From Theory to Tech: Computational Antitrust; Concept, Origins, and a Path Moving Forward

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Introduction

This work draws inspiration from Dr. Thibault Schrepel's paper "Computational Antitrust: An Introduction and Research Agenda", which introduces the concept of *Computational Antitrust*, or *Antitrust 3.0*, to define a new era of Antitrust law. This formulation subsequently inspired the launch of the *Computational Antitrust Project* at Stanford University's Codex Center.

Within this conceptual framework, Dr. Schrepel identifies two earlier stages of competition law: *Political Antitrust* and *Economic Antitrust*.[1] He argues that the last decade has ushered in heightened market complexity and dynamism. Antitrust 3.0 emerges from the recognition that institutions tasked with safeguarding free and open competition must proactively develop robust informational, analytical, and predictive capacities. Achieving this objective requires strategic investments in advanced data science expertise, sophisticated technological tools, and interdisciplinary collaboration to effectively detect, anticipate, and address competitive threats within increasingly complex markets.

In the following sections, I aim to illustrate, albeit inevitably incompletely, the extent to which increases in computing power, network expansion, "datification", and other technology-related advances have radically transformed market dynamics, redefining how firms engage with the paradigm of *intelligent adaptation to market conditions*.

While Computational Antitrust has sparked considerable academic research and international collaboration initiatives, this paper specifically examines what I consider the critical elements for its successful integration, institutionalisation, and advancement within competition agencies, irrespective of their existing level of technological maturity.

Pioneers: Political and Economic Antitrust

In its earliest incarnation, Antitrust Law was grounded in an economic theory that clearly recognised the detrimental effects of monopolies. It emerged amidst a political movement that advocated state intervention to promote individual freedom, foster entrepreneurship,[2] and curb the excessive concentration of private power that could enable a minority to dominate public welfare.[3] Although historical contexts vary by region,[4] antitrust laws have typically emerged as legislative embodiments of a political agenda aimed at democratising market economies, initially interpreted through a predominantly textual lens.[5]

With the rise of pro-market or *laissez-faire* schools of thought, antitrust law began shifting its focus toward evaluating the impact of scrutinised conduct on general welfare, particularly in terms of prices and output. Some scholars went so far as to question the legitimacy of interventions grounded in objectives other than economic efficiency.[6] Although many of the Chicago School's more extreme views have since been superseded, its influence endures: courts and competition agencies generally acknowledge the advantages of a cautious approach to enforcement, often guided by economic analysis and quantitative methods to assess the impact of contested conduct on market efficiency.[7]

This phase, often referred to as "Antitrust 2.0," matured as economic sciences became fully institutionalised within antitrust law policymaking. This period is characterised by (i) judicial reasoning becoming increasingly rooted in

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[1] Thibault Schrepel, *Computational Antitrust. An Introduction and Research Agenda*. Stanford Computational Antitrust, Vol I (2021).
[2] David K. Millon, "The Sherman Act and the Balance of Power", 61 S. Cal. L. Rev. 1219 (1988).
[3] Robert Pitofsky, "The Political Content of Antitrust", *University of Pennsylvania Law Review* (1979).
[4] In the US, its introduction is associated with the Sherman Act (1890); in Europe, with the Treaty of Rome (1957).
[5] Schrepel, *Computational Antitrust*, p.2.
[6] Famously, Robert Bork and the pioneers of the so-called "Chicago School".
[7] In this context, Schmalensee argues that, while some opinions advanced by the Chicago School failed to achieve academic consensus, they positively influenced antitrust policy by compelling proponents of more interventionist approaches to consider economic justifications. This shift redirected the debate towards a more effects-based analysis. Richard Schmalensee, "Thoughts on the Chicago Legacy in US Antitrust" in E. Pitofsky, (ed.) *How the Chicago School Overshot the Mark* (2008), p.25.

economic theory and (ii) the integration of economists and industrial organisation experts into competition agencies and specialised tribunals.[8,9]

The Technological shift

Unlike its predecessors, Antitrust 3.0 did not arise from an ideological movement, a political revolution, or the dominance of a particular school of thought. Instead, its emergence and ongoing development stem from interconnected phenomena over the past decade, fueled by decades of exponential technological advancement in key areas.

Some readers may already be familiar with the concepts and events discussed below. However, before delving into the features of this new era of antitrust, it is essential to set the stage of the technological transformations underlying this shift, and the challenges they may present.

Processing Power

> "We have computer power coming out of our ears"—Carver Mead

In Information Theory, the smallest unit of measurement is the binary digit (bit), representing the minimum uncertainty between two equally probable alternatives—akin to heads or tails in a coin toss.[10] According to this principle, a transistor—a small electronic switch—can exist in one of two possible states: on or off, allowing or blocking the flow of energy. In binary code, these two states are represented as zeros (0) and ones (1).

Grouped into sequences of eight positions, each with two possible states (0 or 1), a byte can represent 256 distinct combinations without any redundancy.[11] For example, a byte can encode basic ASCII text characters[12] or specify primary color intensities in an RGB pixel, the basic building block of digital images and video.[13] Hardware components, such as transistors embedded within the circuits of the Central Processing Unit (CPU), execute logical and arithmetic data operations encoded in binary language. [14]

In the mid-1960s, Intel's Director of Research and Development, Gordon Moore, observed that the number of transistors in integrated circuits doubled approximately every two years at a consistent cost, predicting this trend would continue. However, it was not Moore but his colleague and friend, Carver Mead, who coined the term "Moore's Law." Mead was among the first to realise that advances in microelectronics would eventually lead to "a small computer inside our phones, cars, or even typewriters". Powered by millions of microscopic silicon chips, Mead envisioned that our capacity to transmit, store, and process data would become virtually limitless.[15] The year was 1972.

Having endured the test of time with outstanding accuracy, Moore's Law symbolises both the dizzying pace of technological progress and our steady march into the digital age.[16] If a computer's speed is largely proportional to the number of transistors conforming its processing unit, then the exponential increase in transistors at consistently lower costs enable microprocessors to handle more operations, incorporate additional functionalities, and achieve enhanced performance.[17]

Yet, if digital transformation has been underway for decades, why do we trace the origins of Computational Antitrust to the 2010s? Is this choice of starting point arbitrary?

[8] William Kovacic and Carl Shapiro, "Antitrust Policy: A Century of Economic and Legal Thinking" Journal of Economic Perspectives, 14 (1): 43–60. (2000), p. 19.
[9] For instance, in Chile, the development of 'Economic Antitrust' includes significant milestones such as the tenure of National Economic Prosecutor Pedro Mattar, who sought to balance legal and economic expertise. This approach moved away from perceiving the National Economic Prosecutor's Office (FNE) as primarily a 'law firm' with economic sciences serving merely as a supplementary resource. The inclusion of two economic experts as permanent members of the Chilean Competition Tribunal (TDLC) following the enactment of Law 19.911 represents a pivotal moment in this institutionalisation process. Patricio Bernedo, Historia, p. 168.
[10] James Gleick, *The Information: A History, A Theory, A Flood*. Pantheon/Random House (2011).
[11] Conversely, natural language is often inefficient. Information Theory founder Claude Shannon estimated that English has a 50% redundancy, meaning a typical message could be halved (in terms of characters) and remain comprehensible. Yet this redundancy also serves as a protective mechanism, helping mitigate errors that may arise from typographical mistakes or message interference. J. Gleick, *The Information*, p. 216.
[12] ASCII provides sufficient characters for English text processing but has been superseded by UNICODE, the current global standard.
[13] Each color—red (R), green (G), and blue (B)—can have intensities ranging from 0 to 255, allowing a single pixel to display 16,777,216 different colors.
[14] An assembler is a program that translates binary code into "machine language" for executing instructions on the CPU.
[15] Chris Miller, *Chip Wars*, Scribner (2022), p. 71.
[16] Robert R. Schaller, Moore's Law, past, present and future, IEEE Spectrum 34(6):52–59.
[17] Azeem Azhar, *The Exponential Age*, Diversion Books (2021), p.8.

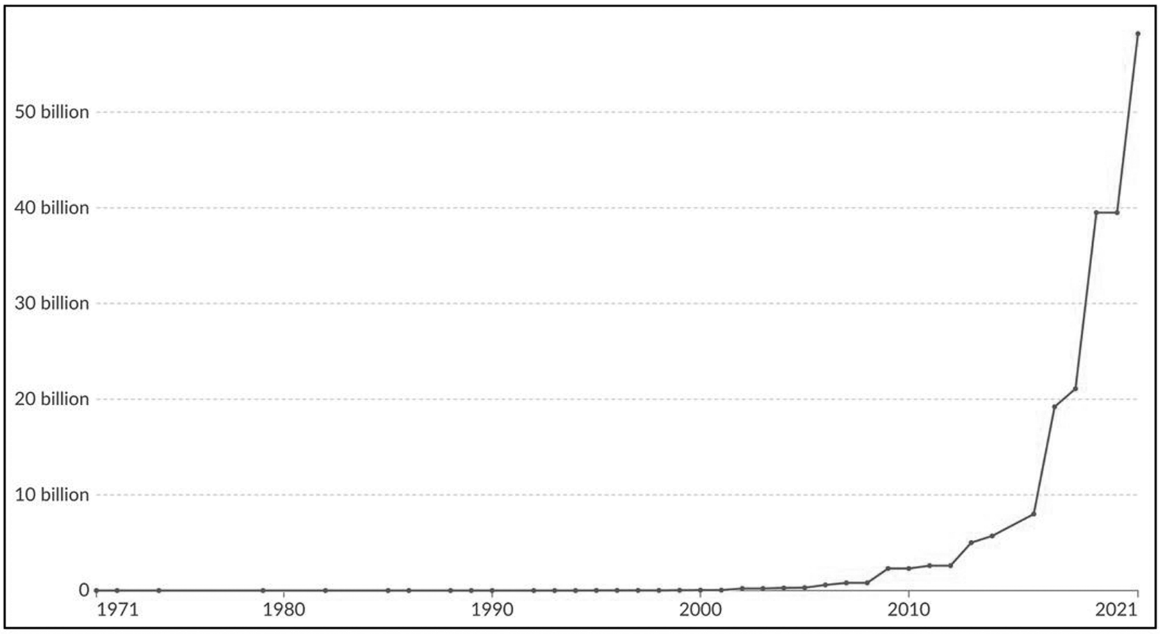

Figure 1: **Number of transistors per microprocessor**

Source: Our World in Data[18]

Exponential growth is a quality according to which something multiplies at a constant proportional rate, characterised initially by subtle gains followed by explosive acceleration.[19] Measured in the billions, the number of transistors per microprocessor significantly increased around 2009, surging dramatically halfway through the following decade. Combined with architectural improvements in other hardware components, this quantitative increase in transistor density represented a qualitative leap in both sequential and parallel processing capabilities, unlocking possibilities that, until then, remained purely theoretical.

For example, longstanding research had suggested that artificial neural network layers could drive predictive analyses, laying the ground for a new era of artificial intelligence (AI). However, the rise of deep learning only became feasible thanks to extraordinary levels of computational power, which has only become available in recent years.[20]

Network Expansion and Datafication

In tandem with advances in processing power, the first quarter of this century has witnessed fast development in fiber-optic and wireless network systems, alongside server infrastructure growth that has enabled ever-faster data transmission with reduced latency.

[18] *https://ourworldindata.org/grapher/transistors-per-microprocessor?yScale=linear*.
[19] This sobering quality of exponential growth is depicted in the fascinating "wheat and chessboard problem": *https://en.wikipedia.org/wiki/Wheat_and_chessboard_problem*.
[20] Azeem Azhar, *The Exponential Age*, p.20.

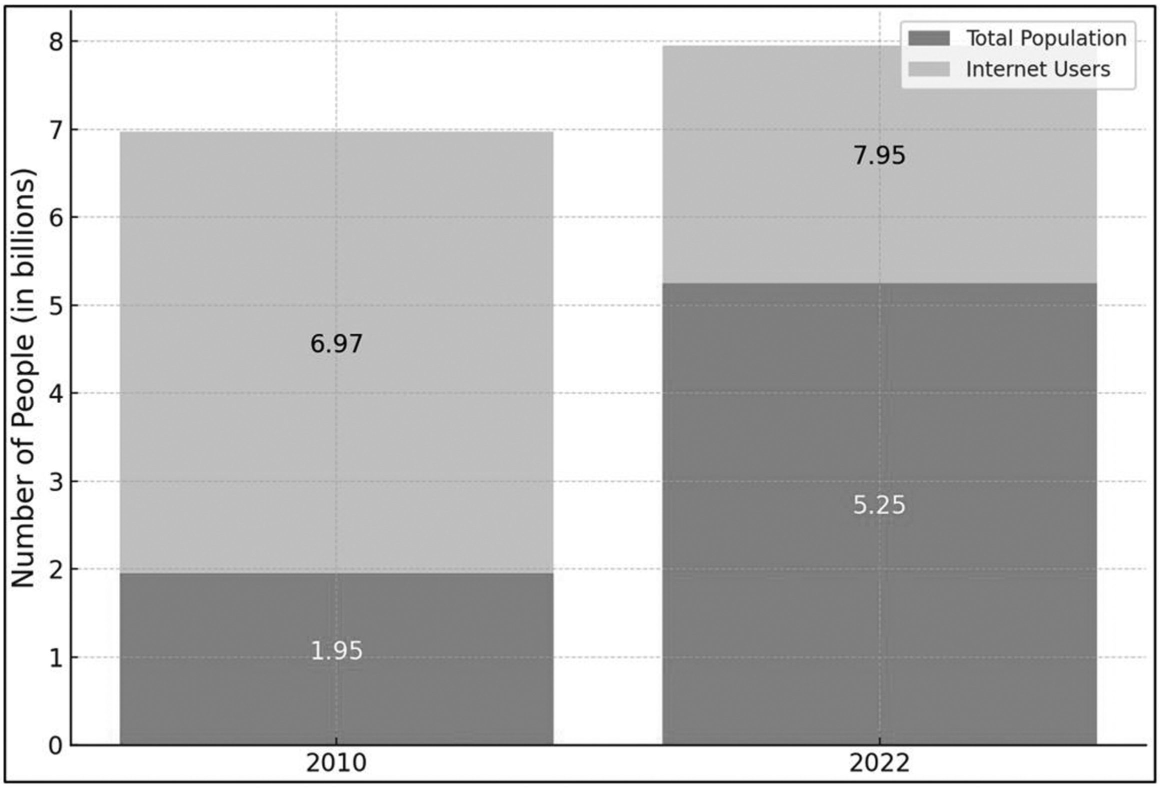

Figure 2: **World population vs Internet users 2010–2022**

Source: Statista[21] and World Bank[22]

In 2010, only 28% of the global population had access to the internet; by 2022, this figure had surged to two-thirds Considering that global demographic growth during this period was just 14%, it is reasonable to conclude that more than 90% of the 3.3 billion new internet users came online primarily due to expanded digital infrastructure.[23] Advances such as centralised and distributed servers, cloud computing, and software-as-a-service (SaaS) platforms have significantly broadened online opportunities for these new users, particularly within the rapidly growing e-commerce sector.[24]

The so-called "digitalisation of nearly everything"—the transformation of documents, photos, videos, maps, music, and other media, into streams of bits amenable to being encoded, saved and loaded—is one of the defining features of our time.[25] This phenomenon has been conspicuously propelled by the emergence of sensors: phones and cars, as Carver Mead once envisioned, along numerous everyday devices, automatically detect, capture, and measure signals from the external world, converting them into data which is then transmitted via integrated Wi-Fi modules.[26]

Since 2010, the volume of data generated annually has grown thirty-fivefold.[27] Unsurprisingly, many businesses have either evolved into or emerged as entirely data-driven endeavors,[28] and hyperscale data centers have become the backbone of the world's most important technology platforms.[29] Data was famously touted "the new oil"—valuable, yet useless without refining.[30] The processing power and transmission speeds now available allow us to do just that.

In sum, the advent of new capabilities for processing, transmitting, and storing massive volumes of data, coupled with the development of digital industries and cloud services, has subtly, and later explosively, paved the way for greater market dynamism and complexity.[31]

[21] *https://www.statista.com/statistics/273018/number-of-internet-users-worldwide/*.
[22] Available at *datacatalog.worldbank.org*.
[23] Of the 3.3 billion new users, only about 280 million can be attributed to population growth.
[24] P. T. Jaeger, J. Lin and J. M. Grimes, (2008) "Cloud Computing and Information Policy: Computing in a Policy Cloud?" *Journal of Information Technology & Politics*, 5(3), 269–283. *https://doi.org/10.1080/19331680802425479*.
[25] Eric Brynjolfson and Andrew McAfee, *The Second Machine Age*, Norton (2016), p.66.
[26] The proliferation of sensors is a source of various moral and social issues. See M. Andrejevic and M. Burdon, *Defining the Sensor Society*, University of Queensland TC Beirne School of Law Research Paper No. 14–21 (2015).
[27] The volume of data generated globally increased from 4 *zettabytes* (ZB) in 2010 to 145 ZB in 2024. A ZB is equivalent to $1*10^{21}$ bytes (a 1 followed by twenty-one zeros). Shirvani Moghaddam, S. *The Past, Present, and Future of the Internet: A Statistical, Technical, and Functional Comparison of Wired/Wireless Fixed/Mobile Internet*. Electronics (2024), 13, 1986.
[28] For instance, the ability to store geological information in vast data lakes has transformed mining into a data science-based industry today. See *https://brimm.ubc.ca/mining-is-now-a-data-science-business/* .
[29] *https://blog.enconnex.com/data-center-history-and-evolution*.
[30] Characteristics associated to the concept of "Big Data". Stucke et al., *Big Data and Competition Policy*, OUP (2016), cap.2. The phrase *data is the new oil* is attributed to the mathematician Clive Humby.
[31] Schrepel, *Computational Antitrust*, p.4.

Algorithmic Competition

A well-established paradigm in competition policy maintains that, while firms are prohibited from colluding or replacing competition with coordination, they may legitimately engage in strategic adaptation to the existing or anticipated behavior of their competitors.[32]

For decades, the practical application of intelligent adaptation focused on business analytics, which involves observing and analyzing market conditions through quantitative methods applied to structured data.[33] In recent years, this approach has evolved significantly, spurring the growth of business intelligence—a suite of analytical techniques applied to large structured and unstructured datasets using computational processes to identify, evaluate, and recommend strategic actions.[34]

Depending on the technology operating under the hood, sophisticated variants of business intelligence employ algorithms refined through iterative calibration to identify patterns and make predictions—namely, Machine Learning (ML) and related techniques.[35] While extensive literature and online resources address this subject, it is valuable to briefly illustrate how different ML model variants may influence the dynamics of Algorithmic Competition through two concrete examples.[36]

Supervised Learning: This type of ML model 'learns' from previously labeled data, adjusting through repeated iterations aiming to make useful predictions about new or unknown data.

Consider a dynamic pricing model designed to suggest optimal prices in real time to maximise profits per unit sold.[37] The process begins with a firm loading preprocessed, identifiable or historical data—such as past prices, quantities sold by SKU or by product category, stock levels, competitor prices, among other variables.[38] Using a popular technique, the program generates hierarchical decision trees that iteratively improve predictive accuracy through adaptive optimisation.[39]

In the initial round, the algorithm might exclusively consider an average price across all SKUs to compute an optimal price for every product—a prediction would clearly be very weak, and practically useless. However, in subsequent iterations, the model incorporates additional labels, such as whether a product belongs to a specific category (e.g., high-end smartphones). Utilising this distinction, the model refines its price recommendations and expands the decision tree into additional branches. The iterative refinement continues by progressively integrating other relevant variables, such as sales frequency, seasonal variations, average profit margins, price differentials relative to close competitors, and weekly or monthly demand volumes.

Unsurprisingly, multiple uncertainties need to be addressed throughout this process, requiring complex engineering and statistical efforts, or trial-and-error testing.[40] For instance, at what rate should the price be adjusted at each level of the decision tree (learning rate)? How deep should decision trees grow, or in other words, how many layers should be included in the prediction?[41]For instance, if inventory levels or weather conditions are deemed insignificant to estimating the optimal price of a particular product, it may be wise to redesign parts of the model, remove irrelevant variables, or prune certain factors to prevent *overfitting* or *noise* from negatively impacting the model's accuracy.[42]

Unsupervised learning: In this approach, the algorithm is provided with unlabeled data and tasked with identifying relevant patterns for a specific application. Let's examine a practical example to illustrate how this type of algorithm works.[43]

Consider an e-commerce site that aims to enhance its pricing and marketing strategies by segmenting its customers into three distinct groups based on purchasing behaviors.

> **Step 1:**
>
> The algorithm randomly selects three customers from the sales database, assigning each as the initial *center* of Groups 1, 2, and 3, respectively.

[32] *T-Mobile* (CJEU Case 8/08) [2009] ECR I-4529, § 33.

[33] Referring to numerical variables (such as market prices, sales, costs, etc.), metrics, and financial results, which are typically stored in relational databases like SQL. In contrast, unstructured data consists of data units that cannot be stored in rows and columns, including formats like video, emails, web pages, and more. Steven Williams, *Business Intelligence Strategy and Big Data Analytics*, Elsevier (2016), p.44.

[34] S. Williams, *Business Intelligence Strategy*, p. 30. The author draws a parallel between unstructured data, that is digital content that is generally not adaptable for categorisation in traditional databases, and Big Data. However, certain metadata within Big Data, like information from sensors or location data, can be structured.

[35] "Intelligent adaptation" also encompasses various forms of advanced machine learning (ML), including artificial neural networks and AI. In McKinsey's 'Global AI Survey,' 72% of participants reported using AI in at least one business function, with half of them employing AI in two or more functions—a significant increase compared to the 2023 survey results. Survey available at: *https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai* .

[36] ML concepts referred on this section were drawn from I. Goodfellow, Y. Bengio, y A. Courville, *Deep Learning*, MIT Press (2016), specially Ch.5. The book is fully available online at: *https://www.deeplearningbook.org/*.

[37] A flexible pricing mechanism, adjusted in real time based on various concurrent factors.

[38] This information, pre-identified as valid, is usually referred to as labels.

[39] This algorithm is known as Gradient Boosting Machine (GBM), which is considered effective for dynamic pricing. Raouya El Youbi et al., "Machine Learning-driven Dynamic Pricing Strategies in E-Commerce", (2023).

[40] This is an example of another machine learning technique called *reinforcement learning*. These algorithms discount and reward functions through trial and error and require adjustments of additional variables, such as the *exploration rate* of rewarded actions versus the exploration of new actions with unknown or uncertain outcomes.

[41] Factors such as the learning rate or the depth of the tree are known as "hyperparameters".

[42] A variant of dynamic pricing is personalised dynamic pricing, which considers various parameters linked to an identifier(user), such as purchasing habits, average ticket amount, and online browsing behaviors. Consumers' aversion to this type of price discrimination has hindered its widespread adoption. G. Hufnagel, et al., "Seeking the perfect price: Consumer responses to personalised price discrimination in e-commerce" *Journal of Business Research*, Volume 143, (2022), pp.346–365.

[43] Examples in this section correspond to Boyu Shen, *E-commerce Customer Segmentation via Unsupervised Machine Learning* (2021).

Step 2:

The program assigns all remaining customers to one of these three groups based on certain attributes—say, the frequency and total value of their purchases.[44] Using a mathematical formula, [45]it calculates the distance between each customer's attributes and those of the group, assigning each customer to the closest group.

Step 3:

The program recalculates the group *centers*. From this step onward, and in each subsequent iteration, centers will represent the average *attributes* of all customers currently assigned to that group, rather than any individual customer's attributes.

Termination:

Steps 2 and 3 are repeated iteratively until convergence occurs-that is, until no customers switch groups between iterations. At this point, the segmentation process is finalised.

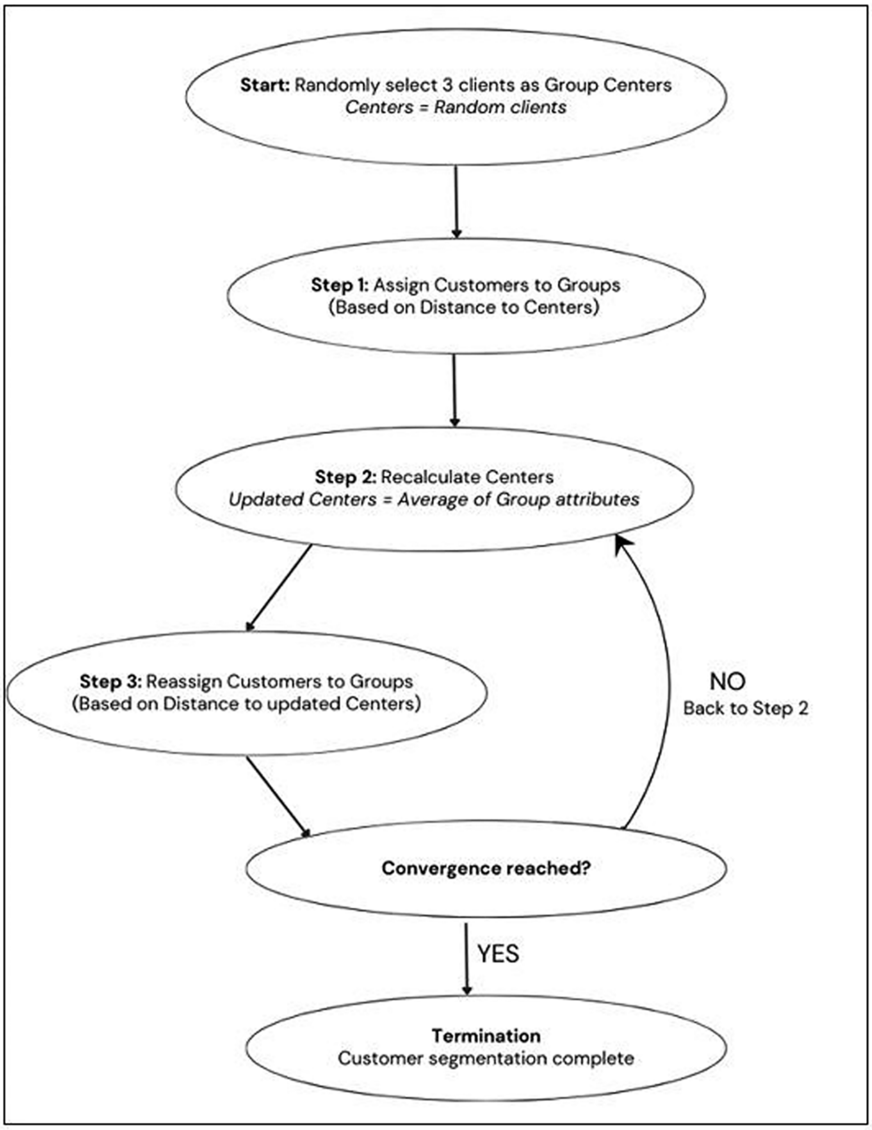

***Figure 3:* Attribute-based unsupervised ML algorithm to segment customers into 3 Groups**

Source: Author's work

Using similar or complementary techniques, the e-commerce platform can link each customer segment to relevant product categories, considering factors such as price and product description. This facilitates predictions of consumer behavior, allows tailored promotions targeting specific segments, and supports bundling strategies for items frequently purchased together.

[44] A process known as *feature engineering*, which involves selecting which real-world characteristics (*features*) to incorporate into the model and transforming them into data for the algorithm to compute.

[45] The Euclidean mathematical formula is used to calculate distance between the two points, taking in this example "frequency of sales" and "purchase ticket" as factors.

Iterative learning models demonstrate how cutting-edge data science utilises data streams to generate increasingly accurate predictions. Crucially, these predictions are achieved at a steeply declining cost. Tasks previously considered unrelated to prediction—such as text translation—are now effectively approached as predictive tasks.[46] Massive and continuously updated structured and unstructured datasets, when coupled with sophisticated learning algorithms, offer unprecedented capabilities to anticipate market fluctuations, predict consumer preferences, forecast future demands, and automate complex decision-making processes.[47,48]

The net effect of widespread algorithm use on market efficiency—whether viewed in terms of opportunities or potential risks—is a topic of extensive academic debate.[49] As noted by the OECD (2023), these impacts remain ambiguous.[50] Some scholars argue that algorithm-driven dynamic pricing could lead to a massive redistribution from buyers to sellers, even in the absence of collusion.[51] Consequently, competition agencies are increasingly recognising the impending need to directly examine these algorithms to better understand their inner workings.[52]

However, there is less consensus—and greater uncertainty—about how to effectively conduct these audits. Depending on the degree of access to the algorithm and its underlying data, suggested investigative methods vary in ambition and complexity, ranging from user surveys to reverse engineering. The OECD identifies several key challenges associated with algorithm audits, which can be summarised as: (i) significant time and costs involved in reviewing thousands of lines of code, often developed by international teams in various programming languages, with multiple dependencies on other software or corporate services; (ii) the sequential or concurrent use of multiple algorithms, some of which are managed by third parties across different jurisdictions; and (iii) human involvement in algorithmic processes, whether by programmers or consumers, further complicates these systems' dynamics.

Indeed, a significant number of issues around algorithmic audits are unresolved. For instance, if an agency creates a replica of an algorithmic system based on observable functionality and tests it using synthetic data that mirrors real-world conditions, could constitute sufficient evidence to establish an infringement? Conversely, if an auditing team seeks real-time access to the algorithm and its data inputs, would a *Request for Information* ("RFI") or even a more intrusive measure, such as a *dawn raid,* be a feasible or appropriate investigative measure?[53,54]

Legislatures and regulatory bodies will be tasked with determining whether modifications are necessary to facilitate access to algorithmic functionality, enforce traceability and explainability requirements, and crucially, decide whether assessments of these applications should focus on their outcomes or their underlying processes.

Computational Antitrust: Origins and goals

Like all public institutions that influence societal functioning, antitrust enforcement bodies require a certain degree of stability to operate effectively. Their capacity to adapt to changing conditions is often characterised as linear: organisational structures, traditions, available resources, and historical contexts constrain these entities, causing them to evolve at a relatively steady pace. Exceptional events aside, the restructuring they are prone to experience does not vary significantly from one year to the next. The dissonance between this reality and the rapid acceleration of technological change creates a rift, aptly termed the "exponential gap", a phenomenon that may be socially disruptive, and a source of opportunistic gains for a few.[55]

Against this backdrop, Computational Antitrust emerges as a branch of legal informatics,[56] a subfield of computer science dedicated to the application of computational tools and techniques to legal analysis.[57] Thus, Computational Antitrust can be viewed as a multidisciplinary scientific endeavor that attempts to

[46] Ajay Agrawal et al., *Prediction Machines. Expanded Edition*, HBR (2022), p.119.
[47] H. Hoffman, and I. Lorenzonni, "Future Challenges for Automation in Competition Law Enforcement" *Stanford Computational Antitrust* (2023), p.37 y ss.
[48] ICN CWG SG2 *Project on Big data and Cartels—The impact of digitalisation in cartel enforcement* (2020).
[49] For a comprehensive review of this topic: C. Coglianese and A. Lai, *Antitrust by Algorithm*, Stanford Computational Antitrust Vol II (2022).
[50] OECD, *Algorithmic Competition*. Background Note by the Secretariat, DAF/COMP/2023(3), 14 June 2023, p.35. See also: OECD, *AI, Data and Competition*, OECD Artificial Intelligence Papers, 18 (2024), p.51.
[51] *"We identify a more fundamental challenge posed by algorithmic pricing: in many markets it will raise prices for consumers even in the absence of collusion. The result could be a massive redistribution of wealth from buyers to sellers"* A. McKay and S. Weinstein, "Dynamic Pricing Algorithms, Consumer Harm, and Regulatory Response", Harvard Business School Working Paper 22-050 (2022), p.55.
[52] OECD (2023), p.6. Along the same lines, the Deputy Head of the OECD Competition Division, Antonio Capobianco (2023), has emphasised the need to continue investing in specialised knowledge rather than treating these algorithms as 'black boxes.' Published in ProMarket (2023), available at: *https://www.promarket.org/2023/05/23/the-impact-of-algorithms-on-competition-and-competition-law/?mc_cid=d6a91bb9ea*.
[53] C. Coglianese y A. Lai suggest antitrust authorities could require companies to share digital data in real time, tailored to each case, as part of the settlement terms negotiated in enforcement actions. *Antitrust by Algorithm*, p.15.
[54] Aside from other complex legal challenges—such as establishing harm attributable to algorithm performance, defining standards for determining firm's liability, or assigning accountability to individuals who supervise or partially intervene in the algorithm's design or implementation.
[55] Azeem Azhar, *The Exponential Age*, p.59. The author explains that this dissonance arises primarily due to (i) underestimating the speed of exponential change, (ii) overestimating our future capacity to adapt to exponentially changing conditions, and (iii) the unforeseen consequences of exponential change that evade even our very best predictions.
[56] Not to be confused with IT law, a branch of legal sciences that typically covers various topics related to the regulation of information processing systems across different legal fields (civil, commercial, criminal, intellectual property, among others).
[57] Schrepel, *Computational Antitrust*, p.2.

bridge the exponential gap between traditional antitrust frameworks and increasingly complex, novel market dynamic.[58] And while competition authorities and regulatory bodies are the primary targets called upon to drive this transformation, all stakeholders in this domain, including consultants, external advisors, compliance officers, firm executives, and consumer organisations, share vested interests in its outcomes.

Like previous groundbreaking movements, Antitrust 3.0 is gradually but steadily making its way into the competition law institutional framework. Its progression is observable in the adoption of analytical tools, automated functions, systematic collection and organisation of relevant data, and the development of predictive models tailored specifically to address the unique demands of competition agencies and other stakeholders. Nevertheless, it must be acknowledged that this is fundamentally a human-centered transformation, its success largely hinging upon establishing the appropriate conditions that enable programmers, data scientists, and analysts to collaborate effectively with economists, lawyers, and competition policy experts.[59]

Algorithmic Competition and other technological breakthroughs discussed above have reshaped market dynamics across industries. Antitrust law enforcement institutions that ignore or delay responding to the need for a digital transformation, do so at their own peril. As Bill Kovacic has remarked, borrowing a line from the movie The Big Short, forgoing these capabilities is akin to competing at the Indianapolis 500 riding an ostrich instead of a racecar.[60]

The Stanford University Computational Antitrust Project

In January 2021, Stanford University's Codex Center launched the Computational Antitrust Project (CAP). This initiative, which does not receive any external funding, brings together a community of scholars from different disciplines to monitor, promote, and showcase innovations on the use of new technological tools in the field of antitrust law.[61] Among its activities, the CAP publishes academic research, hosts working sessions, produces a widely acclaimed podcast,[62] and collaborates with 67 competition agencies worldwide.[63] Every year CAP launches a report offering an overview of how various jurisdictions apply computational tools to antitrust analysis, highlighting noteworthy trends. [64]

In his seminal work, Dr. Thibault Schrepel, founder and current Director of the CAP, identifies three primary areas where this multidisciplinary integration, dubbed Computational Antitrust, may represent a major contribution to competition law: (1) the active detection of anticompetitive practices, the use of forensic tools for analysing evidence, and the development of platforms that facilitate access to data from entities under investigation; (2) the ability, within merger control, to analyse datasets or generate simulations to assess claims related to efficiencies, substitutability, and market contestability, and other relevant issues; and (3) retrospective evaluation of agency interventions and implementation of competition policies, with an emphasis on generating predictive insights.[65]

Over the past years, the CAP has produced three annual reports and numerous projects derived from its research, amplifying contributions and providing a platform for scholars from diverse backgrounds.[66] These reports and research activities provide invaluable resources for fostering concrete actions and expanding opportunities for international cooperation between experts and policymakers worldwide.

In the following section, drawing on CAP research and other relevant literature, I outline a roadmap consisting of three core steps towards advancing and shaping Computational Antitrust.

Rollout plan: a proposal

Organisation, systematisation, and visualisation of proprietary data

> *"The agencies collect and store large amounts of data as a result of complaints, merger filings, and investigations. There are opportunities to both utilise emerging technologies in the analysis of data, as well as to generate new datasets that are relevant to antitrust research" —Jin, Sokol & Wagman*

A critical first step for competition authorities on the path to Antitrust 3.0 is conducting a systematic introspection of their "experience base". In other words, priority should be placed on consolidating and optimising dataflows already at their disposal, which may currently be scattered or fragmented across various 'business units' operating with relative autonomy.

[58] "[T]here is a significant informational gap between the structure of antitrust agencies and the fast moving business world, especially in the use of information and communication technology. This gap has kept antitrust agencies from understanding and using the technology and business frontiers, undermining the agencies' relevance and effectiveness". Jin, Sokol & Wagman, *Towards A Technological Overhaul of American Antitrust*, Antitrust, ABA, Vol. 37, No. 1, (2022).
[59] Schrepel, *Computational Antitrust*, p.14.
[60] "Stanford Computational Antitrust" podcast, episode 22 (January 2024), from minute 13.11 onwards.
[61] Project description available at: *https://law.stanford.edu/codex-the-stanford-center-for-legal-informatics/computational-antitrust-project/*.
[62] *Stanford Computational Antitrust podcast*. Available in Spotify and other platforms: *https://open.spotify.com/show/62DTsUktaAaNoqxR76zlmr?si=eac25c323748488e*.
[63] Agencies list available at: *https://law.stanford.edu/codex-the-stanford-center-for-legal-informatics/computational-antitrust-agencies/*.
[64] The third Annual report was published June 11, 2024, and it is available at: *https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4861858*. See also CeCo publication covering the report here: *https://centrocompetencia.com/computational-antitrust-stanford-un-ano-de-progreso-y-desafios/*.
[65] Schrepel, *Computational Antitrust*, p.5.
[66] T. Schrepel and T. Groza, *The Adoption of Computational Antitrust by Agencies: 2021 Report, 2 Stanford Computational Antitrust*, 78 (2022); T. Schrepel y T. Groza, *The Adoption of Computational Antitrust by Agencies: 2nd Annual Report*, 3 Stanford Computational Antitrust 55 (2023), T. Schrepel and T. Groza, *Computational Antitrust Within Agencies: 3rd Annual Report* 4 Stanford Computational Antitrust, 53 (2024).

The practical implementation of this initiative depends on factors unique to the sise, resources, and specific goals of each institution. Nonetheless, general principles of Big Data management are presented below to frame the main issues relevant to this endeavor.[67]

(i) **Data Challenges:**

Internal informational sources within an organisation encompass a variety of data types, including both structured and unstructured content. These sources may derive from current information flows or archival repositories, ranging from spreadsheets containing industry or corporate data, written submissions provided by parties, and multimedia records from investigative procedures, to associated metadata. Consequently, careful consideration must be given to determining optimal methods for data acquisition, estimating data volumes, selecting suitable storage solutions, and deploying visualisation platforms tailored specifically to the needs of different user groups.

(ii) **Processes Challenges:**

This stage involves data collection, cleaning to remove errors and duplicates, transformation to ensure compatibility and consistency across different formats, and *indexing* to optimise storage and reduce access times. ETL (Extraction, Transformation, and Loading) applications[68] may be utilised to integrate the information into repositories or data warehouses, preparing datasets for storage and subsequent analytical or automated processing.[69]

iii) **Management Challenges:**

Lastly, key issues such as security, privacy, and data governance protocols must be addressed, including the definition of user access control for different roles, and the optimisation of operational costs wherever possible.

Centralising an institution's knowledge base offers a myriad of potential benefits. It minimises disruptions stemming from leadership changes or the departure of key personnel. Additionally, it fosters consistent and objective decision-making, support retrospective evaluations of the agency's actions, reduce retrieval times, improves institutional transparency, and facilitates the assessment of quantitative or econometric methods used in past cases. Furthermore, centralisation enables the development of metrics useful to quantify project success or allocating workloads.

Ultimately, this represents the cornerstone of any technological renovation: once the organisation achieves seamless access to its internal dataflows through robust pipelines and user-friendly platforms, it becomes better positioned to undertake advanced analytical or predictive tasks, as well as integrate its proprietary data with external sources, whether publicly available or sourced from other entities.

Creation of Data Units

> *"In the face of such change, agencies must bring their skills up to date"—Stefan Hunt*[70]

It seems undeniable that the origins of Antitrust 1.0 and 2.0 are firmly rooted in the United States. Similarly, it is a cold fact that the most ambitious and forward-thinking effort to embrace Antitrust 3.0 emerged across the Atlantic. In 2022, the United Kingdom's Competition and Markets Authority (CMA) undertook bold steps towards expanding its capabilities through what it termed *the Technology-Led Transformation*. Under the leadership of Stefan Hunt—a Harvard-trained economist and then-Director of the Data and Technology Insights Unit ("DaTa")—the CMA embarked on a comprehensive overhaul of its resources, aiming to equip itself to confront the challenges presented by digital markets, while substantially enhancing its data-handling practices and overall operational efficiency.[71]

The DaTa working team hosts over 50 engineers and scientists from diverse fields. Notably, instead of adopting a functional approach to hiring, the CMA opted to structure the Unit around specialised fields of knowledge, allowing for the formation of multidisciplinary teams which can be customised for different projects according to specific needs. As of 2022, DaTa was organised as follows:

[67] U. Sivarajah et al., Critical analysis of Big Data challenges and analytical methods, Journal of Business Research (2016).
[68] *https://en.wikipedia.org/wiki/Extract,_transform,_load*.
[69] For example, this is one of the cloud-based services that Amazon Web Services provides to multiple U.S. agencies. See: *https://aws.amazon.com/what-is/etl/#:~:text=Extract%2C%20transform%2C%20and%20load%20*.
[70] Stefan Hunt, *The technology-led transformation of competition and consumer agencies. The Competition and Market's Authority's experience*, Discussion paper (2022), p.4.
[71] Stefan Hunt, *The technology-led transformation*.

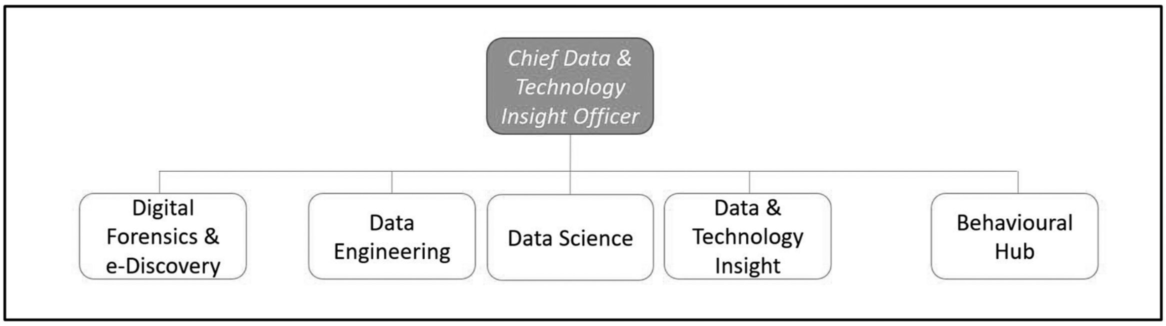

Figure 4: **CMA's DaTa Unit**[72]

(i) **Data Engineering:**

Responsible for organising and integrating internal and external information flows, combining software development with technological infrastructure management.

(ii) **Data Science:**

A team entrusted with designing data extraction models using machine learning (ML).

(iii) **Data & Technology Insight:**

Acts as a *liaison* between investigative teams and the DaTa Unit, actively collaborating on cases that involve technical challenges within their field of expertise.

(iv) **Digital Forensics & e-Discovery:**

Specialises in operating software for digital forensics and evidence review.

(v) **Behavioral Hub:**

Advises teams on cases where behavioral economics is particularly relevant, assisting with tasks such as identifying the information needed to analyze and evaluate the structure of a digital platform, assessing the impact of mergers on consumer choice, and proposing appropriate remedies.[73]

The CMA's work provides valuable practical lessons for other Data Units in different areas, such as role-prioritisation, recruitment, and balancing short-term goals with long-term innovation. In my view, two takeaways warrant special attention:

First, by borrowing software development methodologies from the tech industry,[74] each project is structured around a Project Manager, and teamwork is organised in short-term deliverables or sprints. At the end of each two- or four-week sprint, the Project Team holds collaborative sessions to assess progress, exchange feedback, and plan next steps. Ideally, as the project advances, other incumbent units within the agency become involved early in the product development process as 'clients', participating in testing preliminary or incomplete versions of the product. This iterative approach helps align the final application with the client needs or the objectives of a given case.[75]

Secondly, a crucial yet overlooked principle is the establishment of clear boundaries regarding tasks that fall outside the Data Unit's scope. A Data Unit should *not* be responsible for general IT services, oversight of data management, or cybersecurity protocols, nor it should be directly tasked with investigating potential infringements in "digital markets".[76] While in such cases the Data Unit may provide technical assistance and valuable insights to support decision-making processes, substantive competition policy decisions typically lie beyond its core responsibilities.

Besides DaTa, many national competition and consumer protection agencies are establishing dedicated Data Unit teams. Until these teams achieve a sufficient degree of consolidation, it might be advisable to periodically reassess their structures, functions, and objectives. Whenever feasible, continuous evaluation should be coupled with advocacy efforts aimed at securing funding to recruit specialised talent. In this respect, it is noteworthy that, even among countries where Data Units are operational, the proportion of staff trained in data sciences relative to the rest of the non-administrative personnel remains relatively low, typically below 6%.[77]-[78]

72 Stefan Hunt, *The technology-led transformation*, p.36.
73 Stefan Hunt, *The technology-led transformation*, p.33.
74 Agile Manifesto, available at: *https://agilemanifesto.org/iso/es/principles.html*.
75 Stefan Hunt, *The technology-led transformation*, p.40.
76 This corresponds to the Digital Markets Unit: *https://www.gov.uk/government/collections/digital-markets-unit*.
77 With the exception of Poland's Office of Competition and Consumer Protection, which is at 12%. See OECD (2023), p.31.
78 In Latin America, Chile has created a specialised "Intelligence Unit" which administratively depends on Anti-Cartels Division, and has certain functions comparable to a Data Unit. Other agencies, such as CADE in Brazil, CNDC in Argentina, and SIC in Colombia, have initiated various projects applying computational techniques. See T. Schrepel and T. Groza (eds), *The Adoption of Computational Antitrust by Agencies*, 2021 Report (2022), 2nd Annual Report (2023), and 3rd Annual Report (2024).

Contribution to judicial decision-making

> "[B]y using data more effectively, judiciaries around the world, and particularly those in developing countries, will be able to improve their performance, address deficits in the quality and accessibility of justice, and contribute to prosperity"[79]

As previously discussed, the integration of economic theory into substantive decision-making of antitrust matters marked a pivotal shift, giving rise to Economic Antitrust or Antitrust 2.0. Similarly, the institutionalisation of data and information sciences is essential to advancing toward Computational Antitrust.

Antitrust-related claims initiated by authorities and private litigants, coupled with the increase in damages claims arising from competition disputes, place substantial pressure on the judiciary's workload.[80] While some courts have taken steps to enhance their analytical capabilities,[81] there remain areas in which judicial bodies—like competition agencies and other litigants—will need to pursue their own digital transformation. The following represent promising avenues for future exploration:

Natural Language Processing

Natural language processing,[82] the development of conversational agents able to generate and understand human language, has been a long-standing research goal for computer scientists.[83] Early attempts encountered little success, as the intricacy, redundancy, and semantic depth of language defied reduction to simple rule-set.[84] Recent advances, including the adoption of statistical methods, experimentation with multi-layered architectures, and extensive parallel training on unlabeled data,[85] have yielded highly adaptable applications capable of generating content, answering queries, and classifying text.[86,87]

Text classification methods such as topic analysis and sentiment analysis, which can be pursued through multiple scientific approaches, hold significant potential for research and case resolution in antitrust matters.[88] For instance, these methods could be employed to analyse communications or messaging evidence among individuals involved in a presumptive anticompetitive conspiracy, identifying recurring themes or assessing attitudes or emotional nuances around key terms. Such findings could bolster the prosecution's case or support alternative interpretations adduced by the defense.[89]

Similarly, courts might potentially use Large Language Models (LLMs) and other deep learning techniques to analyse case files, briefs, rulings, and related databases to detect behavioral patterns within relevant contexts, thus refining judicial decision-making processes. This approach might contribute to the establishment or standardisation of quick look or per se rules, simplifying the classification of certain practices and contributing to clearer legal standards.[90]

This raises the legitimate question of whether it is desirable for the judiciary to rely on these applications when issuing judgments or binding decisions.[91] Undoubtedly, there are several risks to consider, spanning from biases inherent in training data to cases where an LLM may output plausible yet inaccurate responses (*hallucinations*). However, as generative AI-based services become increasingly accessible to lawyers,[92] the harder it becomes to justify withholding similar capabilities from the judiciary, and it seems inevitable that these tools will eventually find their way into legal proceedings, one way or another.[93,94]

Provided the outcomes of legal cases remain under human decision-making authority, whether individual or collegial, it is certainly advisable for courts to establish clear standards governing the use and optimisation of generative AI solutions. Courts could employ targeted engineering techniques to fine-tune these models using proprietary data, thereby creating a secure, private ecosystem for internal purposes. Such efforts may

[79] Manuel Ramos-Makeda and Daniel Chen, *The data revolution in justice*, World Development, Volume 186, upcoming (February 2025).
[80] See, for example, the 2024 Chilean Competition Tribunal annual report, available at: *https://www.tdlc.cl/anuarios-tdlc/#anuario-2024/1/*.
[81] Mentioned as one of the objectives for the 2023-2025 term. See 2024 Public Report of the TDLC: *https://www.tdlc.cl/wp-content/uploads/2024/05/Cuenta-Publica-2024.pdf*, p.8.
[82] We define "natural language" as any form of everyday communication between humans, in contrast to programming languages or mathematical notations. See The Natural Language Toolkit, available at *http://nltk.org*.
[83] D. Numa & M. Engler, *Introduction to Generative AI*, Manning (2024), p.5.
[84] Conversely, no noise exists in the processing of numbers or binary code. Consider the challenge of programming outputs in conversational flows that can correctly process homonyms or polysemous words. K. Gugler et al., *Using Natural Language Processing to Delineate Digital Markets, Stanford Computational Antitrust* (2024), p.5.
[85] The development of transformers, or attention-based models, marked a breakthrough that launched the new era of LLMs (Large Language Models). These models generate new versions of a sequence by assigning higher predictive value to key words based on their specific position, considering the entire context in both directions (forward and backwards). See D. Numa and M. Engler, *Introduction to Generative AI*, p.19.
[86] As previously mentioned, LLMs are built on a combination of reinforcement learning with rewards and penalties based on expected prediction outcomes.
[87] This requires extensive *preprocessing*, which among other tasks, encompasses transforming text into tokens or word fragments to be represented numerically in a matrix, and removing prepositions and words with low semantic or predictive value (*stop words*). K. Gugler, *Using Natural Language*, pp.38 et seq.
[88] M.D. Devika et al., *Sentiment Analysis: A Comparative Study On Different Approaches* (Elsevier, 2016).
[89] M.D. Devika et al., *Sentiment Analysis*.
[90] Daryl Lim, *Can Computational Antitrust Succeed?* Stanford Computational Antitrust (2021), p.42.
[91] On the implications of AI use and the questions surrounding hybrid human-machine decision-making systems, see Tim Wu, Will AI Eat the Law? The Rise of Hybrid Social-Ordering Systems, Columbia Law Review, Vol. 119:2001 (2019).
[92] Like CoCounsel (*https://www.thomsonreuters.com/en/cocounsel*) or Harvey (*https://www.harvey.ai/*).
[93] Indeed, in April 2025 the multinational firm Thomson Reuters signed a multi-year contract with the Administrative Office of the U.S. Courts to provide generative AI legal research and AI assistant solutions to the federal judiciary, including the Supreme Court. See: *https://legaltechnology.com/2025/04/09/thomson-reuters-signs-multi-year-contract-to-provide-us-federal-courts-with-access-to-cocounsel/*.
[94] Another possibility, particularly valuable in the field of antitrust law case handling, is to leverage LLMs capabilities to identify and classify specific patterns in structured text, with the aim of redacting sensitive commercial information or preparing public versions of confidential documents. This could significantly reduce the manual, labor-intensive work involved.

significantly contribute to establishing more consistent legal precedents and identifying factual patterns essential for applying, interpreting, or formulating legal rules.[95]

Machine Learning Solutions as Evidentiary Tools

Although Machine Learning (ML) primarily focuses on prediction rather than causality or equilibria, there is broad consensus that ML models can meaningfully contribute to economic analysis.[96] For instance, the predictive nature of ML makes it particularly well-suited for evaluating counterfactual scenarios in merger control cases, including the ability to capture non-price dimensions that enrich competitive analysis.[97]

When econometric estimations or simulations are submitted as evidence, theoretical models and assumed assumptions are subject to scrutiny. Likewise, ML-based analyses will require litigants and adjudicators to develop a fundamental understanding of technical and methodological aspects.[98] This challenge underscores the need to develop rules or guidelines to assess ML-based evidence, allowing courts to replicate or suggest alternative models and introduce methodological variations or parameters potentially overlooked by litigants.[99]

Handling Digital Evidence

Digital evidence is crucial for establishing anticompetitive conduct in legal proceedings, particularly in cartel investigations, and its significance is expected to increase in the coming years.[100] Competition agencies typically hold legal authority to access or seise digital evidence, and to this effect they have developed protocols for its acquisition, extraction, analysis, preservation, and custody. These protocols and practices fall under the umbrella of Computer Forensics.[101]

In litigation, parties may challenge digital evidence on various grounds, including: (i) lack of integrity, (ii) problems with provenance or chain of custody, or (iii) authenticity and verifiability concerns.[102] Furthermore, the emergence of synthetic or AI-generated audiovisual content presents evidentiary challenges extending beyond competition law enforcement.[103]

Courts will increasingly encounter expert reports and depositions addressing complex technical dimensions of digital evidence. It is reasonable to anticipate that the judiciary will seek expert assistance, for instance, when evaluating data extraction methodologies or establishing technical standards for determining the provenance of digital files. Clear standards for the admissibility and assessment of digital evidence are thus essential—not only to guide parties in evaluating authenticity and integrity of evidence prior to trial, but also to discourage dilatory tactics and unfounded objections.

Concluding Remarks

In the coming years, the capacity of competition authorities to meet societal expectations will depend on successfully orchestrating their digital transformations and securing budgets adequate for achieving this objective. Initiatives such as Stanford's PCA and international forums like the OECD underscore a growing commitment to these issues, highlighting the importance of global cooperation.

The extensive spectrum of potential competition violations or restrictions associated with algorithmic tools and AI-driven business intelligence programs presents formidable challenges. Furthermore, legal and practical obstacles to detecting and investigating potential infringements involving algorithmic systems, combined with the proliferation of paid and open-source innovation tools that can be employed either to enforce or circumvent competition laws, create an exceptionally complex, and in some respects, paralyzing environment. Indeed, a central debate today concerns whether competition authorities, as presently structured, will ultimately succeed in confronting the challenges posed by algorithmic competition.[104]

A gradual, phased approach to the digital-led transformation is recommended, particularly for jurisdictions at the earlier stages of institutional development. Agencies may begin by consolidating, integrating, and systematising internal data. Subsequently, they can establish, enhance, or if needed, reorganise Data and Intelligence Units, drawing upon best practices from leading international competition authorities and adopting workflow methodologies inspired by the tech industry.

[95] A reasonable alternative would be to develop these models based on the Application Programming Interfaces (APIs) of existing AI companies.
[96] For literature review on this subject, see Isaiah Hull, Machine Learning for Economics and Finance in TensorFlow 2—Deep Learning Models for Research and Industry (Apress, 2021), Ch.2.
[97] Daryl Lim, *Can Computational Antitrust Succeed?*, p.44.
[98] Key considerations include the choice of model used, how it was fine-tuned, validation cross-checking results, and the regularisation techniques applied, among other factors.
[99] On the need of Competition Authorities to create guidelines setting standards for the submission of ML-based evidence, see Phillip Hanspach, "Economics in the Era of Machine Learning", Stanford Computational Antitrust (2024), p.187.
[100] International Competition Network, *Enforcement Manual*, Ch.3. "Management of Electronically Stored Information (ESI) in searches, raids and inspections" (updated 2021), available at: *https://internationalcompetitionnetwork.org/wp-content/uploads/2022/01/CWG_ACEM_Digital_Evidence_CH3-2021.pdf*.
[101] Computer Forensics "*is the use of specialised techniques for the preservation, identification, extraction, authentication, examination, analysis, interpretation and documentation of digital information. Computer forensics comes into play when a case involves issues relating to the reconstruction of computer system usage, examination of residual data, authentication of data by technical analysis or explanation of technical features of data and computer usage. Computer Forensics requires specialised expertise that generally goes beyond normal data collection and preservation techniques available to end-users or information technology (IT) system support personnel.*" ICN's Enforcement Manual (2021), Ch.3, p.5.
[102] S. Kumar Rana et al. (eds), Blockchain-Based model to preserve authenticity of judicial evidence, in *Fusion of Artificial Intelligence and Machine Learning for Advanced Image Processing, Data Analysis and Cyber Security*, Ch.8, Francis Taylor, 2025 (upcoming).
[103] There is widespread concern that the rise of deepfake technology will require new standards, increasing litigation costs to prevent the admissibility of potentially falsified evidence. See Daniel J. Capra, "Deepfakes Reach the Advisory Committee on Evidence Rules", Vol. 92 Issue 6 Article (2024)7 *Fordham Law Review*.
[104] OECD (2023), p.37.

Lastly, antitrust enforcement will also require allocating sufficient resources to equip courts and judges with the expertise and tools necessary to efficiently manage caseloads and prepare for challenges ahead.

This incremental strategy acknowledges the realities faced by Latin America and other developing regions, where competition agencies often contend with resource constraints and limited staffing or infrastructure to meet the demands posed by the digital economy. Nevertheless, precisely due to these limitations, a well-structured action plan, optimised utilisation of existing resources, and a focus on building local technical capacity could enable these jurisdictions to achieve a comparatively greater productivity boost than their counterparts in more developed economies.

Additionally, competition agencies and courts are often asked to provide informed opinions in legislative or regulatory proceedings within their areas of expertise. Their effectiveness in advocating regulatory changes hinges on their ability to operate at full capacity within the existing regulatory framework. Going back to Bill Kovacic's memorable line from *The Big Short*, they need to be riding a racecar—not an ostrich.

Finally, adopting new technologies for law enforcement does not inherently imply increased intervention, nor does it suggest pursuing actions absent evidence of competitive harm. Nor should competition authorities themselves, in embracing technology-driven transformation, become agents operating behind "black boxes." Antitrust tools must be subject to governance, auditability, and transparency, constitutional safeguards and due process.[105] Implementing best practices from software development, such as detailed logging and responsible testing protocols, offers a good starting point.

[105] M. Matiuzzo and H. Machado, "Algorithmic Governance in Computational Antitrust—a Brief Outline of Alternatives for Policymakers", *Stanford Computational Antitrust*, vol II.