

The Meaning of AI and Its Implications for Antitrust Law

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Abstract

Artificial intelligence (AI) has become an integral part of our daily life and has already reshaped competition dynamics, prompting renewed debate within the antitrust community. Grounds for reconsideration include a disruption of antitrust fundamental principles, such as its consumer welfare goal, and possibly leaving room for alternative forms of regulation. Surprisingly, the scholarly conversation lacks a clear definition of AI. This Article fills this void by examining AI's goals and scope during key historical moments. It defines intelligence in AI to assess whether contemporary AI might be capable of undermining antitrust pillars and a change of antitrust core values is required.

This Article makes two important contributions to contemporary literature: First, it lays out a comprehensive historical framework of the meaning of AI and its intelligence property. Second, it applies this framework to the current antitrust debate. AI will not disrupt antitrust pillars. However, AI will require adapting antitrust core values to a changed technological framework.

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INTRODUCTION

Artificial intelligence (AI) is everywhere, affecting all industries and the way companies do business.¹ This technology is changing virtually every aspect of our life, from what we buy to how we work.² As legal scholars, it is time to appreciate what AI means, how it is affecting our future, and how it has already put antitrust at a crossroads.³ Scholars have extensively debated how antitrust should proceed in this new framework, from changing its goals to recalibrating its law provisions to address conduct like algorithmic collusion while avoiding stifling innovation.⁴ What strikes me the most in this debate is how we can consider requiring antitrust to evolve in light of a technology we cannot even define.

One reason we lack a clear definition of AI is because AI has developed through distinct scopes, that is, conceptual domains or ranges of problems associated with particular approaches to AI, each pursuing different goals and engaging different audiences.⁵ AI began more as a philosophical rather than a practical problem, as it is today.⁶ In 1956, when AI development

¹ See, e.g., Ajay Agrawal, Joshua Gans & Avi Goldfarb, *Economic Policy for Artificial Intelligence*, 19 INNOVATION POL'Y & ECON. 139, 139 (2019) [<https://doi.org/10.1086/699935>].

² Arun Rai, *Explainable AI: From Black Box to Glass Box*, 48 J. ACAD. MKTG. SCI. 137, 137 (2019) [<https://doi.org/10.1007/s11747-019-00710-5>].

³ Daniel A. Crane, *Antitrust After the Coming Wave*, 99 N.Y.U. L. REV. 1187, 1188–89, 1240 (2024); Erik Hovenkamp, *AI, Data, and Leveraging Strategies: Implications for Antitrust*, NETWORK L. REV. (2025) [<https://doi.org/10.2139/ssrn.5372949>].

⁴ Crane, *supra* note 3; see also Salil K. Mehra, *When Dynamic Competition and Static Competition Merge: Antitrust, Innovation Questions, and the Case of Generative Artificial Intelligence*, 87 ANTITRUST L.J. 97, 98–100 (2025); Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition*, U. ILL. L. REV. 1175, 1177–78 (2017); Ariel Ezrachi & Maurice E. Stucke, *Sustainable and Unchallenged Algorithmic Tacit Collusion*, 17 NW. J. TECH. & INTELL. PROP. 217, 220 (2020); ARIEL EZRACHI, COMPETITION AND ANTITRUST LAW: A VERY SHORT INTRODUCTION 127–30 (2021) [<https://doi.org/10.1093/actrade/9780198860303.001.0001>]; Thibault Schrepel & Alex ‘Sandy’ Pentland, *Competition between AI Foundation Models: Dynamics and Policy Recommendations*, INDUS. & CORP. CHANGE 1085, 1093 (2024) [<https://doi.org/10.1093/icc/dtae042>] (“[W]e propose an ‘innovation first’ principle.”).

⁵ See Part I.

⁶ See Part I.A.1.; Diane Proudfoot, *Wittgenstein and Turing on AI: Myth Versus Reality*, in WITTGENSTEIN AND ARTIFICIAL INTELLIGENCE: MIND AND LANGUAGE 17, 20 (Brian Ball, Alice C. Helliwell & Alessandro Rossi eds., 2024) [<https://doi.org/10.2307/jj.18979316.4>].

officially started, the aim was to understand and model aspects of human intelligence so that they could be implemented in machines through behavioral-based models or reasoning-based models.⁷ The goal was to create “intelligent machines.” Conversely, contemporary AI systems are primarily designed to address practical and technical tasks, such as text translation, online search, and voice assistants.⁸ AI systems such as ChatGPT are based on statistics; the problem to solve is not really about intelligence but how to make computers more powerful to increase the processing of data and quality of predictions.⁹ It is more a technical problem.

This Article informs AI’s definition by taking a brief detour through the origins and main phases of AI in terms of scope and goals to grasp the complexity of its meaning and its implications for antitrust law.¹⁰ It investigates whether contemporary AI is genuinely intelligent and, if so, whether this distinguishes it from past technologies, including the telephone, from an antitrust perspective.¹¹ Although this brief essay is not intended to be exhaustive, the following analysis acknowledges the issue by deepening our understanding of what AI is. This seems important to regulate this technology effectively in antitrust and beyond.¹²

Part I offers a comprehensive historical framework for understanding the meaning of AI across its key phases, tracing its different goals and scope. Part II examines whether AI systems are intelligent and how this affects the development of its goals, scope, and meaning in order to anticipate its future development. Drawing on this historical framework and examination of AI intelligence, Part III argues that current AI does not require redefining antitrust law’s core values.

⁷ See Part I.B.

⁸ See Part I.C.

⁹ See Part I.

¹⁰ See Part I.

¹¹ See Part II and III.

¹² See Part III.

Antitrust issues with AI, including Big Tech concentration, tacit collusion through algorithms, and algorithmic bias (self-preferencing) are not novel, and many insights can be drawn from the past.¹³

This is why I have written this paper, and I urge the antitrust community to engage in this discussion. AI is much more complex than the current generative AI, such as ChatGPT or Gemini, though they are increasingly part of our daily life.¹⁴ Although partial, this essay aims to provide a meaningful framework for further inquiry.

I. THE MEANING OF AI THROUGH KEY PHASES

The field of AI encompasses a variety of scopes and goals, which developed differently throughout AI history. Examining AI's historical development is essential for antitrust enforcers to appreciate the limits and normative assumptions embedded in this technology. In this way, antitrust regulation can be grounded in substantive analysis rather than superficial responses to technological hype.¹⁵ The history of AI reflects phases of intense enthusiasm followed by so-called “AI winters.”¹⁶

Importantly, since its rise, AI has never been a monolithic concept.¹⁷ About three centuries ago, mathematicians and philosophers wondered whether a machine could be intelligent and creative rather than simply execute a set of instructions.¹⁸ Despite centuries of studies on decoding

¹³ See Part III; Giovanna Massarotto, *Driving Innovation with Antitrust*, PROMARKET (Apr. 10, 2024), <https://www.promarket.org/2024/04/10/driving-innovation-with-antitrust>.

¹⁴ Cade Metz & Nico Grant, *Google Updates Bard Chatbot With ‘Gemini’ A.I. as It Chases ChatGPT*, N.Y. TIMES (Dec. 6, 2023), <https://www.nytimes.com/2023/12/06/technology/google-ai-bard-chatbot-gemini.html>.

¹⁵ See Part III.

¹⁶ See Part I.B.

¹⁷ See *id.*

¹⁸ See, e.g., Part I.A; Sjoerd Van Tuinen, *Philosophy in the Light of AI*, 25 J. THEORETICAL HUMANS. 97 (2020), [<https://doi.org/10.1080/0969725X.2020.1790838>]; Tomi Kokkonen & Ilmari Hirvonen, *Between Wittgenstein and Turing: Enactive Embodied Thinking Machines*, in WITTGENSTEIN AND ARTIFICIAL INTELLIGENCE: MIND AND LANGUAGE 39, 44 (Brian Ball, Alice C. Hellwell & Alessandro Rossi eds., 2024).

intelligence through mainly philosophy and mathematics, this question remains largely unanswered. The present AI does something different.¹⁹ Rather than pursuing theoretical inquiry into human intelligence through machines, large language models (LLMs), including ChatGPT and Gemini, are primarily designed to solve practical problems, such as how to read an article in a foreign language or finding recipes to cook a nice meal. Contemporary AI systems are known as “machine learning,” a subfield of computational statistics.²⁰ They make predictions leveraging a vast amount of data and substantial computational resources. Part I explores the history of AI from its early studies to contemporary LLMs, mapping out different goals and scopes of AI, to inform the role of antitrust law within this technological framework.

A. Mapping out AI’s Origin

About four centuries ago, philosophers grappled with the nature of reasoning. Among them, Gottfried Wilhelm Leibniz advanced the idea that aspects of reasoning could be mechanized.²¹ The problem was later reframed from a logical and symbolic question into one of behavioral performance in learning machines.²²

1. Reasoning through Mathematical Logic

If we consider the original AI’s goal, important insights can be found in the work of the German philosopher and mathematician—Gottfried Wilhelm Leibniz (1646–1716). Before Adam Smith (1723–1790) developed economic theories about monopolies and collusion foundational for

¹⁹ See Part I.C.

²⁰ Agrawal, Gans & Goldfarb, *supra* note 1, at 140; Jeffrey Dean, *A Golden Decade of Deep Learning: Computing Systems & Applications*, 151 DAEDALUS 58 (2022) [https://doi.org/10.1162/daed_a_01900]; IAN GOODFELLOW, YOSHUA BENGIO & AARON COURVILLE, DEEP LEARNING 98 (2016) (“Machine learning is essentially a form of applied statistics with increased emphasis on the use of computers to statistically estimate complicated functions . . .”).

²¹ See Part I.A.1.

²² See Part I.A.2.

antitrust, Leibniz advanced theories of reasoning that paved the way for AI centuries later.²³ Leibniz believed that machines could resonate because universal principles set human order and these principles can be translated into symbols (symbolic logic).²⁴ Leibniz’s aspiration matters because it aimed to develop a machine for philosophical reasoning that creates thoughts—thinking machines.²⁵ His insights notably inspired scholars like the father of modern computing and AI, Alan Turing, and MIT AI Professor Marvin Minsky.²⁶

In the nineteenth and twentieth centuries, the idea of thinking machines fascinated several British scholars and developed into a debate between those who believed machines could think and those who believed they could not. At Cambridge, scholars conceived what many consider to be the first digital programmable computer.²⁷ Professor Charles Babbage and his fine mathematician assistant Ada Byron, the daughter of the famous British poet Lord Byron, better known as Lady Lovelace (1815–1852), developed the *Analytical Engine*.²⁸ In 1843, Lady Lovelace wrote descriptive, analytical, and visionary commentary about the *Analytical Engine*, exploring

²³ See Van Tuinen, *supra* note 18, at 98–99, 101.

²⁴ See Volker Peckhaus, *Leibniz’s Influence on 19th Century Logic*, STANFORD ENCYC. OF PHIL. (Edward N. Zalta & Uri Nodelman eds., Feb. 2, 2024), <https://plato.stanford.edu/entries/leibniz-logic-influence>. For Leibniz, “reason is purely computational.” Simon Dumas Primbault, *An Ink-and-Paper Automation: The Conceptual Mechanization of Cognition and the Practical Automation of Reasoning in Leibniz’s De Affectibus (1679)*, 13 SOC’Y & POL’Y 87, 88 (2020).

²⁵ Oscar Schwartz, *In the 17th Century, Leibniz Dreamed of a Machine That Could Calculate Ideas*, IEEE Spectrum (Nov. 4, 2019), <https://spectrum.ieee.org/in-the-17th-century-leibniz-dreamed-of-a-machine-that-could-calculate-ideas>; see also Gottfried Wilhelm Leibniz, “*The True Method (1677)*”, in IDEAS THAT CREATED THE FUTURE: CLASSIC PAPERS OF COMPUTER SCIENCE 33 (Harry R. Lewis ed., 2021). Leibniz “would be running for the title of first computer scientist.”

²⁶ See Part I.B.

²⁷ *The Engines*, COMPUT. HIST. MUSEUM, <https://www.computerhistory.org/babbage/engines> (last visited Apr. 11, 2026); L. F. Menabrea, with Notes by the Translator, Ada Augusta, Countess of Lovelace, *Sketch of the Analytical Engine (1843)*, in IDEAS THAT CREATED THE FUTURE: CLASSIC PAPERS OF COMPUTER SCIENCE 40 (Harry R. Lewis ed., 2021) (“The analytical engine of Charles Babbage (1791–1871) was the first device that could be reasonably called a computer rather than a calculator.”) [<https://doi.org/10.7551/mitpress/12274.003.0005>]; A. M. Turing, *Computing Machinery and Intelligence*, 49 MIND 433 (1950) [<https://doi.org/10.1093/mind/LIX.236.433>].

²⁸ See Turing, *supra* note 25, at 450 (discussing Lady Lovelace argument); L. F. Menabrea, with Notes by the Translator, Ada Augusta, Countess of Lovelace, *supra* note 27, at 40. While Babbage and Lady Lovelace met in 1833, it was around 1842 that they began an intense collaboration. *Id.*

both its technical workings and its broader philosophical implications.²⁹ In her notes, Lady Lovelace argued that “[t]he Analytical Engine has no pretensions to originate anything. It can do whatever we know how to order it to perform.”³⁰ It represents in abstract numbers some operations. Thus, a machine is incapable of thinking and going beyond executing a set of instructions, thereby challenging the idea of AI.³¹

At Cambridge, the debate about thinking machines continued in the early twentieth century through important philosophers and mathematicians, including Bertrand Russell, Ludwig Wittgenstein, and Alan Turing.³² On one hand, Cambridge Professor Bertrand Russell (1872–1970) seemed open to the idea of creating thinking machines by recognizing the ingenuity of Leibniz’s groundbreaking work.³³ Russell endorsed Leibniz’s “principle that all truths are analytic”—“Leibniz’s ‘principle of reason.’”³⁴ He saw mathematical logic as a means of clarifying the structure of reasoning. In this way, Russell contributed to establishing the logical and symbolic framework that later influenced early AI based on mathematical logic and symbolic reasoning.

On the other hand, Ludwig Wittgenstein (1889–1951), who Russell saw as his potential successor, challenged this idea by arguing that mathematics and philosophy are distinct activities,

²⁹ Betty Alexandra Toole, *Ada Byron, Lady Lovelace, An Analyst and Metaphysician*, 18 IEEE ANNALS OF THE HIST. OF COMPUTING 4 (1996) [<https://doi.org/10.1109/85.511939>]. This is why many consider Ada Lovelace the first programmer, and why the computer language Ada was named in her honor. *Id.* at 6, 11; *see also* Stephen Wolfram, *Untangling the Tale of Ada Lovelace*, WIRED (Dec. 22, 2015, at 00:00 ET), <https://www.wired.com/2015/12/untangling-the-tale-of-ada-lovelace>.

³⁰ Turing, *supra* note 27, at 450. Although Ada wondered whether the board game solitaire could be written mathematically, she did not believe that a machine could create its own thoughts, and the Analytical Engine was never completed. Christopher Hollings, Ursula Martin & Adrian Rice, *Ada Lovelace and the Analytical Engine*, BODLEIAN LIBRARIES, (July 26, 2018), <https://blogs.bodleian.ox.ac.uk/adalovelace/2018/07/26/ada-lovelace-and-the-analytical-engine>. *See also*, Betty Alexandra Toole, *Ada, An Analyst and a Metaphysician*, 11 ADA LETTERS 60, 63 (1991).

³¹ Kokkonen & Hirvonen, *supra* note 18, at 46.

³² *Id.* at 39–40.

³³ Bertrand Russell, *Recent Work on the Philosophy of Leibniz*, 12 MIND 177, 177–78, 180 (1903) (“Among the papers which he left unpublished, there is contained much that has a far higher value than any philosophical treatise that he permitted the world to see. . . . Symbolic Logic, Arithmetic and Geometry. . . . The work is divided into nine chapters . . . interconnected, and . . . spring[ing] from a common logical root. . . . The construction of a universal language, we saw, was to be based upon the ‘Alphabet of human thoughts’”) [<https://doi.org/10.1093/mind/XII.2.177>].

³⁴ *Id.* at 184.

each governed by different rules and aims.³⁵ Thus, translating philosophical concepts in mathematical language has little sense. Wittgenstein is one of the principal critics of approaches that treat thoughts as computable and machines as capable of genuine thinking.

As a professor at Cambridge, Wittgenstein argued about the hypothesis of building thinking machines with one of his students—Alan Turing.³⁶ In 1939, Alan Turing, a talented mathematician, started his own course at Cambridge on the *Foundations of Mathematics* after being admitted to Wittgenstein’s course.³⁷ Wittgenstein criticized Turing’s effort to conceptualize thinking machines because asking whether machines can think is like asking “[Can] a computer [have] a toothache?” or “Can the number 3 have a color?”³⁸

In other words, Wittgenstein regarded Turing’s research as addressing a non-problem.³⁹ Turing, indeed, acknowledged the linguistic issue and reformulated the problem in terms of an imitation game,⁴⁰ asking whether a machine could take the human’s role in the imitation game such that an interrogator could not reliably distinguish the machine from a human. He set the tone for AI through a behavior-based computation method.⁴¹

³⁵ See RAY MONK, HOW TO READ WITTGENSTEIN 53 (2005) [hereinafter MONK, HOW TO READ WITTGENSTEIN]; RAY MONK, LUDWIG WITTGENSTEIN: THE DUTY OF GENIUS 20, 285 (1990) [hereinafter MONK, LUDWIG WITTGENSTEIN: THE DUTY OF GENIUS]; CHRISTOPHER SYKES, *Wittgenstein: A Wonderful Life (1989)* (YouTube, Sep. 4, 2015), <https://www.youtube.com/watch?v=8BoKjQfMihs>.

³⁶ MONK, LUDWIG WITTGENSTEIN: THE DUTY OF GENIUS, *supra* note 35, at 417; Lydia H. Liu, *Wittgenstein in the Machine*, 47 CRITICAL INQUIRY 425, 426 (2021) [<https://doi.org/10.1086/713551>]; Proudfoot, *supra* note 6, at 22.

³⁷ MONK, LUDWIG WITTGENSTEIN: THE DUTY OF GENIUS, *supra* note 35, at 417; see also Karl Sigmund, *Turing and Wittgenstein: An Entanglement of Math and Philosophy*, BIG THINK (Dec. 19, 2023), <https://bigthink.com/thinking/turing-and-wittgenstein-an-entanglement-of-math-and-philosophy>.

³⁸ Kokkonen & Hirvonen, *supra* note 18, at 41; Liu, *supra* note 36, at 426; Proudfoot, *supra* note 6, at 25.

³⁹ Proudfoot, *supra* note 6, at 22–23; MONK, LUDWIG WITTGENSTEIN. THE DUTY OF GENIUS, *supra* note 35, at 419.

⁴⁰ Turing, *supra* note 27, at 433–34. He drew an unexpected parallel for a mathematician with the U.S. Constitution, which he believed sets principles whose meaning is subject to change. Kokkonen & Hirvonen, *supra* note 18, at 45.

⁴¹ Proudfoot, *supra* note 6, at 21.

2. Reasoning through Behavior and Computation

Since its origins, AI concerned thinking and computation—thinking machines.⁴² The goal was to simulate intelligence (AI goal) through computation, which became a key component in pursuing that goal (AI scope).⁴³ In the 1930s and 1940s, Turing and other famous mathematicians initiated a new mathematical field called “the theory of computation,” which laid important foundations for the later emergence of AI, defining, for example, the limits of what machines can compute—the Turing-Church thesis.⁴⁴

The debate on building intelligent machines expanded across the Atlantic. Between the 1930s and 1960s, while Harvard emerged as a leading economic school for antitrust, Princeton became a central hub for the foundations of computation and logic that influenced artificial intelligence.⁴⁵ In addition to Turing, Princeton Professor Alonzo Church (Turing’s Ph.D. advisor) informed several other key figures in the AI field, many of whom gravitated toward Princeton, including John McCarthy, Marvy Minsky, and Claude Shannon. Turing’s work on computability and his idea of simulating intelligence by using machines introduced what John McCarthy later named AI.⁴⁶

⁴² Dean, *supra* note 20, at 58.

⁴³ *Id.*

⁴⁴ Scotty Hendricks, *3 Advances in Philosophy that Made Science Better*, BIG THINK (July 18, 2023), <https://bigthink.com/thinking/three-advances-philosophy-made-science-better>; see also Sebastian Sunday Grève, *AI’s First Philosopher*, AEON, <https://aeon.co/essays/why-we-should-remember-alan-turing-as-a-philosopher> (last visited Feb. 6, 2026); B. Jack Copeland, *The Church-Turing Thesis*, STANFORD ENCYC. OF PHIL. (Edward N. Zalta & Uri Nodelman eds., Dec. 18, 2023), <https://plato.stanford.edu/entries/church-turing>; CLARK GLYMOUR, THINKING THINGS THROUGH AN INTRODUCTION TO PHILOSOPHICAL ISSUES AND ACHIEVEMENTS 168 (1997). The theory of computation “was developed by a number of people in the 1930s and 1940s, including Gödel, whom I have already mentioned; Alonzo Church, then a professor of mathematics at Princeton; and his students, including Alan Turing, then a young Englishman whom Church brought to Princeton.” GLYMOUR, *supra* note 45, at 168; see also René Peralta, *Alan Turing’s Everlasting Contributions to Computing, AI and Cryptography*, NAT’L INST. OF STANDARDS & TECH. (Jun. 23, 2022), <https://www.nist.gov/blogs/taking-measure/alan-turings-everlasting-contributions-computing-ai-and-cryptography>; GUALTIERO PICCININI, PHYSICAL COMPUTATION: A MECHANISTIC ACCOUNT 244 (2015) [<https://doi.org/10.1093/acprof:oso/9780199658855.003.0016>].

⁴⁵ Solomon Feferman, *Turing’s Thesis*, NOTICES OF THE AM. MATHEMATICAL SOC’Y, Nov. 2006, at 2, <https://math.stanford.edu/~feferman/papers/turing.pdf>; Giovanna Massarotto, *Regulating Tech Titans*, 16 U.C. IRVINE L. REV. 43, 81-82 (2026).

⁴⁶ *Id.*

B. The Rise of AI

In 1956, the Department of Justice (DOJ) and International Business Machines Corporations (IBM) settled their first antitrust case in the Southern District of New York.⁴⁷ At the same time, at Dartmouth, a group of mathematicians laid the foundations of a new field—artificial intelligence (AI).⁴⁸

Central figures in the rise of the AI field included John McCarthy, Marvin Minsky, Claude Shannon, Norbert Wiener, Herbert A. Simon, and Allen Newell. In the years following Turing’s death in 1954, these figures advanced the fields of AI and computer science through their distinct but related research programs. Each contributed to the development of AI from a different angle. McCarthy focused on developing AI through formal logic, while Minsky was more interested in the psychological and neurological aspects of AI, building the foundational concepts of present neural networks.⁴⁹ Shannon worked on mathematical theories of information that underlie the statistical and computational infrastructure of contemporary AI.⁵⁰ Wiener’s cybernetics framed intelligence as feedback-driven control and prediction under uncertainty, which remains relevant for modern AI systems.⁵¹ Simon and Allen aimed to model general intelligence by means of symbolic problem-solving and heuristic search.⁵² The following table (**AI Goal and Scope**)

⁴⁷ United States v. IBM, No. 72-344, 1956 U.S. Dist. LEXIS 3992 (S.D.N.Y. Jan. 25, 1956).

⁴⁸ Dean, *supra* note 20, at 58; STUART J. RUSSELL & PETER NORVIG, *ARTIFICIAL INTELLIGENCE: A MODERN APPROACH* 17 (3d ed. 2010); NILS J. NILSSON, JOHN MCCARTHY 1927–2011, *BIOGRAPHICAL MEMOIRS* 4 (2012), <https://www.nasonline.org/wp-content/uploads/2024/06/mccarthy-john.pdf>.

⁴⁹ See Part I.B.1.

⁵⁰ *Id.*

⁵¹ *Id.*

⁵² Gerd Gigerenzer & Daniel G. Goldstein, *Herbert Simon on Mind as Computer*, in *ELGAR COMPANION TO HERBERT SIMON* 15, 19 (Gerd Gigerenzer, Shabnam Mousavi & Riccardo Viale eds., 2024) [<https://doi.org/10.4337/9781800370685>].

identifies the different goals and scopes pursued by these foundational figures of AI, as discussed throughout this section.

AI Goal and Scope

Foundational Figures of AI	Goal	Scope
McCarthy	Model features of intelligence and learning	Logic-based - common sense
Minsky	Modeling the brain	Psychology - neuroscience
Shannon	Modeling learning machines	Statistical approach to communication and computation
Wiener	Modelling intelligence as feedback driven control	Communication – Behavioral based
Simon & Newell	Modeling general intelligence and (commonsense) knowledge	Heuristic search – symbolic problem-solving

1. Foundational Figures of AI

Just as antitrust law has its foundational figures, including Senator Sherman, John B. Clark, and Justice Louis Brandeis, AI has its own. In 1955, McCarthy, Minsky, Shannon, and the IBM computer scientist Nathaniel Rochester submitted a proposal to the Rockefeller Foundation for what became the 1956 Dartmouth Summer Research Project on Artificial Intelligence.⁵³ It was at this conference, a milestone event, that Professor McCarthy coined the word Artificial Intelligence (AI).⁵⁴ Their proposal argued that “every aspect of learning or any other feature of intelligence” could be modeled.⁵⁵

⁵³ Thomas Greene, *Early Artificial Intelligence Projects A Student Perspective*, MIT (Dec. 2006), <https://projects.csail.mit.edu/films/aifilms/AIFilms.html>.

⁵⁴ See RUSSELL & NORVIG, *supra* note 48, at 17 n.10.

⁵⁵ Jeremy Bernstein, *Profiles: A.I.*, THE NEW YORKER (Dec. 7, 1981), <https://www.newyorker.com/magazine/1981/12/14/a-i>.

In 1959, McCarthy and Minsky created the Artificial Intelligence group at MIT.⁵⁶ McCarthy focused on applying formal logic to AI (AI scope), and his main interest was how a machine could reason formally about the world the way humans do—using assumptions, defaults, and shared background understanding (AI goal). In 1959, his article *Programs with Common Sense* argued that although “[i]nteresting work is being done in programming computers to solve problems which require a high degree of intelligence in humans[,] . . . certain elementary verbal reasoning processes so simple that they can be carried out by any non-feeble minded human have yet to be simulated by machine programs.”⁵⁷ McCarthy, together with Marvin Minsky, envisioned a system endowed with “common sense,” capable of “automatically deduc[ing] for itself a sufficiently wide class of immediate consequences of anything it is told and what it already knows.”⁵⁸ His later paper, *Artificial Intelligence, Logic and Formalizing Common Sense* (published in 1990),⁵⁹ explicitly studied shared assumptions and mutual knowledge as part of formal reasoning in AI, especially in connection with formal logic as a basis for AI. The paper also examined what an intelligent agent can safely assume others know.⁶⁰

While McCarthy approached artificial intelligence primarily through formal logic and computation, Minsky was more deeply engaged with questions about the human mind and human psychology (AI scope), seeking to model intelligence as an emergent property of interacting

⁵⁶ Greene, *supra* note 53 (“The first coordinated AI research at MIT began in 1959 when John McCarthy and Marvin Minsky founded the Artificial Intelligence Project as part of both the Research Laboratory for Electronics (RLE) in Building 26 and the Computation Center. They were junior faculty at the time and had known each other as from graduate school at Princeton, where Minsky had studied artificial neural networks (cybernetics).”).

⁵⁷ John McCarthy, *Programs with Common Sense*, STANFORD UNIV. COMPUT. SCI. DEP’T 1 (1959), <http://jmc.stanford.edu/articles/mcc59/mcc59.pdf>, https://doi.org/10.1007/978-94-009-2448-2_6.

⁵⁸ *Id.* at 2. McCarthy and Minsky “were both interested in mechanizing intelligence—one way or another. They collaborated over the next decade, but their approaches to making machines intelligent ultimately diverged widely.” NILSSON, *supra* note 54, at 4.

⁵⁹ John McCarthy, *Artificial Intelligence, Logic and Formalizing Common Sense*, STANFORD UNIV. COMPUT. SCI. DEP’T 1 (1990), <https://www-formal.stanford.edu/jmc/ailogic.pdf>.

⁶⁰ *Id.*

cognitive processes. The problem of modeling the brain was central to Minsky’s work (AI goal).⁶¹ He tried to advance general theories about intelligence and studied how to make artificial intelligence. For instance, in 1961, Minsky published, *Steps Toward Artificial Intelligence*,⁶² which introduced key ideas about learning and representation.

Minsky developed computational models of learning and cognition, drawing insights from neurology and psychology, including early work on neural networks (AI scope).⁶³ In 1974, Minsky introduced the concept of “frames” as a structure for knowledge representation,⁶⁴ and in 1986, he proposed that intelligence emerges from the interaction of numerous simple, specialized agents.⁶⁵ Later in his career, Minsky explored emotions as computational processes.⁶⁶ In his 2006 book, *The Emotion Machine*,⁶⁷ he argued that what we call emotions “are not especially different from the processes that we call ‘thinking.’”⁶⁸ His book aimed “to suggest how human brains might work and to design machines that can feel and think.”⁶⁹

By contrast, Shannon developed another fundamental research stream grounded in probabilistic and statistical approaches to communication and computation (AI scope).⁷⁰ His research in communication and computation aimed to build learning machines through statistics (AI goal). His work treated language and communication in probabilistic terms, demonstrating that

⁶¹ As Minsky observed, “The problem of intelligence seemed hopelessly profound.” Bernstein, *supra* note 55.

⁶² Marvin Minsky, *Steps Toward Artificial Intelligence*, 49 PROCEEDINGS OF THE IRE 8 (1961) [<https://doi.org/10.1109/JRPROC.1961.287775>].

⁶³ Bernstein, *supra* note 55; Quantum News, *Marvin Minsky. The Brilliant AI Pioneer Behind the Neural Network*, QUANTUM ZEITGEIST (Aug. 9, 2024), <https://quantumzeitgeist.com/marvin-minsky>.

⁶⁴ Marvin Minsky, A Framework for Representing Knowledge, MIT AI Laboratory Memo 306 (June 1974), <https://courses.media.mit.edu/2004spring/mas966/Minsky%201974%20Framework%20for%20knowledge.pdf>.

⁶⁵ MARVIN MINSKY, THE SOCIETY OF MIND 17 (1986).

⁶⁶ *See id.* at 163.

⁶⁷ MARVIN MINSKY, THE EMOTION MACHINE (2006).

⁶⁸ *Id.* at 6.

⁶⁹ *Id.* at 7.

⁷⁰ *See generally* CLAUDE E. SHANNON & WARREN WEAVER, THE MATHEMATICAL THEORY OF COMMUNICATION (6th ed. 1975).

information could be quantified and predicted.⁷¹ Games played a central role in Shannon’s thinking because, as he emphasized, they test computers on problems that are not purely numerical. Programming machines to perform such non-numerical tasks, he argued, broadens our understanding of the scope and limits of computational capabilities.⁷²

Other key figures in mid-twentieth-century debates about artificial intelligence were Norbert Wiener (1894–1964), Herbert Simon (1916–2001), and Allen Newell (1927–1992). Wiener was a professor of mathematics at MIT and was influenced by and studied under Bertrand Russell. Wiener is known as the founder of cybernetics.⁷³ He used a behavioral-based method and mathematical tools to study control, feedback, and communication in both machines and biological systems (AI scope). The goal was to frame intelligence as feedback-driven control and prediction under uncertainty (AI goal).⁷⁴ Cybernetics concerns the idea that intelligence—human, animal or machine—can be understood as feedback, thus driving control and communication in systems that learn by self-correcting errors. Communication is not linear and, in many systems, it forms a loop.⁷⁵ The system becomes “intelligent” if it can retain memories of past performances and use them to

⁷¹ *Id.* at 9 (“[I]nformation is a measure of one’s freedom of choice when one selects a message.”); see also YEHOShUA BAR-HILLEL, ASPECTS OF LANGUAGE: ESSAYS AND LECTURES ON PHILOSOPHY OF LANGUAGE, LINGUISTIC PHILOSOPHY AND METHODOLOGY OF LINGUISTICS 293 (1970); Oscar Schwartz, *Andrey Markov & Claude Shannon Counted Letters to Build the First Language-Generation Models*, IEEE SPECTRUM (Nov. 11, 2019), <https://spectrum.ieee.org/andrey-markov-and-claude-shannon-built-the-first-language-generation-models> (“Shannon’s paper outlined a way to precisely measure the quantity of information in a message, and in doing so, set the foundations for a theory of information that would come to define the digital age.”).

⁷² Marina Kassianidou, Vivek Srinivasan & Brent Villalobos, *Claude Shannon & Information Theory: Artificial Intelligence*, <https://cs.stanford.edu/people/eroberts/courses/soco/projects/1999-00/information-theory/ai.html> (last visited Apr. 11, 2026) (“According to Shannon, games are quite significant because they test computers in something that is not a numerical problem. Programming computers to perform non-numerical tasks widens our understanding of the capabilities of computers.”).

⁷³ See Marcelo Godoy Simões, *Norbert Wiener and the Age of Controls, Communications, and Cybernetics—Animal and Machine—in Electrical Engineering*, IEEE ELECTRIFICATION MAG. 100, 102 (2024); NORBERT WIENER, NORBERT WIENER—A LIFE IN CYBERNETICS: EX-PRODIGY: MY CHILDHOOD AND YOUTH AND I AM A MATHEMATICIAN: THE LATER LIFE OF A PRODIGY 458, 459 (2018). The Quantum Mechanic, *Norbert Wiener The Founder of Cybernetics*, QUANTUM ZEITGEIST (Jan. 10, 2025), <https://quantumzeitgeist.com/norbert-wiener-the-founder-of-cybernetics>.

⁷⁴ *From Cybernetics to AI: The Pioneering Work of Norbert Wiener*, MP NEURO (Apr. 25, 2024), <https://maxplanckneuroscience.org/from-cybernetics-to-ai-the-pioneering-work-of-norbert-wiener>.

⁷⁵ *Id.*

improve. Wiener argued that information-based mechanisms of feedback and adjustment drive many systems and help maintain their stability. From this insight, the field of cybernetics emerged. This approach strongly influenced early thinking about intelligent machines by emphasizing probabilistic models and adaptive behavior. In this way, Wiener’s cybernetics and the AI tradition associated with McCarthy and Minsky diverged.

Lastly, Simon and Newell were both professors at Carnegie Mellon University (CMU) and received the Turing award in 1975 for their work on AI and human cognition.⁷⁶ They developed the *Logic Theorist*, a computer program designed to mimic problem-solving skills.⁷⁷ Their work was inspired by Alfred North Whitehead and Bertrand Russell’s *Principia Mathematica*.⁷⁸ The Logic Theorist was also called a “thinking machine”⁷⁹ because it determined “how a computer can solve any problem.”⁸⁰ Simon and Newell’s contribution aimed to implement general intelligence, as well as commonsense knowledge, in artificial reasoning (AI goal).⁸¹ They were particularly interested in human cognitive task environment,⁸² and unlike McCarthy and Minsky, who focused on logic rules, Simon and Newell developed the idea of heuristic search (AI scope).⁸³

The AI field flourished until it failed to meet the high expectations it generated and investments decreased significantly—especially from the Defense Advanced Research Projects

⁷⁶ Hunter Heyck, *A.M. Turing Award: Allen Newell*, ASS’N FOR COMPUTING MACH., https://amturing.acm.org/award_winners/newell_3167755.cfm (last visited Apr. 11, 2026).

⁷⁷ Newell, Simon & Shaw Develop the First Artificial Intelligence Program, HISTORYOFINFORMATION.COM, <https://www.historyofinformation.com/detail.php?id=742> (last visited Apr. 16, 2026).

⁷⁸ *Id.*; Luis M. Augusto, *From Symbols to Knowledge Systems: A. Newell and H. A. Simon’s Contribution to Symbolic AI*, 2 J. KNOWLEDGE STRUCTURES & SYS. 29, 38 (2021) (“The Logic Theorist (LT) was an information-processing system that was able to discover, using heuristic methods, proofs for theorems in symbolic logic; actually, it could prove in sequence most of the 60 odd theorems in . . . Russell and Whitehead’s celebrated *Principia mathematica*.”).

⁷⁹ Leo Gugerty, *Newell and Simon’s Logic Theorist: Historical Background and Impact on Cognitive Modeling*, 50 PROC. HUM. FACTORS ERGON. SOC’Y ANN. MEETING 880 (2006) [<https://doi.org/10.1177/154193120605000904>].

⁸⁰ Augusto, *supra* note 78, at 30.

⁸¹ *Id.* at 29; Gigerenzer & Goldstein, *supra* note 52, at 19.

⁸² Augusto, *supra* note 78, at 33; *see also* Gigerenzer & Goldstein, *supra* note 52, at 17.

⁸³ Gigerenzer & Goldstein, *supra* note 52, at 19.

Agency (DARPA).⁸⁴ Many have linked the beginning of the AI winter to James Lighthill’s 1973 report, which the UK Science Research Council commissioned to review the state of progress in artificial intelligence. The report was highly critical of the AI field, arguing that “in no part of the field have discoveries made so far produced the major impact that was then promised.”⁸⁵

2. From the AI Winter to the AI Neural Networks Boom

Similar to antitrust law, which experienced phases of heightened interest followed by periods of disappointment,⁸⁶ the AI field went through similar phases over its early decades.⁸⁷ Examining these historical developments is important to ensure that antitrust regulation is grounded in substantive analysis rather than superficial responses to technological hype.

In the early 1980s, expectations and interest in both academia and industry significantly increased, culminating in an AI boom—particularly around expert systems.⁸⁸ These systems were defined as “intelligent programs” capable of solving problems by using knowledge and inference procedures.⁸⁹ But these expert systems exhibited limitations, stemming from bias in encoded rules and incomplete knowledge that limited their capacity to model complex, open-ended frameworks.⁹⁰ It was reported that an expert system once suggested that the cause of a man’s

⁸⁴ See Paulo Carvão, *Are We Heading Into Another AI Winter?*, FORBES (Aug. 24, 2025, at 12:39 ET), <https://www.forbes.com/sites/paulocarvao/2025/08/24/are-we-heading-into-another-ai-winter>.

⁸⁵ James Hendler, *Avoiding Another AI Winter*, 23 IEEE INTELLIGENT SYS., Mar.–Apr. 2008, at 2, 2.

⁸⁶ ROBERT BORK, *THE ANTITRUST PARADOX: A POLICY AT WAR WITH ITSELF* 382 (1978); Lina M. Khan, *Amazon’s Antitrust Paradox*, 126 YALE L.J. 710, 717 (2017).

⁸⁷ Bernard Koch & David Peterson, *The AI History That Explains Fears of a Bubble*, TIME (Dec. 22, 2025, at 11:35 ET), <https://time.com/7340901/ai-history-bubble-benchmarks>.

⁸⁸ See E. A. FEIGENBAUM, STANFORD UNIV., *EXPERT SYSTEMS IN THE 1980S* (1980), <https://stacks.stanford.edu/file/druid:vf069sz9374/vf069sz9374.pdf>; Koch & Peterson, *supra* note 87.

⁸⁹ FEIGENBAUM, *supra* note 88.

⁹⁰ See, e.g., Sandy Pentland, *AI’s Missing Ingredient: Shared Wisdom*, MIT SLOAN SCH. OF MGMT. (Nov. 12, 2025), <https://mitsloan.mit.edu/ideas-made-to-matter/ais-missing-ingredient-shared-wisdom>.

infection might have been a prior amniocentesis, which is a procedure performed for pregnant woman.⁹¹

In the years of the landmark AT&T break-up, AI went through the so-called “AI winter.”⁹² In 1984, at the annual meeting of the American Association of Artificial Intelligence, the term “AI winter” was used to reflect periods of reduced enthusiasm and funding for AI research.⁹³ A deep disappointment followed high expectations and important investments made in the field.⁹⁴

But in the mid-1980s, building on earlier work by John Hopfield, AI experienced a revival through neural networks, particularly following the development of a backpropagation learning algorithm by David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams.⁹⁵ This was the result of an interdisciplinary work involving psychology, cognitive science, and computer science. Backpropagation allowed machine learning algorithms to optimize artificial neural networks by repeatedly adjusting their internal settings to improve performance.⁹⁶ Thus, how to train multilayer neural networks efficiently became a key goal (AI goal). These neural network methods, drawing from statistical mechanics, increasingly shaped AI research and scholarly debate (AI scope). AI became an industry. In 1988, from a few million dollars, the AI field boomed to billions of dollars.⁹⁷

⁹¹ Koch & Peterson, *supra* note 87 **Error! Bookmark not defined.** (“It turned out researchers had forgotten to add a rule for gender.”).

⁹² *Id.*; *AI Winter: The Highs and Lows of Artificial Intelligence*, HIST. OF DATA SCI. (Sep. 1, 2021), <https://www.historyofdatascience.com/ai-winter-the-highs-and-lows-of-artificial-intelligence>; Carvão, *supra* note 84. On the AT&T break-up, see, e.g., Bret Swanson, *Lessons from the AT&T Break Up, 30 Years Later*, AM. ENTER. INST. (Jan. 3, 2014), <https://www.aei.org/technology-and-innovation/lessons-att-break-30-years-later>.

⁹³ See Carvão, *supra* note 84.

⁹⁴ Koch & Peterson, *supra* note 87 **Error! Bookmark not defined.** DARPA, for example, changed management and felt the need to “spread the wealth” beyond AI. Hender, *supra* note 85, at 2.

⁹⁵ David E. Rumelhart, Geoffrey E. Hinton & Ronald J. Williams, *Learning Representations by Back-Propagating Errors*, 323 NATURE 533 (1986) [<https://doi.org/10.1038/323533a0>]; *History: The 1980's to the Present*, NEURAL NETWORKS, <https://cs.stanford.edu/people/eroberts/courses/soco/projects/neural-networks/History/history2.html> (last visited Mar. 2, 2026); RUSSELL & NORVIG, *supra* note 48, at 24.

⁹⁶ Dave Bergmann & Cole Stryker, *What is Backpropagation?*, IBM, <https://www.ibm.com/think/topics/backpropagation> (last visited Feb. 1, 2026).

⁹⁷ RUSSELL & NORVIG, *supra* note 48, at 24.

But following the mid-1980s revival of neural networks, AI entered a second “AI winter” in the late 1980s and early 1990s. Then the field reemerged with a shift from predominantly symbolic and logic-based methods toward statistical and probabilistic approaches (AI scope).⁹⁸ The primary goal was how to build systems that could reason by focusing on learning from data, rather than logic-based rules (AI goal). In 1997, IBM’s Deep Blue defeat of world chess champion Garry Kasparov marked a symbolic moment in this transition. IBM’s Deep Blue demonstrated the power of large-scale computation, as well as data-driven methods, which was also made possible thanks to the World Wide Web, released in 1991.⁹⁹

C. Contemporary AI

Around 2008, powerful computers, increasingly vast datasets, and neural networks started to emerge through sophisticated AI systems able to engage in what was called “deep learning”, which adopts a statistical approach to modeling and optimization (AI scope) to learn representations from data through neural network architectures (AI goal).¹⁰⁰ Deep learning is a kind of machine learning that attains flexibility and great power “by representing the world as a nested hierarchy of concepts, with each concept defined in relation to simpler concepts”¹⁰¹ This approach remains the central paradigm in contemporary AI.¹⁰² Scholars such as Yann LeCun and Yoshua Bengio, as well as increasingly powerful computers, vast datasets and sophisticated techniques to train deeper networks, made its development and success possible.¹⁰³ Deep learning enabled the development of accurate AI systems capable of performing domain-specific tasks very

⁹⁸ See GOODFELLOW, BENGIO & COURVILLE, *supra* note 20, at 96.

⁹⁹ *Id.* at 50. *Deep Blue*, IBM, <https://www.ibm.com/history/deep-blue> (last visited Apr. 12, 2026); *A History of the Web*, CERN, <https://home.cern/science/computing/birth-web/short-history-web> (last visited Apr. 12, 2026).

¹⁰⁰ Dean, *supra* note 20, at 59, 69.

¹⁰¹ GOODFELLOW, BENGIO & COURVILLE, *supra* note 20, at 8, 26.

¹⁰² See Dean, *supra* note 20, at 59.

¹⁰³ GOODFELLOW, BENGIO & COURVILLE, *supra* note 20, at 18–26.

well, such as language translation and voice assistance. Human-level semantic understanding goes beyond deep learning, which focuses on solving pragmatical problems. In other words, contemporary AI developed as a result of the renewed interest in neural networks, which rely on neural architectures that learn statistical regularities from large-scale data.¹⁰⁴ ChatGPT symbolizes the broader wave of success of contemporary AI systems.¹⁰⁵

In practice, LLMs underlying AI systems, such as ChatGPT, generate responses by predicting the most statistically likely next word (a token) in a sequence based on the context of the inputs it receives. Consider when your phone suggests words based on terms you have used before. Similarly, ChatGPT predicts the next word based on the probabilities from the text it learned. This approach is based on statistics and learning rather than semantic and logic models.¹⁰⁶ Probabilistic models trained on huge amounts of data define a probability distribution over a (potentially infinite) collection of symbols.¹⁰⁷ Google Search works so well largely because it moved away from explicit semantic search toward large-scale statistical inference, leveraging vast amounts of data, computation, and large models.¹⁰⁸

¹⁰⁴ See, e.g., Ernest Fokoué, No Intelligence Without Statistics: The Invisible Backbone of Artificial Intelligence (Oct. 23, 2025) (Rochester Institute of Technology), [https://arxiv.org/pdf/2510.19212#:~:text=It%20is%20against%20this%20rich,is%20applied%20statistics%20at%20scale;see also,Agrawal,Gans & Goldfarb, supra note 1, at 140–41; Crane, supra note 3, at 1206; Dean, supra note 20, at 58.](https://arxiv.org/pdf/2510.19212#:~:text=It%20is%20against%20this%20rich,is%20applied%20statistics%20at%20scale;see%20also,Agrawal,Gans%20&%20Goldfarb,supra%20note%201,at%20140-41;Crane,supra%20note%203,at%201206;Dean,supra%20note%2020,at%2058.)

¹⁰⁵ See Stefan Szeider, *Shannon's Linguistic Playground*, ALGORITHMS AND COMPLEXITY GRP., <https://www.ac.tuwien.ac.at/people/szeider/shannon> (last visited Feb. 1, 2026).

¹⁰⁶ David Auerbach, *The Limits of Language*, SLATE (Sep. 1, 2015, at 09:56 ET), <https://slate.com/human-interest/2015/09/take-a-wittgenstein-class-he-explains-the-problems-of-translating-language-computer-science-and-artificial-intelligence.html> (“Google succeeded—by ignoring semantics as much as possible . . . Google could count the popularity of a word . . .”).

¹⁰⁷ See GOODFELLOW, BENGIO & COURVILLE, supra note 20, at 485, 555. (“Many of the research frontiers in deep learning involve building a probabilistic model of the input, p model (x).”).

¹⁰⁸ *Id.* at 19–20. Sergey Brin & Lawrence Page, *The Anatomy of a Large-Scale Hypertextual Web Search Engine* (Stanford InfoLab Working Paper, 1998), <http://infolab.stanford.edu/pub/papers/google.pdf>.

In summary, AI has developed through multiple and different scopes and goals. Contemporary AI's primary goal is to build learning machines (AI goal) using statistical methods of computation (AI scope). Building on these insights, the central question in defining AI and its implications for antitrust law is whether contemporary AI systems are genuinely intelligent, and whether they differ from other technologies because of that property. Part II engages with this question by using our roadmap of different AI goals and scopes as guidance to inform the current AI antitrust debate.

II. IS AI INTELLIGENT? A LINGUISTIC PROBLEM

“Turing’s machines. These machines are humans who calculate.”
Ludwig Wittgenstein (Philosophy of Psychology)¹⁰⁹

Much of the present debate on contemporary AI concerns its capability to reach artificial general intelligence (AGI), a moment that many, including the great scientist Stephen Hawking, regarded as the end of the world.¹¹⁰ As in any debate, there are two main camps: those who believe that contemporary AI exhibits intelligence and can bring us to AGI, and those who embrace the opposite view. Assessing which camp’s vision is more grounded is critical to anticipating AI’s future trajectory in the economy and the corresponding role of antitrust law and AI regulation.

As of now, AI systems are generally classified as “narrow AI” (or weak AI),¹¹¹ meaning that they can perform highly specific tasks very well. The primary question is: Could modern LLMs underlying AI systems, such as ChatGPT and Gemini (GenAI), lead us beyond narrow AI

¹⁰⁹ See Proudfoot, *supra* note 6, at 20 (citing LUDWIG WITTGENSTEIN, REMARKS ON THE PHILOSOPHY OF PSYCHOLOGY, VOL. I, at § 1096 (G. E. M. Anscombe & Georg H. von Wright eds., G. E. M. Anscombe trans., Univ. Chi. Press 1988)).

¹¹⁰ Agrawal, Gans & Goldfarb, *supra* note 1, at 140.

¹¹¹ Augusto, *supra* note 78, at 32.

and reach a system capable of understanding, learning, and employing knowledge in a variety of situations like humans do (thus AGI)? The enthusiasm of those who believe the answer is “Yes” has generated an AI gold rush.¹¹²

Sam Altman and Elon Musk have argued that contemporary GenAI represents a transformative technology with the potential to lead us to the development of AGI. Elon Musk predicted that AGI could occur this year.¹¹³ Prominent figures, including Presidents Trump and Putin, argued that who wins the AI race will rule the world because of its magnitude.¹¹⁴

Against this backdrop of AI euphoria driving massive investments, some scholars, most notably Professor Noam Chomsky, argued that LLMs and AI systems, such as ChatGPT, are the wrong place to look for AGI.¹¹⁵ Chomsky reduced GenAI to advanced statistics and an engineering effort (a practical exercise), which tells us little or nothing about how the human brain works.¹¹⁶ Leading AI scientist Yann LeCun also claimed that LLMs are “a dead end” on the path to AGI because they lack models that can reason.¹¹⁷

¹¹² Shane Greenstein, *The AI Gold Rush*, IEEE MICRO, Nov./Dec. 2023, at 126, 126 [https://doi.org/10.1109/MM.2023.3322049].

¹¹³ Agrawal, Gans & Goldfarb, *supra* note 1, at 140; Sam Altman, *Three Observations*, BLOG: SAM ALTMAN (Feb. 9, 2025, at 16:05 ET), https://blog.samaltman.com/three-observations; Matteo Wong, *Do You Feel the AGI Yet?*, ATLANTIC (Feb. 2, 2026), https://www.theatlantic.com/technology/2026/02/do-you-feel-agi-yet/685845.

¹¹⁴ Agrawal, Gans & Goldfarb, *supra* note 1, at 140; *White House Unveils America’s AI Action Plan*, WHITE HOUSE (Jul. 23, 2025), https://www.whitehouse.gov/articles/2025/07/white-house-unveils-americas-ai-action-plan; Giovanna Massarotto, *Rethinking the AI Race*, REG. REV. (Sep. 15, 2025), https://www.theregreview.org/2025/09/15/massarotto-rethinking-the-ai-race.

¹¹⁵ Jeremy Kahn, *Generative A.I. is Fun. Just Don’t Assume it Will Lead to AGI*, FORTUNE (Nov. 8, 2022, at 12:07 ET), https://fortune.com/2022/11/08/generative-a-i-fun-but-dont-assume-will-lead-to-agi.

¹¹⁶ Noam Chomsky, Ian Roberts & Jeffrey Watumull, *Noam Chomsky: The False Promise of ChatGPT*, N.Y. TIMES (Mar. 8, 2023), https://www.nytimes.com/2023/03/08/opinion/noam-chomsky-chatgpt-ai.html.

¹¹⁷ Kristin Houser, *LLMs Are a Dead End to AGI, Says François Chollet*, FREETHINK (Aug. 3, 2024), https://www.freethink.com/robots-ai/arc-prize-agi; Tanner Stening, *Will Large Language Models Survive the Coming AI Innovation?* NE. GLOB. NEWS (Mar. 26, 2023), https://news.northeastern.edu/2023/05/26/large-language-models-ai-godfather, *see also* Tomaso Aste, *What Machines Can Learn About Our Complex World—and What Can We Learn From Them?* (Oct. 2, 2021) [https://doi.org/10.2139/ssrn.3797711].

A. Machines Can Exhibit Intelligence

AI started from the goal of creating thinking machines mainly framed as a linguistic problem and became an imitation game problem giving rise to contrasting views.¹¹⁸ In the eighteenth century, writer Jonathan Swift sarcastically criticized Leibniz’s concept of thinking machines in his famous book *Gulliver’s Travels* (1726). In his travels, Gulliver “encounters a device known as ‘the engine,’” which its inventor intends “to enable anyone to ‘write books in philosophy, poetry, politics, laws, mathematics, and theology, without the least assistance from genius or study.’”¹¹⁹ Swift observed that “language is not a formal system that represents human thought” and that building a machine that generates language “requires the ability to understand the meaning of words”¹²⁰ Through satire, Swift uncovered the limits of reason, language, and abstract systems. In other words, intelligence implies thinking, which is reasoning translated into language that we can interpret (language and semantic).

In this vein, almost two centuries later, Wittgenstein argued that intelligence is about understanding the meaning of the word intelligence, which requires practical knowledge of what he called the language-game.¹²¹ Wittgenstein’s concept of language games prompts further questions about whether a machine can meaningfully be said to make a mistake. He observed that a system that merely reacts to external stimuli without being embedded in a rule-governed practice of correction would lack the normative framework in which mistakes can be meaningfully identified.¹²²

¹¹⁸ See Part I.A.

¹¹⁹ Jonathan Gray, “*Let us Calculate!*” *Leibniz, Llull, and the Computational Imagination*, PUB. DOMAIN REV. (Nov. 10, 2016), <https://publicdomainreview.org/essay/let-us-calculate-leibniz-llull-and-the-computational-imagination>.

¹²⁰ Schwartz, *supra* note 25.

¹²¹ MONK, HOW TO READ WITTGENSTEIN, *supra* note 35, at 69 (“Language games are the forms of language with which a child begins to make use of words.”); MONK, THE DUTY OF GENIUS, *supra* note 35, at 337; MARIE MCGINN, WITTGENSTEIN AND THE PHILOSOPHICAL INVESTIGATIONS 89 (1997); Auerbach, *supra* note 106.

¹²² See, e.g., LUDWIG WITTGENSTEIN, PHILOSOPHICAL INVESTIGATIONS §§ 138–242 (G.E.M. Anscombe, R. Rhees & G.H. Von Wright eds., G.E.M. trans., 3d ed. 1967); Kokkonen & Hirvonen, *supra* note 18, at 42, 56 (“Thinking is not,

Following Wittgenstein, Turing recognized that investigation of whether computers can think “should begin with definitions of the meaning of the terms ‘machine’ and ‘think.’”¹²³ He also noted that the question “Can machines think?” is “too meaningless to deserve discussion,” because “at the end of the century the use of words and general educated opinion will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted.”¹²⁴ Therefore, Turing and other mathematicians reframed the longstanding search for thinking machines as a problem of formal computation, laying the foundation for the theory of computation, discussed in Part I (AI goal and scope).¹²⁵

1. The Imitation Game

With Turing, intelligence became a concept that could be better assessed through a game-like test. Turing aimed at challenging dogma, such as, “Thinking is a function of man’s immortal soul. God has given an immortal soul to every man and woman, but not to any other animal or to machines. Hence no animal or machine can think.”¹²⁶ Since the meaning of the word “think” is subject to change,¹²⁷ Turing reformulated the problem, “Can Machines Think?,” in terms of the imitation game.¹²⁸ Thus, he developed a test to provide a scientific definition of intelligence

for instance, mere mechanical manipulation of signs. Nevertheless, if someone is trying to figure out a complicated mathematical problem, manipulating signs in that context can be considered an instantiation of thinking.”); *id.* at 42 (“What I am saying comes to this that mathematics is normative.”); *id.* at 42 (citing Wittgenstein 1978: RFM, V §424 f).

¹²³ Turing, *supra* note 27, at 433.

¹²⁴ *Id.* at 442.

¹²⁵ Kokkonen & Hirvonen, *supra* note 18, at 47 (“Turing believes that Lovelace’s reasoning rests on wrong assumptions. Even though a machine requires inputs to produce outputs, we can- not necessarily know, based on the inputs, what outputs the machine could achieve.”).

¹²⁶ Turing, *supra* note 27, at 443.

¹²⁷ *Id.* at 442.

¹²⁸ *Id.* We can use machines to imitate/simulate intelligence. Turing replaced the question “Can Machines Think?” with “Are there imaginable digital computers which would do well in the imitation game?” *Id.*

through simulation, which took his name—the *Turing test*.¹²⁹ A machine, Turing argued, “can be constructed to play the imitation game satisfactorily”¹³⁰ because it can learn and generate results that are unpredictable by behaving in novel ways. Turing’s contributions laid the ground for the fundamental principles of modern computing and “some of the most successful theoretical approaches in the field of AI and machine learning.”¹³¹

2. Shannon’s Statistical Foundations in the Study of Intelligence

Claude Shannon, for whom Anthropic chatbot Claude is named, when asked whether he thinks machines can think: “*You bet. I’m a machine and you’re a machine, and we both think, don’t we?*” (From his biography in the *Collected Papers*)¹³²

Similar to Turing, Claude Shannon used games to examine aspects of intelligence. Shannon explored machine game-playing and authored a seminal paper on programming computers to play chess. He used games like chess to program computers to perform non-numerical tasks and better understand computers’ capabilities.¹³³ In 1950, Shannon wrote what was considered “the first significant modern paper on chess-playing programs,”¹³⁴ in which he analyzed a set of so-called game trees, where like in a chess game, each move creates more possible moves.

In the 1950s, Shannon also developed probabilistic approaches to modeling information and language that later informed theories of machine intelligence. He was strongly influenced by the Russian mathematician Andrey Andreyevich Markov.¹³⁵ In his seminal paper *A Mathematical*

¹²⁹ Grève, *supra* note 44; Turing, *supra* note 27 (arguing that “[t]he whole thinking process is still rather mysterious to us, but I believe that the attempt to make a thinking machine will help us greatly in finding out how we think themselves”); *see also* Russell & Norvig, *supra* note 48, at 2; Kokkonen & Hirvonen, *supra* note 18, at 46.

¹³⁰ Turing, *supra* note 27, at 434–35.

¹³¹ Grève, *supra* note 44.

¹³² Kassianidou, Srinivasan & Villalobos, *supra* note 72.

¹³³ *Id.*

¹³⁴ Bernstein, *supra* note 55.

¹³⁵ Schwartz, *supra* note 71; *see also* BAR-HILLEL, *supra* note 71, at 294–95.

Theory of Communication, Shannon used a Markov chain to build a statistical model of the sequences of letters in a sample of English text.¹³⁶ The Markov chain is considered “an early example of generative AI,”¹³⁷ because in 1906, Markov introduced a statistical approach to model the behavior of random processes. This has long been adopted for next-word tasks, including within email programs.¹³⁸ Markov was interested in understanding the fundamental mathematical structure of language; that is, how we can describe language mathematically.¹³⁹ To that end, Markov examined “the sequence of 20,000 letters in A. S. Pushkin’s poem ‘Eugeny Onegin’, discovering that the stationary vowel probability $p = 0.432$, that the probability of a vowel following a vowel is $p_1 = 0.128$, and that the probability of a vowel following a consonant is $p_2 = 0.663$.”¹⁴⁰ In other words, he was testing a theory of probability, based on the assumption that most things occur in chains of causality and rely on prior outcomes,¹⁴¹ by showing how “the chance of a certain letter appearing at some point in the text is dependent, to some extent, on the letter that came before it.”¹⁴²

Drawing from these insights, Shannon demonstrated that in a given text, the likelihood of some letters or words could be approximated by developing a statistical model of language that could create text according to statistical rules. In his classic work, *A Mathematical Theory of*

¹³⁶ Schwartz, *supra* note 71; NOAM CHOMSKY & ANDREA MORO, *THE SECRETS OF WORDS* 5 (2023) [<https://doi.org/10.7551/mitpress/14237.001.0001>] (“Claude Shannon’s information theory was developed from wartime research. Along with Norbert Wiener’s cybernetics, it looked as if a new era was coming.”); BAR-HILLEL, *supra* note 71, at 295.

¹³⁷ Adam Zewe, *Explained: Generative AI*, MIT NEWS (Nov. 9, 2023), <https://news.mit.edu/2023/explained-generative-ai-1109>; see also Oscar Schwartz, *For Centuries, People Dreamed of a Machine That Could Produce Language. Then OpenAI Made One*, IEEE SPECTRUM (Dec. 2, 2019), <https://spectrum.ieee.org/for-centuries-people-dreamed-of-a-machine-that-can-produce-language-then-openai-made-one> (“GPT-2 can be seen as a descendant of the statistical language modeling that the Russian mathematician A.A. Markov developed in the early 20th century . . .”).

¹³⁸ Zewe, *supra* note 137.

¹³⁹ Shwartz, *supra* note 71.

¹⁴⁰ Gely P. Basharin, Amy N. Langville & Valeriy A. Naumov, *The Life and Work of A. A. Markov*, 386 LINEAR ALGEBRA & ITS APPLICATIONS 3, 19 (2004) [<https://doi.org/10.1016/j.laa.2003.12.041>].

¹⁴¹ Schwartz, *supra* note 71.

¹⁴² *Id.*

Communication, Shannon explained how the quantity of information can be precisely measured, laying the groundwork for the theory of information foundational of the digital age.¹⁴³ Building on Markov's work, Shannon demonstrated that text can be generated according to statistical rules. As you make the statistical model even more complex, you get increasingly more comprehensive results.¹⁴⁴ This insight later informed statistical approaches to language and the development of modern language models, including LLMs.¹⁴⁵

In summary, while Turing focused on whether intelligence can be conceptualized through behavior by building machines that imitate humans, Shannon, drawing on Markov's work, revealed that information can be formally quantified and modeled using probabilistic approaches. Contemporary LLMs are fundamentally based on Shannon-inspired probabilistic approaches to language.¹⁴⁶

ChatGPT can be seen as a descendant of statistical language modeling, which Markov developed in the early-twentieth century.¹⁴⁷ The main difference is that ChatGPT uses over 1.5 million parameters and huge computational power. Conversely, Markov manually trained his model with two parameters.¹⁴⁸ Through a learning process, contemporary AI systems, such as ChatGPT, predict what comes next based on statistical patterns learned from millions of examples, a process that may be described as an optimized form of brute force.¹⁴⁹

¹⁴³ *Id.*; see also CHOMSKY & MORO, *supra* note 136, at 5.

¹⁴⁴ Schwartz, *supra* note 71.

¹⁴⁵ Kassianidou, Srinivasan & Villalobos, *supra* note 72. See also, [Richard Hughes Gibson, Language Machinery Who Will Attend to the Machines' Writing?](https://hedgehogreview.com/issues/markets-and-the-good/articles/language-machinery#:~:text=In%20the%201940s%2C%20the%20mathematician%20Claude%20Shannon,statistics%20and%20imitated%20with%20statistics%2C%20whether%20those.), THE HEDGEHOG REV. (2023), <https://hedgehogreview.com/issues/markets-and-the-good/articles/language-machinery#:~:text=In%20the%201940s%2C%20the%20mathematician%20Claude%20Shannon,statistics%20and%20imitated%20with%20statistics%2C%20whether%20those.>

¹⁴⁶ See Schwartz, *supra* note 71.

¹⁴⁷ *Id.*

¹⁴⁸ *Id.*

¹⁴⁹ See, e.g., CHOMSKY & MORO, *supra* note 136, at 47.

Despite their significant utility, many maintain that what current AI systems do resemble the execution of program instructions (a mechanical process), regardless of the output, which might be unpredictable.¹⁵⁰ In other words, AI does not differ fundamentally from other breakthrough technologies, such as computers, with similar antitrust implications.¹⁵¹

B. A Contrasting Perspective

If AI systems are mechanical processes not fundamentally different from other technologies, two questions follow: First, does the label “intelligent” remain meaningful? Second, must antitrust law evolve in its foundations? This Section examines some important works by scholars who criticize contemporary approaches to AI in an effort to better understand human intelligence.

Renowned scholars challenged the fact that contemporary AI is intelligent. They challenged Turing’s argument that intelligence could be framed in terms of observable behavior by building machines that imitate humans and through statistical approaches.¹⁵² For instance, Noam Chomsky, the father of modern linguistics, and the cognitive and computer scientist, Marvin Minsky,¹⁵³ regarded the Turing test as largely irrelevant to the scientific study of human language because it tested behavioral imitation rather than providing insights on human reasoning.¹⁵⁴

1. Chomsky’s Cognitive Revolution

¹⁵⁰ *Id.* at 9, 15.

¹⁵¹ *See* Part III.

¹⁵² *See* Part II.B.2.

¹⁵³ *See Marvin Minsky on AI: The Turing Test is a Joke!*, SINGULARITY WEBLOG (June 10, 2022), <https://www.singularityweblog.com/marvin-minsky>.

¹⁵⁴ *See* Bernardo Gonçalves, *Can Machines Think? The Controversy that Led to the Turing Test, 1946–1950*, at 2, <https://philsci-archive.pitt.edu/19291/1/turing-test-controversy.pdf#:~:text=9%20Marvin%20Minsky%20said%20that%20the%20Turing,'as%20one%20way%20to%20evaluate%20a%20machine>.

Some commentators have argued that computer science (e.g., LLMs) itself cannot achieve AGI because understanding intelligence requires the combination of multiple disciplines, not only mathematics and engineering.¹⁵⁵ In the 1950s, Chomsky helped initiate what became known as the cognitive revolution in the study of the human brain and intelligence, based on methods and concepts from linguistics, psychology, philosophy, computer science, neuroscience, artificial intelligence, and anthropology.¹⁵⁶ He challenged the then-dominant behaviorist school of thought, led by Harvard Professor B. F. Skinner who, like Turing, believed that human behavior and thinking could be understood mechanically.¹⁵⁷ Chomsky revived a rationalist approach to the study of the mind (AI scope), criticizing approaches that focused on human responses to stimuli (behavior) and on learning through reinforcement learning.¹⁵⁸ According to Chomsky, humans are born with an innate capability to learn new languages because children in their early years learn quickly without receiving enough examples of language.¹⁵⁹ In other words, children learn languages and develop complex grammatical competence from limited inputs, suggesting that language is not merely based on statistics and learning process, but is governed by an innate

¹⁵⁵ Hendricks, *supra* note 44; see also Yarden Katz, *Noam Chomsky on Where Artificial Intelligence Went Wrong*, ATLANTIC (Nov. 1, 2012), <https://www.theatlantic.com/technology/archive/2012/11/noam-chomsky-on-where-artificial-intelligence-went-wrong/261637> (“For Chomsky, the ‘new AI’—focused on using statistical learning techniques to better mine and predict data—is unlikely to yield general principles about the nature of intelligent beings or about cognition.”); Liu, *supra* note 36, at 430.

¹⁵⁶ Hendricks, *supra* note 44; Paul Thagard, *Cognitive Science*, STANFORD ENCYC. OF PHIL. (Edward N. Zalta & Uri Nodelman eds., Jan. 31, 2023), <https://plato.stanford.edu/entries/cognitive-science>.

¹⁵⁷ Hendricks, *supra* note 44; *B.F. Skinner (1904–1990)*, HARVARD UNIV.: DEP’T OF PSYCH., <https://psychology.fas.harvard.edu/people/b-f-skinner> (last visited Apr. 12, 2026); CHOMSKY & MORO, *supra* note 136, at 10, 11 (“Karl Lashley, one of the great neuroscientists, in the late 1940s gave a very important lecture, the Hixon Symposium lecture, it came out in print in 1951. He demonstrated that the entire behaviorist framework was hopeless.”). Professor Marvin Minsky was also very critical of Skinner. See Bernstein, *supra* note 55.

¹⁵⁸ Hendricks, *supra* note 44. The leading theory led by Skinner “in the early 1950s was that children heard large numbers of words and learned to use them by positive reinforcement [Chomsky] overthrew the behaviorist model.” *Id.*; see also Katz, *supra* note 155 (“Chomsky and his colleagues had to overthrow the then-dominant paradigm of behaviorism, championed by Harvard psychologist B.F. Skinner, where animal behavior was reduced to a simple set of associations between an action and its subsequent reward or punishment.”).

¹⁵⁹ See, e.g., THE PUBLIC MIND DENVER, *Noam Chomsky Speaks About Universal Linguistics: Origins of Language*, (YouTube, Dec. 7, 2015), <https://www.youtube.com/watch?v=7Sw15-vSY8E>; Noam Chomsky, *Reflections on Language* (Dec. 18–30, 2007), <https://www.math.chalmers.se/~ulfp/Review/chomsky2.pdf>.

language structure.¹⁶⁰ He called this theory universal grammar,¹⁶¹ which advanced the idea that reasoning involves something beyond statistical pattern-matching.¹⁶² In the 1950s, Chomsky proved, in mathematical terms, that the Markovian chains that Shannon used were insufficient to understand the mind.¹⁶³

Similar to his MIT colleague Minsky, Chomsky was interested in developing a philosophy of the mind, thus in investigating its general nature rather than building a super sophisticated computer system that could solve technical/engineering problems. Minsky and Chomsky agreed on a cognitive approach to understanding the mind, rejecting a purely behaviorist approach.¹⁶⁴

Building on these insights, we can consider contemporary discussions on GenAI. In a 2023 *New York Times* article entitled *Noam Chomsky: The False Promise of ChatGPT*,¹⁶⁵ Chomsky argued:

The human mind is not, like ChatGPT and its ilk, a lumbering statistical engine for pattern matching, gorging on hundreds of terabytes of data and extrapolating the most likely conversational response or most probable answer to a scientific question. On the contrary, the human mind is a surprisingly efficient and even elegant system that operates with small amounts of information; it seeks not to infer brute correlations among data points but to create explanations.¹⁶⁶

Because LLM systems like ChatGPT rely on “brute-force statistical crunching of data,”¹⁶⁷ they reveal nothing about how intelligence or language work.

¹⁶⁰ See Noam Chomsky, *Things No Amount of Learning Can Teach*. Noam Chomsky interviewed by John Gliedman (Nov. 1983), <https://chomsky.info/198311>.

¹⁶¹ See V. J. Cook, *Chomsky's Universal Grammar and Second Language Learning*, 6 APPL. LINGUISTICS 2 (1985), [<https://doi.org/10.1093/applin/6.1.2>].

¹⁶² *Id.*; CHOMSKY & MORO, *supra* note 136, at 10, 11.

¹⁶³ *Id.* at 24.

¹⁶⁴ See Hendricks, *supra* note 44; see also Bernstein, *supra* note 55.

¹⁶⁵ Chomsky, Roberts & Watumull, *supra* note 116.

¹⁶⁶ *Id.* Chomsky also argued that “[t]he crux of machine learning is description and prediction; it does not posit any causal mechanisms or physical laws. Of course, any human-style explanation is not necessarily correct; we are fallible. But this is part of what it means to think: To be right, it must be possible to be wrong. Intelligence consists not only of creative conjectures but also of creative criticism.” *Id.*

¹⁶⁷ Cameron Shackell, *Noam Chomsky Turns 95: The Social Justice Advocate Paved the way for A.I. Does it Keep Him up at Night?*, CONVERSATION (Dec. 6, 2023, at 14:07 ET), <https://theconversation.com/noam-chomsky-turns-95->

The *New York Times* piece echoes the sentiment of Chomsky’s previous interview with *The Atlantic* in 2012, titled *Noam Chomsky on Where Artificial Intelligence Went Wrong*.¹⁶⁸ Before the introduction of ChatGPT, Chomsky was already highly critical of modern AI: “[I]f you get more and more data, and better and better statistics, you can get a better and better approximation to some immense corpus of text, like everything in *The Wall Street Journal* archives—but you learn nothing about the language,”¹⁶⁹ and thus nothing about intelligence. He argued that a more appropriate approach is to deepen our understanding of the fundamental principles, the core properties of things, by recognizing them in the practical usage.¹⁷⁰

Chomsky is not the only linguist who strongly opposes the idea that GenAI can lead us to AGI by formulating valuable theories of the mind. The Italian linguist Andrea Moro demonstrated that LLMs can compute all sorts of languages that are impossible to us and cannot distinguish them from natural languages in his book *Impossible Languages*¹⁷¹ and later work.¹⁷² Drawing on this insight, Moro and other Italian linguists argue that these systems are not human-like machines.¹⁷³ Therefore, “LLM are not good models for the human language faculty . . . [T]hey do outperform us, showing that the real difference between machines and humans is that the former do not have our limits.”¹⁷⁴ Chomsky echoed this argument, noting that LLMs work “just as well with

[the-social-justice-advocate-paved-the-way-for-ai-does-it-keep-him-up-at-night-218034](https://doi.org/10.64628/AA.ha5tdshj7).
[https://doi.org/10.64628/AA.ha5tdshj7].

¹⁶⁸ Katz, *supra* note 155.

¹⁶⁹ *Id.*

¹⁷⁰ *Id.* (“So, you get things that *look* exciting, just as the artifacts that were constructed by artisans in the sixteenth and seventeenth century were exciting, but they are not providing a model for understanding how the world works.”); CHOMSKY & MORO, *supra* note 136, at 48.

¹⁷¹ ANDREA MORO, IMPOSSIBLE LANGUAGES (2016).

¹⁷² Andrea Moro, Matteo Greco & Stefano F. Cappa, *Large Languages, Impossible Languages and Human Brains*, 167 CORTEX 82, 84 (2023) [https://doi.org/10.1016/j.cortex.2023.07.003]; *see also*, CHOMSKY & MORO, *supra* note 136, at 15.

¹⁷³ *See* Moro, Greco & Cappa, *supra* note 172, at 82; *see also*, Johan J. Bolhuis et al., *AI Doesn’t Model Human Language*, 627 NATURE 489 (2024).

¹⁷⁴ Moro, Greco & Cappa, *supra* note 172, at 84.

impossible languages that infants cannot acquire,”¹⁷⁵ admitting that LLMs do have important practical value, but not significant theoretical value.¹⁷⁶

Economists also recognized that contemporary AI “is not true artificial intelligence,” but rather what is known as “machine learning,” a subfield of computational statistics.¹⁷⁷ Similar arguments have contributed to contemporary concerns about an AI bubble.

2. The Fear of an AI Bubble

There was an ubiquitous and overwhelming feeling around the Laboratory that with the new insights of cybernetics and the newly developed techniques of information theory the final breakthrough towards a full understanding of the complexities of communication “in the animal and the machine” had been achieved. Linguists and psychologists, philosophers and sociologists alike hailed the entrance of the electrical engineer and the probability mathematician into the communication field¹⁷⁸

Chomsky believes that Bar-Hillel was describing a form of euphoria in the 1970s comparable to what we are experiencing today with “big data.”¹⁷⁹ Chomsky is not the only one fearing another AI winter.¹⁸⁰ As with contemporary LLMs, many in the 1980s believed that so-called “expert systems” were progressing toward real intelligence, and when it became clear that such systems could not progress further, an AI winter followed.¹⁸¹

¹⁷⁵ Noam Chomsky Interviewed by C.J. Polychroniou, *Noam Chomsky Speaks on What ChatGPT Is Really Good For*, COMMON DREAMS (May 3, 2023), <https://chomsky.info/20230503-2>.

¹⁷⁶ *Id.* (“One is that the LLM systems are designed in such a way that they cannot tell us anything about language, learning, or other aspects of cognition, a matter of principle, irremediable. Double the terabytes of data scanned, add another trillion parameters, use even more of California’s energy, and the simulation of behavior will improve, while revealing more clearly the failure in principle of the approach to yield any understanding.”).

¹⁷⁷ Agrawal, Gans & Goldfarb, *supra* note 1, at 140.

¹⁷⁸ BAR-HILLEL, *supra* note 71, at 294; *see also* CHOMSKY & MORO, *supra* note 136, at 1, 2, 48, 133.

¹⁷⁹ CHOMSKY & MORO, *supra* note 136, at 33. “The excitement coming out from Silicon Valley, basically—lots of hype and propaganda about how amazing the achievements are—has a certain similarity to the technological euphoria that Bar-Hillel was describing.” *Id.* at 9.

¹⁸⁰ *See* Koch & Peterson, *supra* note 87.

¹⁸¹ *Id.*

Presently, it is argued that one of the issues with AI is that we do not have clear benchmarks to assess its accuracy and objectively measure its progress.¹⁸² The interpretation of AI results has become a fundamental issue in the AI debate, given that as models become more sophisticated, interpreting their results becomes increasingly difficult—a phenomenon known as the AI black box.¹⁸³ The AI black box problem persists because we are largely incapable of interpreting AI results.¹⁸⁴ In other words, although contemporary AI systems function particularly well largely because of the vast amount of data (Big Data) and powerful computers (Big Computation), these systems are typically poor at explaining their outputs.¹⁸⁵

Harvard Professor Andy Wu debated the issue of an AI euphoria from a technical perspective.¹⁸⁶ He observed that “[w]hile generative AI can do amazing things, it is also perhaps the most wasteful use of a computer ever devised,”¹⁸⁷ because if you ask ChatGPT to calculate 1+1, it would potentially require a trillion calculations to receive a response.¹⁸⁸ He identified two main challenges with current GenAI: (1) the scale of building expensive facilities, such as data centers; and (2) the fact that data centers and electric grids seem too slow to keep up with the demand necessary to meet investors’ expectations.¹⁸⁹ “We need more data centers, more chips, and more electricity to handle the escalating computing needed to both create frontier AI models (training) and use them (inference),” Wu argued.¹⁹⁰

¹⁸² *Id.*

¹⁸³ Aste, *supra* note 117, at 8; Rai, *supra* note 2, at 138.

¹⁸⁴ See, e.g., Cynthia Rudin, *Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead*, 1 NATURE MACH. INTELL. 206 (2019), [<https://doi.org/10.1038/s42256-019-0048-x>] (“A black box model could be either (i) a function that is too complicated for any human to comprehend, or (ii) a function that is proprietary. Deep learning models, for instance, tend to be black boxes of the first kind because they are highly recursive.” (citation omitted)); see also Rai, *supra* note 2, at 138.

¹⁸⁵ See GOODFELLOW, BENGIO & COURVILLE, *supra* note 20, at 19–20.

¹⁸⁶ Christina Pazzanese, *Should U.S. be Worried About AI Bubble?*, HARVARD GAZETTE (Dec. 15, 2025), <https://news.harvard.edu/gazette/story/2025/12/should-u-s-be-worried-about-ai-bubble>.

¹⁸⁷ *Id.*

¹⁸⁸ *Id.*

¹⁸⁹ *Id.*

¹⁹⁰ *Id.*

In other words, in the ChatGPT and GenAI era, the meaning of words and building theoretical frameworks for intelligence seems to have lost attraction in favor of prioritizing scale and performance in models trained on large datasets that cannot be rigorously evaluated.¹⁹¹ Contemporary AI largely ignores semantics by counting the popularity of words (thus using statistical patterns).¹⁹² LLMs cannot understand *cause and effect action* through action¹⁹³ by defining abstract concepts as word patterns and compute languages that are impossible for humans to compute, unlike machines.¹⁹⁴

This brings us back to the original question: Is contemporary AI intelligent and what are the implications for antitrust law?

III. POLICY IMPLICATIONS FOR ANTITRUST

Having framed the meaning of AI as a non-monolithic term through its distinct goals and scope, and having discussed contrasting views in the debate of intelligence in contemporary AI, Part III evaluates the implications for antitrust law. What can the antitrust community learn from the richness of AI through its different scopes and goals and its challenged property of intelligence?¹⁹⁵ Does antitrust need to evolve by changing its core values or is another AI winter coming? Grasping the meaning of AI seems fundamental for antitrust enforcers and other regulators seeking to predict its future and what role law may take.

¹⁹¹ Koch & Peterson, *supra* note 87; Aste, *supra* note 117.

¹⁹² See Auerbach, *supra* note 106; Schwartz, *supra* note 137; GOODFELLOW, BENGIO & COURVILLE, *supra* note 20, at 2.

¹⁹³ See *supra* note 122; Kokkonen & Hirvonen, *supra* note 18, at 56 (“Can a machine make mistakes? A robot that causally reacts to external triggers—whether pre-programmed or acquired through machine learning algorithms—cannot.”).

¹⁹⁴ See Moro, Greco & Cappa, *supra* note 172 at 84.

¹⁹⁵ See *supra* Part I.B; *supra* Part II; Kokkonen & Hirvonen, *supra* note 18, at 57.

AI raises three fundamental concerns for antitrust: (1) concentration of power in the hands of Big Tech companies,¹⁹⁶ (2) algorithmic collusion,¹⁹⁷ and (3) algorithmic bias.¹⁹⁸ First, Big Tech companies made multi-billion dollar investments into OpenAI and other AI companies such as Anthropic.¹⁹⁹ This raised a high risk of concentration in an already quite concentrated industry.²⁰⁰ As a consequence, antitrust enforcers started requiring Big Tech companies, including Google and Microsoft, to provide information about their investments in AI to better appreciate if and how this technology was reshaping competition dynamics in digital markets.²⁰¹

Furthermore, in the Google Search antitrust case, Judge Amit P. Mehta of the U.S. District Court for the District of Columbia importantly recognized the role of Generative AI in shaping antitrust remedies for Google.²⁰² On December 5, 2025, Judge Mehta entered a supplemental memorandum opinion clarifying some remedy terms, including “GenAI Product.”²⁰³ It

¹⁹⁶ See, e.g., Giovanna Massarotto, *Algorithmic Remedies for Google’s Data Monopoly* 3 (Nov. 27, 2025), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5394028, <https://doi.org/10.2139/ssrn.5394028>.

¹⁹⁷ See ORGANISATION FOR ECON. CO-OPERATION & DEV., ALGORITHMIC COMPETITION—BACKGROUND NOTE, OECD COMPETITION POLICY ROUNDTABLE 8–9 (2023), [https://one.oecd.org/document/DAF/COMP\(2023\)3/en/pdf](https://one.oecd.org/document/DAF/COMP(2023)3/en/pdf) [hereinafter OECD Report]; Antonio Capobianco, *The Impact of Algorithms on Competition and Competition Law*, PROMARKET (May 23, 2023), See generally Ezrachi & Stucke, *supra* note 206. <https://www.promarket.org/2023/05/23/the-impact-of-algorithms-on-competition-and-competition-law>.

¹⁹⁸ Massarotto, *supra* note 209, at 2; Ezrachi & Stucke, *supra* note 206, at 77, 203.

¹⁹⁹ See Cade Metz, *OpenAI Completes Deal That Values It at \$500 Billion*, N.Y. TIMES (Oct. 2, 2025), <https://www.nytimes.com/2025/10/02/technology/openai-deal-500-billion.html>; Eugene Kim, *Amazon’s \$8 Billion Anthropic Investment Balloons to \$61 Billion*, BUS. INSIDER (Feb. 6, 2026, at 14:42 ET), <https://www.businessinsider.com/amazon-ai-bet-anthropic-soars-61-billion-valuation-2026-2>.

²⁰⁰ Crane, *supra* note 3, at 1218; see also Daniel F. Spulber, *Antitrust and Innovation Competition*, 11 J. ANTITRUST ENF’T 5, 48 (2023) [<https://doi.org/10.1093/jaenfo/jnac013>]; Michal S. Gal & Daniel L. Rubinfeld, *Algorithms, AI, and Mergers*, 85 ANTITRUST L.J. 683, 684 (2024); Hovenkamp, *supra* note 3.

²⁰¹ See *FTC Launches Inquiry into Generative AI Investments and Partnerships*, FED. TRADE COMM’N (Jan. 25, 2024), <https://www.ftc.gov/news-events/news/press-releases/2024/01/ftc-launches-inquiry-generative-ai-investments-partnerships>; David McCabe, *U.S. Clears Way for Antitrust Inquiries of Nvidia, Microsoft and OpenAI*, N.Y. TIMES (Jun. 5, 2024), <https://www.nytimes.com/2024/06/05/technology/nvidia-microsoft-openai-antitrust-doj-ftc.html>.

²⁰² *United States v. Google LLC*, No. 1:20-cv-3010, at 4, 128 (D.D.C. Sept. 2, 2025) (Dkt. No. 1436); see also, Herbert Hovenkamp, *Google Search and Antitrust’s Remedial Goals*, 106 B.U. L. REV. 101, 138 (Forthcoming 2026) [<https://doi.org/10.2139/ssrn.5117989>].

²⁰³ *United States v. Google LLC*, No. 1:20-cv-3010, at 9 (D.D.C. Dec. 5, 2025) (Dkt. No. 1461).

emphasized “the growing integration of GenAI into search products”²⁰⁴ in defining antitrust remedies.

Second, in another important case, antitrust enforcers dealt with the issue of algorithmic collusion through AI. On August 23, 2024, the Department of Justice and several states sued Real Page Inc., a software company, for providing AI tools to set real estate prices.²⁰⁵ According to the complaint, Real Page leveraged AI algorithms to engage in price fixing, thus enabling landlords to collude under Section 1 of the Sherman Act, by what is known as algorithmic collusion.²⁰⁶ The software company was also charged with a Section 2 violation for possible monopolization conduct.²⁰⁷ Ultimately, the case was settled and the court missed the opportunity to clarify what algorithmic collusion is and how it could manifest through AI.²⁰⁸

Last, but not least, is the issue of algorithmic bias which primarily concerns AI.²⁰⁹ Are Big Tech companies discriminating against competitors and creating bias in consumers by leveraging AI algorithms that limit consumers’ choices in their favor?

²⁰⁴ *Id.* at 8.

²⁰⁵ Press Release, Dep’t of Just., Justice Department Sues RealPage for Algorithmic Pricing Scheme that Harms Millions of American Renters (Aug. 23, 2024), <https://www.justice.gov/archives/opa/pr/justice-department-sues-realpage-algorithmic-pricing-scheme-harms-millions-american-renters>.

²⁰⁶ Complaint at 6, United States v. RealPage, Inc., No. 1:24-cv-00710 (M.D.N.C. Aug. 23, 2024). For a discussion on algorithmic collusion see, e.g., Crane, *supra* note 3, at 1200; Giovanna Massarotto, *Defining AI Collusion Depends on Consumer Harm and Algorithms*, BLOOMBERG LAW (Oct. 3, 2024, at 08:38 ET), <https://news.bloomberglaw.com/us-law-week/defining-ai-collusion-depends-on-consumer-harm-and-algorithms>; ARIEL EZRACHI & MAURICE E. STUCKE, VIRTUAL COMPETITION: THE PROMISE AND PERILS OF THE ALGORITHM-DRIVEN ECONOMY (2016) [<https://doi.org/10.4159/9780674973336>]; Agrawal, Gans & Goldfarb, *supra* note 1, at 155; Gal & Rubinfeld, *supra* note 200, at 695–98; Edward M. Iacobucci, *Algorithmic Pricing, Anticompetitive Counterfactuals, and Antitrust Law*, 2024 U. CHI. L. REV. ONLINE 1, 2 (2024); Mehra, *supra* note 4, at 98, 120; Suzanne Rab, *Artificial Intelligence, Algorithms and Antitrust*, 18 COMPETITION L.J. 141 (2019) [<https://doi.org/10.4337/clj.2019.04.02>].

²⁰⁷ Complaint at 5–6, United States v. RealPage, Inc., No. 1:24-cv-00710 (M.D.N.C. Aug. 23, 2024).

²⁰⁸ Press Release, Department of Justice, Justice Department Requires RealPage to End the Sharing of Competitively Sensitive Information and Alignment of Pricing Among Competitors (Nov. 24, 2025), <https://www.justice.gov/opa/pr/justice-department-requires-realpage-end-sharing-competitively-sensitive-information-and>.

²⁰⁹ See, e.g., Giovanna Massarotto, *What Is Algorithmic Bias and Why Antitrust Agencies Should Care?*, CPI ANTITRUST CHR., June 2023, at 1, <https://www.competitionpolicyinternational.com/wp-content/uploads/2023/06/1-WHAT-IS-ALGORITHMIC-BIAS-AND-WHY-ANTITRUST-AGENCIES-SHOULD-CARE-Giovanna-Massarotto.pdf>.

1. Big Tech Concentration Problem

AI is not the first technology to raise concentration problems. Both the computer (IBM) and the telephone (AT&T) raised similar antitrust problems.²¹⁰ Presently, Big Tech companies are the AI-gold protagonists, and fear of the AI industry becoming concentrated is concrete. On February 4, 2026, Google announced that “it would double its spending on capital expenditures this year to \$175 billion to \$185 billion as it raced to build A.I. data centers across the country to ensure Gemini’s wide distribution.”²¹¹ Gemini is now integrated into Google Search queries.²¹² Last year, in 2025, Google spent over \$90 billion on these projects.²¹³ Meta and Microsoft showed signs of investments of similar magnitude.²¹⁴ On the other hand, these massive investments can create significant barriers to entry into the AI industry that might deter new companies,²¹⁵ with Big Tech establish themselves as “the guardians” in the AI industry.²¹⁶ The issue of market concentration in digital markets is well known.²¹⁷ For instance, network and learning effects can contribute to market concentration, since the more users use Google Search, the more its search results improve, thereby attracting new users.²¹⁸

²¹⁰ See, e.g., Massarotto, *supra* note 13; Giovanna Massarotto, *From Standard Oil to Google: How the Role of Antitrust Law Has Changed*, 41 WORLD COMPETITION 395 (2016) [<https://doi.org/10.54648/WOCO2018022>].

²¹¹ Tripp Mickle, *Google Plans to Double Spending Amid A.I. Race*, N.Y. TIMES (Feb. 5, 2026), <https://www.nytimes.com/2026/02/04/business/google-earnings-ai.html>.

²¹² *Id.*

²¹³ *Id.*

²¹⁴ *Id.*

²¹⁵ Christophe Carugati, *Antitrust Issues Raised by Answer Engines* 7–8 (Bruegel, Working Paper, No. 07/2023, 2023), <https://www.bruegel.org/working-paper/antitrust-issues-raised-answer-engines>; Michal Gal & Amit Zac, *Is Generative AI the Algorithmic Consumer We Are Waiting For?*, NETWORK L. REV. (Winter 2024), <https://www.networklawreview.org/gal-zac-generative-ai>; Crane, *supra* note 3, at 1197.

²¹⁶ Shaoul Sussman, *AI Poses a New Antitrust Problem*, FIN. TIMES (Dec. 8, 2025), <https://www.ft.com/content/307d5bb6-d02c-4052-8251-b0dad90a1c5f>.

²¹⁷ Crane, *supra* note 3, at 1216.

²¹⁸ See U.S. DEPT. OF JUST. & FED. TRADE COMM’N, MERGER GUIDELINES 24 (2023), <https://www.justice.gov/d9/2023-12/2023%20Merger%20Guidelines.pdf>; see also John M. Yun, *Overview of Network Effects & Platforms in Digital Markets*, in GLOBAL ANTITRUST INSTITUTE REPORT ON THE DIGITAL

With that in mind, Big Tech investments in and acquisitions of AI start-ups warrant a careful antitrust scrutiny and assessment of market dynamics. Accordingly, some scholars suggest a more aggressive review of these mergers and to carefully consider the effects of AI in the context of a merger.²¹⁹

2. Algorithmic Collusion

AI algorithms tacitly collude, and tacit collusion is another antitrust issue that has occupied the antitrust community for about a century.²²⁰ Ultimately, the Supreme Court in *Monsanto Co. v. Spray-Rite Service Corp.* (1984)²²¹ clarified that tacit collusion is lawful. Observing your competitor and consequently fixing the price is rational, and antitrust refrains from punishing rational conduct. The risk of false positives and the administrative costs associated with extending unlawful collusion to tacit collusion were considered too high. Fast forward to today, economists and legal scholars seem to agree that AI can tacitly collude (even without any communication among themselves).²²²

Despite its legality, some commentators argue that tacit collusion through AI could be prosecuted, and if AI algorithms are “intelligent,” they could be used to engage in collusive practices effectively in a way that evades detection.²²³ Therefore, the issue of whether the present

ECONOMY 2, 3 (Nov. 11, 2020), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3733656; John M. Yun, *How Epic v. Apple Operationalizes Ohio v. Amex*, 42 YALE J. ON REG. BULL. 1, 11–12 (2024).

²¹⁹ Gal & Rubinfeld, *supra* note 200, at 684; Nancy L. Rose & Carl Shapiro, *What Next for the Horizontal Merger Guidelines?*, 36 ANTITRUST, Spring 2022, at 4.

²²⁰ See, e.g., Giovanna Massarotto, *Detecting Algorithmic Collusion*, 86 OHIO ST. LAW J. 818 (2025).

²²¹ *Monsanto Co. v. Spray-Rite Svc. Corp.*, 465 U.S. 752, 760–64, 768 (1984).

²²² See, e.g., Emilio Calvano et al., *Artificial Intelligence, Algorithmic Pricing and Collusion*, 110 AM. ECON. REV. 3267 (2020) [<https://doi.org/10.1257/aer.20190623>]; EZRACHI & STUCKE, *supra* note 206, at 77–78, 203; Agrawal, Gans & Goldfarb, *supra* note 1, at 155.

²²³ See, e.g., EZRACHI & STUCKE, *supra* note 206, at 77–79, 203.

law can effectively address collusion has engaged several scholars, including myself.²²⁴ It has reinforced the idea of tackling AI collusion from a consumer welfare perspective,²²⁵ and much of the debate concerns the actual goal of antitrust law in a changed technological framework.²²⁶

3. Algorithmic Bias

Self-preferencing and discriminatory practices that generate bias are also not novel. In the context of AI, the issue concerns bias in AI algorithms, due to the selection of data, as well as unrepresentative and insufficient data.²²⁷ Bias can also be exhibited in the algorithm design. Software developers designing AI algorithms can be biased.²²⁸ Big Tech, including Amazon, have been accused of using algorithms to favor its own products over those of competitors, thus engaging in self-preferencing.²²⁹ While the U.S. effort to ban self-preferencing has failed,²³⁰ Europe has prohibited the so-called digital markets’ “gatekeepers” from engaging in self-preferencing.²³¹

These are only some of the key issues that occupy antitrust agencies and courts, with antitrust law at the forefront of what many have called “the AI revolution.”²³² But although the

²²⁴ See, e.g., Massarotto, *Detecting Algorithmic Collusion*, *supra* note 220.

²²⁵ EZRACHI & STUCKE, *supra* note 206, at 79, 203.

²²⁶ See *supra* note 4. On the U.S. antitrust core values see, e.g., Giovanna Massarotto, *Regulating Tech Titans*, 16 IRVINE L. REV. 43 (2026).

²²⁷ Massarotto, *supra* note 209, at 2.

²²⁸ *Id.*; see also Agrawal, Gans & Goldfarb, *supra* note 1, at 148.

²²⁹ Christopher K.L. Young, *Technological Monopolies, Innovation, and the Personal Freedom to Form Businesses: Like Oil and Water?* 33 COMPETITION J. 59, 63 (2023), <https://calawyers.org/publications/antitrust-unfair-competition-law/competition-spring-2023-vol-33-no-1-technological-monopolies-innovation-and-the-personal-freedom-to-form-businesses-like-oil-and-water>.

²³⁰ See, e.g., Herbert Hovenkamp, *Antitrust and Self-Preferencing*, 38 ANTITRUST 5 (Fall 2023) [<https://doi.org/10.2139/ssrn.4526022>].

²³¹ Digital Markets Act. Regulation (EU) 2022/1925 of the European Parliament and of the Council of 14 September 2022 on Contestable and Fair Markets in the Digital Sector and Amending Directives (EU) 2019/1937 and (EU) 2020/1828, art. 6, 2022 O.J. (L 265) 2; MARTIN PEITZ, CERRE, *THE PROHIBITION OF SELF-PREFERENCING IN THE DMA* 7 (2022), https://cerre.eu/wp-content/uploads/2022/11/DMA_SelfPreferencing.pdf.

²³² See, e.g., Mustafa Suleyman, *How the AI Revolution Will Reshape the World*, TIME (Sep. 1, 2023, at 07:05 ET), <https://time.com/6310115/ai-revolution-reshape-the-world>.

technology is new, these antitrust issues have been discussed for about a century, and important insights can be drawn from its history to inform the present debate.

Two fundamental questions concerning AI are whether antitrust law needs to evolve because of the nature of this technology, which is reshaping markets, and whether a “coming wave,” as Professor Daniel Crane calls it, has the potential to disrupt the pillars of antitrust.²³³ Using our roadmap, contemporary AI can be considered a science developing modeling learning machines (AI goal) using statistical methods of computation (AI scope). The issue of AI magnitude from an antitrust perspective is far from being simple, and much relies on what intelligence means and if we consider the increasingly precise and infallible statistical learning machine as equivalent to intelligence.

But AI is not the first breakthrough technology that antitrust law has encountered in its enforcement action. Computers and the Internet might have been even more “revolutionary” than the current GenAI, which leverages sophisticated statistical language models, vast amounts of data, and significant computational power. As Turing recognized, words can change their meaning. Many, however, might consider that computers, even those empowered by LLMs, do not really think when performing something that is not so different from a set of instructions and machine automation. Importantly, these systems typically can neither explain nor interpret their results.²³⁴

In summary, this technology seems in many respects disruptive, although not more disruptive than computers and the Internet of decades ago. Issues of network effects, tacit collusion, and bias are not novel. Previous breakthrough technologies did not require antitrust to evolve or swamp antitrust by disrupting its pillars. We are here at this pivotal moment, where antitrust enforcers are facing violations that need to be interpreted and prosecuted in an

²³³ Crane, *supra* note 3, at 1189, 1200.

²³⁴ See, e.g., Aste, *supra* note 117, at 8.

algorithmic-driven framework consistent with a century of antitrust core values.²³⁵ Rather than asking whether contemporary AI disrupts core antitrust principles, the antitrust community could focus on understanding its capabilities and limits by engaging with relevant computer science frameworks, as this paper seeks to do.

²³⁵ Massarotto, *supra* note 196; Massarotto, *supra* note 220, at 3; Massarotto, *supra* note 226.