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Artificial Intelligence and Machine Learning in Financial Services

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Artificial Intelligence and Machine Learning in Financial Services

The financial industry’s adoption of artificial intelligence (AI) and machine learning (ML) is evolving as financial firms employ ever greater levels of technology and automation to deliver services. Expanding on earlier models of quantitative analysis, AI/ML has often been adopted in finance to solve discrete challenges, such as maximizing profit and minimizing risk. Yet the industry’s adoption of the newer technology also occurs against perceptions that are steeped in tradition and historical financial regulation, and regulators want to ensure that the technology does not sidestep regulations frequently described as technology neutral.

Technological advances in computer hardware, capacity, and data storage—which permit the collection and analysis of data—helped fuel the development and use of AI/ML technologies in finance. Unlike older algorithms that automated human-coded rules, new AI models can “learn” by themselves and make inferences and recommendations not identified by modelers in advance. This shift in technology has also enabled the use of new types of data including alternative data (i.e., data that the consumer credit bureaus do not traditionally use), unstructured data (images or social media posts, etc.), and unlabeled information data—which, when combined, extend the technologies’ uses to new financial services or products.

Different parts of the financial services industry have adopted AI/ML technology to varying degrees and for various purposes. Some uses of AI/ML include powering chatbots in customer service functions, identifying investment opportunities and/or executing trades, augmenting lending models or (more sparingly) making lending decisions, and identifying and preventing fraud. The extent to which a sector or firm adopts various technologies reflects a variety of factors, including a firm’s ability to fund internal development and regulatory requirements.

The increased use of AI/ML to deliver financial services has attracted attention and led to numerous policy issues and subsequent policy actions. Such policy actions culminated in (1) the establishment of a task force on AI in the 116th Congress and the more recent working group in the House Committee on Financial Services in the 118th and (2) 2019 and 2023 executive orders. The evolving legislative and regulatory framework regarding AI/ML use in finance is likely, at least in part, to influence the development of AI/ML financial services applications. Various financial regulators have indicated that regulated entities are subject to the full range of laws and regulations regardless of the technology used. Additionally, some regulators have identified regulations and issued guidance of particular relevance to financial firms employing AI/ML technologies.

Financial industry policymakers face competing pressures. Financial service providers and technology companies are likely to continue adopting and promoting AI/ML to save time and money and promote accessibility, accuracy, and regulatory compliance. However, challenges and risks in the form of bias, potential for systemic risk and manipulation, affordability, and consequences for employment remain. Determining whether the existing regulatory structure is sufficient—or whether one that is more closely tailored to the technological capacities of the evolving technology is necessary—has emerged as a key consideration. Should Congress consider the legislative framework governing AI/ML in finance, industry and consumers alike will expect that it weighs the benefits of innovation with existing and potential future challenges and risks.

Contents

Introduction	1
Technology Overview in Brief	2
What Are Artificial Intelligence and Machine Learning?	2
Recent Advances in Data and Technology	2
Big Data	3
Finance and Artificial Intelligence	4
AI/ML Applications in Finance	5
Credit Underwriting	6
Chatbots	7
Regtech.....	7
Monitoring Fraud and Illicit Financial Activity	8
Capital Markets Applications	8
Sentiment Analysis.....	9
Asset Management.....	10
Trading Applications.....	11
AI-as-a-Service	12
Policy Issues Regarding the Role of AI/ML in Finance	13
Legislative and Regulatory Considerations.....	13
AI/ML Model Bias	14
Explainability	15
Data-Related Policy Issues.....	16
Concentration Risk and Systemic Risk Concerns	17
Herding Behavior.....	18
Market Manipulation.....	19
Conflicts of Interest.....	20
Supervisory Technology.....	21
Big Tech in Finance.....	22
AI/ML and Financial Industry Employment	22
Conclusion.....	23

Contacts

Author Information.....	24
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Introduction

Artificial intelligence (AI) is the general term used to describe the process of programming computers and machines to think and operate like humans. Machine learning (ML) is a subset of AI that describes computers and programs that may be programmed to operate with minimal human intervention and can in some instances learn and/or update themselves. Various events over the past few years have helped raise the profile of AI/ML and its role in delivering financial services. OpenAI’s introduction of the large language model (LLM) ChatGPT in 2022 was a rare moment when an AI/ML technology became directly accessible by the broad public. While momentum around AI/ML had been building over the past decade at least, the ubiquity of competing prominent technologies concentrated attention on all manner of applications, including those in the financial sector.

AI/ML is accelerating a long, ongoing shift in finance from face-to-face interactions conducted in a customer’s community to online products and services fueled by advanced algorithms that require little or no human interaction and can occur anywhere. Such applications may have benefits for financial institutions and their clients. Relative to human operation (or models built using earlier technology), AI/ML provision of financial services may be faster and cheaper due to their speed and efficiency, and they may be able to expand service to more individuals due to their ability to analyze alternative data and find latent connections. The financial industry’s use of technology is not new, and there are elements to its adoption of AI/ML that resemble past periods. While regulators are used to dealing with these cycles, there is a recognition that the growth of AI/ML is likely to be especially transformative.¹

Adoption of the technology also brings challenges and risks. While AI may eliminate some human bias in financial services, it may also introduce or exacerbate bias. Certain AI-market specific factors—such as using the same data to train models and concentration of technology and technological capacity—may encourage monocultures, or herd-like behavior, that introduce systemic risk. The ability of certain models to learn on their own, free from human oversight, may also allow them to engage in market manipulation, conflicts of interest, or other unlawful activity.

Financial industry use of the technology has attracted policymaker interest. For example, Executive Order 14110 on the “Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence” briefly discusses the Biden Administration’s view of AI/ML in finance, among a host of other issues. In addition, the House Committee on Financial Services created a bipartisan AI Working Group to address these issues in January 2024.²

This report discusses the role of AI/ML in financial services broadly. First, it provides a brief overview of some technical terms. Next, it discusses the motivations for the financial industry’s use of AI/ML. It then provides an overview of some financial applications of the technology. Finally, it addresses the regulatory framework and considers various policy issues, including any applicable regulations.

¹ CNBC Television, “SEC Chair Gary Gensler: AI is the Most Transformative Technology of Our Time,” YouTube video, December 14, 2023, https://www.youtube.com/watch?v=J3tT44ASI_w&t=168s.

² House Financial Services Committee, “McHenry, Waters Announce Creation of Bipartisan AI Working Group,” press release, January 11, 2024, <https://financialservices.house.gov/news/documentsingle.aspx?DocumentID=409108>.

Technology Overview in Brief

What Are Artificial Intelligence and Machine Learning?³

AI is the broad label for technologies that give computer systems the ability to learn new concepts or tasks and to reason and draw useful conclusions about the world.⁴ Earlier versions of AI were largely dependent on their human developers that programmed machines with a series of deterministic rules, such as “if ... then” statements, alongside troves of subject matter content.⁵ Such technology required specific syntax for questions or commands and produced responses on topics for which it had been programmed. When faced with a situation for which it had not been programmed, it would “freeze.”⁶ That dependency would likely disqualify it from the AI in current taxonomy and is largely disappearing. According to some, most applications of AI now are ML, so the terms as used are synonymous.⁷

ML is a subset of AI focused on constructing computer systems that can automatically improve through experiencing and determining certain characteristics inherent in *all learning systems*, which can include computers, humans, and organizations.⁸ ML attempts to give computers the ability to learn and change without being reprogrammed. It uses algorithms—sequenced actions designed to solve specific problems—that improve automatically with various degrees of—and often, little or no—human interaction.⁹ In other words, unlike earlier AI, it is meant to be adaptable. ML systems are intended to determine relationships among variables or recognize patterns in large data sets.¹⁰ Yet ML is not one thing, such as a discrete computer application, nor is it even one technology. Instead, it is a group of systems that is defined in part by the type of information used to train the model (labelled or unlabeled data, for example) and the amount of involvement provided by human trainers (supervised or unsupervised).

Recent Advances in Data and Technology

Technological developments in computing and telecommunications have been a boon to AI/ML, and the financial industry’s use of it includes advanced performance computing, which includes hardware, cloud and edge computing, and communication technologies.¹¹ However, the financial

³ This report will collectively refer to the technologies it examines as AI/ML. The individual terms (or other terms) will be used when a distinction is necessary.

⁴ Shukla Shubhendu and Jaiswal Vijay, “Applicability of Artificial Intelligence in Different Fields of Life,” *International Journal of Scientific Engineering and Research (IJSER)*, vol. 1, no. 1 (September 2013), <https://www.ijser.in/archives/v1i1/MDExMzA5MTU=.pdf>.

⁵ Dorothy Leonard-Barton and John J. Sviokla, “Putting Expert Systems to Work,” *Harvard Business Review*, March 1988.

⁶ Marko Kolanovic and Rajesh T. Krishnamachari, *Big Data and AI Strategies: Machine Learning and Alternative Data Approach to Investing*, J. P. Morgan, May 2017, p. 16, <https://cpb-us-e2.wpmucdn.com/faculty.sites.uci.edu/dist/2/51/files/2018/05/JPM-2017-MachineLearningInvestments.pdf>.

⁷ Sara Brown, “Machine Learning, Explained,” MIT Management Sloan School, April 21, 2021, <https://mitsloan.mit.edu/ideas-made-to-matter/machine-learning-explained>.

⁸ M. I. Jordan and T. M. Mitchell, “Machine Learning: Trends, Perspectives, and Prospects,” *Science*, vol. 349, no. 6245 (July 17, 2015), <https://www.science.org/doi/10.1126/science.aaa8415>.

⁹ Financial Stability Board, *Artificial Intelligence and Machine Learning in Financial Services: Market Developments and Financial Stability Implications*, November 1, 2017, p. 10, <https://www.fsb.org/wp-content/uploads/P011117.pdf>.

¹⁰ Kolanovic and Krishnamachari, *Big Data and AI Strategies*, p. 13.

¹¹ Gary Gensler and Lily Bailey, *Deep Learning and Financial Stability*, November 1, 2020, p. 8, (continued...)

industry’s adoption of AI/ML depends upon the availability of data, including alternative data not traditionally used in financial decisionmaking, and the ability to process and analyze unstructured data. These technological advances move in tandem with the amassing of large quantities of data (including that which is coming from alternative sources) that require “scalable architecture for efficient storage, manipulation, and analysis.”¹²

Recently, graphics processing units—hardware previously used in gaming (and subsequently crypto mining)—has fueled development of deep learning and other advanced forms of AI.¹³ Cloud computing has also increased the amount of data and programs that individuals or companies may store or access, while edge computing allows them to process data at its source in real time.

Some of today’s technologies have their conceptual origins decades ago, and they are now being developed.¹⁴ Unsupervised learning’s ability to process unlabeled data may identify relationships—for example, in market interactions or among loan applications—where its programmers had not thought to look. Similarly, the ability to process unstructured and alternative data that previously could not be analyzed—such as images and social media posts—has opened it to analysis.

Big Data

Big data refers both to a type of information and how it is used. It refers to large data sets that exhibit specific characteristics such as volume, velocity, variety, and/or variability and requires “scalable architecture” to store, manage, and analyze.¹⁵ The term also generally refers to the data use by managers, companies, and industries to facilitate business decisions.¹⁶

Some advances in ML have been directly attributed to the ability to process more data.¹⁷ The specific big data used in finance depends on the sector or use case. For example, some firms may use big data—including social media—when deciding whether to make loans.¹⁸ In a capital markets and trading environment, big data may include continuous data feeds from various stock exchanges, which can include stock prices and broader market moves and histories of

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3723132; and Alessio Azzutti, Wolf-Georg Ringe, and H. Siegfried Stiehl, “Machine Learning, Market Manipulation, and Collusion on Capital Markets: Why the ‘Black Box, Matters,” *University of Pennsylvania Journal of International Law*, vol. 43, no. 1 (2021), p. 85, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3788872.

¹² National Institute of Standards and Technology (NIST), *NIST Big Data Interoperability Framework: Volume 1, Definitions*, October 2019, pp. 6, 9, <https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.1500-1r2.pdf>.

¹³ David Rotman, “We’re Not Prepared for the End of Moore’s Law,” *MIT Technology Review*, February 24, 2020, <https://www.technologyreview.com/2020/02/24/905789/were-not-prepared-for-the-end-of-moores-law/>.

¹⁴ See discussions of history at Financial Stability Board, *Artificial Intelligence and Machine Learning in Financial Services*, p. 10; and Ben Weiss, “Banks Have Used A.I. for Decades—but Now It’s Going to Take Off Like Never Before,” *Fortune*, July 22, 2023, <https://fortune.com/2023/07/21/ai-finance-history-regressions-generative-artificial-intelligence-pagaya-kasisto/>.

¹⁵ NIST, *NIST Big Data Interoperability Framework: Volume 1, Definitions*, pp. 6, 9. For more on big data’s use in finance, see CRS Report R46332, *Fintech: Overview of Innovative Financial Technology and Selected Policy Issues*, coordinated by David W. Perkins.

¹⁶ Andrew McAfee and Erik Brynjolfsson, “Big Data: The Management Revolution,” *Harvard Business Review*, October 2012, <https://hbr.org/2012/10/big-data-the-management-revolution>.

¹⁷ McAfee and Brynjolfsson, “Big Data: The Management Revolution,” p. 11.

¹⁸ Government Accountability Office, *Data and Analytics Innovation: Emerging Opportunities and Challenges*, GAO-16-659SP, September 2016, p. 95, <https://www.gao.gov/assets/gao-16-659sp.pdf>.

transactions. Data in this environment may also include company-level data that may influence a stock performance, including financial statements and quarterly and annual regulatory filings.

Alternative data refers to information that has not traditionally been used to make financial decisions. In consumer credit underwriting, *alternative data* refers to non-credit data that has not traditionally been used in determining credit scores, such as rent and utility payments.¹⁹ Banks and credit card and payment companies may also use alternative and *unstructured data*—such as transaction information and location or GPS data—in their fraud detection and anti-money laundering activities. Asset managers and other capital markets participants may also use GPS and satellite imagery of retailer parking lots or social media mentions that provide insight into a company's performance.²⁰ The availability of different forms of data and the models they use have expanded the ways financial firms may use both.

Recent interest in AI has been marked by a period of increased investment in and development and adoption of AI/ML technologies by various sectors, including the financial industry. According to one bank's research, investment in AI is expected to climb to around \$100 billion in the United States in 2025 and nearly \$200 billion globally.²¹ Notably, there is likely broad investment from traditional financial institutions—one market research firm suggested retail banks will spend more than \$4 billion on AI in 2024—with finance-focused startups attracting investment from venture capital firms.²²

Finance and Artificial Intelligence

According to the Organisation for Economic Co-operation and Development (OECD), AI is “powering digital transformation” that has been rapidly deployed in finance.²³ Adoption of this newer technology is not surprising as finance has often been linked with cutting-edge technology. However, the industry is also known for its use of often obsolete technology and associations with traditional practices that are at odds with new technologies. While in the past, personal banking was rooted in community relationships and conducted in person, now nearly all transactions can be performed online. In capital markets transactions, electronic trading has essentially ended the need for trading to be conducted person to person at the physical location of exchanges.²⁴ Meanwhile, the use of AI/ML (like the related adoption of a broad set of financial technology, or “fintech”) over the past few decades also has implications for regulation, which

¹⁹ See CRS In Focus IF11630, *Alternative Data in Financial Services*, by Cheryl R. Cooper. For a description of alternative data for credit underwriting, see Consumer Financial Protection Bureau (CFPB), *Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process*, February 16, 2017, https://files.consumerfinance.gov/f/documents/20170214_cfpb_Alt-Data-RFI.pdf.

²⁰ BlackRock, “Artificial Intelligence and Machine Learning in Asset Management,” October 2019, <https://www.blackrock.com/corporate/literature/whitepaper/viewpoint-artificial-intelligence-machine-learning-asset-management-october-2019.pdf>.

²¹ Goldman Sachs, “AI Investment Forecast to Approach \$200 Billion Globally by 2025,” August 1, 2023, <https://www.goldmansachs.com/intelligence/pages/ai-investment-forecast-to-approach-200-billion-globally-by-2025.html>.

²² For banking figures, see Sherry Fairchok, “In the Global AI ‘Arms Race,’ Banks Are Stretching Their Tech Experimentation,” *Insider Intelligence eMarketer*, June 5, 2023, <https://www.insiderintelligence.com/content/global-ai-arms-race-banks-stretching-their-tech-experimentation>. For a discussion on venture capital investment, see OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, September 24, 2021, pp. 19-21, <https://doi.org/10.1787/ba682899-en>.

²³ OECD, *OECD Business and Finance Outlook 2021*, p. 17.

²⁴ Randall Dodd, *Financial Markets: Exchange or Over the Counter*, International Monetary Fund, <https://www.imf.org/en/Publications/fandd/issues/Series/Back-to-Basics/Financial-Markets>. See also CRS Insight IN11447, *The Closing of the New York Stock Exchange's Trading Floor Due to COVID-19*, by Gary Shorter.

prioritizes industry transparency, explainability, and fairness.²⁵ Finance’s adoption of AI/ML thus takes place as technology and its capacity may be evolving more rapidly than societal and regulatory expectations.

Motivation behind the financial sector’s adoption of AI is not new. Finance’s adoption of AI has been compared to the 13th-century development of net-present-value calculations, the more recent invention of the automated teller machine, use of expert systems for personal financial planning, and automated trading, all of which employed different technologies.²⁶

In addition to a general gravitation to technology, various characteristics of the financial industry have made it a ripe testing ground for AI/ML. As one commentator expressed: “information processing is the central function of financial markets.”²⁷ For example, AI/ML generally requires large quantities of data on which to train its systems. Data is a quintessential feature across the various financial sectors. The industry amasses data from economic indicators, financial markets, individual consumers and businesses, and payments and transactions, among countless other sources. Moreover, while comprised of different subsectors—with diverse functions, services, and products—finance presents quantifiable problems, the solutions for which are often reduced (perhaps overly simplistically) to maximizing returns considering a given risk tolerance while considering some number of other quantifiable variables. As such, the industry is generating large amounts of data and providing the operating environment for AI/ML technologies.

AI/ML may also increase the speed with which financial transactions may take place. For example, high-frequency trading, which is also increasingly automated and programmatic, allows trades to occur in the smallest fractions of a second, speeds at which neither human analysis nor execution are possible. Also, if a financial institution uses AI/ML to determine whether it should make a loan, the speed may be evident in multiple ways. AI/ML-induced speed may allow financial institutions to update their lending models.²⁸ Lenders may also use AI/ML-based lending models, integrated with digital platforms and web-interfaces, to deliver decisions to customers more quickly.

AI/ML Applications in Finance

Financial industry and market participants use AI for a variety of functions. These functions have multiple purposes, including improving efficiency, assisting with decisionmaking, producing analysis and forecasting, increasing profitability, managing risk, and underwriting credit.²⁹ Moreover, they may be used in support functions or front office functions. Back office applications may include post-trade processing, trading profit and loss reconciliations, and data

²⁵ For more on fintech, see CRS Report R46332, *Fintech: Overview of Innovative Financial Technology and Selected Policy Issues*, coordinated by David W. Perkins.

²⁶ See discussions in Gensler and Bailey, *Deep Learning and Financial Stability*, p. 8; Weiss, “Banks Have Used A.I. for Decades;” Carol E. Brown, Norma L. Nielson, and Mary Ellen Phillips, “Expert Systems for Personal Financial Planning,” *Journal of Financial Planning*, vol. 3, no. 3 (July 1990), pp. 137-143, <https://prism.ucalgary.ca/server/api/core/bitstreams/e044857a-17a6-4927-8ab5-c65539d61fa1/content>; and K. C. Chen and Ting-Peng Liang, “PROTRADER: An Expert System for Program Trading,” *Managerial Finance*, vol. 15, no. 5 (1989), pp. 1-6, <http://www.ecrc.nsysu.edu.tw/liang/paper/3/PROTRADER%20An%20Expert%20System%20for%20Program%20Trading.pdf>.

²⁷ Mihir A. Desai, “What the Finance Industry Tells Us About the Future of AI,” *Harvard Business Review*, August 9, 2023, <https://hbr.org/2023/08/what-the-finance-industry-tells-us-about-the-future-of-ai>.

²⁸ Julie Lee, “AI-Driven Credit Risk Decisioning: What You Need to Know,” Experian, October 27, 2022, p. 13, <https://www.experian.com/blogs/insights/2022/10/ai-driven-credit-risk-decisioning/>.

²⁹ Gensler and Bailey, *Deep Learning and Financial Stability*, p. 7.

analytics.³⁰ Other applications may include regulatory compliance functions, such as know-your-customer checks and customer identification programs, anti-money laundering and countering the financing of terrorism programs, and anti-fraud. AI may also assist in asset allocation, robo-advising, and trade execution. Many of the actions taken by financial firms are multistep and closely related, and AI may be used for and benefit from different parts of a business or phases of a business process. Moreover, there may be overlap in use cases with different definitions. For example, while asset managers may use AI to assist with asset allocation, certain asset management firms may also employ algorithmic trading. This section provides a brief overview of various financial applications and services that may use AI but is not intended to be exhaustive.

Credit Underwriting

Credit underwriting—assessing the risk of prospective borrowers defaulting on loan repayment—is one of banks’ and other financial institutions’ primary businesses. Loan-making financial institutions have automated the methods for making loan decisions, including through the use of electronic data.³¹

For example, for consumer loans, such methods generally entail using a mathematical formula (called a scoring model) to determine a consumer’s credit score and subsequently whether the firm should make the loan and at what interest rate.³² Various factors—including bill paying history, unpaid debt, outstanding loans, and accounts—go into determining a credit score.³³ Recently, however, some financial companies have considered using AI/ML to augment or replace traditional credit scoring.

Lenders have been using predictive models for decades.³⁴ Traditionally, statistical regression methods used data from the credit reporting bureaus, assigning weights to different variables to help forecast whether an applicant would default on a loan and to determine the likelihood of on-time loan repayment.³⁵ More recently, firms may use ML-based measures based on their ability to analyze large amounts and different types of data—including transaction data—and their ability to discern other important relationships not visible in traditional models.³⁶ According to one study, some ML underwriting models are “more adaptive” and have shown improvements in predictiveness and cost savings relative to traditional models.³⁷

Adoption of AI/ML for credit underwriting may differ among banks and nonbank fintech. Various regulatory requirements may make banks hesitant to use the technology for credit underwriting decisions (see “Policy Issues Regarding the Role of AI/ML in Finance”). Generally, because nonbanks may have different (and in certain ways more permissive) regulatory requirements and

³⁰ OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 39.

³¹ See CRS In Focus IF12399, *Automation, Artificial Intelligence, and Machine Learning in Consumer Lending*, by Cheryl R. Cooper.

³² CFPB, “What Is a Credit Score?,” August 28, 2023, <https://www.consumerfinance.gov/ask-cfpb/what-is-a-credit-score-en-315/>.

³³ CFPB, “What Is a Credit Score?”

³⁴ FinRegLab, “Explainability and Fairness in Machine Learning for Credit Underwriting,” December 2023, p. 7, https://finreglab.org/wp-content/uploads/2023/12/FinRegLab_2023-12-07_Research-Report_Explainability-and-Fairness-in-Machine-Learning-for-Credit-Underwriting_Policy-Analysis.pdf.

³⁵ FinRegLab, “Explainability and Fairness,” p. 7. The predictive models were logistic regressions.

³⁶ FinRegLab, “Explainability and Fairness,” p. 7.

³⁷ Amir E. Khandani, Adlar J. Kim, and Andrew W. Lo, “Consumer Credit Risk Models via Machine-Learning Algorithms,” *Journal of Banking Finance*, vol. 34, no. 11 (November 2010), p. 2, <https://core.ac.uk/download/pdf/4430264.pdf>.

supervision than banks do, they may be more willing to use AI/ML technology. Some fintechs claim to have adopted the technology for underwriting, including reportedly for consumer loans, as well as for “buy now, pay later” credit products.³⁸ While banks may be more hesitant to use AI base models for credit underwriting decisions, some have reportedly not shunned the practice altogether. According to various reports, banks may use AI/ML to identify useful variables or relationships and to “explore the potential ... to refine” their traditional statistical models used in the credit underwriting process.³⁹ Moreover, some banks—especially large ones and some solely in experimentation phases—reportedly use ML underwriting models for lending.⁴⁰

Chatbots

Chatbots are computer programs that interact (e.g., converse and provide answers) with people online by simulating human conversation through text and voice commands. Banking chatbots provide immediate assistance 24/7, reducing wait times, addressing customer inquiries, providing information on account balances and transaction history, and guiding users through various banking processes. Chatbots used in banking provide \$8 billion in cost savings annually, according to one estimate.⁴¹

Regtech

Regtech (regulatory technology) refers to regulated financial institutions’ use of technology to meet various regulatory, compliance, and data reporting functions.⁴² Regtech has existed for around a decade.⁴³ Regtech had focused on compliance with regulations related to onboarding and identifying new customers, but more recently it has been described as being instrumental in anti-money laundering, countering the financing of terrorism, fraud prevention, risk management, stress testing, and micro and macroprudential reporting.⁴⁴ For example, banks and other financial institutions use “robotics process automation” to help them comply with reporting requirements

³⁸ John Adams, “Buy Now/Pay Later Fintechs Lean on AI to Survive the Banking Crisis,” *American Banker*, March 27, 2023, <https://www.americanbanker.com/payments/news/buy-now-pay-later-fintechs-lean-on-ai-to-survive-the-banking-crisis>; and Upstart, “Our Story: Result to Date,” <https://www.upstart.com/our-story#results-to-date>. Some researchers report success when using AI to predict corporate defaults; see reference in OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 44. For more on “buy now, pay later,” see CRS Insight IN11784, *Rapidly Growing “Buy Now, Pay Later” (BNPL) Financing: Market Developments and Policy Issues*, by Cheryl R. Cooper and Paul Tierno.

³⁹ See FinRegLab, “The Use of Machine Learning for Credit Underwriting: Market and Data Science Context,” September 2021, p. 24, https://finreglab.org/wp-content/uploads/2021/09/The-Use-of-ML-for-Credit-Underwriting-Market-and-Data-Science-Context_09-16-2021.pdf; and Federal Reserve Governor Christopher J. Waller, “Innovation and the Future of Finance,” speech at the Cryptocurrency and the Future of Global Finance, Sarasota, Florida, April 20, 2023, <https://www.federalreserve.gov/newsevents/speech/waller20230420a.htm>.

⁴⁰ For references to large banks using ML underwriting models, see FinRegLab, *Explainability and Fairness*, pp. 12, 33; for experimentation, see Penny Crosman, “The Banks Warming to AI-Based Lending,” *American Banker*, October 21, 2019, <https://www.americanbanker.com/news/the-banks-warming-to-ai-based-lending>.

⁴¹ CFPB, *Chatbots in Finance*, June 6, 2023, <https://www.consumerfinance.gov/data-research/research-reports/chatbots-in-consumer-finance/chatbots-in-consumer-finance/#chatbot-use-in-consumer-finance>.

⁴² For a definition and general discussion on regtech, see Financial Stability Board, *The Use of Supervisory and Regulatory Technology by Authorities and Regulated Institutions*, October 9, 2020, <https://www.fsb.org/wp-content/uploads/P091020.pdf>.

⁴³ Matthias Memminger, Mike Baxter, and Edmund Lin, “BankThink: You’ve Heard of Fintech, Get Ready for ‘Regtech,’” *American Banker*, September 7, 2016, <https://www.americanbanker.com/opinion/youve-heard-of-fintech-get-ready-for-regtech>.

⁴⁴ Memminger, Baxter, and Lin, “BankThink;” and Tobias Adrian, “AI and Regtech,” International Monetary Fund, October 29, 2021, <https://www.imf.org/en/News/Articles/2021/10/29/sp102921-ai-and-regtech>.

and repopulating required data on a regular basis.⁴⁵ In many cases, banks' and other financial institutions' adoption of regtech may involve partnering with third-party providers with expertise in the field.

Monitoring Fraud and Illicit Financial Activity

A key form of regtech aided by AI/ML is detecting, preventing, and reporting unauthorized and illicit financial activities for banks and other financial institutions. The shift to AI/ML solutions is due to its more adaptable approaches and its ability to leverage more types of data. Banks and other financial institutions must detect, prevent, and report on unauthorized and illicit financial activity, and there has been an increase in the number of financial institutions using AI/ML to address the issue.⁴⁶ Banks and other financial institutions can train models on huge volumes of consumer behavior data they generate, allowing the ML models to learn fraud patterns and to then detect fraudulent behavior in practice.⁴⁷ One payment processor, for example, has stated it uses time and location and GPS data to determine whether activity occurring in distant geographies may be fraudulent.⁴⁸ The same company also suggested that ML models can learn and subsequently evaluate certain behaviors, including swiping speed and gestures, when assessing the likelihood of fraud.⁴⁹ Similarly, there may be benefits to using the technology across the "anti-money laundering value chain," including at onboarding and client screening and with particular and immediate benefits coming from transaction monitoring.⁵⁰ In addition, researchers suggest that the technology is also useful in reducing false positives, freeing banks to dedicate resources to actual instances of fraud.⁵¹

Capital Markets Applications

Technology has always played a large role in the financial sector's capital markets activities. AI/ML may be seen as natural extensions of areas such as quantitative finance, which embraced advanced statistical analysis. As such, financial institutions, including the asset management industry and other investment companies, have adopted the technology to identify and exploit investment opportunities, allocate capital, execute trades, and reduce cost, with the latter ultimately allowing them to reach more customers.

⁴⁵ American Bankers Association, "Understanding Regtech," July 25, 2018, <https://www.aba.com/-/media/documents/reference-and-guides/understanding-regtech.pdf>.

⁴⁶ Unauthorized and illicit financial activity is broadly defined for the purposes of this report as including fraud, money laundering, and terrorist financing. According to one industry survey, fraud at financial institutions increased at 43% of financial institutions, with average costs increasing by 65% between 2022 and 2023. PYMNTS, "The State of Fraud and Financial Crime in the U.S. 2023," September, 2023, pp. 4, 10, <https://www.pymnts.com/wp-content/uploads/2023/09/PYMNTS-The-State-of-Fraud-and-Financial-Crime-in-the-US-2023-September-2023.pdf>.

⁴⁷ Ryan Williamson, "Benefits of AI to Fight Fraud in the Banking System," *Data Science Central*, December 22, 2022, <https://www.datasciencecentral.com/benefits-of-ai-to-fight-fraud-in-the-banking-system/>; Stripe, "How Machine Learning Works for Payment Fraud Detection and Prevention," June 27, 2023, <https://stripe.com/resources/more/how-machine-learning-works-for-payment-fraud-detection-and-prevention>; and Adrian, "AI and Regtech."

⁴⁸ Stripe, "How Machine Learning Works for Payment Fraud Detection and Prevention."

⁴⁹ Stripe, "How Machine Learning Works for Payment Fraud Detection and Prevention."

⁵⁰ P. K. Doppalapudi et al., "The Fight Against Money Laundering: Machine Learning Is a Game Changer," McKinsey and Company, October 7, 2022, <https://www.mckinsey.com/capabilities/risk-and-resilience/our-insights/the-fight-against-money-laundering-machine-learning-is-a-game-changer>.

⁵¹ Adrian, "AI and Regtech."

Sentiment Analysis

AI/ML technologies help participants distinguish meaningful data points from noise in a practice referred to as signal processing.⁵² AI has become adept at identifying events from which a viable, profitable trading strategy can be generated but where the limited information would have made devising the strategy difficult without the benefit of AI.

Sentiment analysis is the analysis of financial sector news to forecast individual stock or market directions.⁵³ Advances in AI allow firms to analyze a wide variety of data, including unstructured data, to determine a company's popularity—for example, by surveilling social media posts and analyzing traffic through satellite imagery and GPS data. Sentiment analysis may be used across the spectrum of capital markets services where firms or individuals interpret data to allocate capital and determine strategy, including asset management and securities trading.

Structured and Unstructured Data

Some AI models are able to analyze only *structured data*, which is organized and “quantifiable,” thereby limiting the data that could be used.⁵⁴

Unstructured data, on the other hand, has no “predefined data model” and may be uniquely consumed by contemporary AI. *Unstructured data* includes data in text, audio, visual, and other formats, an example of which may be social media posts and/or connections.⁵⁵

While sentiment analysis is not new, LLMs and computer capacity may outperform human methods and abilities to evaluate or forecast potential market moves.⁵⁶ The financial press and various researchers have suggested that LLMs may provide an edge in a number of contexts, from deciphering statements from the Federal Reserve to forecasting stock prices.⁵⁷ Some studies have shown that AI-enabled market participants (such as hedge funds) are quick to respond to new data, especially machine-readable disclosures, moving stock prices quickly.⁵⁸ Subsequently, companies have begun to adjust corporate disclosure practices to account for these market practices by learning “how to talk when a machine is listening,” with research showing that public companies are adjusting how they speak and the language used in reporting to account for AI used by market participants.⁵⁹

⁵² Azzutti, Ringe, and Stiehl, “Machine Learning, Market Manipulation, and Collusion on Capital Markets,” footnote at p. 85.

⁵³ Gartner, “Sentiment Analysis,” accessed July 19, 2023, <https://www.gartner.com/en/finance/glossary/sentiment-analysis>.

⁵⁴ Goldman Sachs, “The Role of Big Data in Investing,” July 11, 2016, https://www.gsam.com/content/dam/gsam/pdfs/common/en/public/articles/perspectives/2016/big-data/GSAMPerspectives_BigDataInvesting.pdf?sa=n&rd=n.

⁵⁵ For definitions and a discussion of unstructured data, see OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 146; and FinRegLab, “The Use of Machine Learning for Credit Underwriting,” p. 69.

⁵⁶ OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 41.

⁵⁷ Robin Wigglesworth, “ChatGPT vs the Markets,” *Financial Times*, April 18, 2023, <https://www.ft.com/content/c76cd6c0-e965-4c76-beec-e0b2deafd1ec>.

⁵⁸ Sean Cao et al., *How to Talk When a Machine Is Listening? Corporate Disclosure in the Age of AI*, National Bureau of Economic Research, Working Paper no. 27950, October 2020, pp. 18-19, <https://www.nber.org/papers/w27950>.

⁵⁹ Cao et al., “How to Talk When a Machine Is Listening?,” p. 3.

Hearing and Writing Like a Human

Natural language processing (NLP) is a branch of AI that trains computers to understand and process language as humans do.⁶⁰ NLP can be used to develop LLMs that can create content in the form of essays or computer code from prompts using techniques that predict the next word in a sequence of words based on certain probabilities.⁶¹ This technology supports applications in finance, including powering chatbots, surveying companies' own large troves of data, and writing code.⁶² LLMs are examples of *artificial neural networks* that attempt to reflect the functioning of the human brain by replicating neurons as mathematical representations, organizing layers of such so-called nodes or artificial neurons into clusters or layers.⁶³ Nodes receive signals from upstream nodes to which they are connected and will process signals forward if a certain threshold is met.⁶⁴ Connections between neurons can be amplified or attenuated by weights that are constantly adjusted in the model learning process.⁶⁵

ChatGPT, which has attracted attention in recent years, is an example of an LLM. Aside from finance-specific applications, LLMs and ChatGPT in particular provided general public audiences with some of the first concrete and directly applicable examples of AI that until now had been reserved for specialists.

Asset Management

Asset managers are companies that manage individuals' and businesses' capital for a fee, identifying suitable investments based on stated preferences.⁶⁶ The industry has been using AI for "a number of years," according to one report, to generate ideas and for portfolio allocation.⁶⁷ Recent applications employ deep learning models, including neural networks.⁶⁸ Specifically, AI is used to perform various types of analyses to suggest asset allocations (where and how much to invest) that optimize a portfolio (to maximize profit), with evidence suggesting that they may be better at meeting targets than "traditional methods" are.⁶⁹

Robo-advisors are a form of financial advisors under the broader asset management category that use AI to automate investment management. These digital investment advisors may employ various types of AI/ML (including NLP, LLMs, etc.) to develop a profile of an investor including budget, time horizon, and risk tolerance. They came to prominence more than a decade ago as a

⁶⁰ Ross Gruetzemacher, "The Power of Natural Language Processing," *Harvard Business Review*, April 19, 2022, <https://hbr.org/2022/04/the-power-of-natural-language-processin>.

⁶¹ Lucas Mearian, "What Are LLMs, and How Are They Used in Generative AI?," *Computerworld*, May 30, 2023, <https://www.computerworld.com/article/3697649/what-are-large-language-models-and-how-are-they-used-in-generative-ai.html>.

⁶² Carter Pape, "Here's How Banks Are Using and Experimenting with Generative AI," *American Banker*, July 7, 2023, <https://www.americanbanker.com/news/heres-how-banks-are-using-and-experimenting-with-generative-ai>.

⁶³ Christian Janiesch, Patrick Zschech, and Kai Heinrich, "Machine Learning and Deep Learning," *Electronic Markets*, April 8, 2021, p. 687, <https://doi.org/10.1007/s12525-021-00475-2>; and Larry Hardesty, "Explained: Neural Networks," *MIT News*, April 14, 2017, <https://news.mit.edu/2017/explained-neural-networks-deep-learning-0414>.

⁶⁴ Janiesch, Zschech, and Heinrich, "Machine Learning and Deep Learning," p. 687; and Hardesty, "Explained: Neural Networks."

⁶⁵ Janiesch, Zschech, and Heinrich, "Machine Learning and Deep Learning," p. 687; and Hardesty, "Explained: Neural Networks."

⁶⁶ "Asset management companies—also referred to as investment management companies, money managers, funds, or investment funds—are collective investment vehicles that pool money from various individual or institutional investor clients and invest on their behalf for financial returns." For this definition and more, see CRS Report R45957, *Capital Markets: Asset Management and Related Policy Issues*, by Eva Su.

⁶⁷ OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, pp. 39-40.

⁶⁸ Gensler and Bailey, *Deep Learning and Financial Stability*, pp. 6-7. See also Söhnke M. Bartram, Jürgen Branke, and Mehrshad Motahari, "Artificial Intelligence in Asset Management," CFA Institute Research Foundation, 2020, p. 6, <https://www.cfainstitute.org/-/media/documents/book/rf-lit-review/2020/rflr-artificial-intelligence-in-asset-management.pdf> for a full summary of AI/ML techniques used in asset management.

⁶⁹ Bartram, Branke, and Motahari, "Artificial Intelligence in Asset Management," p. 8.

fintech application in part to introduce investment management to a subset of the population that may not have previously engaged with the service. Generally, these advisors may charge lower fees and require lower minimum balances than personal advisors do.⁷⁰ Additionally, robo-advisor algorithms may be programmed to rebalance a portfolio and perform “tax loss harvesting” and digital document delivery.⁷¹

Some asset managers have also created LLMs and generative AI models to assist with other services. Morgan Stanley, for example, announced in March 2023 that it had partnered with OpenAI (the company that created ChatGPT) to create a tool based on internal content to assist financial advisors in serving clients.⁷² The tool is said to function much like ChatGPT but uses Morgan Stanley’s “own expansive range of intellectual capital” to provide answers in “an easily digestible format.”⁷³

Trading Applications

Algorithmic Trading and Trade Execution

Algorithmic trading is a subset of quantitative finance that dates to the 1950s that uses “mathematical models, computers, and telecommunications networks to automate the buying and selling of financial securities.”⁷⁴ In earlier iterations, algorithmic trading was based on—in technological terms—“deterministic ‘rules based’ systems,” which impose certain constraints.⁷⁵ As discussed earlier (see “Technology Overview in Brief”), these models took their cues directly from humans and lacked the ability to learn. As in other financial industry subfields, technological advances have pushed firms to use newer methods, whose algorithm-enabling trading are considered more robust, adaptable to market conditions, and capable of operating at greater levels of autonomy.⁷⁶ Traders may combine supervised (i.e., learning with the assistance of humans) and unsupervised (i.e., learning without human supervision) learning models, employing a variety of techniques based on how a firm’s adoption of AI/ML capacity evolved with technology.⁷⁷ For example, one investment firm may use an LLM such as ChatGPT to develop an investment thesis that is subsequently fed into more traditional “statistical AI” models to back test a hypothesis or determine whether the theory would have been profitable based on previous data.⁷⁸

⁷⁰ Securities and Exchange Commission, “Investor Bulletin: Robo-Advisers,” press release, February 23, 2017, https://www.sec.gov/oiea/investor-alerts-bulletins/ib_rob-advisers.

⁷¹ BlackRock, “Artificial Intelligence and Machine Learning in Asset Management,” p. 4.

⁷² Morgan Stanley, “Morgan Stanley Wealth Management Announces Key Milestone in Innovation Journey with OpenAI,” press release, March 14, 2023, <https://www.morganstanley.com/press-releases/key-milestone-in-innovation-journey-with-openai>.

⁷³ Morgan Stanley, “Morgan Stanley Wealth Management Announces Key Milestone.”

⁷⁴ Andrei A. Kirilenko and Andrew W. Lo, “Moore’s Law versus Murphy’s Law: Algorithmic Trading and Its Discontents,” *Journal of Economic Perspectives*, vol. 27, no. 2 (Spring 2013), pp. 52-53, <https://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.27.2.51>.

⁷⁵ Azzutti, Ringe, and Stiehl, “Machine Learning, Market Manipulation, and Collusion on Capital Markets,” p. 85.

⁷⁶ Azzutti, Ringe, and Stiehl, “Machine Learning, Market Manipulation, and Collusion on Capital Markets,” pp. 85-86.

⁷⁷ Azzutti, Ringe, and Stiehl, “Machine Learning, Market Manipulation, and Collusion on Capital Markets,” p. 86.

⁷⁸ Tracy Alloway, Joe Weisenthal, and Isabel Webb Carey, “Bridgewater’s Greg Jensen Explains How the World’s Biggest Hedge Fund Is Investing in AI,” *Bloomberg*, July 3, 2023, <https://www.bloomberg.com/news/articles/2023-07-03/bridgewater-s-greg-jensen-explains-how-the-world-s-biggest-hedge-fund-is-investing-in-ai>.

Supervised and Unsupervised Learning

Supervised learning refers to a type of ML in which the system is ‘fed’ or trained on labeled data that allows it to make inferences about the different types of data. Supervised learning models are trained using a data set that includes inputs (the raw data that, once trained, a model may be expected to decipher) as well as labeled outputs (how that input is traditionally classified) so that the model can learn.⁷⁹ One generic example of supervised learning’s use is email spam. Once trained on enough examples of “spam” versus “not spam” emails, an effective model should be able to decipher the two.⁸⁰

Unsupervised learning uses unlabeled data—the relationship between inputs and outputs is obscured or not readily apparent—and the model is directed to find patterns among data without labels or specifications.⁸¹

Reinforced learning is a method in which an algorithm seeks to maximize outcomes, in successive steps, using trial and error in which successful intermediate solutions are rewarded.⁸² Reinforcement learning is described as being well-equipped to deal with problems that resemble games, with rules and “incentive structures” and, by extension, capital markets applications.⁸³

Various market participants may also use ML for vital process-oriented tasks such as order placement and execution, especially when *price impact* occurs—the phenomenon in which buyers or sellers of large quantities of securities experience adverse price movements brought about by market reactions to their large buy and sell orders.⁸⁴ As such, traders may employ algorithms and, more recently, neural networks to execute orders in a dynamic way, taking into consideration market forces.⁸⁵

AI-as-a-Service

AI-as-a-service refers to third-party service providers offering AI models to financial firms lacking their own capacity to develop them internally. In the financial services industry, BlackRock’s Aladdin resembles such a service. BlackRock describes Aladdin as “end-to-end portfolio management software” that offers trading, operations, and compliance functions on a single platform.⁸⁶ The platform is used by a large number of other financial firms that, together with BlackRock, manage more than \$10 trillion in assets.⁸⁷ It uses AI to develop some of its insights, including pricing data or data cleansing, extending those services to its clients. The firm reportedly offers AI/ML-fueled sustainability evaluation and assessment tools and is integrating

⁷⁹ Janiesch, Zschech, and Heinrich, “Machine Learning and Deep Learning,” pp. 685-695.

⁸⁰ Julianna Delua, “Supervised vs. Unsupervised Learning: What’s the Difference?,” IBM, March 12, 2021, <https://www.ibm.com/blog/supervised-vs-unsupervised-learning/>.

⁸¹ Janiesch, Zschech, and Heinrich, “Machine Learning and Deep Learning,” pp. 685-695.

⁸² Richard S. Sutton and Andrew G. Barto, *Reinforcement Learning: An Introduction*, 2nd ed. (Cambridge, MA: MIT Press, 2020), p. 1, <http://incompleteideas.net/book/RLbook2020.pdf>.

⁸³ Gensler and Bailey, *Deep Learning and Financial Stability*, p. 8.

⁸⁴ André F. Perold, “The Implementation Shortfall: Paper Versus Reality,” *Journal of Portfolio Management*, vol. 14, no. 3 (1988), pp. 5-6, <https://www.proquest.com/docview/195579087>.

⁸⁵ OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 40; and JP Morgan, “Machine Learning in FX,” August 8, 2019, <https://www.jpmorgan.com/insights/markets/forex/machine-learning-fx>.

⁸⁶ BlackRock, “Aladdin Enterprise,” <https://www.blackrock.com/aladdin/offerings/aladdin-overview>.

⁸⁷ Tracy Alloway, “BlackRock’s Aladdin: Genie Not Included,” *Financial Times*, July 14, 2014, <https://www.ft.com/content/300145d2-0841-11e4-acd8-00144feab7de>; and Brooke Masters, “BlackRock to Roll Out First Generative AI Tools to Clients Next Month,” *Financial Times*, December 6, 2023, <https://www.ft.com/content/3f3431f1-d6dc-4310-9edc-3bc8cdc46caa>. The \$10 trillion figure is cited in Andrew Ross Sorkin et al., “Why BlackRock’s C.E.O. Wants to Rethink Retirement,” *New York Times*, March 26, 2024, <https://www.nytimes.com/2024/03/26/business/dealbook/blackrock-fink-letter-retirement.html>.

LLM capabilities to let its clients query Aladdin to help them find information more quickly.⁸⁸ Similarly, core services providers that serve small banks and credit unions, such as Jack Henry and Fiserv, also advertise AI/ML services, including fraud detection and chatbot services.⁸⁹

Policy Issues Regarding the Role of AI/ML in Finance

Not all policy issues associated with AI/ML in finance are new, but concerns have grown as its use becomes more prevalent and as the scope of technology appears capable of exacerbating potential risks. Some policy issues, such as whether AI may introduce or magnify bias, deal with broad issues such as fairness in the provision of financial services. Others, which hinge on the scope of the technology and its potential uniformity, include whether the technology creates or increases systemic risk.

This section provides a brief treatment of the legislative and regulatory framework and selected policy issues: (1) the potential for the technology to introduce or exacerbate bias in the provision of financial services; (2) the lack of “explainability” that stems from increasing model complexity, potentially introducing risk to the financial system; (3) the ability to encourage herd-like behavior, leading to financial stability concerns; (4) data security and privacy issues; (5) the potential to promote market manipulation; (6) the evolving role of big tech’s position at the intersection of data, AI/ML, and financial services; and (7) whether, and the extent to which, AI may disrupt financial sector jobs.

Legislative and Regulatory Considerations

Broadly speaking, the legal and regulatory framework applicable to financial institutions and activities are “technology neutral,” meaning they do not take into consideration the specific tools or methods used by institutions. For example, lending laws apply to lending whether the lender uses a pencil and paper or a cutting-edge AI-enabled model, and securities laws apply equally to traders on an exchange floor and ultra-fast high-frequency trading rigs. Given this, many policy debates in the area relate to questions about whether existing rules, when applied to new or innovative uses of AI/ML technologies, are adequate and effective, overly restrictive and stifling to beneficial advances, or overly permissive and inadequate protections against the risks presented by the technology.

Policymakers have increasingly focused their attention on AI/ML financial issues, although to date, few legislative or regulatory changes have been specifically directed at AI/ML use in finance. Meanwhile, regulators have communicated their positions and concerns about AI/ML in various areas. For example, in a March 2021 Request for Information (RFI), various federal banking regulators solicited “views on the use of AI in financial services to assist in determining whether any clarifications from the agencies would be helpful for financial institutions’ use of AI.” The RFI includes a list of existing laws, regulations, guidance, and other regulatory

⁸⁸ BlackRock, “BlackRock Boosts Aladdin’s Forward-Looking Sustainability Analytics and Reporting Capabilities Through Strategic Partnership with Clarity AI,” press release, January 14, 2021, <https://www.blackrock.com/corporate/newsroom/press-releases/article/corporate-one/press-releases/blackrock-announced-minority-investment-in-clarity-ai>; and Masters, “BlackRock to Roll Out First Generative AI Tools to Clients Next Month.”

⁸⁹ See, for example, Jack Henry, “Now Is the Time to Add AI and ML to Combat Fraudsters,” August 4, 2023, <https://www.jackhenry.com/fintalk/now-is-the-time-to-add-ai-and-ml-to-combat-fraudsters>; and Nicole Howson, “Understanding the Generative AI Industrial Revolution,” Fiserv, August 30, 2023, <https://www.fiserv.com/en/insights/articles-and-blogs/understanding-the-ai-industrial-revolution.html>.

statements relevant for AI and notes that “[s]ome laws and regulations are applicable to any process or tool a financial institution employs, regardless of whether a financial institution utilizes AI or how.”⁹⁰ The RFI essentially acknowledged the central issue of assessing the adequacy of existing regulation in the context of an evolving technology, acknowledging that new rules may not be immediately necessary considering that existing ones are still applicable. Yet the acknowledgement appears to be more of a reminder to financial firms of their existing obligations and not the agencies’ final stance on policy. Some commentators suggest existing laws should already motivate corporations not to engage in bad behavior and reject additional attempts to regulate as “intrusions” that will “slow American innovation.”⁹¹ Alternatively, many firms may be choosing not to use AI because of legal risks, and they may be more likely to employ the technology with clearer regulations.

AI Executive Order

In October 2023, President Biden issued Executive Order 14110 on the *Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence*.⁹² The E.O. in particular acknowledges the potential for the technology as well as the risks; it broadly aims to serve as a roadmap for the technology and for use of the technology for commercial and governmental purposes.⁹³ The E.O. addresses financial services by, among other things, encouraging relevant agencies to use their authority to ensure regulated entities follow laws that prohibit bias and to issue guidance regarding the appropriate use of data and advertising of services that use algorithms.

AI/ML Model Bias

Bias in financial services is the overprovision, limitation, or existence of cost difference in the provision of financial services based on an individual’s identity as part of a specific group. While conventional and newer AI/ML may remove one avenue for bias outcomes by eliminating the interpersonal interactions that may lead to discrimination, some believe the technology may introduce or exacerbate biases.⁹⁴ These biases generally fall into two main groups: bias introduced from data and bias introduced by models.⁹⁵ Data may introduce bias in a number of ways, including if the data on which a model is trained includes certain historical biases, which in a financial services context may include discrimination against protected classes.⁹⁶ Models trained on such data may provide credit decisions in ways that perpetuate biases and are illegal.

Model construction and training may also introduce bias. In training periods, for example, certain models may take a longer time to process observations for which there is less information and

⁹⁰ Comptroller of the Currency, the Federal Reserve System, the Federal Deposit Insurance Corporation, CFPB, and National Credit Union Administration, “Request for Information and Comment on Financial Institutions’ Use of Artificial Intelligence, Including Machine Learning,” 86 *Federal Register* 16837, March 31, 2021 <https://www.federalregister.gov/documents/2021/03/31/2021-06607/request-for-information-and-comment-on-financial-institutions-use-of-artificial-intelligence>.

⁹¹ *Wall Street Journal*, “Biden’s AI Order Is Government’s Bid for Dominance,” November 7, 2023, <https://www.wsj.com/articles/joe-biden-ai-executive-order-china-artificial-intelligence-regulation-64024988>.

⁹² Executive Office of the President, “Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence,” 88 *Federal Register* 75191, November 1, 2023, <https://www.federalregister.gov/documents/2023/11/01/2023-24283/safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence>.

⁹³ For an overview of E.O. 14110, see CRS Report R47843, *Highlights of the 2023 Executive Order on Artificial Intelligence for Congress*, by Laurie A. Harris and Chris Jaikaran.

⁹⁴ OECD, *Artificial Intelligence, Machine Learning, and Big Data in Finance*, 2021, pp. 10, 30, <https://www.oecd.org/finance/financial-markets/Artificial-intelligence-machine-learning-big-data-in-finance.pdf>.

⁹⁵ FinRegLab, *The Use of Machine Learning for Credit Underwriting*, pp. 75-79.

⁹⁶ FinRegLab, *The Use of Machine Learning for Credit Underwriting*, pp. 75-79. In a services context, bias in data may include previous discrimination against protected classes.

“learn” how to treat low information interactions. If institutions limit how long they train models, they may adversely affect how such models treat instances with low levels of information in practice.⁹⁷

Regulators have addressed bias in various venues. Federal Reserve Vice Chair for Supervision Michael S. Barr cited a case in which Meta was charged with violating a law that “prohibits discrimination in housing, including housing-related advertising” on the basis of protected classes.⁹⁸ On June 1, 2023, the federal banking agencies requested public comment on a proposed rule that would require companies that use automated valuation models “to adopt policies, practices, procedures, and control systems” that, among other things, ensure the models comply with nondiscrimination laws.⁹⁹ Also, in 2020, the Consumer Financial Protection Bureau issued an RFI on the Equal Credit Opportunity Act (Regulation B/ECOA)—which prohibits discrimination in credit applications because of race, color, religion, national origin, sex, marital status, or age, among others—posing the question of whether it should provide more “regulatory clarity” regarding Regulation B/ECOA to facilitate innovation that would expand credit access without unlawful discrimination.¹⁰⁰

Explainability

Explainability in AI/ML generally refers to the ability of a firm or model designer to understand a model’s outputs or how it came to its conclusions. A lack of explainability has significant regulatory ramifications. Regulation B/ECOA requires that when taking adverse actions (such as refusing credit), banks and other financial institutions must provide notice to applicants explaining why they were rejected.¹⁰¹ Such notice should be “specific and indicate the principal reason(s) for the adverse action.”¹⁰² Therefore, a firm’s use of an overly complex model whose decision and rationale cannot be adequately and specifically explained may directly conflict with Regulation B/ECOA. As use of AI/ML for credit underwriting expands, and as regulatory guidance evolves, determining what is a satisfactory explanation—one that is not too general nor overly technical—may emerge as a key area of negotiation between industry and regulators.

Banks also have risk management requirements, which require they understand the theory and logic of models that manage their risk.¹⁰³ Assuming that AI/ML technologies would be considered

⁹⁷ FinRegLab, *The Use of Machine Learning for Credit Underwriting*, pp. 75-79.

⁹⁸ Federal Reserve Vice Chair for Supervision Michael S. Barr, “Making the Financial System Safer and Fairer,” speech at the Brookings Institution, Washington, D.C., September 7, 2022, <https://www.federalreserve.gov/newsevents/speech/barr20220907a.htm>; and *United States of America v. Meta Platforms, Inc. f/k/a Facebook, Inc.*, 22-cv-05187 (United States District Court Southern District of New York 2022).

⁹⁹ Comptroller of the Currency, the Federal Reserve System, the Federal Deposit Insurance Corporation, the National Credit Union Administration, the Consumer Financial Protection Bureau, and the Federal Housing Finance Agency, “Quality Control Standards for Automated Valuation Models,” 88 *Federal Register* 40638, June 21, 2023, <https://www.federalregister.gov/documents/2023/06/21/2023-12187/quality-control-standards-for-automated-valuation-models>.

¹⁰⁰ Consumer Financial Protection Bureau, “Request for Information on the Equal Credit Opportunity Act and Regulation B,” 85 *Federal Register* 46600, August 3, 2020.

¹⁰¹ 12 C.F.R. §1002.9(b)(1). See CRS In Focus IF12399, *Automation, Artificial Intelligence, and Machine Learning in Consumer Lending*, by Cheryl R. Cooper.

¹⁰² 12 C.F.R. §1002.9(b)(1). See CRS In Focus IF12399, *Automation, Artificial Intelligence, and Machine Learning in Consumer Lending*, by Cheryl R. Cooper.

¹⁰³ Federal Reserve, *Supervisory Guidance on Model Risk Management*, April 4, 2011, p. 5, <https://www.federalreserve.gov/supervisionreg/srletters/sr1107a1.pdf>; and Office of the Comptroller of the Currency, “Sound Practices for Model Risk Management: Supervisory Guidance on Model Risk Management,” April 4, 2011, <https://www.occ.gov/news-issuances/bulletins/2011/bulletin-2011-12.html>.

models, for the sake of compliance, banks' inability to explain its results may be of supervisory concern.¹⁰⁴

For capital markets participants, such as traders, lack of explainability creates risks for firms insofar as traders may not be able to detect the rationale for a successful or losing strategy.¹⁰⁵ Lack of explainability may also cause compliance issues for market participants if a model engages in illegal practices, such as market manipulation.

There may be ways for developers to mitigate challenges from the lack of explainability and potential bias of certain AI/ML models. For example, researchers have shown that diagnostic tools and testing can address transparency-related challenges and that some such tools can identify what model features may be responsible for an adverse action.¹⁰⁶ In addition, policy and technology experts have recommended—including in response to a 2019 executive order—technical standards that may, among other things, eliminate the accidental or intentional promotion of bias.¹⁰⁷

Data-Related Policy Issues

Use of data by financial firms is subject to data protection and security requirements such as those established under the Gramm-Leach-Bliley Act (GLBA, P.L. 106-102).¹⁰⁸ GLBA requires that financial institutions ensure the privacy and confidentiality of customers and protect against threats and unauthorized access and use of data. GLBA also limits what financial institutions can do with information they have collected, generally requiring that they not disclose information to nonaffiliated third parties unless they notify customers and give them the opportunity to opt out.¹⁰⁹ To comply, banks and financial institutions subject to GLBA typically anonymize or “de-identify” their data before selling it.¹¹⁰

However, concerns about data privacy have increased as models improve and may be able to accurately identify owners of previously anonymized data.¹¹¹ In other words, anonymizing data

¹⁰⁴ Matthew Bisanz and Tori K. Shinohara, “Supervisory Expectations for Artificial Intelligence Outlined by US OCC,” Mayer Brown, April 13, 2020, <https://www.mayerbrown.com/en/perspectives-events/publications/2022/05/supervisory-expectations-for-artificial-intelligence-outlined-by-us-occ#Two>.

¹⁰⁵ OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 42.

¹⁰⁶ Laura Blattner et al., “Machine Learning Explainability and Fairness: Insights from Consumer Lending,” FinRegLab, July 2023, p. 7, https://finreglab.org/wp-content/uploads/2023/07/FRL-ML-EWP_July2023.pdf.

¹⁰⁷ Executive Office of the President, “Maintaining American Leadership in Artificial Intelligence,” 84 *Federal Register* 3967, February 14, 2019, <https://www.federalregister.gov/documents/2019/02/14/2019-02544/maintaining-american-leadership-in-artificial-intelligence>; NIST, “U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools,” August 10, 2019, <https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.1500-1r2.pdf>; and Darrell M. West, “Six Steps to Responsible AI in the Federal Government,” Brookings Institution, March 30, 2022, <https://www.brookings.edu/articles/six-steps-to-responsible-ai-in-the-federal-government/>.

¹⁰⁸ For more on financial data rights and privacy, see CRS Report R47434, *Banking, Data Privacy, and Cybersecurity Regulation*, by Andrew P. Scott and Paul Tierno; and CRS Insight IN12291, *CFPB Proposes New Regulation on Consumer Data Rights*, by Cheryl R. Cooper.

¹⁰⁹ P.L. 106-102, §502.

¹¹⁰ Avi Gesser et al., “Alternative Data Goes Mainstream, and Gets Increased Attention from Regulators,” New York University School of Law Program on Compliance and Enforcement, February 25, 2019, https://wp.nyu.edu/compliance_enforcement/2019/02/25/alternative-data-goes-mainstream-and-gets-increased-attention-from-regulators/.

¹¹¹ Steven T. Mnuchin and Craig S. Phillips, *A Financial System That Creates Economic Opportunities: Nonbank Financials, Fintech, and Innovation*, U.S. Department of the Treasury, July 8, 2018, p. 58, <https://home.treasury.gov/sites/default/files/2018-08/A-Financial-System-that-Creates-Economic-Opportunities—Nonbank-Financials-Fintech-and-Innovation.pdf>.

may no longer be enough to comply with GLBA. Furthermore, because keeping data anonymous is becoming more difficult, even more information may qualify as sensitive.¹¹² As AI/ML models use increasingly more alternative data (see “Big Data”), more of a consumer’s social behavior may become subject to commercial surveillance.¹¹³ In other words, as financial institutions seek more alternative types of information to grant financial decisions, individuals may begin to suffer from a greater lack of privacy. While consumers may opt out of information disclosure, this may limit what services they can receive, forcing them to choose between disclosure and collection or going without a service or product.¹¹⁴

Concentration Risk and Systemic Risk Concerns

The market for developing AI/ML may exhibit traditional economic forces seen in other technology sectors, such as high barriers to entry and economies of scale. The high cost to purchase equipment and hire staff may limit to large companies those that are able to develop technology and attract and retain talent.¹¹⁵ Subsequently, companies that have made the investment and attracted market share may be able to offer AI/ML services broadly, profitably, and more easily than new entrants, which would have to begin making the expensive investment and then wrest market share away from the incumbents. Therefore, developing robust models may be economically feasible only for very large companies, while smaller financial institutions may not be able to develop these technologies on their own and may rely on third-party technology providers for the technology.¹¹⁶

The concentration of human capacity and model development at a handful of firms means the number of firms using the same underlying model or data may create or exacerbate systemic risk—financial market risk that poses a threat to financial stability.¹¹⁷ Conditions in the market for AI/ML may create financial system risk in various ways, including through various dynamics that may create herd-like behavior.

In addition, there is a general assumption that the continued growth of data quantity and access contributes to improving AI/ML models. This may improve predictive ability and mitigate potentially harmful attributes such as myopia and human subjectivity that may precipitate asset market bubbles. An alternative theory suggests that current access to data may still not be enough to model all potential outcomes. For example, a model’s predictive ability may be good for examples that are represented in the data on which it was trained, but it may be of minimal or no use for situations that do not appear in data (referred to as “overfit”).¹¹⁸ “Idiosyncratic” or once-in-a-lifetime events—such as COVID-19, for example—may introduce scenarios that were not

¹¹² Mnuchin and Phillips, *A Financial System That Creates Economic Opportunities*, p. 5.

¹¹³ U.S. Department of the Treasury, *Assessing the Impact of New Entrant Non-Bank Firms on Competition in Consumer Finance Markets*, November 2022, p. 88, <https://home.treasury.gov/system/files/136/Assessing-the-Impact-of-New-Entrant-Nonbank-Firms.pdf>.

¹¹⁴ U.S. Department of the Treasury, *Assessing the Impact of New Entrant Non-Bank Firms*, p. 88.

¹¹⁵ OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 40; and Gensler and Bailey, *Deep Learning and Financial Stability*, p. 23.

¹¹⁶ OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 40.

¹¹⁷ See CRS In Focus IF10700, *Introduction to Financial Services: Systemic Risk*, by Marc Labonte.

¹¹⁸ OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 55.

represented in training data and for which models cannot account.¹¹⁹ This could cause some AI/ML model performance to “change or deteriorate.”¹²⁰

In addition, models created using the same data sets may reach the same or similar insights, informing the collective investment decisions and encouraging similar behavior in large portions of the investment community.¹²¹ Errors, risks, and unrepresentative conditions in the data would be propagated across the system, potentially fostering systemic risks.

Herding Behavior

Herding refers to an investment behavior wherein, for an array of reasons, investors may copy the behavior and strategy of other investors, moving markets as a result and creating risk. Literature suggests that herding has exacerbated previous financial crises and is not a new feature of finance created by AI/ML.¹²² However, commentators (including regulators) suggest that herding is a key risk inherent in use of AI/ML.¹²³ Herding manifests itself through AI if a number of market participants use the same or sufficiently similar algorithms, models, or data sets, creating homogeneity in the market or one-way markets.¹²⁴ This may occur when firms (knowingly or not) use the same third-party provider or an “off the shelf” model employed by others or if an AI/ML vendor’s technology encourages the same activity among all clients.¹²⁵ Herding could create illiquidity or price spikes if there are not enough other market participants to take the opposite trade, which may be exacerbated in periods of stress and when financial conditions change.

A related challenge may be that individuals capable of creating or managing systems may be concentrated in a relatively few institutions, which may drive an over-reliance on third-party vendors, comparable to other services, such as cloud computing.¹²⁶ As in other areas with a limited number of providers, concentration of third-party service providers and models may pose risk in the event of technical or other failure of the intermediary.

There are some laws and regulations governing financial institutions’ use of third-party service providers, although these are not necessarily aimed at curtailing the risks of herding. For example, depository banks that rely on third-party service providers—particularly those that provide financial AI/ML services—must ensure that these vendors satisfy safety and soundness regulatory requirements under the Bank Services Company Act (P.L. 87-856). According to bank

¹¹⁹ See OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 56; and Alloway, Weisenthal, and Webb Carey, “Bridgewater’s Greg Jensen Explains How the World’s Biggest Hedge Fund Is Investing in AI” for various discussions of the issue.

¹²⁰ David Bholat, Mohammed Gharbawi, and Oliver Thew, “The Impact of Covid on Machine Learning and Data Science in UK Banking,” Bank of England, December 18, 2020, <https://www.bankofengland.co.uk/quarterly-bulletin/2020/2020-q4/the-impact-of-covid-on-machine-learning-and-data-science-in-uk-banking>.

¹²¹ See Gensler and Bailey, *Deep Learning and Financial Stability*, p. 3; and OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance* for general challenges surrounding data.

¹²² Sushil Bikhchandani and Sunil Sharma, “Herd Behavior in Financial Markets,” *IMF Staff Papers*, vol. 47, no. 3 (2001), <https://www.imf.org/external/pubs/ft/staffp/2001/01/pdf/bikhchan.pdf>.

¹²³ See, for example, Gary Gensler, “Isaac Newton to AI,” remarks before the National Press Club, Securities and Exchange Commission, July 17, 2023; and CNBC Television, “SEC Chair Gary Gensler: AI is the Most Transformative Technology of Our Time.”

¹²⁴ OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 40. *One-way market* refers to a market in which market participants overwhelmingly favor one side of a market or trade—for example, overwhelmingly being long such that there is little appetite to sell.

¹²⁵ Gensler, “Isaac Newton to AI;” and OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 42.

¹²⁶ OECD, *OECD Business and Finance Outlook 2021: AI in Business and Finance*, p. 40. For similar challenges in cloud computing, see CRS In Focus IF11985, *Bank Use of Cloud Technology*, by Paul Tierno.

regulators' guidance, a bank's "use of third parties does not diminish its responsibility to meet these requirements to the same extent as if its activities were performed by the banking organization in-house."¹²⁷ Similarly, LabCFTC, the technology-focused division of the Commodity and Futures Trading Commission (CFTC), stipulated in a primer document that CFTC-regulated firms remain responsible for any services performed by third-party service providers of AI.¹²⁸

Flash Crashes

Flash crashes are sudden, substantial declines in financial markets, including equity indices, individual stocks, or government securities. One potential cause is when a programmatic error induces panic selling by a large number of asset holders in a short period of time, which can destabilize financial markets, at least temporarily.¹²⁹ Panic selling is not a new phenomenon, but the signal processing and automated and recursive nature of the technology used in contemporary trading may instigate or exacerbate the associated risks.

One specific flash crash that occurred on May 6, 2010, attracted significant attention. The flash crash involved traders using technology and algorithms that resembled current or past AI/ML technology discussed in this report (programs following explicit commands, operating without the direct oversight of humans, occurring at speeds significantly faster than those at which humans operate, and based in some cases exclusively on market conditions) and identifies several distinct AI/ML-related risks. According to certain reports, the 2010 flash crash was sparked in part by a spoofing algorithm employed by a British trader in a futures contracts market that drove the price of the market lower.¹³⁰

In addition, automated execution algorithms were programmed to execute trades based strictly on previous levels of volume traded in the market. Transactions that day triggered selling by the automated traders that initiated a feedback loop among other agents using algorithmic agents, which drove prices down quickly. Thus the ever present concern of panic selling *may be* exacerbated when unrelated automated models interact with each other. Flash crashes are a microcosm of various AI/ML-related risks, including herding—represented by high frequency traders (HFTs) engaging in similar actions—and a lack of explainability, as various participants were not prepared for the outcome. (HFTs trade securities using sophisticated computers to execute trades in micro- or milliseconds.¹³¹)

Market Manipulation

Market manipulation occurs when an individual or firm tries to influence the supply of or demand for a security. It traditionally comes in a variety of forms, including "pump and dump" schemes in which someone engages in a series of securities transactions to make a security seem more

¹²⁷ Federal Reserve, Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency, *Interagency Guidance on Third-Party Relationships: Risk Management*, June 7, 2023, p. 1, <https://www.federalreserve.gov/supervisionreg/srletters/SR2304a1.pdf>.

¹²⁸ LabCFTC, *A Primer on Artificial Intelligence in Financial Markets*, 2019, downloads directly at https://www.cftc.gov/media/2846/LabCFTC_PrimerArtificialIntelligence102119/download.

¹²⁹ See a discussion of the 2010 flash crash in CRS Report R44443, *High Frequency Trading: Overview of Recent Developments*, by Rena S. Miller and Gary Shorter; and SEC and CFTC, *Findings Regarding the Market Events of May 6, 2010: Reports of the Staffs of the CFTC and SEC to Joint Advisory Committee on Emerging Regulatory Issues*, September 30, 2010, p. 10, <https://www.sec.gov/files/marketevents-report.pdf>.

¹³⁰ U.S. Department of Justice, "Futures Trader Pleads Guilty to Illegally Manipulating the Futures Market in Connection with 2010 'Flash Crash,'" press release, November 9, 2016, <https://www.justice.gov/opa/pr/futures-trader-pleads-guilty-illegally-manipulating-futures-market-connection-2010-flash>. See SEC and CFTC, *Findings Regarding the Market Events of May 6, 2010*, p. 10. The OECD includes this as a case study in collusion in OECD, *Algorithms and Collusion: Competition Policy in the Digital Age*, 2017, p. 25, <https://www.oecd.org/daf/competition/Algorithms-and-collusion-competition-policy-in-the-digital-age.pdf>.

¹³¹ For more information on high-frequency trading, see CRS Report R44443, *High Frequency Trading: Overview of Recent Developments*, by Rena S. Miller and Gary Shorter.

actively traded than it is.¹³² ML techniques that aim to improve profit maximization may inadvertently lead to market manipulation. Academic studies indicate that autonomous AI agents may—in an effort to optimize profitability—learn ways to manipulate markets without involving input from a developer.¹³³ Some manipulative tactics that AI/ML may perpetuate include “spoofing” and “pinging,” both of which are intended to learn certain information about a market and use it to participants’ advantage.¹³⁴ While human traders generally would and should know that these manipulative actions are illegal, AI/ML models may not know, or they may otherwise ignore the prohibition. Additionally, LLMs (and generative AI) may be used to create images or text to fabricate news stories that could move markets in a way that could prove beneficial for certain transactions.¹³⁵ Securities, commodities, and derivatives markets are governed by laws that prohibit market manipulation.¹³⁶ Therefore, manipulation would be considered illegal, regardless of the technology used to perpetrate it.

Conflicts of Interest

AI/ML may create conflicts of interest between firms using the technology and their customers. As with market manipulation, AI agents that are programmed to learn on their own could conceivably maximize benefits to a firm by taking advantage of the firm’s own clients. Combined with a lack of explainability and the complexity of large financial operations in general, this could create scenarios in which a conflict of interest is just another inexplicable variable in a large model.

Various securities laws and regulations are intended to protect customers from such conflicts of interest. Regulation Best Interest and the Investment Advisory fiduciary standards, established under the Investment Advisers Act of 1940, for example, oblige advisors to act in their clients’ best interest and not put their own interests ahead of their clients’ interests.¹³⁷ Additionally, the Securities and Exchange Commission (SEC) proposed a rule that would require firms to identify conflicts of interest that may arise from firms using “predictive data analytics” tools and related technologies and neutralize any such conflicts associated with predictive analytics

¹³² Securities and Exchange Commission, “Market Manipulation,” <https://www.investor.gov/introduction-investing/investing-basics/glossary/market-manipulation>.

¹³³ Takanobu Mizuta, “Can an AI Perform Market Manipulation at Its Own Discretion? A Genetic Algorithm Learns in an Artificial Market Simulation,” 2020 IEEE Symposium Series on Computational Intelligence, 2020, <https://ieeexplore.ieee.org/document/9308349>.

¹³⁴ Azzutti, Ringe, and Stiehl, “Machine Learning, Market Manipulation, and Collusion on Capital Markets,” p. 99. *Spoofing* refers to a trader initiating a large buy order (thus driving market price for a security higher), and placing a sell order at the higher price while cancelling the false buy order, thereby capitalizing on the sale at the elevated price. *Pinging* involves submitting an order into the market with the intention of determining participants’ intention of selling large quantities in the future and then selling prior to such large sales moving the markets down. For a diagram, see LabCFTC, “A Primer on Artificial Intelligence in Financial Markets.” See also Greg Scopino, “The Questionable Legality of High-Speed ‘Pinging’ and ‘Front Running’ in the Futures Markets,” Columbia Law School, May 29, 2014, <https://clsbluesky.law.columbia.edu/2014/05/29/the-questionable-legality-of-high-speed-pinging-and-frontrunning-in-the-futures-markets/>.

¹³⁵ Gillian Tett, “Investors Must Beware Deepfake Market Manipulation,” *Financial Times*, June 8, 2023, <https://www.ft.com/content/7b352945-9295-42f5-a5d1-a01edf48ba51>.

¹³⁶ See, for example, 15 U.S.C. §78i and 18 U.S.C. §1348.

¹³⁷ Securities and Exchange Commission, “Staff Bulletin: Standards of Conduct for Broker-Dealers and Investment Advisers,” August 3, 2022, <https://www.sec.gov/tm/iabd-staff-bulletin-conflicts-interest>.

technologies.¹³⁸ Some market participants have criticized the proposed rule, claiming the SEC’s definition of the technology is too broad.¹³⁹

Supervisory Technology

Financial market regulators and supervisors may also use AI/ML-driven technology to oversee companies in their jurisdiction. According to the Financial Stability Board, various drivers are precipitating the development and use of supervisory technology (i.e., “suptech”), including enhanced efficiency (the ability to demand, store, and analyze large quantities of digital data); real-time data analysis; and “pro-active” and “forward-looking” supervision and surveillance.¹⁴⁰ Supervisors may use NLP to manage and synthesize unstructured data and for sentiment and network analysis, among other uses.¹⁴¹

In testimony before the House Committee on Financial Services Task Force on Artificial Intelligence, an official from the Office of the Comptroller of the Currency addressed the agency’s initiative of upgrading “core supervision systems ... evaluating and exploring use of ... technologies, including AI,” and hiring and retaining staff with expertise.¹⁴² The Federal Deposit Insurance Corporation also noted in its 2022-2026 strategic plan that it will expand its own use of suptech over the coming years, including ML.¹⁴³

Market regulators such as the CFTC and SEC have begun using deep learning tools to detect market manipulation and money laundering. In its primer on AI, the CFTC has suggested it could leverage AI to identify risk, perform market and risk surveillance, and identify market manipulation and abuse.¹⁴⁴ It has also suggested employing AI to evaluate the troves of data to which it has access—including from registrants, clearinghouses, and public data—and to perform systemic monitoring in ways that *may* forestall crises.

Similarly, the SEC purportedly first used NLP to determine whether it should have predicted the financial crisis and has reportedly incorporated AI into several of its risk assessment programs.¹⁴⁵ The SEC’s use of NLP has evolved, and it has since begun using a form of unsupervised learning capable of reading documents, extracting insight, and identifying themes. Likewise, the agency uses these insights to train other models using supervised learning. The SEC claims that these methods combined may help it determine the likelihood of possible fraud when it reviews documents. According to the SEC and based on back-testing analysis, algorithms are five times

¹³⁸ SEC, “Conflicts of Interest Associated with the Use of Predictive Data Analytics by Broker-Dealers and Investment Advisers,” 88 *Federal Register* 53960, August 9, 2023, <https://www.federalregister.gov/documents/2023/08/09/2023-16377/conflicts-of-interest-associated-with-the-use-of-predictive-data-analytics-by-broker-dealers-and>.

¹³⁹ Sidley, “SEC Proposes Sweeping New Rules on Use of Data Analytics by Broker-Dealers and Investment Advisers,” press release, August 8, 2023, <https://www.sidley.com/en/insights/newsupdates/2023/08/sec-proposes-sweeping-new-rules-on-use-of-data-analytics-by-broker-dealers-and-investment-advisers>.

¹⁴⁰ Financial Stability Board, *The Use of Supervisory and Regulatory Technology*, p. 5.

¹⁴¹ Kenton Beerman, Jeremy Prenio, and Raihan Zamil, “Suptech Tools for Prudential Supervision and Their Use During the Pandemic,” Bank for International Settlements, December 2021, pp. 2, 11, <https://www.bis.org/fsi/publ/insights37.pdf>.

¹⁴² Statement of Kevin Greenfield, Deputy Comptroller for Operational Risk Policy, OCC, before the Task Force on Artificial Intelligence, Committee on Financial Services, May 13, 2022, <https://www.occ.gov/news-issuances/congressional-testimony/2022/ct-occ-2022-52-written.pdf>.

¹⁴³ Federal Deposit Insurance Corporation, *2022-2026 Strategic Plan*, December 14, 2021, p. 19, <https://www.fdic.gov/news/board-matters/2021/2021-12-14-notice-sum-d-fr.pdf>.

¹⁴⁴ LabCFTC, *A Primer on Artificial Intelligence in Financial Markets*.

¹⁴⁵ Scott W. Bauguess, “The Role of Big Data, Machine Learning, and AI in Assessing Risks: A Regulatory Perspective,” SEC, June 21, 2017, <https://www.sec.gov/news/speech/bauguess-big-data-ai>.

better than random at identifying language that may indicate whether an investment advisor could merit enforcement referral.¹⁴⁶ After the flash crash in 2010, the SEC imposed requirements on national securities exchanges and the Financial Industry Regulatory Authority to “create, implement, and maintain” a consolidated audit trail (CAT) that could provide additional opportunities for AI-enabled suptech.¹⁴⁷ The CAT requires national securities exchanges, associations, and members to report various details of orders, providing the SEC with additional details and still more data, which it will use to improve market surveillance and likely use to develop, train, test, and then implement still newer models. Therefore, CAT was a product of a flash crash that was arguably the result of AI/ML-like technology and is expected to serve as a tool for the SEC to keep pace with various risks, including those from AI.¹⁴⁸ The extent to which market regulators are able to keep pace with the technologies used by regulated entities—and to develop their own techniques to manage the large quantities of data—may depend in part on how Congress evaluates their use and investments in such technologies.

Big Tech in Finance

Companies with large repositories of information may be poised to reap the benefits of that data and the models they may sustain. Big tech companies—technology-based businesses of considerable scale that have played a substantial role in transforming the internet economy, attracting billions of users—have large repositories of data and are developing their own AI models and products.¹⁴⁹ They have the financial capacity to make the necessary IT investments and may be best situated to capitalize on this investment by selling access to certain products or services.¹⁵⁰ This would represent a further consolidation of data and model creation and reinforce third-party dependency, potentially exacerbating concentration or systemic risk.

Another policy issue of the central role of data is that it may also create opportunities for big tech to increase its presence in financial services. Big tech companies currently have some presence in finance, mostly on the consumer products side. Their ability to accumulate and process data and AI/ML capabilities could make this transition easier, which would raise issues about regulatory arbitrage, as they are subject to uneven regulation for financial services. Separately, big-tech-related data privacy and a concentration of economic activity could be exacerbated if they successfully expand their presence in financial markets. For more information on this issue area, see CRS Report R47104, *Big Tech in Financial Services*, by Paul Tierno.

AI/ML and Financial Industry Employment

Since its origins, AI/ML has led to fears that it would disrupt the job market by replacing humans who were performing the jobs that would be automated. Some unsubstantiated recent projections suggest AI/ML may lead to a loss of 300 million jobs by 2035 across sectors.¹⁵¹ Research on the

¹⁴⁶ Bauguess, “The Role of Big Data, Machine Learning, and AI in Assessing Risks.”

¹⁴⁷ 17 C.F.R. §242.613.

¹⁴⁸ Commissioner Caroline A. Crenshaw, “Statement Regarding the Order Approving an Amendment to the National Market System Plan Governing the Consolidated Audit Trail,” SEC, September 6, 2023, <https://www.sec.gov/news/statement/crenshaw-statement-cat-funding-090623>.

¹⁴⁹ For more information, see CRS Report R47104, *Big Tech in Financial Services*, by Paul Tierno. *Big tech* typically refers to Alphabet (Google), Amazon, Apple, Meta, (formerly Facebook), and Microsoft.

¹⁵⁰ Gensler and Bailey, *Deep Learning and Financial Stability*, p. 23.

¹⁵¹ Tracy Alloway, “Job Cuts from AI Are Just Beginning, the Latest Challenger Report Suggests,” *Bloomberg*, June 1, 2023, <https://www.bloomberg.com/news/articles/2023-06-01/job-cuts-from-ai-are-just-beginning-the-latest-challenger-report-suggests>.

impact of past technological advances on jobs has been mixed. Broadly speaking, economists generally think that automated technologies replaced routine jobs but that those job losses can be offset by gains in other industries or by new jobs actually created by new technologies.¹⁵² The overall effect is often described as technologies having eliminated middle-income jobs and increased the portion of jobs that are either low or high paying.¹⁵³ Recent advances in AI/ML—including most recently of LLMs, such as ChatGPT—may increasingly challenge the conventional wisdom that white-collar jobs are safe from automation while only routine jobs and manual labor would be replaced. Instead, it is now widely believed that certain jobs requiring higher education may be at risk, including those in finance.¹⁵⁴

Use of AI/ML in finance seems poised to perpetuate the traditional dichotomy: that it will both boost and reduce demand for different types of workers. The AI/ML boom is expected to increase financial institution demand and competition for workers with AI/ML-specific skills.¹⁵⁵ One 2022 report suggested there may be as many as 100,000 AI/ML and related roles in banking and other financial institutions globally.¹⁵⁶ Whether or to what degree the technology will replace workers is up for debate, and it may be uneven across sectors. A 2023 survey of bank employees found that only 21% of those surveyed believed AI will replace many jobs in the banking industry, while 75% believe AI will change the nature of jobs but not replace human workers.¹⁵⁷ A slightly higher but similar number of global banking chief executives expect generative AI, in particular, to lead to a reduction of at least 5% in headcount in 2024.¹⁵⁸ Academic reports and empirical reviews also find that some financial services companies—such as asset management, in particular—have experienced job cuts and are likely to experience the largest number of job cuts in the near future.¹⁵⁹

Conclusion

As financial industry policymakers focus their attention on AI/ML in finance, they face competing pressures. Certain financial service providers and technology companies will tout the potential for AI/ML to lower costs, increase speed and accessibility, and improve accuracy and

¹⁵² For a literature review of technology’s impact on employment, see F. Ted Tschang and Esteve Almirall, “Artificial Intelligence as Augmenting Automation: Implications for Employment,” *Academy of Management Perspectives*, vol. 35, no. 4 (2021), p. 6, https://ink.library.smu.edu.sg/lkcsb_research/6669.

¹⁵³ Tschang and Almirall, “Artificial Intelligence as Augmenting Automation,” p. 6.

¹⁵⁴ Annie Lowrey, “How ChatGPT Will Destabilize White-Collar Work,” *The Atlantic*, January 20, 2023, <https://www.theatlantic.com/ideas/archive/2023/01/chatgpt-ai-economy-automation-jobs/672767/>.

¹⁵⁵ William Shaw, “Wall Street Banks Are Poaching Rival AI Talent,” *Bloomberg*, November 28, 2023, <https://fortune.com/2023/11/28/goldman-sachs-ai-employees-wall-street/>.

¹⁵⁶ Joy Macknight, “Why Talent Is Critical to the AI Revolution,” *The Banker*, June 27, 2023, <https://www.thebanker.com/Why-talent-is-critical-to-the-AI-revolution-1687855797>. This article uses the term *banks*, *financial institutions*, and *payment providers* when discussing this topic.

¹⁵⁷ Claire Williams, “Will the Uncertainty Continue for Financial Institutions?,” *American Banker*, December 13, 2023, <https://www.americanbanker.com/research-report/will-the-uncertainty-continue-for-financial-institutions>. Respondents to the survey were 65% banks or credit unions. The remaining 35% were fintechs, tech vendors, payments companies, and other companies.

¹⁵⁸ Sam Fleming, “Generative Artificial intelligence Will Lead to Job Cuts This Year, CEOs Say,” *Financial Times*, January 15, 2024, <https://www.ft.com/content/908e5465-0bc4-4de5-89cd-8d5349645dda>.

¹⁵⁹ Bartram, Branke, and Motahari, “Artificial Intelligence in Asset Management,” p. 2. In 2017, asset manager BlackRock announced a restructuring in which it eliminated roles of key stock pickers, choosing to replace them with algorithms and other models. See Amie Tsang, “Morning Agenda: The Robots Are Coming ... for Your Stocks,” *New York Times*, March 29, 2017, <https://www.nytimes.com/2017/03/29/business/dealbook/blackrock-fink-stocks-trading.html>.

regulatory compliance. Consumer advocates and smaller firms may oppose adoption on the grounds that it introduces bias, risk, and potential for manipulation; eliminates jobs; and is unaffordable. Policymakers may decide to balance these competing priorities while assessing whether the existing regulatory structure is sufficient or whether one that is more closely tailored to the technological capacities of the evolving technology is necessary. Any legislative proposals considered by Congress will be evaluated by industry and consumers on whether it will lead to fair outcomes, not dampen the environment for innovation, and be based on quantifiable concerns but adaptable to future technology.

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