they play a pivotal role in driving innovation and shaping the working conditions in the oligopolistic internet sector, where research and development define the competition (Dolata, 2017). As emphasised by Rikap (2023b), the foremost company in the AI domain leverages its capability to extract significant value from the knowledge generated within its Collaborative Innovation System (CIS). This process builds the firm's strategic direction, emphasising the critical role of innovation in defining the competitive edge of these major players.

One of the reasons big companies invest, particularly in Machine Learning R&D, is the technology's flexible application to many data types, ranging from numerical and text to audio and visual. This wide variety facilitates innovations in both software and hardware programs, which can be used in later generations of their products (Hatcher & Yu, 2018).

Previous studies show that Machine Learning is particularly researched among many firms focusing on Deep Learning (DL). Deep Learning comprises a class of ML algorithms that employ Deep Neural Networks (DNNs), which is a large neural network with numerous hidden layers to generate features (Luckow et al., 2016). The relationship between deep learning, machine learning, and artificial intelligence is "DL ⊂ ML ⊂ AI" (Akinosho et al., 2020, p. 2). Deep Learning can be applied to various datasets, even in cases with limited data (Sharma et al., 2021). Big Tech companies are especially known for using DL, with Apple's voice recognition and dialogue systems of Siri, The Google Assistant, and Amazon's virtual assistant named Alexa (Luckow et al., 2016).

Another subset of AI gaining an increase in research is Computer Vision, which derives information from images, videos and other visual digital inputs (Sharma et al., 2021). For example, Google Photos and Facebook also contribute to its research, as they utilise image classification systems (Luckow et al., 2016). According to Akinosho et al. (2020), the breakthrough in Computer Vision happened in 2012 with the use of Convolutional Neural Networks for image recognition. In light of the significant impact and rising popularity of Deep Learning and Computer Vision in the field of AI, our research centers on exploring and understanding these two pivotal domains.

Probst (2022) underscores that universities and the largest tech companies are major contributors to both basic and applied research, with NVIDIA, a hardware company, notably applying ML technology to computer graphics. Furthermore, Tsay & Liu (2020) analyse the patent output and highlight its substantial growth since 2011. This accelerated output in patenting is explained by global strategic initiatives, primarily by China, the United States, the United Kingdom, and Japan.

A thorough examination of research, patents, and networks is crucial in the field of artificial intelligence and machine learning for a variety of reasons, including the identification of trends and innovations, comprehension of market dynamics, mapping collaborative efforts, development of policies and regulations, and the enhancement of knowledge sharing. Tsay & Liu (2020) note the significant growth in cooperative patents since 2002, with a particularly rapid increase from 2011 onwards, significantly contributing to the field's progress.

Research and patenting foster knowledge exchange within the AI and ML community. These resources allow researchers and practitioners to build on each other's work, thereby accelerating advancements in the discipline. This is evident in both inter and intra-industries, as Rikap (2023) shows that knowledge flows between major technology companies and academia can be demonstrated by frequent double affiliations (cases when people work for both universities and Big Tech companies).

Besides university-industry collaboration, scholars are interested in studying international collaboration and the strategic outcomes associated with it. A study by Tsay & Liu (2020) reveals that China leads in total AI patent production but has a relatively lower percentage of cooperative patents, comprising only 15.95% of the total output. However, when analysing the countries where AI originated, the US, China, and Japan stand out as the largest contributors to cooperative patents, accounting for more than 80% of all such patents (Tsay & Liu, 2020).

Examining Big Tech approaches in the AI field reveals each company pursuing distinct strategies. Microsoft is associated with active cooperation, fostering affiliations with Chinese partners, and investing in AI startups that eventually offer services to competitors. Google adopts a more academic-oriented approach, actively participating in AI conferences, patenting, and acquisitions. Amazon's strategy is the opposite, leaning towards secrecy, with a focus on applying AI when it directly benefits customers and enhances profits, often limiting disclosure. Finally, Facebook's AI strategy remains closely aligned with its core businesses, emphasising practical applications in its efforts. Such distinct strategies illustrate the multifaceted nature of AI development in major tech companies (Rikap, 2023b).

Studying the strategies of leading companies in the field is becoming prevalent due to their significant influence in the AI and ML landscape. As industry leaders like Google, Apple, Facebook, and Amazon continue to expand their power, they also exert control through political means, illustrated by the substantial $55 million spent on lobbying the US federal government in 2021 (Rikap, 2023a). Notably, Microsoft and Google, among these tech giants, have the most considerable influence in the AI field, so any changes in their AI research focus can impact the entire industry (Rikap, 2023b).

The global perspective in terms of international collaborations is also a frequent topic for research driven by scientific and geopolitical considerations. Microsoft, in particular, acts as a bridge between Western countries and China. This dual role positions Microsoft as a unifying force within the network, strengthening ties between various entities, including US and European universities (Rikap, 2023b).

However, a substantial body of research on networks in the AI field is predominantly centered on Google (Alphabet), Apple, Facebook (Meta), Amazon, and Microsoft (GAFAM) (Miguel De Bustos and Izquierdo-Castillo, 2019). Besides focusing on only GAFAM, a lot of papers have a US-centric perspective, even though other countries actively develop AI, ML, and DL. For instance, Japan comprises Toshiba, SONY, and Mitsubishi; Samsung is a prominent player from South Korea; and China includes China Power Grid, Huawei, Tsinghua University, and Alibaba (Tsay & Liu, 2020).

In our paper, our focus extends beyond the intellectual output of GAFAM in ML. We also explore the contributions of other significant players. For example, NVIDIA’s spending on R&D accounted for USD 3.92 billion, surpassing the R&D investments of 101 countries (Bajpai, 2021). Moreover, both NVIDIA and Intel companies contribute a lot to enhancing deep learning algorithms (Luckow et al., 2016).

In geographical terms, we aim to take a more inclusive approach by not confining our investigations solely to the United States and Europe. Previous literature shows that artificial intelligence and machine learning are also developed in countries like South Korea, Russia, Brazil, and China, even though their collaborative patent output remains comparatively lower, accounting for less than 30% of all patents (Tsay & Liu, 2020).

Our research will delve into various topics within the machine learning landscape and consider collaborative efforts that span different regions. By doing so, we aim to provide a holistic view of the dynamics and knowledge-sharing networks within the field of ML, thus contributing to a more comprehensive understanding of the evolving AI and ML landscape.

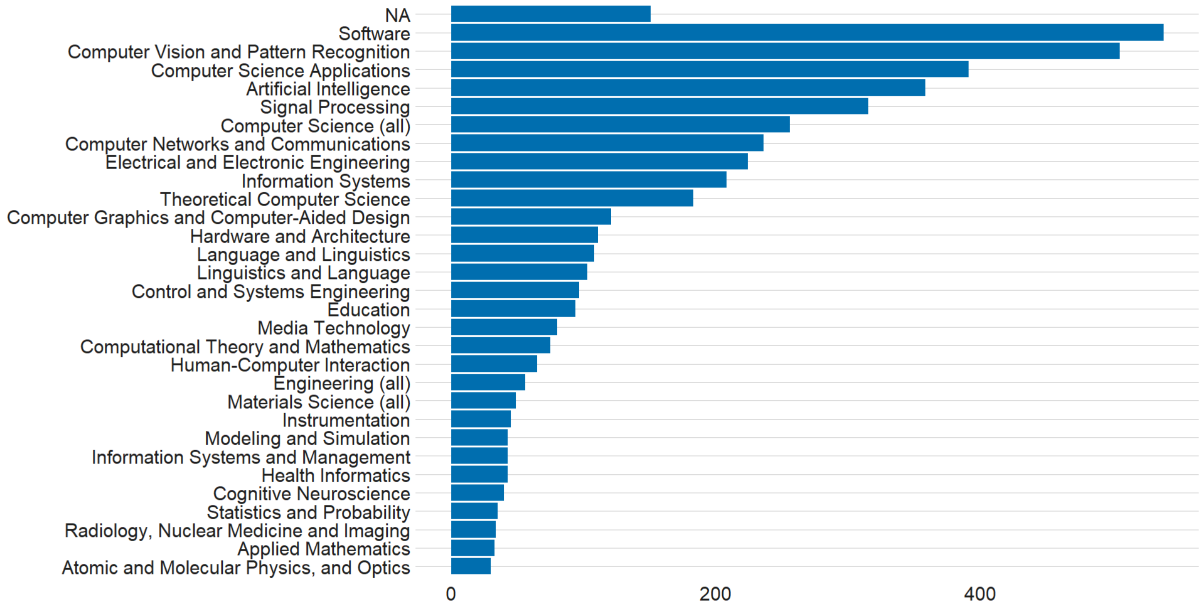
Data and Methodology

Objective. Our aim is to analyse research output from major players in the field of Machine Learning to uncover patterns and points of intersection (Tsay & Liu, 2020). To achieve this, we identified scientific papers funded by private sector entities in this domain, particularly focusing on Computer Vision and Deep Learning, resulting in a selection of seven prominent corporations and technology companies actively involved in research.

Data Selection. We gathered data from the Web of Science, which covers publications since 2008. This time frame was chosen to accommodate the substantial growth in open datasets and benchmarks within the Deep Learning field, which started around the start of 2008 (Wang et al., 2018). Our dataset comprises 1,907 unique papers published from 2008 to September 5th, 2023, which were funded by Nvidia, Google, Samsung, Microsoft, Intel Corporation, Amazon, and Qualcomm.

It is important to acknowledge that this method of data selection comes with certain limitations. Specifically, it allows us to identify the flow of funding directed towards external researchers within the field, but it does not encompass the research contributions of in-house, full-time, or part-time researchers who are affiliated with these corporations (Conroy, 2020). However, given our specific focus on external knowledge contributions, this selection method aligns with our research goals. Further investigation is required to explore the number of articles associated with corporate affiliations. In addition to avoiding an exclusive emphasis on external knowledge generation, we also enrich our dataset by incorporating patents accumulated by these major tech companies.

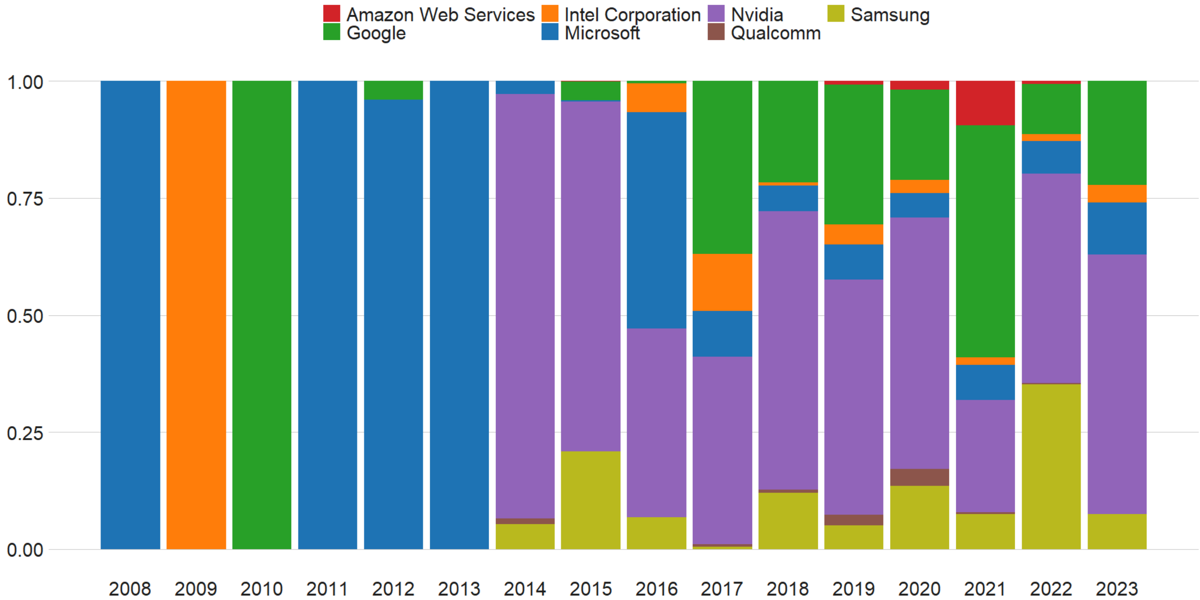
Graph-1. Papers' Subject Areas



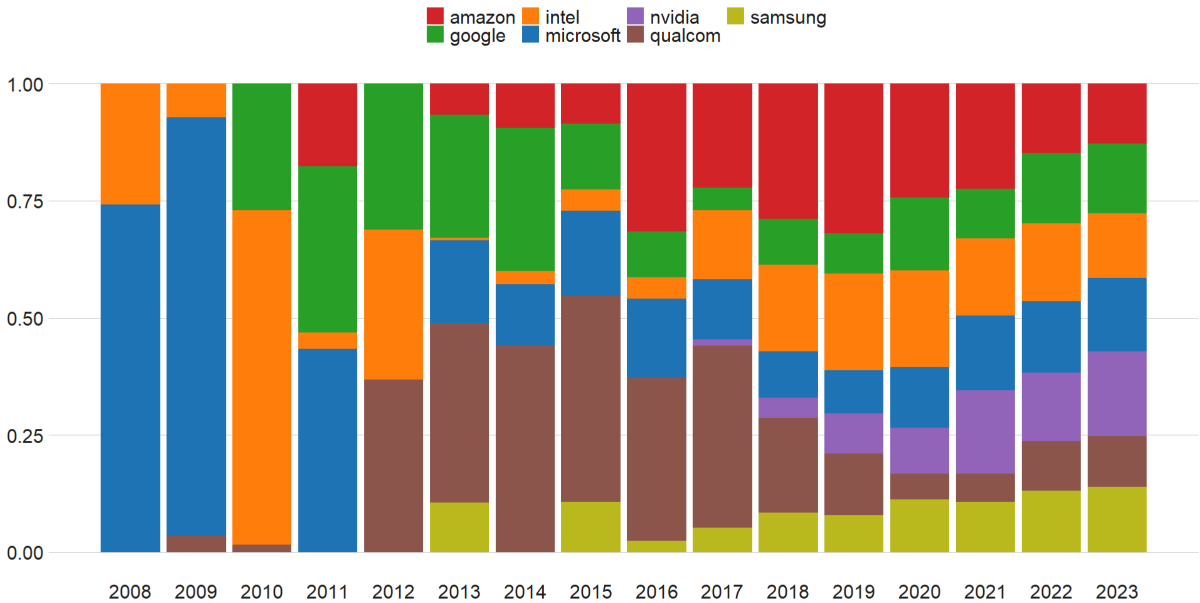
Notes: This figure shows the distribution of All Science Journal Classification (ASJC) codes assigned by Scopus to each paper. Papers may be assigned to more than one ASJC code.

Data Enrichment. To gain a comprehensive view of these companies' intellectual property domains, we expanded our analysis to patents (Tsay & Liu, 2020; Zhang et al., 2020). We utilised the Derwent Innovation platform and focused on Machine Learning to filter specific topics from the extensive patent portfolios of these tech giants. To filter very specific topics out of millions of papers that the tech giants owned, we tried to keep the most relevant ones to machine learning. This approach helped us to maintain a uniform number of patents from each corporation, facilitating a more streamlined analysis. We collected a total of 6,490 patents from 2008 to October 15th, 2023.

Graph-2. Deep Learning and Computer Vision Articles Funded by Big Tech Giants: Count Normalised by Citations (2008-2023). Source: Authors' analysis through Web of Science.



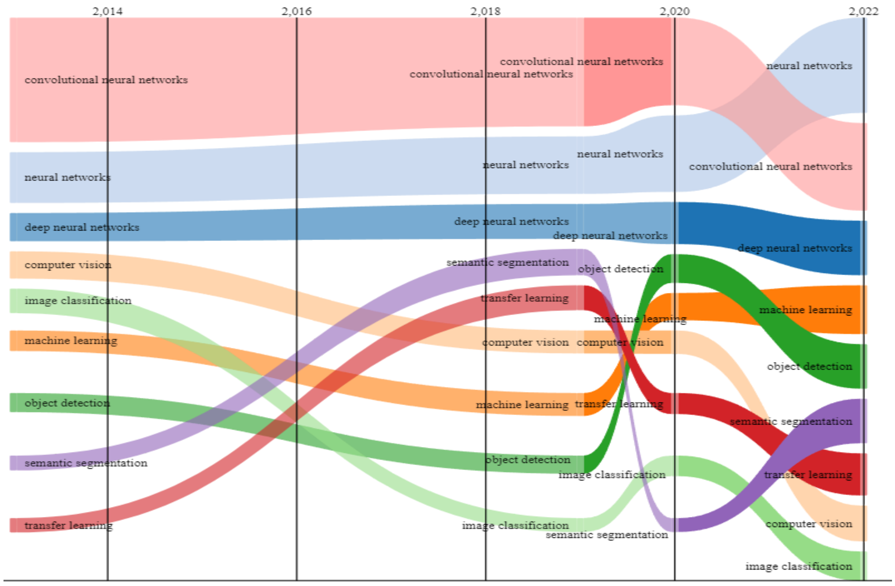
Graph-3. Machine Learning Patents Owned by Big Tech Giants: Count Normalised by Combined Impact (2008-2023). Source: by the Authors through Web of Science Analysis.



Data Analysis. With the acquired data, we conducted various analyses, including sentiment analysis, extraction of multi-term phrases, semantic analysis and profiling, together with network mapping to reveal relationships between related topics within and among these corporations. Initial observations from the descriptive graphs indicate that the articles primarily concentrate on fields such as Software and Computer Applications, as well as Artificial Intelligence. Notably, there are interesting clusters of research in Radiology, Imaging, and Health Informatics. Over the years, we have observed the emergence of tech giants like NVIDIA and Amazon as they begin to play a more significant role in the research landscape, especially in terms of recruiting and funding external research (Ren, 2019; Moorhead, 2017).

In order to analyse the direction of research in the field, we conducted a semantic analysis of the research articles. The tube layout of teams (*Graph-4*) that was created dividing the list of multi-terms extracted from the Web of Science articles into homogeneous four periods. The most interesting shift in the research direction, according to the extracted multi-terms, takes place with semantic segmentation, transfer learning, and object detection, all of which see a steep boost and then a slow decline in the last period. Neural networks and, more specifically, convolutional neural networks and deep neural networks are primary research fields that keep them in the spotlight. While computer vision and image classification have lost prominence over the years. More detailed results are discussed in the data and results section.

Graph 4. Tubes layout of terms, 2008–2022. Authors' analysis based on Web of Science.



Results

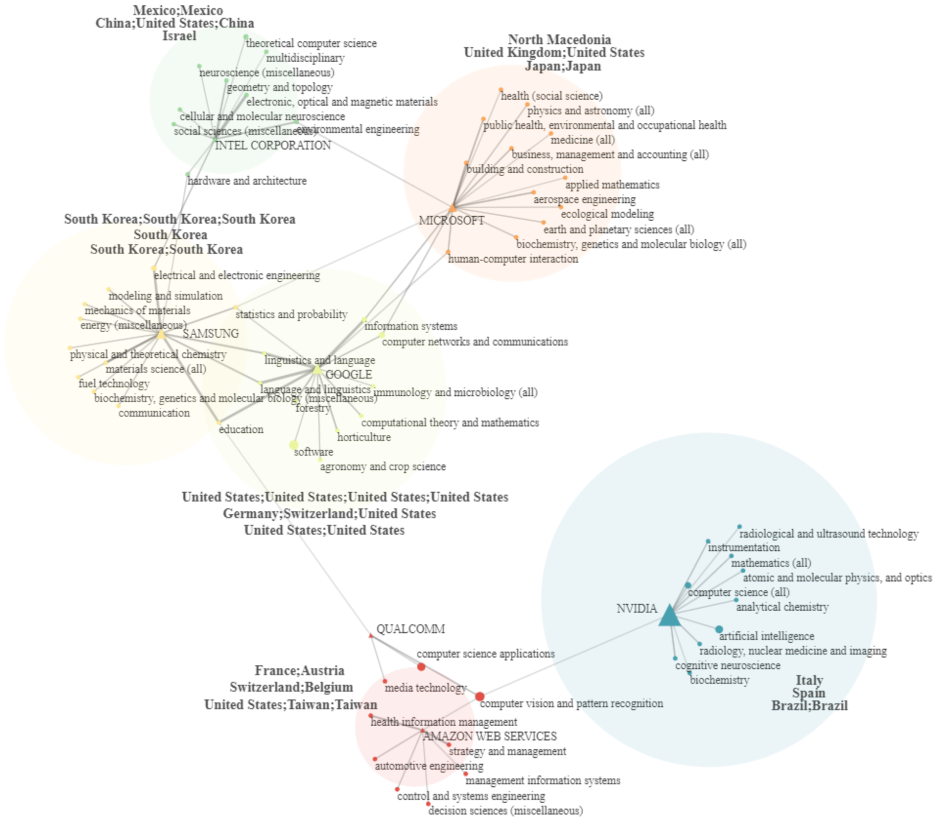
Network Mapping. We constructed network maps using multi-term phrases that prominently featured in the sentiment analysis of both research articles and patents. These multi-terms were extracted from abstracts, titles, author keywords (for articles), and patent claims.

For Research Articles. Looking at the network map of multi-terms in Appendix, the key connecting multi-terms in articles signified aspects such as the target domain, language models, instance segmentation, object detection, speech recognition, deep generative models, and face recognition. *These terms represent the diverse and pivotal research areas and* *technologies within the domain of Deep Learning and Computer Vision that are the focus of the analysed articles (*Wang, 2018*).*

For Patents. The multi-terms connecting the patents represented various facets, including data processing systems, machine learning, neural networks, computer-implemented methods, computer-executable instructions, and neural network layers. *These terms collectively represent the core elements and techniques used in the development of Machine Learning technologies and applications (*Zhang, 2020*).*

In the graph-4, we gain a clearer visualisation of subject areas that cluster according to the analysed companies. It is not surprising to find that Samsung has more affiliations in funding with South Korean institutions, whereas Google is more strongly associated with U.S. institutions. Other companies tend to fund research in more diverse locations and regions. Microsoft's funding is notable for its emphasis on human-computer interactions, as well as involvement in subject fields such as earth and planetary science and applied mathematics. In contrast, Qualcomm and NVIDIA primarily focus on traditional machine learning domains, including computer science, artificial intelligence, and pattern recognition. Samsung, Intel, and Google, on the other hand, appear to have a broader application and general-purpose technology focus in this regard.

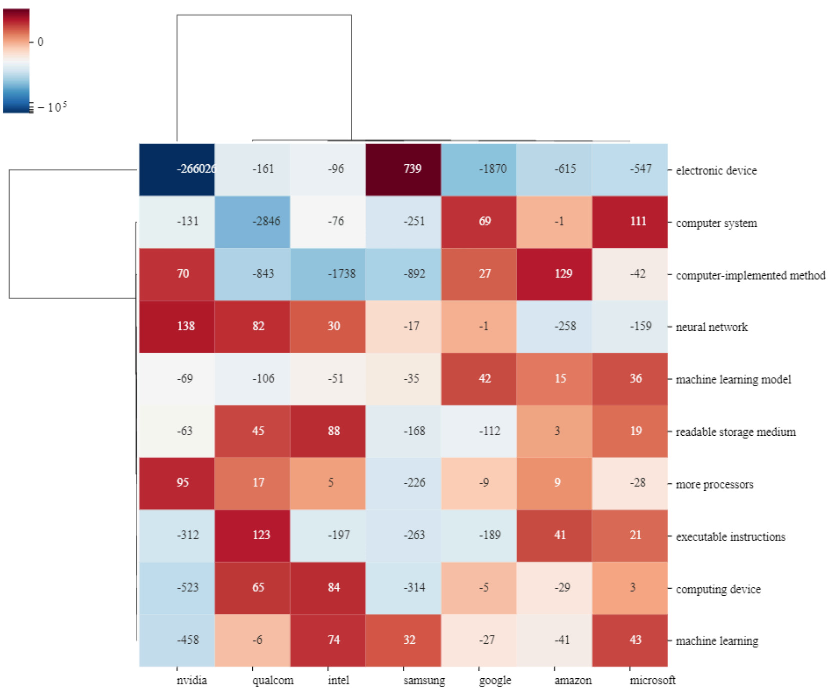
Graph-5. Mapping Subject Areas and Author Affiliations in Deep Learning and Computer Vision Articles Funded by Seven Big Tech Companies (2008-2023). Source: Authors' analysis based on Web of Science.



Object detection, instance segmentation, 3D shapes, speech recognition, deep generative models, machine learning models, target domain, neural networks, data processing systems, and machine learning algorithms serve as common bridges between these companies, indicating their shared and significant interests in these key topics.

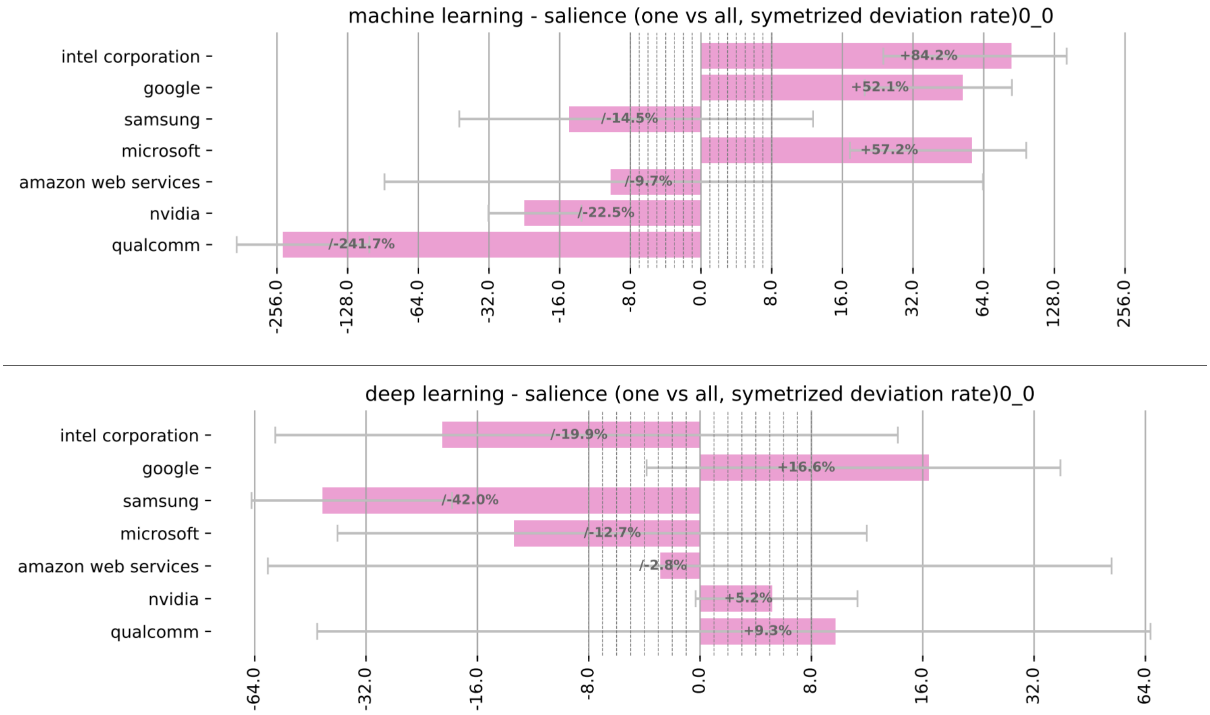
When we delve into the semantic analysis of patents, distinct clusters emerge for each corporation. Samsung's patent portfolio is notably associated with machine learning and electronic devices, highlighting its commitment to these areas. In contrast, NVIDIA's focus is prominently on neural networks and processing power, reflecting their specialisation. Google, Intel, Microsoft, and Amazon exhibit a common emphasis on machine learning models and readable storage mediums, with a clear relevance to cloud storage solutions (Wall Street Journal, 2022). This aligns with their business strategies and the broader technological landscape.

Graph-6. Cluster Map of Multi-Terms in Machine Learning Patents Through Profiling Seven Big Tech Companies (2008-2023). Source: Authors' analysis based on Derwent Innovation.



A closer look at the histograms (graphs 6 and 7 as well as in Appendix) reveals distinct patterns. Intel, Google, Microsoft, and Amazon display a strong emphasis on "Machine Learning" and "Artificial Intelligence," underlining their commitment to these core aspects of the field. In contrast, NVIDIA and Qualcomm take a more streamlined approach, with a predominant focus on "Deep Learning" and "Object Detection." This nuanced perspective provides valuable insights into the research priorities and intellectual property strategies of these corporations in the Machine Learning domain.

Graph-7. Detailed view: Histogram of the terms "Machine Learning" and "Deep Learning" profiled on the Seven Big Tech Companies - symmetrised deviation rate (2008-2023). Source: Authors' analysis based on Web of Science.



Technological cooperation and public policy implications

Technological cooperation may exist between firm leaders at the intersection of multiple innovation circuits conducted and planned by different intellectual monopolies. When big leaders cooperate, it can lead to an oligopolistic cooperation model (Rikap, 2019).

Technology guides new forms of cooperation and competition that surpass traditional price competition contexts (Rikap, 2018) since it can also be based on the joint production of generic knowledge or general-purpose technology modules that might lead to jointly owned patents. While leaders cooperate in certain steps of the innovation processes, they also undertake fierce technological competition with the aim of achieving innovations to remain ahead of the rest and profit from intellectual monopolies (Rikap, 2019).

Evidence shows many examples of how cooperation can pass from major basic research, for example, Rikap (2018) found how Apple, Google, Facebook, and Microsoft are publishing together with co-authorship analysis of scientific papers. Furthermore, a patent analysis in big pharma shows how leaders are jointly patenting, although it is a less frequent strategy (Rikap, 2019). An additional example is the "Partnership of AI to benefit people and society," founded and integrated by Microsoft, Google, Amazon, IBM, Facebook, and Apple, which has the aim of research together in the field (PartnershipAI, 2023).

A better understanding of the implications of technological cooperation or competition for the innovation ecosystem is needed. With that aim, we developed a simulation using network analysis with the social platform simulation NetLogo, among these leading companies in the field of machine learning and computer vision.

As features of each company, Amazon, Google, Microsoft, Siemens, Qualcomm, Nvidia, and Intel, we consider the resources allocated in R&D activities and the number of patent applications for 2022.

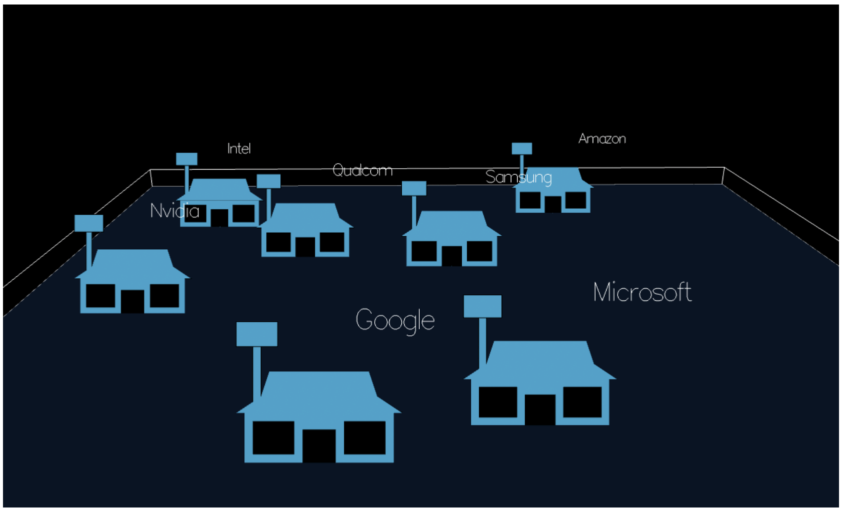
Using the number of patents and R&D expenses, we calculated an "innovation level" for each company, which will capture an efficiency indicator that will impact the final outcome, the innovation ecosystem, which will be represented by the potential number of patents that each environment is able to produce.

For the simulation, we consider three different scenarios:

1. **Competition scenario**

   Assumes that companies are working individually. It is characterised by high technological competition and in-house innovation, where rents are reinvested in R&D activities and cooperation with other leaders is not the preferred strategy (Rikap, 2019) even though given their intellectual monopolies conditions, they could subordinate and predate knowledge with the outsourcing of research modules from smaller companies in the field, and patenting individually as evidence has shown for the case of Apple and Amazon (Rikap, 2023a), (Rikap, 2023b). This scenario is represented in Figure 1.

Figure 1. Competition scenario environment

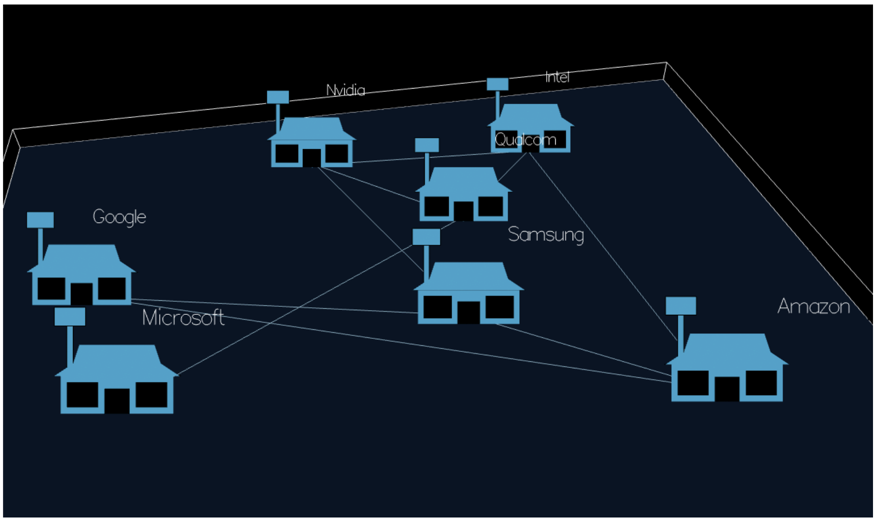


Source: own elaboration using NetLogo platform

2. **Cooperation scenario**

Assumes that companies will share resources, represented by the innovation level, and with the total accumulated knowledge will be able to produce more patent applications. As our Network Mapping identified in the previous section, these seven companies are sharing research topics in the machine learning and computer vision field, in that sense, the simulation will assume that companies will create connections if they share more than two research fields of the four that they are working out of the ten fields existing in our environment. These numbers are computed and scaled by the Network Mapping that identifies 159 total subject areas of research with 61 on average, where 16 are common fields among the companies. This scenario is represented in Figure 2.

Figure 2. Cooperation scenario environment

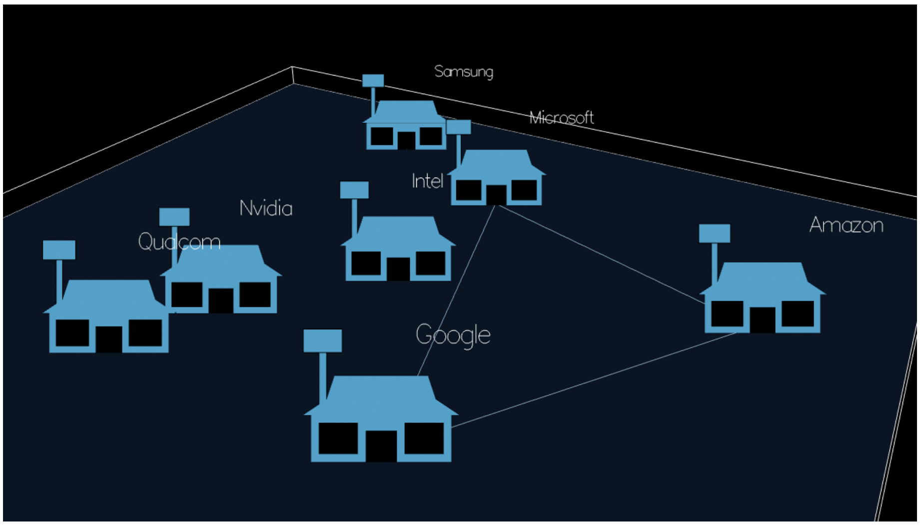


Source: own elaboration using NetLogo platform

3. **Oligopoly scenario**

Assumes that companies with bigger R&D resources will cooperate and share their innovation level. As Rikap (2019) describes, this scenario will follow the "wannabe leader" and "leader" behaviour, where it considered that leaders compete not mainly in terms of price but in technological competition hence, to remain as leader, companies need to plan innovation circuits with other leaders on how to produce in the collaborative way generic modules of knowledge that can be integrated to their innovation circuits, while wannabe leaders try to achieve systematic innovation by themself to continue in the race in specific subfields. This scenario is represented in Figure 3.

Figure 3. Oligopoly scenario environment

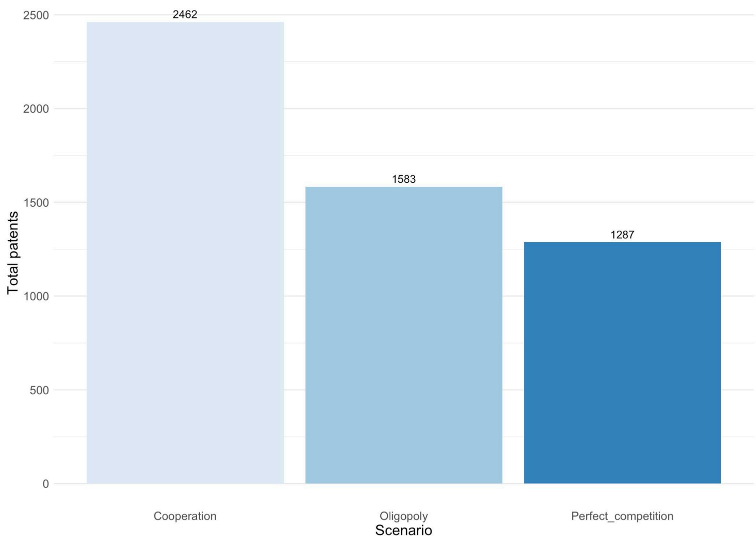


Source: own elaboration using NetLogo platform

In each scenario, when companies cooperate and a link is made, companies merge their innovation levels, allowing them to have a higher potential for innovation, such as the generation of patents in the environment.

Results

Graph 8. Main results of the simulation: total patents after a year



Source: own elaboration with data obtained by Netlogo simulation

After running the scenarios, graph 8 represents the total outcome by the number of patents that each scenario is capable of producing in the same conditions. Between the three scenarios, after a year, more patents are achieved if the companies cooperate, given that more connections are created between companies with more efficiency or innovation levels. The oligopoly scenario is less effective for creating patents because connections are made with the biggest companies in terms of resources, which are Microsoft, Amazon and Google, but among these companies, the innovation levels are not the most efficient.

Public policy implications

The conditions for the production and use of intangibles have changed radically in the past 20 years. (Durand & Milberg, 2020), according to (Pagano, 2014), the tightening of property rights, IPRs, since the 1980s by the Bayh Dole Act has created an era of intellectual monopoly capitalism, referring to the stage where capital accumulation and distribution is led by a core of companies that base their accumulation and power on their permanent and expanding monopoly of predated knowledge (Rikap, 2021).

The emergence of leaders can be conceived as the result of innovation's monopoly; this also reduces the remaining firm's possibilities to invest in future innovations (Rikap, 2018). As the results show, the machine learning and computer vision research field is dominated by seven big techs distributed in two markets, the US and China; in this scenario, technological cooperation is key for the concentration of knowledge.

The simulation shows the potential that cooperation has in achieving innovation. For the innovation ecosystem, a higher achievement of patents can lead to the development of new general-purpose technologies. Nevertheless, cooperation could lead to more concentration of knowledge, which can be detrimental to the technological catching up by other companies and markets and the creation of natural monopolies.

As Pagano (2014) proposed, public policy should imply a radical shift from a world mainly organised around closed science and closed markets to a world centred on open markets and open science. The communism of human knowledge can promote open competition among different firms.

Additionally, democratising access to knowledge through a new commons regime should simultaneously be considered by public policy. (Rikap, 2021). Global knowledge commons with an equal and fair distribution of the tools to access and use knowledge within and across national borders (Rikap & Lundvall, 2022) implies that the World Trade Organization should also include rules stating that fair participation requires each member to invest a fraction of their GDP in open science and to be made available to all countries as a global common (Pagano, 2014).

Moreover, Pagano (2014) suggests that the exit from the crisis requires a (i) Marxian policy of asset redistribution, a (ii) liberal anti-monopoly pro-market policy, and a (iii) Keynesian public investment policy that relaunches open science as a fundamental requisite of genuinely open markets. These strategies can generate more basic knowledge in the global public domain and less concentration of power in a few companies.

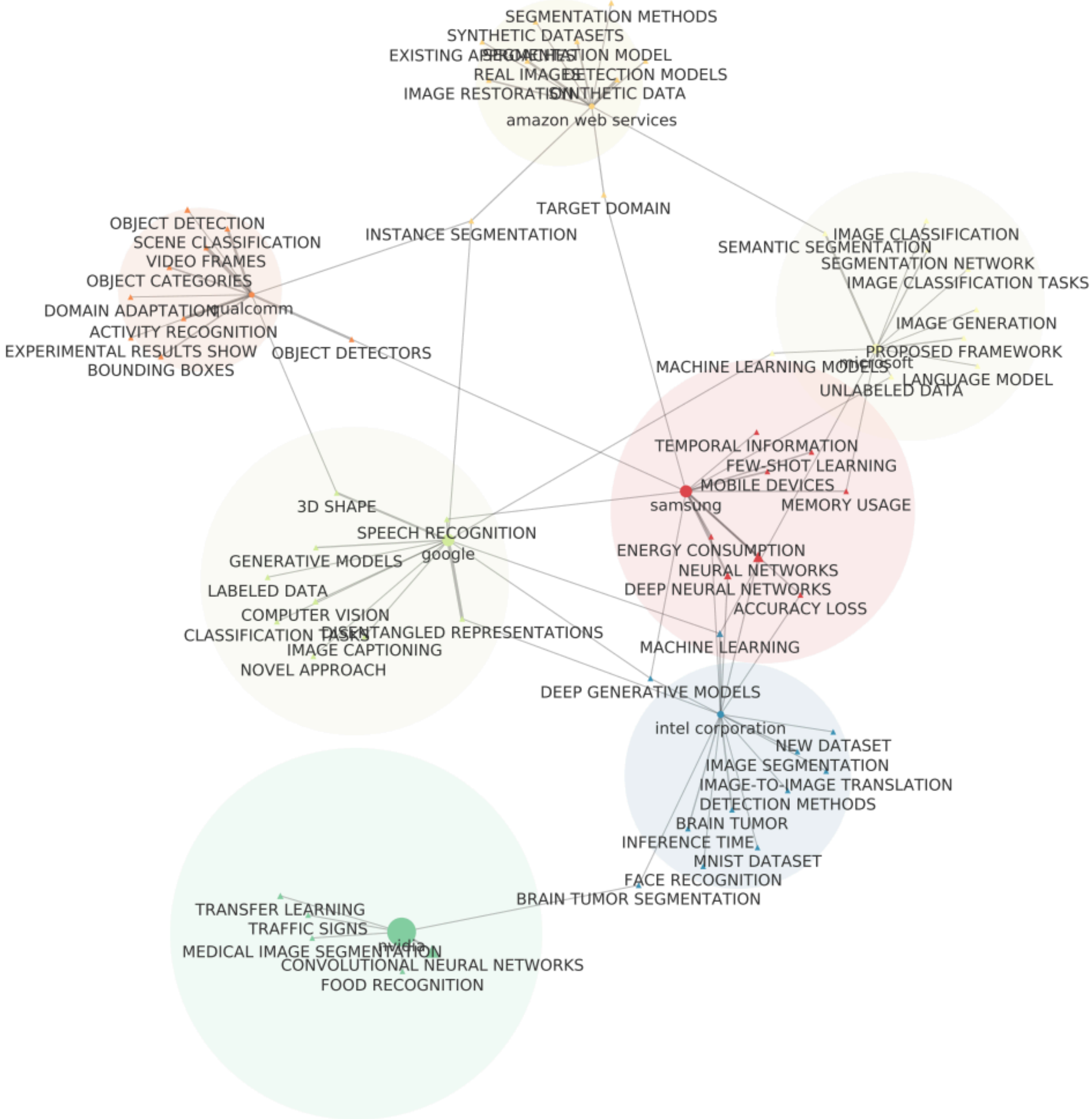
Conclusion.

Our bibliometric analysis of 1,907 academic papers and 6,490 patents in Machine Learning (ML), reveals a landscape significantly influenced by major tech corporations. Clusters also highlight the growing importance of AI applications in healthcare. Key findings highlight the superiority of collaborative innovation over competition, suggesting that cooperative efforts lead to more effective advancements in ML technologies.

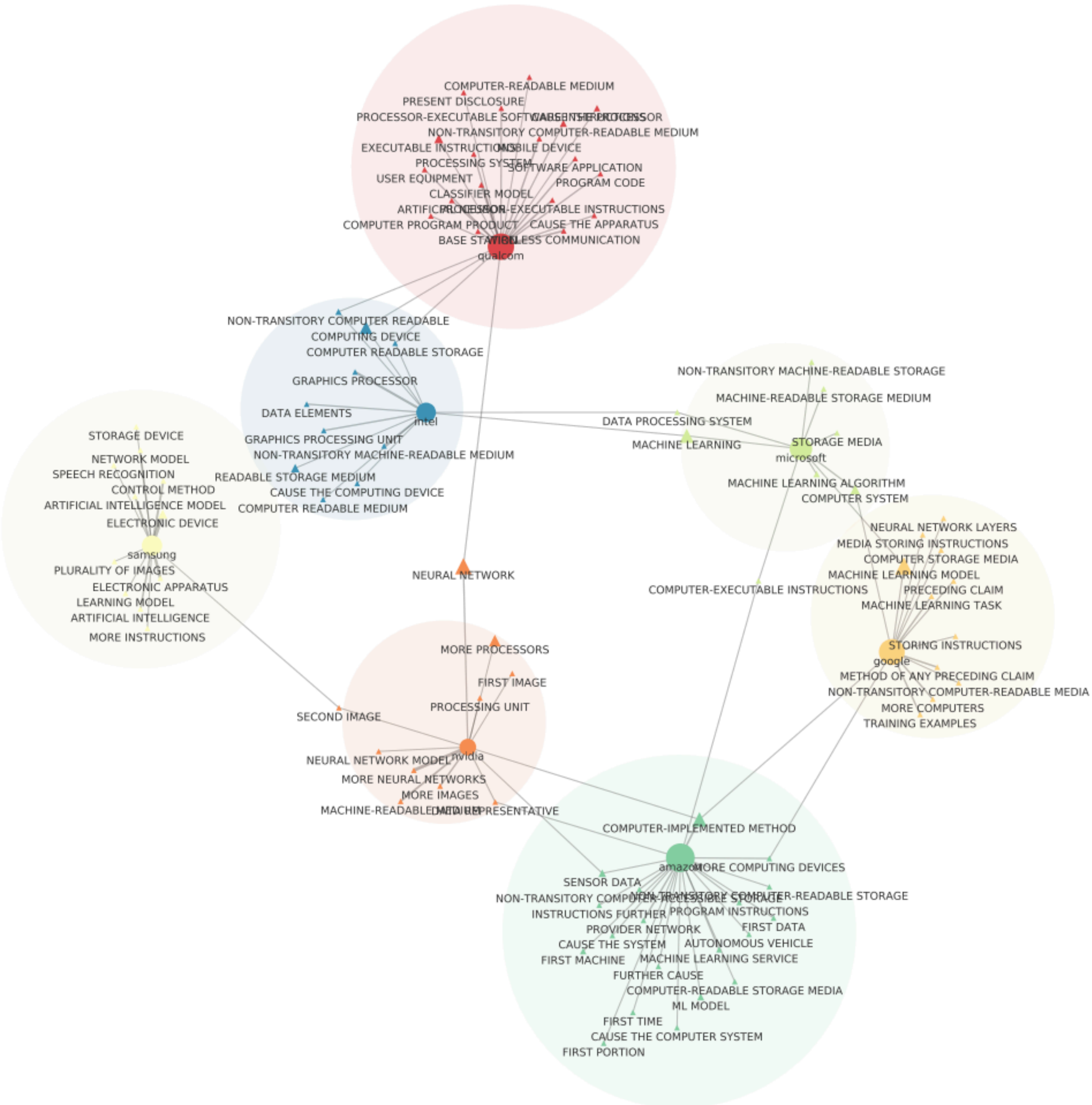
The study also highlights the importance of global participation and the role of public policies in promoting open science and democratized access to knowledge. This research advocates for a collaborative, inclusive approach in ML development, aiming to guide future strategies and policies towards a more equitable and comprehensive advancement in the field of Machine Learning

Appendix: Descriptives and more details

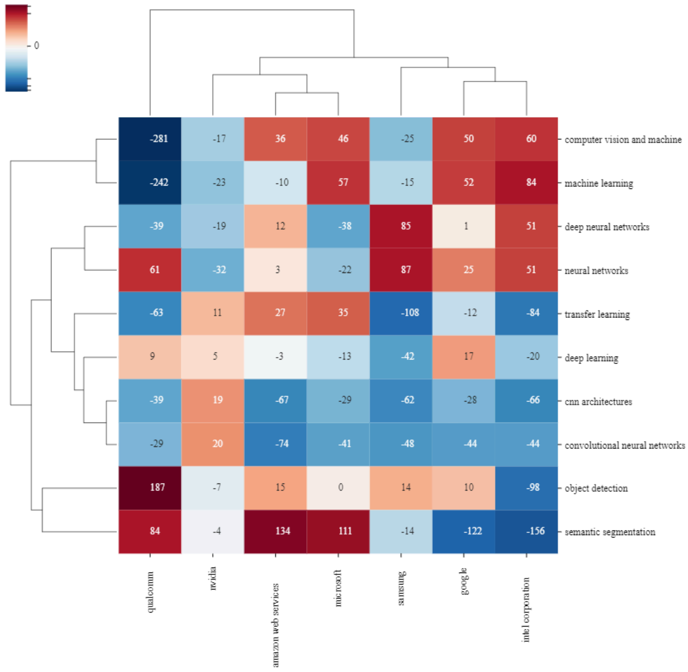
Graph-A. Network mapping of the most frequent multi-terms in articles written on Deep Learning and Computer vision and funded by the seven analysed big tech companies (2008-2023). Source: Authors' analysis based on Web of Science.



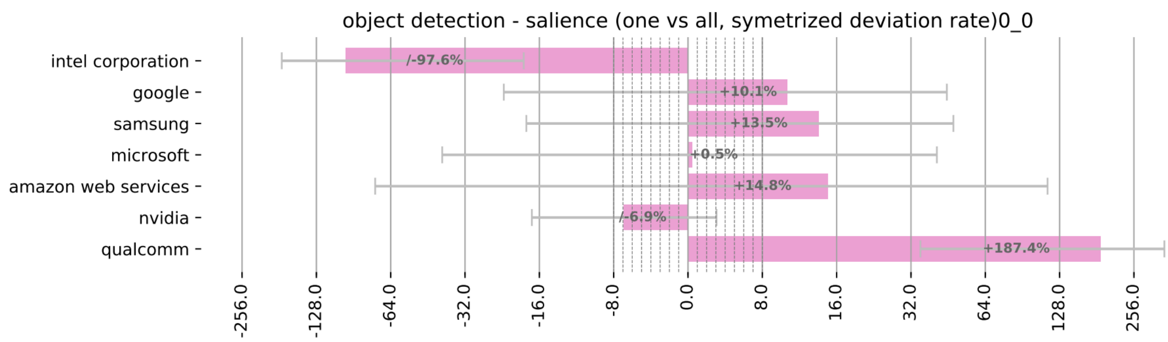
Graph-B. Network mapping of the most frequent multi-terms in patents written on Machine Learning and owned by the seven analysed big tech companies (2008-2023). Source: Authors' analysis based on Derwent Innovation.



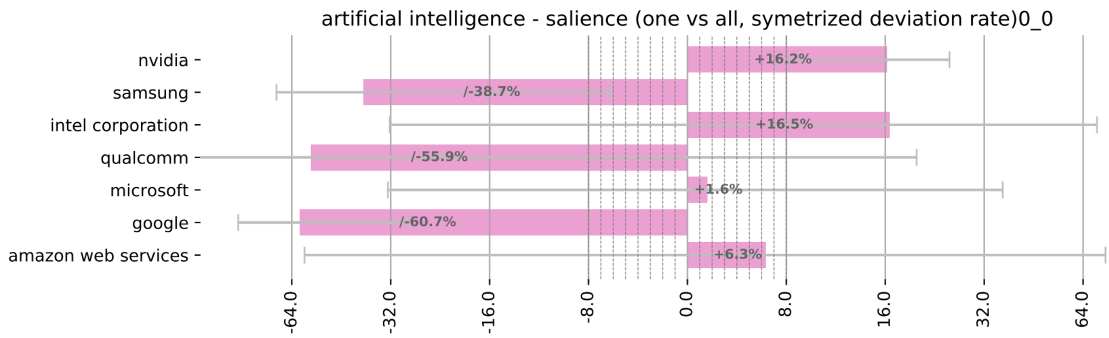
Graph-C. Cluster Mapping of Multi-Terms in Deep Learning and Computer Vision Articles Profiling Seven Big Tech Companies (2008-2023). Source: Authors' analysis based on Web of Science.



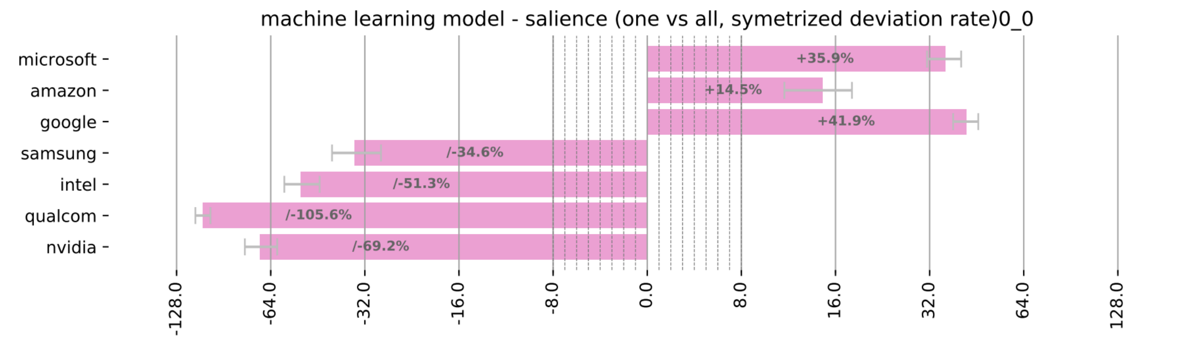
Graph-D. Detailed view: Histogram of the term "Object Detection" profiled on the Seven Big Tech Companies - symmetrised deviation rate (2008-2023). Source: Authors' analysis based on Web of Science.



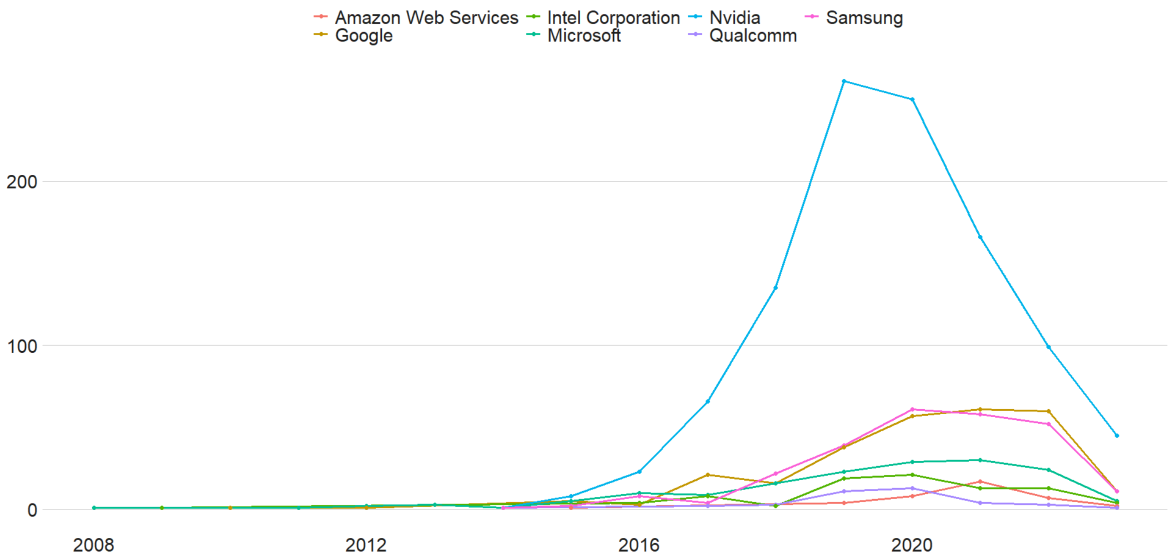
Graph-E. Detailed view: Histogram of the term "Artificial Intelligence" profiled on the Seven Big Tech Companies - symmetrized deviation rate (2008-2023). Source: Authors' analysis based on Derwent Innovation.



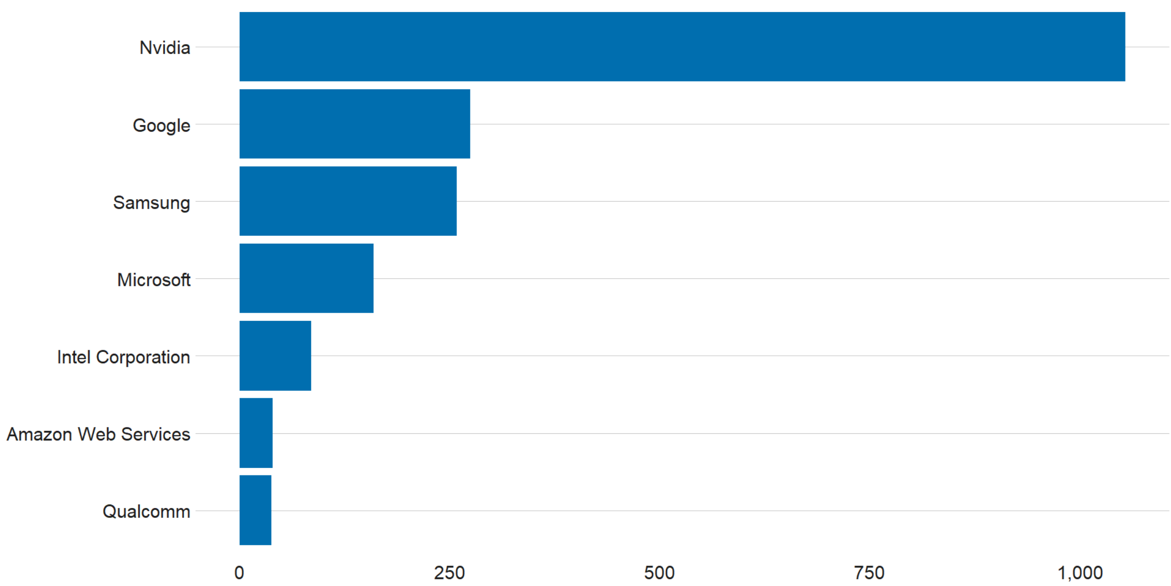
Graph-F. Detailed view: Histogram of the term "Machine Learning Model" profiled on the Seven Big Tech Companies - symmetrised deviation rate (2008-2023). Source: Authors' analysis based on Derwent Innovation.



Graph-G. Evolution of Funding Trends in Big Tech Giants (2008-2023): Source: by the Authors through Web of Science Analysis.



Graph-H. Total number of DL and CV articles funded by Big Tech Giants (2008-2023): Source: by the Authors through Web of Science Analysis.



References

Conroy, N., Bock, A., & Littman, M. (2020). Six researchers who are shaping the future of artificial intelligence. Nature, 588 (7838), 397–400

Durand, C., & Milberg, W. (2020). Intellectual monopoly in global value chains. *Review of International Political Economy*, *27*(2), 404-429. https://doi.org/10.1080/09692290.2019.1660703

Moorhead, P. (2017, October 27). Amazon and NVIDIA simplify machine learning. Forbes

Ren, Y., Yoo, S., & Hoisie, A. (2019). Performance analysis of deep learning workloads on leading-edge systems. In Proceedings of the 10th IEEE/ACM Performance Modeling, Benchmarking and Simulation of High Performance Computer Systems (PMBS) (pp. 103-113). IEEE.

Wall Street Journal. (2022). Google chases Microsoft, Amazon in cloud market share with AI tools. Retrieved from: [https://www.wsj.com/tech/ai/google-chases-microsoft-amazon-cloud-market-share-with-ai-tools-a7ffc449]

Wang, Z., Bovik, A. C., Sheikh, H. R., & Simoncelli, E. P. (2018). Deep learning for computer vision: A brief review. Computational Imaging and Vision, 47, 1–27.

Zhang, Y., Li, J., Wang, Z., & Liu, Y. (2020). Machine learning system with neural network layers. U.S. Patent No. 10,853,717.

Akinosho, T. D., Oyedele, L. O., Bilal, M., Ajayi, A. O., Delgado, M. D., Akinade, O. O., & Ahmed, A. A. (2020). Deep learning in the construction industry: A review of present status and future innovations. *Journal of Building Engineering*, *32*, 101827. https://doi.org/10.1016/j.jobe.2020.101827

Bajpai, P. (2021). Which Companies Spend the Most in Research and Development (R&D). *URL: https://www.nasdaq. com/articles/which-companies-spend-the-most-in-research-and-development-rd-2021-06-21*.

Dash, R., McMurtrey, M., Rebman, C., & Kar, U. K. (2019). Application of artificial intelligence in automation of Supply Chain Management. *Journal of Strategic Innovation and Sustainability*, *14*(3). https://doi.org/10.33423/jsis.v14i3.2105

Chen, Z., Quan, W., Wen, M., Fang, J., Yu, J., Zhang, C., & Luo, L. (2020). Deep Learning Research and Development Platform: Characterizing and Scheduling with QoS Guarantees on GPU Clusters. *IEEE Transactions on Parallel and Distributed Systems*, *31*(1), 34–50. https://doi.org/10.1109/TPDS.2019.2931558

Dolata, U. (2017.). *Apple, Amazon, Google, Facebook, Microsoft: Market concentration—Competition—Innovation strategies*.

Hatcher, W. G., & Yu, W. (2018). A Survey of Deep Learning: Platforms, Applications and Emerging Research Trends. *IEEE Access*, *6*, 24411–24432. https://doi.org/10.1109/ACCESS.2018.2830661

Jan, B., Farman, H., Khan, M., Imran, M., Islam, I. U., Ahmad, A., Ali, S., & Jeon, G. (2019). Deep learning in big data Analytics: A comparative study. Computers & Electrical Engineering, 75, 275–287. https://doi.org/10.1016/j.compeleceng.2017.12.009

Luckow, A., Cook, M., Ashcraft, N., Weill, E., Djerekarov, E., & Vorster, B. (2016). Deep learning in the automotive industry: Applications and tools. *2016 IEEE International Conference on Big Data (Big Data)*, 3759–3768. https://doi.org/10.1109/BigData.2016.7841045

Miguel de Bustos, J. C., & Izquierdo-Castillo, J. (2019). Who will control the media? The impact of GAFAM on the media industries in the digital economy. *Revista Latina de Comunicación Social*, (74), 803-821.

PartnershipAI (2023). Partnership on AI is bringing together diverse voices from across the AI community. Retrieve from: https://partnershiponai.org

Pagano, U. (2014). The crisis of intellectual monopoly capitalism. *Cambridge Journal of Economics*, *38*(6), 1409-1429. https://doi.org/10.1093/cje/beu025

Pramod, A., Naicker, H. S., & Tyagi, A. K. (2021). Machine Learning and Deep Learning: Open Issues and Future Research Directions for the Next 10 Years. In A. K. Tyagi (Ed.), *Computational Analysis and Deep Learning for Medical Care* (1st ed., pp. 463–490). Wiley. https://doi.org/10.1002/9781119785750.ch18

Probst, D. (2022). *Social and environmental impact of recent developments in machine learning on biology and chemistry research* (arXiv:2210.00356). arXiv. https://doi.org/10.48550/arXiv.2210.00356

Raschka, S., Patterson, J., & Nolet, C. (2020). Machine Learning in Python: Main Developments and Technology Trends in Data Science, Machine Learning, and Artificial Intelligence. *Information*, *11*(4), Article 4. https://doi.org/10.3390/info11040193

Rikap, C (2018). Innovation as economic power in Global Value Chains. Revue d'économie industrielle, 35-75. https://doi.org/10.4000/rei.7226

Rikap, C (2019). Asymmetric Power of the Core: Technological Cooperation and Technological Competition in the Transnational Innovation Networks of Big Pharma, Review of International Political Economy, DOI: 10.1080/09692290.2019.1630309

Rikap, C. (2021). *Capitalism, Power and Innovation; Intellectual Monopoly Capitalism Uncovered*.

Rikap, C., & Lundvall, B. Å. (2022). Big tech, knowledge predation and the implications for development. *Innovation and Development*, *12*(3), 389-416. https://doi.org/10.1080/2157930X.2020.1855825

Rikap, C. (2023a). Capitalism as Usual? Implications of Digital Intellectual Monopolies. *New Left Review*, *139*(Jan), 145-160.

Rikap, C. (2023b). *Same End by Different Means: Google, Amazon, Microsoft and Meta's Strategies to Organize Their Frontier AI Innovation Systems*. City, University of London.

Sharma, N., Sharma, R., & Jindal, N. (2021). Machine Learning and Deep Learning Applications-A Vision. *Global Transitions Proceedings*, *2*(1), 24–28. https://doi.org/10.1016/j.gltp.2021.01.004

Tsay, M., & Liu, Z. W. (2020). Analysis of the patent cooperation network in global artificial intelligence technologies based on the assignees. *World Patent Information*, *63*, 102000. https://doi.org/10.1016/j.wpi.2020.102000