UNIVERSIDAD ADOLFO IBÁÑEZ

Sección Diálogos

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From Theory to Tech: Computational Antitrust

Concept, origins, and a path moving forward

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Abstract: Building upon the characterization of "Political Antitrust" and "Economic Antitrust" as successive 'waves' in the evolution of Antitrust law, this paper explores the hypothesis—originally introduced by Dr. Thibault Schrepel—that we are now entering a phase termed "Computational Antitrust" or "Antitrust 3.0." This emerging era arises from exponential advances in computing power, the expansion of network infrastructure, and digital transformation of nearly all aspects of economic life. These and other technological achievements have driven the emergence of "Algorithmic Competition," a phenomenon that has garnered attention from both international organizations and competition authorities, as it may pose significant challenges to the institutions tasked with preserving competitive markets. These developments might also call into question established paradigms in competition policy.

In response, authorities face the task of implementing a strategy aimed at integrating analytical tools and computational methods throughout multiple dimensions of their workflow. This paper underscores the importance of investing in both technological infrastructure and specialized human resources, fostering a collaborative environment among data scientists, computer science experts, economists, and legal professionals. Additionally, it examines the Stanford University Computational Antitrust Project and its contributions to advancing interdisciplinary research networks to connect experts, academics, and competition agencies globally.

Finally, this work proposes a roadmap to Computational Antitrust is envisioned as a bottom-up structured progression, with Latin America and other developing jurisdictions in mind. It is structured around three key milestones: Adopting Big Data management methods for optimizing and organizing internal 'experience-base' resources, establishing Data Units following best international experiences, and deploying advanced predictive tools to support judicial decision-making and legal reasoning. The paper concludes offering reflections on the challenges ahead.

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GLOSSARY

INTRODUCTION

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

Within this framework, Dr. Schrepel identifies two early stages of competition law, referred to as *Political Antitrust and Economic Antitrust*.[1] He argues that the last decade has ushered in a new era marked by heightened market complexity and dynamism. Antitrust 3.0 emerges from the acknowledgment that, to fulfill their critical role, institutions entrusted with promoting and defending free and unfettered competition must undertake plans to acquire informational, analytical, and predictive capabilities, alongside experts in data science and related fields.

In the following sections, I will attempt to explain, albeit inevitably incomplete, the extent to which increases in computing power, network expansion, and 'datification', amid other technology-related advances, have radically transformed market dynamics to the point of redefining how firms engage with the *intelligent adaptation to market conditions* paradigm.

While Computational Antitrust has sparked considerable academic research and international collaboration initiatives, this paper will focus on what I consider to be the most critical aspects of its development and institutionalization by competition agencies, irrespective of their current progress.

I. PIONEERS: POLITICAL AND ECONOMIC ANTITRUST

In its earliest incarnation, Antitrust Law was grounded in an economic theory that clearly recognized the detrimental effects of monopolies. It emerged amidst a political movement that demanded state intervention to promote individual freedom, foster entrepreneurship[2], and curb the excessive concentration of private power, which risked enabling a minority to control public welfare[3]. Although historical contexts vary by region,[4] antitrust laws have typically emerged as legislative embodiments of a political agenda focused on democratizing 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 scrutinized conduct on general welfare, particularly in terms of prices and output. Some scholars went as far as to call into question the legitimacy of intervention based on objectives other than economic efficiency.[6] Although many of the Chicago School's more extreme views have been superseded, its influence endures: Courts and competition agencies generally recognize the benefits of a cautious approach to enforcement, often guided by economic analysis and quantitative methods for assessing the impact of contested conduct on market efficiency.[7]

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 U.S., 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'.

This phase, often referred to as "Antitrust 2.0," matured as economic sciences became fully institutionalized within antitrust law policymaking. This period is characterized by (i) judicial reasoning becoming increasingly rooted in economic theory and (ii) the integration of economists and industrial organization experts into competition agencies and specialized tribunals.[8-9]

II. 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.

II. (a). Processing Power

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

In Information Theory, the smallest unit of measurement is a binary digit (*bit*), which represents the smallest degree of uncertainty between two equally probable alternatives—akin to heads or tails in a coin toss.[10] According to this principle, a *transistor* - a small electrical circuit or switch - can exist in one of two possible states: on or off, allowing or blocking the flow of energy. In binary code, we represent these two states with zeros (0) and ones (1).

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

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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 Pitrofsky, E. (ed.) *How the Chicago School Overshot the Mark* (2008), p. 25.

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 permanent inclusion of two economic experts as Ministers in the Chilean Competition Tribunal (TDLC) following the enactment of Law 19.911 represents a pivotal moment in this institutionalization 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. However, this redundancy also serves as a protective mechanism, mitigating 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 range in intensity 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.

In the mid-1960s, Intel's Director of Research and Development, Gordon Moore, observed that the number of transistors in integrated circuits doubled every two years at a constant cost, and predicted that 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 forerunner in realizing that advances in microelectronics would eventually lead to "a *small computer inside our phones, cars, or even typewriters*". Powered with millions of microscopic silicon chips, he envisioned the power to transmit, store, and process data would become virtually limitless.[15] The year was 1972.

Carver Mead and some of his Microelectronics module students

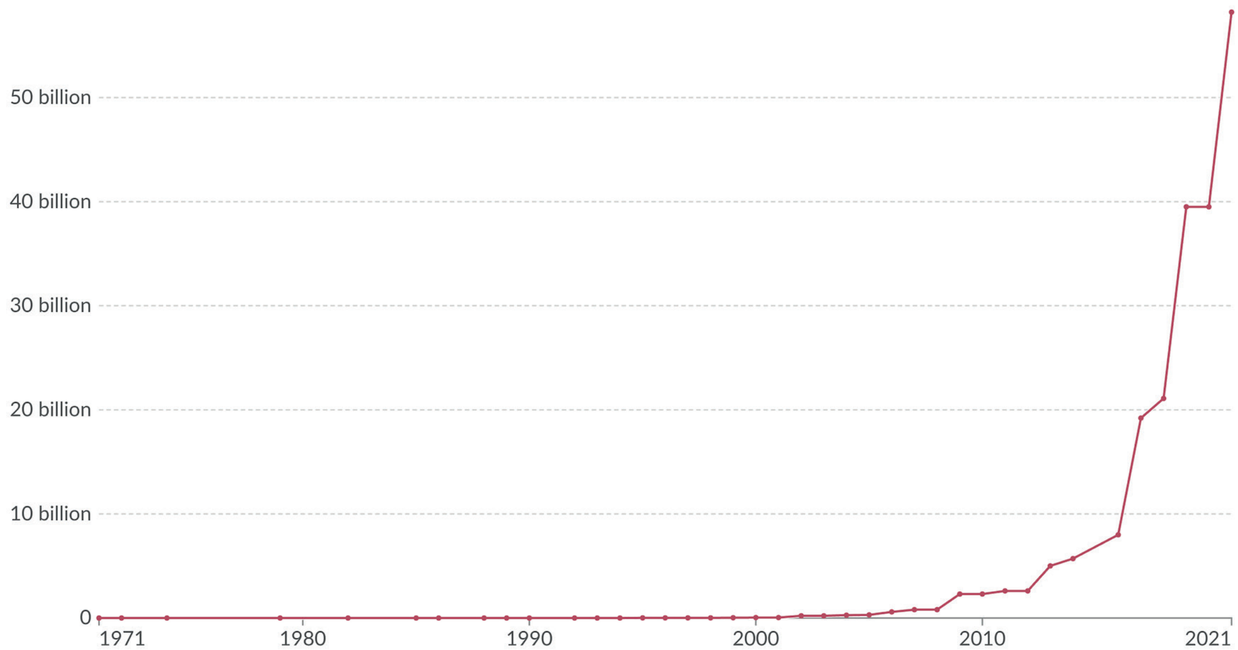
Source: Caltech Library[16]

Having endured the test of time with outstanding levels of accuracy, Moore's Law symbolizes both the dizzying pace of technological change and our steady march into the digital age.[17] If a computer's speed is largely proportional to the number of transistors conforming its processing unit, growing numbers of transistors at consistently lower cost enable microprocessors to handle more operations, with additional functionalities and enhanced performance.[18]

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

15 Chris Miller, *Chip Wars*, Scribner (2022), p. 71.
16 https://calteches.library.caltech.edu/303/1/mead.pdf .
17 Robert R. Schaller, *Moore's Law, past, present and future*, *IEEE Spectrum 34(6):52 - 59.*
18 Azeem Azhar, *The Exponential Age*, Diversion Books (2021), p.8.

Figure 1: Number of transistors per microprocessor



Source: Our World in Data[19]

Exponential growth is a quality according to which something multiplies at a constant rate with subtle gains followed by explosive acceleration.[20] 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, quantitative increase in transistors represented a qualitative leap in sequential and parallel processing capabilities, bringing about novel possibilities that, until then, had been purely theoretical.

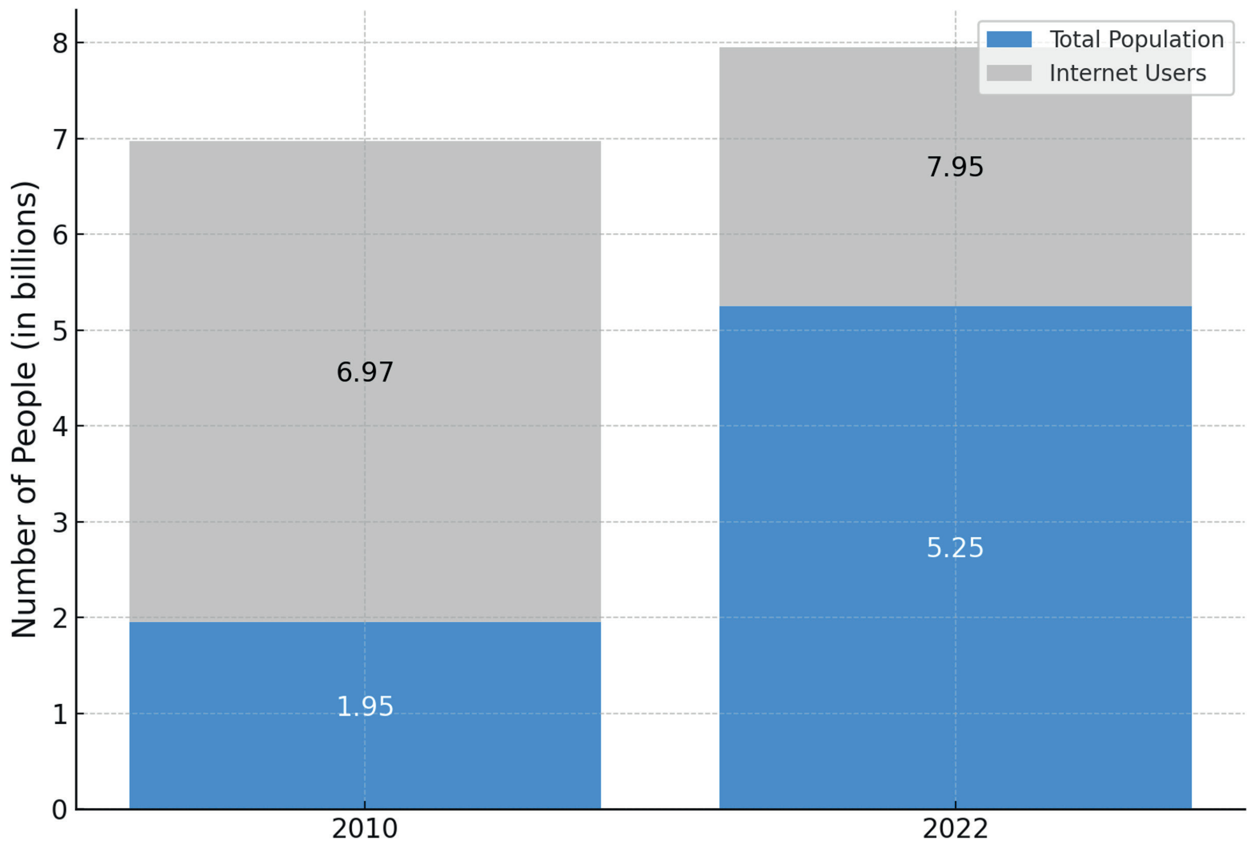
For instance, longstanding research has suggested that artificial neural network layers may drive predictive analyses to lay the ground for a new era of artificial intelligence (AI). However, the rise of deep learning was made possible only thanks to extraordinary levels of computational power only available in recent years.[21]

II (b). 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.

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

Figure 2: World population v/s Internet users 2010-2022



Source: Statista[22] and World Bank[23]

In 2010, 28% of the global population had access to the internet; by 2022, it had reached two-thirds. Given that demographic growth amounts to a mere 14% increase over this period, it is safe to conclude that over 90% of the 3.3 billion new users are online primarily by virtue of expanded internet infrastructure.[24] Centralized and distributed servers, cloud computing, and software-as-a-service (SaaS) have created endless online possibilities for this influx of new users, especially in the realm of e-commerce.[25]

The so-called "*digitalization of nearly everything*"—the transformation of documents, photos, videos, maps, music, and other media, into streams of *bits* amenable to be encoded, saved and loaded—is one of the defining features of our time.[26] This phenomenon has been conspicuously propelled by the emergence of *sensors*: phones and cars, as once envisioned by Carver Mead, alongside other devices we use every day, automatically detect, capture, and measure signals from the external world and convert them into data, which is then transmitted via integrated Wi-Fi modules.[27]

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22 https://www.statista.com/statistics/273018/number-of-internet-users-worldwide/ .
23 Available at datacatalog.worldbank.org.
24 Of the 3.3 billion new users, only about 280 million can be attributed to population growth.
25 Jaeger, P. T., Lin, J., & Grimes, J. M. (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
26 Eric Brynjolfson y Andrew McAfee, *The Second Machine Age,* Norton (2016), p.66.
27 The proliferation of sensors is a source of various moral and social issues. See M. Andrejevic y M.Burdon, *Defining the Sensor Society*, University of Queensland TC Beirne School of Law Research Paper No. 14-21 (2015).

Since 2010, the volume of data generated annually has grown thirty-fivefold.[28] It is no wonder many businesses have either become or transformed into data-driven endeavors[29] and that hyperscale data centers became the backbone of the world's most important technology platforms.[30] Data was famously touted "the new oil"—valuable, yet useless without refining.[31] Processing power and transmission speeds currently at our disposal allow us to do just that.

In sum, the advent of new capabilities for processing, transmitting, and storing large volumes of data, coupled with the development of digital industries and cloud services, has subtly, and later explosively, paved the way to increasing market dynamism and complexity.[32]

III. ALGORITHMIC COMPETITION

A well-established paradigm in competition policy holds that, while firms are barred from colluding or substituting competition with coordination, they may legitimately engage in *intelligent adaptation* to existing or anticipated behavior of their competitors.[33]

For decades, the practical application of intelligent adaptation focused around *business analytics*, which involves observing and analyzing market conditions through quantitative methods applied to structured data.[34] 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.[35]

Depending on the technology operating under the hood, sophisticated variants of *business intelligence* utilize algorithms refined through iterative calibration to identify patterns and make predictions[36] - this is **Machine Learning (ML)** and related techniques.[37] While extensive literature and online resources

28 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.

29 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/ .

30 https://blog.enconnex.com/data-center-history-and-evolution .

31 Characteristics associated to the concept of 'Big Data'. Stucke et al, B*ig Data and Competition Policy*, OUP (2016), cap.2. The phrase *data is the new oil* is attributed to the mathematician Clive Humby.

32 Schrepel, *Computational Antitrust,* p.4.

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

34 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.

35 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 categorization in traditional databases, and Big Data. However, certain metadata within Big Data, like information from sensors or location data, can be structured.

36 A useful simplification of a learning algorithm: an algorithm that uses **Experience (E)** to improve its **Performance (P)** on a specific **Task (T)**. If say the algorithm is intended to recognize cats in photos, **T** is be correctly identifying cats in images, **P** represent accuracy in the **T**, and **E** is the number of images analyzed. Then (provided the algorithm works) the larger the **E** count, the better its **P** becomes for the assigned **T**. (Mitchell, 1997, cited in Deep Learning, ch. 5, p. 97). These algorithms operate on probabilistic rather than logical rules, maximizing the likelihood of prediction or generalization based on common patterns or features—which can make them flexible in the face of unknown data they may encounter in the future.

37 '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/

exist on this subject, it's worth presenting two examples of how variants of ML models may contribute to the shaping Algorithmic Competition.[38]

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 maximize profits per sold unit.[39] The process begins with a firm loading preprocessed, identifiable or historical data—such as past prices, quantities sold by SKU or product category, stock levels, competitor prices, among other variables[40]. Using a popular technique, the program generates hierarchical decision trees that iteratively improve predictive accuracy through adaptive optimization.[41]

In the initial round, the algorithm might consider exclusively an *average price across all SKUs* to compute an optimal price for every product. Such a prediction would be demonstrably very weak, and practically useless. But in a subsequent iteration, the model incorporates other *labels*, such as whether the product belongs to a specific category (e.g., high-end smartphones). Based on this distinction, the model adjusts prices accordingly and generates additional branches in the decision tree. The refinement process continues by incorporating additional relevant variables, such as sales frequency, seasonal changes, average profit margin, price differences with close competitors, and weekly or monthly demanded quantities.

Unsurprisingly, multiple uncertainties need to be addressed throughout this process, requiring complex engineering and statistical efforts, or trial-and-error testing.[42] For example, 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?[43]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.[44]

Unsupervised learning: In this approach, the program is fed with *unlabeled data* and is tasked with identifying patterns relevant to a specific application. Let's provide a practical example to illustrate how these kinds of algorithms work.[45]

capabilities/quantumblack/our-insights/the-state-of-ai .

38 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/ .

39 A flexible pricing mechanism, adjusted in real time based on various concurrent factors.

40 This information, pre-identified as valid, is usually referred to as *labels*.

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

42 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.

43 Factors such as the learning rate or the depth of the tree are known as '*hyperparameters*.'

44 A variant of dynamic pricing is *personalized dynamic pricing*, which considers various parameters linked to an identifier(user), such as purchasing habits, average ticket amount, and online browsing behaviors. However, consumers' aversion to this type of price discrimination has hindered its widespread adoption. Hufnagel, G. et al, S*eeking the perfect price: Consumer responses to personalized price discrimination in e-commerce*. Journal of Business Research, Volume 143, (2022), p. 346-365.

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

An e-commerce site wants to enhance its pricing and marketing strategy by segmenting customers into three different groups('Groups') based on their client's purchasing habits.

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

Step 2: The program assigns the remaining customers to one of the three Groups based on some of their specific attributes—say, the frequency and total value of their purchases[46]. Using a mathematical formula,[47] it calculates the distance between each customer's attributes those of the *centers*, categorizing customers into Group 1, 2, or 3 based on proximity.

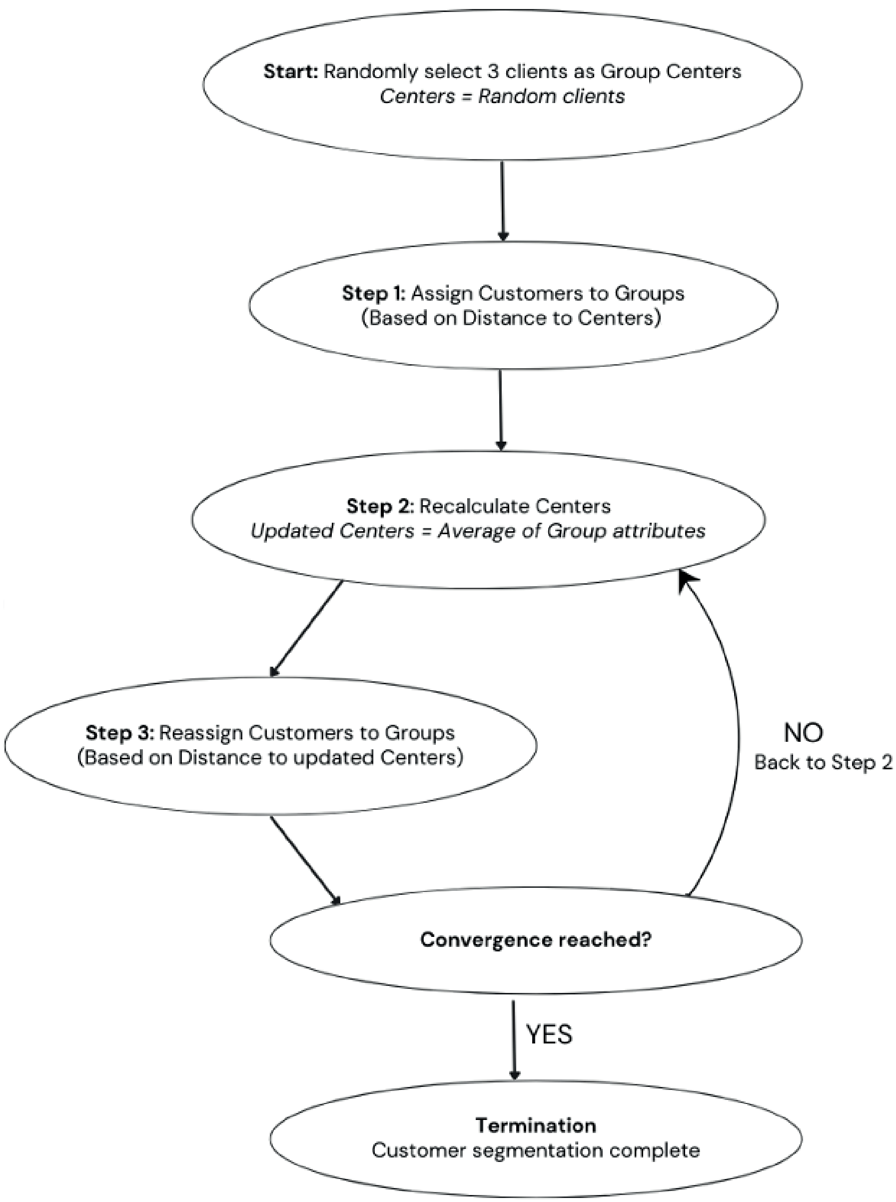
Step 3: The program recalculates the *centers*. From this step onward, and in every subsequent iteration, *centers* will not represent the attributes of any given member, but the *average of the attributes* of each Group's current members.

Termination: Until convergence is reached, Steps 2 and 3 are repeated, reassigning customers to groups based on their updated distances from the *centers*, as determined after each iteration. The process converges when no customer changes groups, finalizing the segmentation.

46 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.

47 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.

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 associate each customer segment with product categories based on price and description. This enables predictions on consumer behavior, tailored promotions for specific segments, or bundling for items frequently purchased together.

Iterative learning models demonstrate how cutting-edge data science utilizes data streams to generate increasingly accurate predictions. Crucially, these predictions are achieved at a steeply declining cost. Tasks such as text translation, once completely unrelated to prediction, are now framed as prediction tasks.[48] Massive, continuously updated structured and unstructured datasets, combined with learning algorithms, offer unprecedented capabilities to anticipate fluctuations, predict preferences, project future needs, and automate decision-making processes.[49-50]

The net effect of widespread algorithm use on market efficiency —whether in terms of opportunities or potential risks—is the subject of extensive academic debate.[51] As the OECD (2023) notes, these impacts are ambiguous.[52] Some scholars argue that algorithm-driven dynamic pricing could lead to a massive redistribution from buyers to sellers, even absent collusion.[53] Consequently, competition agencies are increasingly recognizing an impending need to directly examine these algorithms to attempt understanding their inner workings.[54]

However, there is less consensus—and greater uncertainty— on how about conducting these audits. Contingent on access to the algorithm and its underlying data, the suggested investigative methods vary in audacity and complexity, ranging from user surveys to reverse engineering. The OECD identifies several challenges with algorithm audits, which can be summarized as: (i) time and cost in reviewing thousands of lines of code, often developed by international teams in various programming languages, with dependencies on other software or company services; (ii) the sequential or concurrent use of multiple algorithms, some managed by third parties in 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 its observable functionality and tests it with synthetic data mirroring real-world conditions, could this serve as 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?[55-56]. Let's briefly examine these issues.

Requiring a party under investigation to produce documents or records, whether voluntarily or under a legal obligation, may provide access to relevant information, such as the supervisory protocols and human oversight measures that govern the implementation of an algorithmic system ('*governance audit*').

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48 Ajay Agrawal et.al, *Prediction Machines. Expanded Edition*, HBR (2022), p.119.
49 H. Hoffman, H. y I. Lorenzonni, *Future Challenges for Automation in Competition Law Enforcement* Stanford Computational Antitrust (2023), p.37 y ss.
50 ICN CWG SG2 *Project on Big data and Cartels - The impact of digitalization in cartel enforcement* (2020).
51 For a comprehensive review of this topic: C. Coglianese y A. Lai, *Antitrust by Algorithm,* Stanford Computational Antitrust Vol II (2022).
52 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.
53 *"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, y S. Weinstein, *Dynamic Pricing Algorithms, Consumer Harm, and Regulatory Response",* Harvard Business School Working Paper 22-050 (2022), p.55.
54 OECD (2023), p.6. Along the same lines, the Deputy Head of the OECD Competition Division, Antonio Capobianco (2023), has emphasized the need to continue investing in specialized 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 .
55 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.
56 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.

Yet without access to inputs and outputs, source code, program architecture, and other components, it is not possible to conduct *empirical or technical* audits, which involve detailed analysis and practical testing to evaluate the system's internal functioning.[57]

Similarly, on-site inspections or searches are not a suitable approach. Even in jurisdictions where investigative bodies are authorized to conduct prolonged on-site analyses, audits differ substantially from evidence-collection based inspections. The former usually require testing and evaluating interconnected systems that may be live or in operation, interacting with developers or specialists that are privy to the system's inner workings, which can hardly be achieved in the context of a *dawn raid*. Lastly, but not least, in-person inspections on the private premises are exceptional and highly invasive measures that affect privacy and other fundamental rights. Thus, they may be neither reasonable nor proportional, especially if audits can be conducted through less invasive means.

Legislatures and regulatory bodies will be tasked with determining whether modifications are needed to facilitate access to algorithmic functionality, impose traceability and explainability requirements, and, most importantly, decide whether it is appropriate to assess these applications based on their outcomes or their underlying processes.[58]

IV. COMPUTATIONAL ANTITRUST: ORIGINS AND GOALS

Like all public institutions that shape society's functioning, antitrust enforcement bodies require a certain level of stability to function effectively. Their ability to adapt to changing conditions is often described as *linear*: their organization, traditions, resources, and historical context constrain these entities 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 "*exponential gap*", a phenomenon that may be socially disruptive and a source of opportunistic gains for a few.[59]

Against this backdrop, **Computational Antitrust** emerges as a branch of legal informatics,[60] a field within computer science focused on applying computational tools and techniques to legal analysis.[61] Thus, Computational Antitrust can be viewed as a multidisciplinary scientific endeavor aimed at *bridging the exponential gap* in applying antitrust law to complex and novel market dynamics.[62] And while competition

57 *Empirical audits* require access to the flow of inputs and outputs of data, without necessarily having direct access to the algorithm's internal mechanics. In contrast, *technical audits* aim to assess the algorithm's functioning under the hood, thereby identifying risks, biases, optimization criteria, and more. See *Digital Regulation Cooperation Forum, Auditing algorithms: the existing landscape, role of regulators and future outlook*, Discussion Paper, 2023.

58 Susan Atey, *The Impact of Machine Learning on Economics*, en The Economics of Artificial Intelligence: An Agenda Eds. Ajay Agrawal, Joshua Gans, and Avi Goldfarb (2019), p.542.

59 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.

60 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).

61 Schrepel, *Computational Antitrust, p.2.*

62 *"[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, Zokol & Wagman, *Towards A Technological Overhaul of American Antitrust*, Antitrust, ABA, Vol. 37, No. 1, (2022).

authorities and regulatory bodies are the primary targets called upon to drive this transformation, all actors in this realm, including consultants, external advisors, compliance officers, firm executives, and consumer organizations, hold vested interests.

Like previous groundbreaking movements, **Antitrust 3.0** is gradually but steadily making its way into antitrust law institutions. Its progression is observable in the adoption of analytical tools, automated functions, systematic collection and organization of relevant data, and the development of predictive models crafted to address the unique demands of competition agencies and other stakeholders. Nevertheless, it must be remembered that this is fundamentally a *human-centered transformation*, its success largely hinging on the appropriate conditions that will enable programmers, data scientists, and analysts to collaborate effectively with economists, lawyers, and competition policy experts.[63]

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.[64]

V. THE STANFORD UNIVERSITY COMPUTATIONAL ANTITRUST PROJECT

In January 2021, Stanford University's Codex Center inaugurated 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.[65] Among its activities, the CAP publishes academic research, hosts working sessions, produces a widely acclaimed podcast,[66] and collaborates with 67 competition agencies worldwide.[67] Every year CAP launches a report offering an overview of how various jurisdictions apply computational tools to antitrust analysis, highlighting noteworthy trends.[68]

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 analyzing evidence, and the development of platforms that facilitate access to data from entities under investigation; (2) the ability, within merger control, to analyze 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 the implementation of competition policies, with an emphasis on generating predictive insights.[69]

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63 Schrepel, *Computational Antitrust,* p.14.
64 "Stanford Computational Antitrust" podcast, episode 22 (January 2024), from minute 13.11 onwards.
65 Project description available at: https://law.stanford.edu/codex-the-stanford-center-for-legal-informatics/computational-antitrust-project/ .
66 *Stanford Computational Antitrust podcast*. Available in Spotify and other platforms: https://open.spotify.com/show/62DTsUktaAaNoqxR-76zlmr?si=eac25c323748488e .
67 Agencies list available at: https://law.stanford.edu/codex-the-stanford-center-for-legal-informatics/computational-antitrust-agencies/ .
68 The third Annual report was published June 11th, 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/ .
69 Schrepel, *Computational Antitrust,* p.5.

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.[70] 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.

VI. ROLLOUT PLAN: A PROPOSAL

VI. (a). Organization, systematization, and visualization 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 utilize 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 into their "experience base". In other words, priority should be placed on unifying and optimizing dataflows already at their disposal, which may be scattered or fragmented across various 'business units' operating with relative autonomy.

The practical implementation of this project depends on variables unique to the size, resources, and specific goals of each institution. This notwithstanding, general principles of Big Data management are suggested below to frame the main issues relevant to this endeavor.[71]

i) Data Challenges: Internal informational sources within an organization span various data types, encompassing both structured and unstructured content. These sources may originate from current information flows or archival repositories and can range from spreadsheets containing industry or corporate data, written presentations submitted by parties, multimedia records of investigative procedures, and associated metadata. Thus, careful consideration must be given to optimal methods for data acquisition, volume estimation, potential storage solutions, and the implementation of appropriate visualization platforms tailored to the needs of various user groups.

ii) Processes Challenges: This stage involves data collection, cleaning to remove errors or duplicates, transformation to ensure compatibility and consistency across formats, and *indexing* to optimize storage and reduce access times. **ETL (Extraction, Transformation, and Loading) applications**[72] may be employed to integrate the information into a repository or data warehouse, preparing it for storage and subsequent analytical or automated processes.[73]

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70 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).

71 U. Sivarajah et al, *Critical analysis of Big Data challenges and analytical methods,* Journal of Business Research (2016).

72 https://en.wikipedia.org/wiki/Extract,_transform,_load .

73 For example, this is one of the services that Amazon Web Services provides from the cloud to multiple agencies in the U.S. See: https://aws.amazon.com/what-is/etl/#:~:text=Extract%2C%20transform%2C%20and%20load%20

iii) Management Challenges: Lastly, key issues such as security, privacy, and data governance protocols must be addressed, including user access management for different roles and the optimization of operational costs wherever possible.

Centralizing an institution's knowledge base offers a myriad of potential benefits. It minimizes disruptions caused by leadership changes or the departure of key personnel. It can foster consistent and objective decision-making, support retrospective evaluations on the agency's actions, reduce search times, improve institutional transparency, and allow for the assessment of quantitative or econometric methods used in past cases. Furthermore, it enables the development of metrics that can be used to quantify project success or distribute workloads.

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

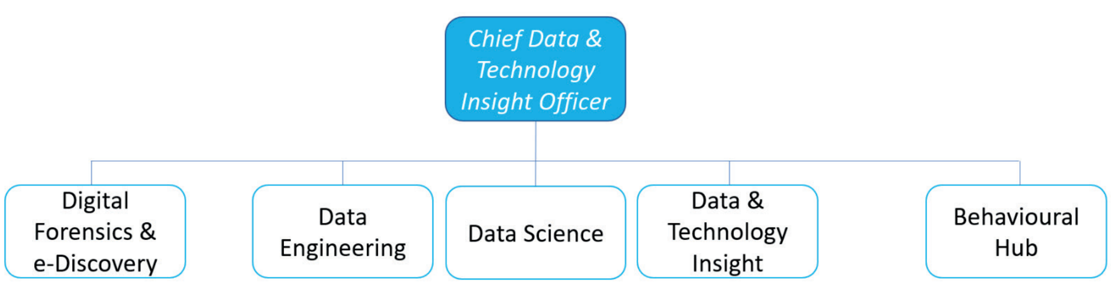
VI. (b). Creation of Data Units

"In the face of such change, agencies must bring their skills up to date" - Stefan Hunt[74]

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 attempt to embrace Antitrust 3.0 emerged at the opposite coastline of the Atlantic. In 2022, the United Kingdom's Competition and Markets Authority (CMA) undertook bold steps to expand its capabilities in what was termed *the Technology-Led Transformation*. Under the leadership of the Harvard-trained economist and then-Director of Data and Technology Insights Unit ("DaTa"), Stefan Hunt, the CMA sought to overhaul the agency's resources to equip it for the challenges surging from 'digital markets', while significantly improving its data-handling methods and overall operational efficiency.[75]

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 specialized fields of knowledge, allowing for the formation of multidisciplinary teams which can be customized for different projects according to specific needs. As of 2022, **DaTa** was organized as follows:

Figure 4: CMA's DaTa Unit[76]



74 Stefan Hunt, *The technology-led transformation of competition and consumer agencies. The Competition and Market's Authority's experience*, Discussion paper (2022), p.4.
75 Stefan Hunt, *The technology-led transformation.*
76 Stefan Hunt, *The technology-led transformation*, p. 36.

(i) **Data Engineering:** is responsible for organizing and integrating internal and external information flows, combining software development with technological infrastructure management.

(ii) **Data Science:** A team entrusted to the design of data extraction models using machine learning (ML).

(iii) **Data & Technology Insight:** Functioning as a *liaison* between investigative teams and the DaTa Unit, it actively collaborates on cases that present technical challenges within their field of expertise.

(iv) **Digital Forensics & e-Discovery:** Specializes on operating software for digital forensics and evidence review.

(v) **Behavioral Hub:** Advises teams on cases where behavioral economics is particularly relevant, assisting in tasks such as determining what information is needed to understand and evaluate a digital platform's structure, assessing a merger's impact on consumer choice, and suggesting appropriate remedies.[77]

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

First, by borrowing software development methodologies from the tech industry,[78] each project is structured around a **Project Manager**, and teamwork is organized into short-term deliverables or **sprints**. At the end of each two- or four-week sprint, the **Project Team** holds collaborative sessions to evaluate progress, provide and receive feedback, and plan the next steps. Ideally, as the project progresses, other incumbent units within the agency become involved early in product development 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.[79]

Secondly, a crucial yet overlooked principle is the establishment of clear boundaries for tasks that fall *outside* the Data Unit's scope. A Data Unit should not be responsible for general IT services, overseeing data handling or cybersecurity protocols, nor it should be tasked with investigations into potential infringements in 'digital markets'.[80] While in these cases the Data Unit may offer technical assistance and provide valuable insights to enhance decision-making processes, substantive competition policy typically falls beyond its core activities.

Besides DaTa, many national competition and consumer protection agencies are establishing dedicated Data Unit teams. Until these teams achieve some degree of consolidation, it might be desirable to engage in periodic reassessment of their structure, functions, and objectives. Whenever feasible, continuous evaluation should be coupled with advocacy efforts to secure increased funding to support the recruitment of specialized talent. In this respect, it is noteworthy that only considering the countries where Data Units are in operation, the proportion of staff trained in data sciences, relative to the rest of the non-administrative personnel, remains relatively low, usually below 6%.[81-82]

77 Stefan Hunt, *The technology-led transformation*, p.33.
78 Agile Manifesto, available at: https://agilemanifesto.org/iso/es/principles.html .
79 Stefan Hunt, *The technology-led transformation*, p. 40.
80 This corresponds to the Digital Markets Unit. https://www.gov.uk/government/collections/digital-markets-unit .
81 With the exception of Poland's Office of Competition and Consumer Protection, which is at 12%. See OECD (2023), p.31.
82 In Latin America, Chile has created a specialized "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).

VI. (c). 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" – Ramos-Makeda & Chen[83]

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 institutionalization of data and information sciences is essential to advancing the field towards **Computational Antitrust**.

The surge in antitrust-related claims initiated by authorities and private litigators, alongside the increase in damages claims tied to competition disputes, has placed substantial pressure on the judiciary's workload.[84] While some courts have attempted to increase their analytical capacity,[85] there remain areas where judicial bodies - like competition agencies and other litigants - will need to consider their own digital transformation. The following are promising avenues for future exploration:

i) Natural Language Processing

Natural language processing,[86] the development of conversational agents able to generate and understand human language, has been a long-standing research goal for computer scientists.[87] Early attempts encountered little success, as the intricacy, redundancy, and semantic depth of language defied reduction to a simple rule set.[88]Recent advances, including the adoption of statistical approaches, experimentation with multi-layered architectures, and extensive training on unlabeled data processed in parallel,[89] have yielded highly adaptable applications capable of generating content, answering queries, and classifying text.[90-91]

Text classification methods such as **topic analysis** and **sentiment analysis**, which can be approached through multiple scientific frameworks, hold significant potential for research and case resolution in antitrust cases.[92] For instance, these methods could be applied to analyze communications or messaging evidence between individuals involved in a presumptive anticompetitive conspiracy, identifying common themes or analyzing attitudes or emotional nuances around key terms. Such findings could strengthen the prosecution's case or support alternative interpretations adduced by the defense.[93]

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83 Manuel Ramos-Makeda and Daniel Chen, *The data revolution in justice*, World Development, Volume 186, upcoming (February 2025).
84 See, for example, the 2024 Chilean Competition Tribunal annual report, available at: https://www.tdlc.cl/anuarios-tdlc/#anuario-2024/1/
85 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.
86 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.
87 D. Numa & M. Engler, *Introduction to Generative AI*, Manning (2024), p.5.
88 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.
89 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.
90 As previously mentioned, LLMs are built on a combination of reinforcement learning with rewards and penalties based on expected prediction outcomes.
91 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*). Gugler, *Using Natural Language*, p.38 y ss.
92 Devika M D et al, S*entiment Analysis: A Comparative Study On Different Approaches*, Elsevier (2016).
93 Devika M D et al, S*entiment Analysis*.

Similarly, courts could potentially use **Large Language Models (LLMs)** and other deep learning techniques to analyze case files, briefs, rulings, and other available databases to detect behavior patterns in relevant areas, thus refining the judicial decision-making processes. This approach might contribute to the establishment or standardization of **quick look** or **per se** rules, facilitating the classification of certain practices and contributing to clearer legal standards.[94]

This raises the legitimate question of whether it is desirable for the judiciary to rely on these applications for issuing judgments or binding decisions.[95] Undoubtedly, there are several risks to consider, spanning from biases inherent to the training data to cases where an LLM may output plausible but incorrect answers (*hallucinations*). However, as GenAI-based services for lawyers become increasingly available,[96] the rationale for denying the judiciary similar advantages is harder to justify, and it seems inevitable these tools will eventually find their way into judicial processes in one way or another.[97]

Provided the outcome of legal cases remains privy to human decision-making, either individual or collegial, it is certainly desirable courts aim to create standards for the use and optimization of generative AI solutions. Courts can employ specific engineering techniques to fine-tune these models with proprietary data, creating a private and secure ecosystem for internal use.[98] These efforts could significantly aid in establishing more consistent precedents and in identifying factual patterns to apply, interpret, or formulate legal rules.[99]

ii) Machine Learning Solutions as Evidentiary Tools

Although **Machine Learning** (ML) primarily focuses on prediction rather than causality and equilibria, there is broad consensus that ML models can contribute to economic analysis.[100] For instance, ML's prospective nature makes it particularly well-suited to evaluating counterfactual scenarios in merger control, including capturing non-price dimensions that can enhance competitive analysis.[101]

When econometric estimations or simulations are presented as evidence, theoretical models and assumed relationships are subject to scrutiny. Likewise, ML-based reports will require litigants and adjudicators to understand fundamental technical and methodological aspects.[102] This challenge highlights the need to develop rules to assess ML-based evidence, enabling courts to replicate or propose alternative models and introduce methodological variations or parameters that litigants may have overlooked.[103]

94 Daryl Lim, *Can Computational Antitrust Succeed?* Stanford Computational Antitrust (2021), p.42.
95 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).
96 Like Cocounsel https://casetext.com/ o Harvey https://www.harvey.ai/ .
97 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.
98 Commonly referred to as "*prompt engineering*" . See D. Numa and M. Engler, *Introduction to Generative AI*, p.245.
99 A reasonable alternative would be to develop these models based on the Application Programming Interfaces (APIs) of existing AI companies.
100 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), Chapter 2.
101 Daryl Lim, *Can Computational Antitrust Succeed?*, p.44.
102 Key considerations include the choice of model used, how it was fine-tuned, validation cross-checking results, and the regularization techniques applied, among other factors.
103 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.

iii) Handling Digital Evidence

Digital evidence is essential for proving anticompetitive conduct in legal proceedings, particularly in cartel cases, and its significance is expected to grow in the years ahead.[104] Competition agencies are typically granted legal powers to access or seize digital evidence, and to this effect they have developed protocols for acquisition, extraction, analysis, preservation, and custody. These protocols and practices fall under the umbrella of **Computer Forensics**.[105]

In litigation, parties may challenge digital evidence on different grounds, including: (i) lack of integrity (ii) issues with provenance or chain of custody, or (iii) problems of authenticity or verifiability.[106] Moreover, the emergence of non-authentic AI-generated audiovisual content poses challenges to evidentiary rules that extend beyond the realm of competition law enforcement.[107]

Courts will increasingly encounter expert reports and depositions addressing complex technical aspects of digital evidence. It is only reasonable to expect the judiciary to seek expert assistance, for example, in evaluating data extraction methodologies or advancing technical criteria for deciding on the provenance of digital files. The importance of admissibility and valuation standards in relation to digital evidence is substantial: not only as guidance to parties in assessing authenticity and integrity criteria of the evidence at their disposal in preparation for a trial, but also in terms of incentives to discourage purely dilatory strategies or baseless objections.

VII. CONCLUDING REMARKS

The digital transformation of antitrust law is poised to become a subject of extensive future research. Over the coming years, the ability of competition authorities to meet social expectations will hinge on orchestrating their digital transformation and securing budgets that meet the minimum requirements for this objective. Initiatives such as Stanford's PCA and forums like the OECD demonstrate commitment to these issues, emphasizing the importance of international cooperation.

The broad spectrum of possible violations or restrictions to competition associated with algorithmic tools or AI-based business intelligence programs poses a formidable challenge. Moreover, legal and practical hurdles in detecting and investigating potential infringements involving algorithmic systems, combined with the proliferation of a wide array of paid and open-source innovation services —which can be used either to enforce or evade competition laws—create a highly complex and, in some respects, paralyzing landscape. Indeed, one of the central debates today is whether competition authorities, as currently structured, will ultimately be successful in addressing the challenges brought about by *algorithmic competition*.[108]

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104 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

105 Computer Forensics "*is the use of specialized 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 specialized 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.

106 Kumar Rana, S. 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).

107 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*, Fordham Law Review, Volume 92 Issue 6 Article 7(2024).

108 OECD (2023), p.37.

A gradual, phased approach to the digital-led transformation is recommended, particularly for jurisdictions at the early stages of institutional development. Agencies can start by consolidating, integrating, and systematizing their internal data. Then, move on to create, strengthen, or, if necessary, reorganize Data and Intelligence Units, drawing on best practices from leading competition authorities abroad, while adopting workflows inspired by the tech sector. Lastly, antitrust enforcement will also require allocating resources to equip courts and judges with the expertise and tools necessary to manage caseloads and prepare for the challenges ahead.

This incremental strategy acknowledges the realities faced by Latin America and other developing regions, where competition agencies often contend with resource constraints, limited staffing and infrastructure to meet the demands of the digital economy. However, precisely because of these limitations, a well-planned action plan, optimized use 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 countries.

Additionally, competition agencies and courts are often asked to provide informed opinions in legislative or regulatory proceedings within areas of their expertise. Their effectiveness in advocating for regulatory changes depends 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 more intervention, nor does it suggest pursuing actions in the absence of competitive harms. Nor should the authorities themselves, in embracing a technology-led transformation, become agents behind "black boxes." In this regard, antitrust tools must be subject to governance, auditability, and transparency, as well as constitutional safeguards and due process.[109] Adopting best practices for software development, such as detailed logging and responsible testing of new tools, offers a good starting point.

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

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