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Artificial Intelligence, Data and Competition – Note by Greece

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1. Introduction

1. Conventional Machine Learning (ML) algorithms focus on analyzing relationships from historical data to perform specific tasks, such as classification, forecasting, clustering, recommendation, or anomaly detection. However, none of them can generate human-like content, such as text, image, video, or audio, which is the primary purpose of Generative Artificial Intelligence (GenAI). GenAI technology has transformative power for many industries, particularly the data-rich ones. It is indicative that GenAI tools for Natural Language Processing (NLP) processes could increase global GDP by 7% and boost productivity growth 1.5% in the next decade according to a Goldman Sachs Research [2]. GenAI advancements urge public and private organizations to increase their investments in the integration of AI services in their workflows. IBM Global AI Adoption Index states that above 40% of companies have already deployed AI solutions as part of their operations [3]. Given this wide AI adoption, competition authorities are faced with emerging competition challenges, including data and AI monopolies, price discrimination, data privacy, or algorithmic collusion [4, 5].

2. On the other side, the massive text datasets that competition and antitrust authorities collect and produce, formulate a promising landscape for the successful application of AI and GenAI. In this way, AI capabilities could prove valuable for competition monitoring, investigations, and enforcement purposes. Leveraging data collected from online sources and dawn raids can help investigators and case handlers in their everyday activities, *e.g.*, text generation, extraction, summarization, classification, translation, or complex questions answering. Such NLP applications are built on top of sophisticated GenAI models, known as Large Language Models (LLMs) [6] or Foundation Models (FMs) [7]. LLMs are a type of Deep Neural Network (DNN) that result in better performance with more data and computational power [8] (hence the "large" term) and are specialized to work with textual data (hence the "language" term). More precisely, they can infer relations between words, expressions, sentences, paragraphs and produce text that mimics the human writing style. Well-known examples of LLMs are OpenAI's GPT, Google's PaLM, and Meta's LlaMA [9]. FMs are often used with LLMs interchangeably but refer to systems with broader scope and capabilities that can adapt to new purposes and perform varied tasks [7]. On top of that, FMs allow data scientists to use an original model as a base (*i.e.*, foundation) and thus build new applications faster, rather than developing a GenAI model from scratch. Ultimately, FMs empower GenAI systems to evolve and adapt in response to the ever-evolving user demands.

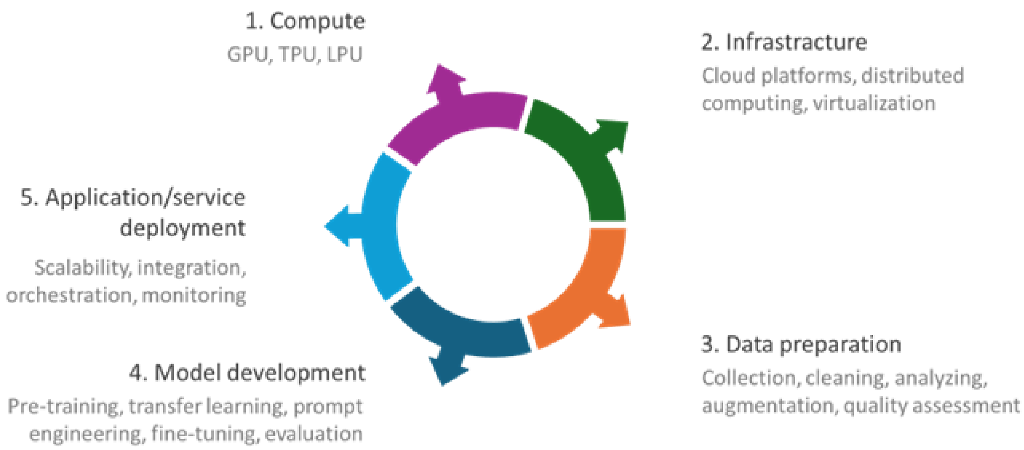
2. The Emergence of AI and its Business Models

2.1. What is AI and the key parts of the value chain?

3. GenAI is revolutionizing an entire business ecosystem, from hardware providers to software builders. In general, the distribution of a state-of-the-art AI-powered system requires substantial investments in technical expertise, computational resources, data, and capital [10]. The GenAI value chain encompasses a series of interconnected components, as shown in *Figure 1* [10, 11, 12, 13, 14]. Firstly, computational power (or *compute*) provided by specialized processors, such as Graphics Processing Units (GPUs), Tensor

Processing Units (TPUs), or Language Processing Units (LPUs), are essential to handle heavy mathematical calculations (*e.g.*, matrix multiplication) with large datasets, accelerate model training, and support inference tasks [15]. Therefore, GenAI is considered a compute-bound technology, since it has the unique property that the performance of the model improves by adding more computational resources [16]. This way, even if such AI processors are nice-to-have for traditional ML projects, they are a fundamental element in a standard GenAI pipeline. The next component is the *infrastructure*, *i.e.*, an underlying technology stack of hardware and software elements that enables data science, engineering, and DevOps teams to manage resources and workflows required to develop, train, and deploy ML models in dev and production environments. The decision between hosting the IT infrastructure on cloud or on-premises is critical, since it entails differences for the company in operational cost, control, security, flexibility, and compliance [17]. However, since GenAI is resource-intensive, most companies prefer cloud to access scalable computational power. In any case, infrastructure leverages architectures, such as edge, distributed, or cluster computing, which facilitate the needs of training large-scale models [18, 19]. Apart from that, infrastructure supports a wide range of tasks, including data storage, data governance, service networking, orchestration, and virtualization. Having secured the computational and infrastructural needs of AI models and applications, the next component in the value chain relates with the *data*. It is commonly accepted that Big Data along with its quality is the key for any successful AI and GenAI project [12]. In this stage, companies develop data pipelines and automate programming procedures to collect data from various web sources (*e.g.*, news, social media, blogs). Then, companies must clean, curate, and assess the quality of the collected data (*e.g.*, bias check) that will be used to feed the models [20]. Following the data preparation component, *model development* involves an iterative process of building neural network architectures, training the model effectively, and evaluating its performance. Data professionals and product managers work tirelessly to design, customize, and optimize algorithms to analyze complex patterns within the raw data and generate high-quality content across several domains [11]. Finally, *deployment* of GenAI services and products involves maintaining and integrating models into Business-to-Business (B2B) and Business-to-Consumer (B2C) applications (*i.e.*, interfaces) for real-world usage [13]. In this component, developing services with Application Programming Interface (APIs) for seamless integration into affiliate systems enables the application to be part of a larger ecosystem and thus augments its inherent capabilities automatically. An interoperable system promotes innovation and fosters a more competitive and collaborative GenAI community.

Figure 1. The GenAI value chain



4. Overall, GenAI value chain is quite similar to a traditional AI value chain, albeit there are some new additions that this novel technology requires (*e.g.*, computer hardware, FMs) [14]. However, GenAI systems are more complex than traditional AI systems, thus there are differences in market opportunities for new entrants, startups, and Small and Medium-sized Enterprises (SMEs). It needs to be noted that across the AI value chain, data is a critical factor in meeting the company's expectations about its investments in GenAI. An AI application has no chance to succeed without adequate and qualitative data, even if all the other components are well-developed and maintained. On top of that, companies involved in AI must be committed to the trustworthy application of AI to ensure fair competition and drive sustainable development [21]. Understanding the complexities of the GenAI value chain is essential for both stakeholders and competition authorities looking to harness the full potential of this novel technology and capitalize on its benefits.

2.2. What is required to successfully develop AI models and deploy them?

5. The development of AI models is at the heart of the AI ecosystem. Developing a successful AI model entails a multi-step process for the companies. The first step is to understand the purpose of the model, collect appropriate amount and variety of data relevant to the target, and prepare it for use by the algorithm. Then, according to the complexity of the input data, data scientists must select a model architecture. A top performing architecture for NLP tasks is the "Transformer", a deep learning technique by Google designed to capture relationships in sequential data, like the words in a sentence [15, 22]. After building, model training is the following process enabling the model to learn underlying patterns in the data. In the case of GenAI, high computational costs are associated with the training of large-scale FMs, which may contain billions of parameters [7]. This way, it is essential to incorporate specialized hardware resources to accelerate the training process on large amounts of data [23]. In the context of LLM and FMs, several optimization methods must be further applied to ensure an acceptable model performance, such as pre-training, prompt engineering, transfer learning, Retrieval-Augmented Generation (RAG), or fine-tuning [7, 10, 22, 24]. Techniques such as limiting the type of responses, training on a smaller dataset related to the target task, or condensing knowledge from a complex model into a simpler one (knowledge distillation), allow a better application on a specific task or domain [22]. The final step is the model validation and evaluation that allows to measure objectively and transparently the results of the AI model [15]. The goal here is to achieve an acceptable model performance according to the stakeholders' needs. Model hubs act as repositories for storing and accessing FMs. The whole process is iterative and demands research and experimenting with different architectures, optimization techniques, or more computational resources.

6. Once the model is developed, data professionals must deploy it in a real-time production environment (*e.g.,* an application or a user interface) [13]. The objective here is to ensure that the trained model generates output and content based on the patterns it learned, so that consumers can enjoy accurate and reliable results. Model deployment entails two main challenges in real-world scenarios: *(i)* integration, *(ii)* scalability [22]. Modern commercial AI services communicate with the target application or third parties through Application Programming Interfaces (APIs) to provide a seamless user experience and deliver added value. Furthermore, today's evolving needs require a flexible and modular architectural design that allows scaling the model to handle more amounts of data. Once deployed, AI models need further fine-tuning and continuous monitoring to detect potential performance degradation due to unexpected variables [11]. Thus, developers should establish automations to monitor the performance with system alerts, optimize prompts (prompt-tuning), and maintain high-quality outcomes. ML Operations (ML Ops)

tools and practices help to adapt and deploy the model in end-user applications and services.

7. It needs to be mentioned that deploying AI and GenAI models comes with several ethical considerations and challenges that need to be addressed [21]. More specifically, data bias may lead to discriminatory results. Ensuring high data quality is an effective way to mitigate biases and promote fairness in the model [25]. In addition, lack of transparency can raise concerns about accountability. It is a fact that complex AI models function as “black boxes” where it is difficult to achieve transparency. Incorporating mechanisms to develop interpretable and explainable models (explainable AI) can help understand the model outputs, build trust, and improve decision-making throughout the value chain [19]. Data privacy and protection issues are also of paramount importance for the users who prefer companies like Apple which showcase strong privacy principles [26]. Towards this end, data professionals face a trade-off between achieving high accuracy and ensuring compliance with latest privacy laws and regulations by leveraging techniques such as data anonymization, encryption, differential privacy, user consent, and access control [27]. Lastly, since AI and GenAI models assist in the decision-making processes of individuals, businesses, and society, they should follow the recent frameworks and guidelines for responsible and trustworthy AI, especially in sensitive domains, such as healthcare [28, 29]. Apart from actions at EU-level, there are innovative works that concentrate on creating ethically aligned AI systems, such as the ECCOLA method [30].

8. Overall, successful development and deployment of GenAI models demands a holistic end-to-end approach that balances technical innovation with ethical responsibility. People with different areas of expertise, from data engineers to business experts and lawyers, need to work together effectively by aligning goals, sharing insights and feedback. By collaboration and solid advice from competition authorities, companies can overcome GenAI ethical challenges and make applied AI projects a success.

2.3. What are/will be the business models underpinning the development of AI?

9. The business model is considered the DNA of a company, a tool to implement business strategies. It concerns the way in which the company does business, commercializes its products, services, or technology, and explains how it creates, delivers, and captures value [31]. Each company configures its business model according to the unique value proposition it delivers and the current needs in the target market. GenAI technology and its undeniable capability to speed up work will possibly influence the business models across companies in the GenAI value chain in various ways [32]. In the fashion industry, brands like Zara, H&M, and Nike, are already using GenAI to drive product design and personalization. In e-commerce, GenAI personalizes recommendations for the consumers. Developers are heavily using platforms like ChatGPT and Copilot to speed up their coding. Graphic design companies, like Adobe or Canva, have incorporated GenAI to allow their users to design like professionals. Content Management Systems (CMS), like WordPress and HubSpot empower their users to create AI content for their blog posts, articles, product descriptions, and more. Communication platforms, like Slack and Zoom, offer real-time language translation with GenAI enhancing international collaborations. GenAI chatbots and virtual assistants enhance customer service and support in the digital channels of companies. Delta Airlines and Expedia use them to improve their customer communications and manage customer complaints efficiently. Consulting firms, such as EY, Deloitte, and Accenture, use their GenAI technical and business expertise to expand their offerings to organizations seeking to capitalize on GenAI. Businesses with marketplaces can also leverage AI-generated content for their marketing operations, like Amazon and Meta, which have integrated GenAI solutions for product advertising [33]. It

is highlighted that targeted advertising to users with specific behavior and preferences is highly attractive to businesses since it is the most effective method to increase their conversion rates and measure their Return on Investment (ROI) in practice. It is obvious that many opportunities arise for companies to increase their efficiency and reduce operational costs with GenAI. There are partnerships between companies, research institutions, startups, and technology providers to accelerate GenAI innovation, overcome technical challenges, and drive market adoption.

10. On the other hand, companies that develop and distribute GenAI adopt existing pricing strategies that have been used for the more conventional AI products and services. This way, Software as a Service (SaaS) is the most frequently used business model for AI and GenAI software licensing [34]. In SaaS, companies offer tailored subscription-based solutions, where customers pay a respective recurring fee to access the service. In this strategy, a common standard is to provide flexibility in billing, for example by the “pay-per-use” model, where customers pay only according to the usage of the AI service, or by the “freemium” model, where companies offer basic services free but premium features (*i.e.*, enhanced capabilities) are available only after paying [35]. To penetrate the market, famous chatbots, like ChatGPT and Gemini, have introduced a tiered subscription model, where the first package is free, but the next package has “pay-as-you-go” charging, according to the number of requests or tokens per minute. This way, companies allow potential customers to experiment with the tool, understand its capabilities, and finally feel the need to acquire it before committing to a paid plan. It is worth mentioning that even if the first version of many conversational chatbots leveraging LLMs was available openly and freely, the latest versions are closed-source and subscription-based (*e.g.*, GPT-4). Furthermore, cloud platforms offering AI solutions, usually come under a Platform as a Service (PaaS) business model that allows developers to build and deploy AI applications without the management necessity of the respective underlying infrastructure [36]. Established platforms also provide ready-to-use pre-trained models on specific domains that can be quickly deployed.

11. To adapt to the continuous changes of the external environment (*e.g.*, economic, technological, competitive, sustainability, social factors), companies should reconfigure their business models through innovation to be able to meet the new conditions and maintain their value proposition [37]. The rapid advancements of AI along with the unique characteristics of GenAI require a deeper analysis of possible business models and how AI influences the over digital strategy and transformation of the company, including Business Model Innovation (BMI) [32, 38]. On top of that, for an AI and GenAI application to be successful, access to large and reliable data volumes plays a prominent role. This way, companies that have collected large datasets (*e.g.*, social media platforms, online retailers) have a competitive advantage to develop GenAI models and applications. These companies are experimenting with new ways to monetize their data assets either directly (*i.e.*, by selling data in raw form to a third party), or indirectly (*i.e.*, by selling insights and analytics from data) [39]. A form of indirect monetization is advertising and marketing campaigns with personalized chatbot experiences. It is noted that apart from the revenue perspective, data monetization fosters interdisciplinary collaboration and innovation among companies.

3. Competition in the Supply of AI

3.1. How do/will firms compete at different stages of the value chain? Are there risks to effective competition in the supply of AI, for example through the availability of key inputs?

12. Firms compete in every stage of the GenAI value chain, as is presented in *Figure 1*. Initially, regarding hardware, companies invest in Research and Development (R&D) and compete in producing processing boards that facilitate the training and deployment of AI applications. More specifically, the power of FMs is based on processes, like pre-training and inference, which imply high computational costs. Furthermore, since most AI applications run over "Cloud Continuum" and edge devices, AI processing depends on the computing constraints of the host [18]. With this capacity, vendors provide specialized hardware platforms for AI with different processing capabilities targeting specific hosting devices. For example, NVIDIA has developed various hardware "accelerators", from powerful data center GPUs for cloud processing to flexible embedded hardware solutions. On the other hand, Google offers TPUs for cloud processing, and Coral for building local AI products. Apart from these two large companies, there are a few smaller players in the mix who are active or plan to enter the market (mostly in the fabrication stage), but the design and production of these specialized AI processors is concentrated [40]. Companies trying to enter the market will face high start-up costs and difficulties in accessing semiconductors and necessary raw materials to produce AI chips. However, as GenAI market is evolving, hardware designers must develop capabilities to increase their capacity and serve the growing market needs, while in parallel explore alternatives in production as the operation costs increase [41].

13. Regarding the next stage of the GenAI value chain, big tech companies provide integrated cloud-based AI platforms, following mostly the PaaS model, enabling smaller companies to develop and deploy their own AI services. These platforms involve processes and mechanisms for the rest of the stages in the GenAI value chain. For instance, Amazon's SageMaker, Google's Vertex AI, IBM's watsonx, and Microsoft's Azure ML, are ML cloud platforms that support the entire lifecycle of AI and GenAI applications. Apart from the underlying hardware "accelerators" described above, cloud infrastructure includes computing (*e.g.*, server clusters, storage systems), and networking resources (*e.g.*, routers, switches), which are managed using virtualization technologies. Typically, cloud providers also offer the essential software tools for resource orchestration. Although this alleviates the overhead of managing the infrastructure, the pre-built software for cloud resource management may raise compatibility and interoperability issues with AI products developed by small companies and thus restrict their wide adoption from potential customer and users. In this way, tech giants, *i.e.* Google (Alphabet), Amazon, Microsoft, Meta, Apple, can easily keep and expand their market share by acquiring competitive products or adopting aggressive pricing strategies.

14. Since AI systems are data-driven, data collection and analysis are of vital importance for creating meaningful datasets that can be used for the training of accurate AI models at the next stage. The source of data can be public or proprietary. For example, LLMs are usually trained using public datasets from the web. However, recent studies estimate that public data sources for LLM training could be exhausted soon [42]. Furthermore, it is obvious that big tech companies, which have access to huge datasets through their own cloud or social platforms, have a dominant position in the market and this could lead to data monopolies by preventing access to competitors [43]. The creation of open-access data spaces with high-quality datasets for AI model development would facilitate the democratization of the AI ecosystem. Towards this direction, EU encourages

the creation of data spaces that will enable the development of AI products for specific business domains [44]. Lastly, managing AI modeling as a "black box" to feed production decision-making processes entails several risks. Underlying data should cover all aspects of the target to train unbiased AI models that guarantee fair analytics and results.

15. The development of successful FMs relies heavily on the previous stages of the AI supply chain. Currently, there are two ways of AI model deployment: the proprietary "closed-source" and the "open-source" model. The first one allows access only to executable software for a fee, while the last one allows access to source code enabling scalability and interoperable solutions. In either way, model development requires expertise on theoretical and applied data science. Thus, large companies invest substantial financial resources in acquiring top AI experts and researchers to develop novel algorithms with higher performance and lower costs. This situation can lead to a scenario where a few dominant players dictate the direction of AI model development and innovation, stifling diversity and limiting the alternative approaches. To mitigate this risk, startups and SMEs can collaborate with each other and with the academia to build open-source models (*e.g.*, LLMs and FMs on Hugging Face) [45]. Furthermore, ML technology allows an initial model to be extended and improved by other developers [46]. Adopting such a development approach will increase the model's diversity and lead to more innovative products and services.

16. AI products have a wide application range in various industries, such as finance, healthcare, manufacturing, and law. Popular products, *e.g.*, AI-powered chatbots, recommendation systems and content generation, must be deployed as part of the above ecosystems. Towards this direction, the final stage of the AI value chain is the maintenance of the AI products and services and their integration with other digital systems and markets, as depicted in *Figure 1*. Since most of the AI platform providers adopt the PaaS model, they offer a set of essential tools for integrating AI products in their own platform. Under this setting, the data exchange is performed using proprietary APIs and custom formats. The lack of standardized data formats and protocols impedes smaller firms to integrate their AI services with other commercial cloud platforms and prevents them from attracting new customers and users. Furthermore, the lack of data interoperability poses additional challenges regarding security and regulatory compliance. More specifically, data sharing and processing between proprietary systems increases the risk of data leaks and cybersecurity attacks. To overcome the interoperability challenges, research community, industry, and standardization organizations should collaborate to develop protocols and trust mechanisms for transparent data exchange that guarantee security and privacy [47]. Furthermore, competition regulatory intervention would assist in the enforcement of interoperability requirements to guarantee that there exist alternatives in the AI market.

3.2. Are there parallels to be drawn with digital markets?

17. AI and the rest digital markets have close relationships and interactions because products of the AI supply are deployed in other digital markets and vice versa. The market of GenAI and FMs could raise indirect network effects as the broad adoption of these products by other digital markets increases the value of these applications. Since all these markets rely mainly on cloud infrastructure and focus on processing vast amounts of data with AI, there are common competition challenges that emerge from technological convergence, market dynamics, and regulatory complexities. Regarding technological convergence, AI intersects with various digital technologies such as Blockchain, Metaverse, Internet of Things (IoT), Big Data analytics, and cloud computing that enable innovation and development of new products [32]. However, this intensifies the competition between companies to address interoperability challenges, and integration of

heterogeneous products in a single platform to stay ahead in the market. Furthermore, platform dominance by tech giants creates barriers for smaller AI suppliers. As it is already mentioned, concerns about data privacy, vendor lock-in, and anti-competitive practices amplify the platform dominance. Apart from infrastructure and software, human resources play a significant role in the AI market. Due to lack of skilled AI professionals, companies struggle to attract top talents capable of developing novel products and services.

18. The digital markets are data-driven ecosystems and rely on personal and contextual data of the users. Access to high-quality data is crucial for AI modeling, recommendation systems, cybersecurity threats detection, and service development. Firms with access to vast datasets may easily exclude competitors in the future. Towards privacy and fairness, data sharing initiatives and regulatory interventions could prevent data monopoly. Navigating regulatory frameworks poses a significant challenge for companies operating in digital ecosystems, especially in sectors such as software, finance, healthcare, media, and e-commerce. Compliance with regulations such as GDPR or industry-specific standards is imperative to avoid legal liabilities, fines, and reputational damage. Furthermore, there are common ethical concerns of AI, GenAI, and the other digital markets, which include threads regarding privacy violation, data leaks, misuse, and biased algorithms that can negatively affect the firm reputation and the trust between companies and consumers. Finally, although AI supply is a fast-growing market, like other digital markets, the risk of market saturation is realistic. Adopting price competition strategies to enter the market or expand the existing market share could vanish the difference between the offered AI services and products.

4. Competition Policy and Enforcement in AI

19. Companies of all sizes have realized that GenAI technology is not only a trend or a buzzword, but it has the power to transform entire business operations and disrupt traditional business models. This way, they try to adopt AI tools to unlock growth opportunities, drive operational excellence, and gain a competitive advantage. On top of that, GenAI can expand and increase development opportunities in emerging markets, while it has also created new markets [1]. Nevertheless, these markets introduce regulatory uncertainties in competition that malicious actors could exploit. Undoubtedly, AI wide adoption generates a new landscape for competition law, since traditional enforcement processes may seem inadequate, especially for high-tech industries [48]. Therefore, competition and antitrust authorities must take action to adapt to the changing circumstances, perform effective investigations, and safeguard competition considering the recent AI advancement.

4.1. What could competition authorities do in the face of AI developments? What are the practical options for enforcement or advocacy of competition law from AI?

4.1.1. Understanding AI

20. As a first step, competition and regulatory authorities must carefully study and understand the AI and GenAI fundamental principles and functions, and map out the competitive landscape in the entire value chain, including the upstream markets for inputs (data, computing resources, foundation models) and the downstream markets for applications and plug-ins. This essential knowledge should enable competition authorities to adapt their processes and mindset to the fast-paced evolving nature of GenAI, navigate its challenges, and analyze the potential implications of AI systems in competition policy effectively [49, 50]. Since GenAI technology is in progress, authorities should adopt agile

approaches to monitor and stay up-to-date with the developments in computing resources, data, and GenAI advancements. To achieve this, authorities must invest in the development of in-house expertise, including for example providing training programs to legal practitioners, hiring specialized personnel with data science and analytical skills who will work together with experienced economists and lawyers, and engaging closely with market players and key stakeholders to gain a holistic view of how AI is affecting and could affect competition. Furthermore, competition authorities should foster collaborative projects with universities and research institutions. A starting point could be to conduct market studies to assess the current and future impact of AI and GenAI on competition dynamics. These studies may help in multiple directions: *(i)* increase the awareness of AI and GenAI technology in competition authorities, *(ii)* monitor the impact of AI and GenAI on the market, *(iii)* identify potential distortions in data-driven markets, and *(iv)* act as a deterrent against AI-related anti-competitive practices. In fact, many European competition authorities (*i.e.*, the EU Commission, the UK CMA, as well as the French, Portuguese, and Hungarian competition authorities) have taken steps towards this direction.

4.1.2. Striking the right balance between regulatory intervention and a hands-off approach

21. There are several regulatory and competition law challenges arising from the deployment of GenAI (*e.g.*, monopolistic behavior by AI-powered firms, collusion facilitated by AI algorithms, discriminatory practices in AI-driven markets, use of copyrighted or personal data in GenAI models, data licensing or access issues). Regulatory and competition law authorities must strike the right balance between intervening early on and letting the market forces shape the competitive landscape. On the one hand, an interventionist approach risks upending the fundamental business models that drive innovation and growth; a complex regulatory environment might put SMEs at a competitive disadvantage in terms of compliance and access to financing, thus raising barriers to entry or expansion. On the other hand, given the speed at which AI technology advances and the characteristics of AI markets, a "wait and see" approach is not recommended. Indeed, the EU has identified existing risks and endeavors to mitigate them by enforcing competition rules in the AI domain. The most prominent one is the AI Act [28], which was adopted by the European Parliament on March 13, 2024. It is considered the first comprehensive horizontal legal framework for establishing obligations for AI applications based on potential risks and impact level. Furthermore, EU shows strong intention to safeguard users' rights and control content on large platforms such as X, Google, or Amazon with the Digital Services Act (DSA) [51]. With the Digital Markets Act (DMA) EU establishes a set of objective criteria to qualify a large online platform as a "gatekeeper" thus ensuring fair and open digital markets [52]. One-step further, competition authorities may force companies to be more transparent related to their data and algorithm practices. This way, they should issue clear guidelines on how competition law applies to AI technologies, covering modern topics such as data sharing, protection, privacy, and interoperability. Recent published frameworks, such as Data Act [53], Data Governance Act [54], and Ethics guidelines for trustworthy AI [29], assist towards this direction providing clarity to businesses and stability in the market. In the United States, there are also some first endeavors to prevent collusive activity in pricing algorithms with the Preventing Algorithmic Collusion Act [55]. In any case, developing policies and regulations that promote transparency and accountability in AI models and their outputs, can help mitigate the risks associated with GenAI in AI-driven markets (*e.g.*, bias, discrimination) and thus promote healthy competition.

4.1.3. Rethinking competition law tools

22. From a substantive standpoint, the decisional practice and case-law on digital markets over the past decade have given authorities sufficient ammunition to address the concerns that may arise in GenAI markets using existing competition law rules. What requires rethinking, however, the choice enforcement tools. Past antitrust cases against digital incumbents at the EU level have shown that traditional ex post competition law enforcement, i.e. the imposition of fines after lengthy investigations, might not be flexible or timely enough to prevent anti-competitive practices that tip the market in favor of big companies or result in collusive outcomes. Competition authorities should remain agile and consider the use of innovative tools, such as competition sandboxes, comfort/no action letters, or similar initiatives to enable companies to partner and experiment with AI in a responsible and trustworthy manner. Moreover, in the EU, close coordination and cooperation among national competition authorities and the EC is important to address competition law issues in a consistent manner across the internal market.

23. In the field of ex ante merger control, mergers review involving companies owning Big Data and AI algorithms might require taking into account new parameters to ensure they do not gain unfair input advantages [5]. Three key challenges arise: (a) the acquisition of minority stakes that fall short of control, (b) the acquisition of small, innovative start-ups by incumbents, and (c) the substantive assessment of vertical and/or conglomerate mergers that help incumbent firms expand an ecosystem of digital products and services by integrating GenAI tools into core platforms. The first two issues might require revisiting jurisdictional rules, whereas the third issue might require rethinking existing theories of harm.

4.1.4. *Tapping the GenAI potential*

24. Competition authorities should exploit the GenAI capability for competition enforcement purposes. For example, AI can help authorities to analyze the vast amounts of open and public data to identify anti-competitive behavior or even develop automated processes for market monitoring. One such tool is data screening for detecting bid-rigging in public procurement [56]. Several countries have tried to develop such a tool, both in EU [57] and abroad [58]. Another idea might be tools for conducting price discrimination analysis. GenAI tools can also be used to make dawn raids more effective and streamline the work of case teams. Coupling modern competition tools with knowledge and insights gained from market studies will enable the potential identification of anti-competitive practices and improve the efficiency of competition law enforcement.

4.1.5. The need for interdisciplinary action

25. Since the challenges raised by the fast-paced development of GenAI markets are not exclusively related to competition law, actions of a single authority have little chance of being effective. Building trust and authentic cooperation and coordination mechanisms with other entities on AI and GenAI issues is a key factor in the deterrence and detection of cartels. Competition authorities should be open to exchange experience and develop common positions, policies, and practices on trustworthy AI. Within their country, authorities should collaborate with public bodies that have crosscutting jurisdictions and concerns on AI issues, *e.g.,* with data protection authorities on privacy frameworks, or consumer protection agencies on consumer harm regulation. Across the borders, authorities should seek cooperation and synergies with competition authorities of other countries, competition umbrella organizations, such as the European Competition Network (ECN), or even other organizations which are not directly engaged in competition but have know-how in legal, economic, and technology disciplines. For instance, Interpol has developed a

Toolkit for Responsible AI Innovation in Law Enforcement (AI Toolkit) which aims to assist law enforcement agencies in institutionalizing responsible AI [59]. Approaching cases, research, and other policy tools from such an interdisciplinary perspective, will allow competition authorities to deliver fair and undistorted competition in the AI and GenAI market.

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