TECHNICAL

NOTES & MANUALS

Regulatory Considerations Regarding Accelerated Use of AI in Securities Markets

Xiang-Li Lim, Puja Singh, and Richard Stobo

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Abbreviations

AEs	advanced economies
AI	artificial intelligence
ChatGPT	Chat Generative Pre-Trained Transformer
EMDEs	emerging market and developing economies
ESMA	European Securities and Markets Authority
FCA	Financial Conduct Authority
FSB	Financial Stability Board
GenAI	generative artificial intelligence
HFT	high-frequency trading
IOSCO	International Organization of Securities Commissions
IT	information technology
ML	machine learning
SEBI	Securities and Exchange Board of India
SEC	Securities and Exchange Commission
SME	small and medium-sized enterprises

I. Introduction

Capital markets play a significant role in the global economy, facilitating the exchange of financial securities, enabling economic growth, and driving technological innovation. Although most incremental technological advances have played a role in transforming financial markets, the rise of artificial intelligence (AI) has the potential to alter the landscape in new and significant ways.[1] AI can analyze vast amounts of data, identify patterns, and make rapid decisions. This is driven by a larger volume of available data, cheaper and more easily accessible computing power and cloud storage, more advanced algorithms, greater investment in AI companies, and the availability of open-source AI platforms. Moreover, increasing integration of AI use cases is influencing many aspects of capital markets, including portfolio management, trading and investment strategies, investment advisory services (such as the emergence of robo-advisors), client interfaces, and risk management. AI applications have a long history in finance. Much of what is categorized as AI in finance is not technically new; similar methods have long existed as statistical or econometric modeling techniques. There are multiple AI use cases across global capital markets, with varying degrees of adoption. Although some overlap with the banking and insurance sectors, such as risk management, capital market use cases are significantly more extensive across the entire ecosystem, including intermediaries and customer interactions, such as robo-advisory, asset management, trade execution, post-trade settlement, trade anomaly detection, and crowdfunding. Meanwhile, AI use cases like client-facing bots need to take into account the fiduciary nature of the relationship between the intermediary and investor/client that is typically found in capital markets.

As AI-based tools continue to evolve and add complexity to the underlying models, understanding their role in capital markets becomes crucial for financial market supervisors. More importantly, integrating AI models into various capital market processes also requires measures to ensure regulatory compliance and data privacy, prevent overreliance on algorithms, and adequately address risks of increased market volatility.[2]

Increased AI adoption may lead to the concentration of systems and models among key players, such as entities that provide capital market infrastructure or systemically important financial institutions offering multiple financial services.[3] Consequently, such situations require close market monitoring to ensure that AI developments and potential risks are well understood by financial sector authorities and given due consideration when adjusting or developing regulations and supervisory frameworks. However, the adoption of AI techniques remains highly heterogeneous across jurisdictions. As a result, the direction, timing, and overall magnitude of AI's effect on financial systems remain uncertain and will likely vary across countries, depending on each country's regulatory capacity and stage of capital market development.

1 Artificial intelligence (AI) lacks a standard, unanimously agreed-upon definition and is rather a blanket term used to determine a broad set of methods that facilitate problem-solving via an amalgamation of statistics and computer science. Although no single definition of AI exists, international and supranational bodies have adopted broadly similar definitions in recent years. Both the Organization of Economic Cooperation and Development (OECD 2024) and Financial Stability Board (FSB 2024) define an AI system as "a machine-based system that for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments." The International Organization of Securities Commissions (IOSCO 2021) defines AI as "the science and engineering of making intelligent machines, or simply, the study of methods for making computers mimic human decisions to solve problems."

2 The application of AI techniques in algorithmic and high-frequency trading can potentially increase market volatility and create bouts of illiquidity or even flash crashes (IMF 2024b).

3 This could include, for example, a large bank offering robo-advisory, asset management, and algorithmic trading services.

This technical note takes stock of the uptake of AI in securities markets and of approaches to its regulation and supervision. In this context, the note seeks to complement ongoing work by the International Organization of Securities Commissions (IOSCO), other standard-setting bodies, and initiatives within the IMF.[4] It provides a broad overview of the rapid spread of AI across financial services, the increasing shift to generative AI, and the risks stemming from its rapid adoption. The IMF (IMF 2023) has notably raised concerns about various risks, including data-related risks (privacy and bias), performance risks (robustness, synthetic data, and explainability), new cybersecurity threats (data manipulation attacks), and broader risks to financial stability.[5] Although the technology holds some promise for the financial sector, adoption should be approached with caution, because its inherent risks could undermine the financial sector's reputation and soundness.

The technical note sheds light on how authorities have sought to address these challenges by providing an overview of regulatory and supervisory developments and trends. This includes a stock take of regulatory and supervisory guidance on the use of AI in capital markets from standard setters and other international forums, as well as authorities in advanced economies (AEs) and emerging market and developing economies (EMDEs). An important area of interest is examining the extent to which developments in EMDEs differ from or are similar to those in AEs and outlining specific challenges and recommendations for authorities in EMDEs. Although the paper compares AEs and EMDEs, it is important to recognize that the latter group is both vast and extremely diverse in terms of technology adoption and capacity. The conclusions drawn are, therefore, necessarily broad and should not mask the fact that, by some metrics, some EMDEs are more advanced than AEs in this area. Similarly, there may be cases in which the disparity between low-income countries and the most advanced EMDEs is much larger than between those EMDEs and AEs.

Finally, the technical note summarizes key takeaways from the adoption of AI in capital markets and the regulatory and supervisory responses thus far. It identifies practices that authorities could usefully consider adopting as part of their supervisory frameworks as they seek to confront the challenges posed by AI while also leveraging AI capabilities in the context of limited resources, particularly for some regulatory authorities in EMDEs.

4 For example, a departmental paper (IMF 2021) discusses potential AI risks for the financial sector, a fintech note (IMF 2023) highlights risk considerations for the use of generative AI in finance, while the October 2024 Global Financial Stability Report (IMF 2024a) highlights the potential financial stability implications for the use of AI in capital markets activities, with focus on developments in AEs.

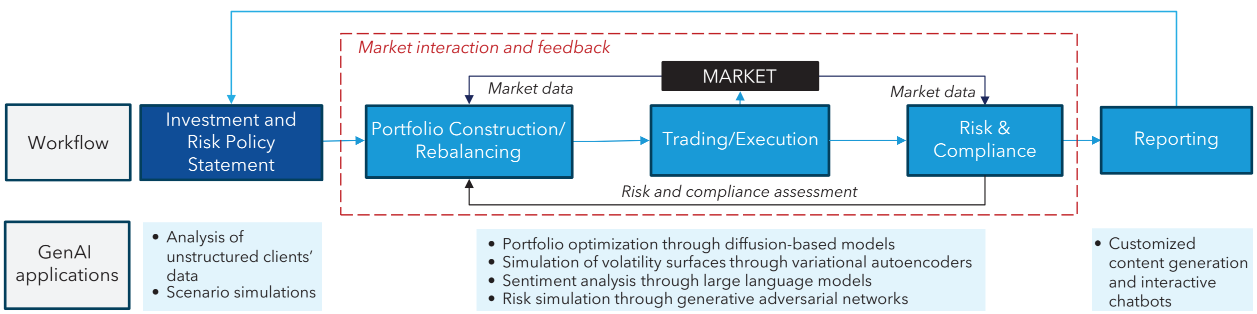
5 Financial stability risks include the increased homogeneity in risk assessments and credit decisions, while out-of-sample risks, in conjunction with interconnectedness, may foster conditions conducive to the accumulation of systemic risks (IMF 2023). Additionally, the emergence of generative AI introduces new concerns, such as herd mentality bias, mispricing risks, hallucinations, and potential solvency and liquidity challenges, as well as the threat of data manipulation attacks.

II. AI Adoption in Capital Markets

The use of machine learning (ML) in capital markets is not new. Algorithmic trading has been in place for several decades. Recent developments in generative artificial intelligence (GenAI) are starting to affect how capital market entities conduct their business. This applies throughout the investment process (Figure 1), such as the use of alternative data sets and the development of forward-looking indicators by buy-side firms. Meanwhile, sell-side institutions are using AI for risk assessment, pricing, and forecasting. Across the broader financial services industry, firms are increasing AI investments to enhance internal operations, improve efficiency, boost productivity by reducing costs, and enhance client experience (IMF 2021). A recent consultation report by the International Organization of Securities Commissions (IOSCO) highlights that financial services firms are leveraging GenAI and large language models primarily for internal applications, such as task automation, productivity enhancement through chatbots, and improved risk management, rather than for customer-facing purposes (IOSCO 2025a). Similarly, the CFA Institute (2024b) found that 35 percent of investment professionals are already using AI tools like ChatGPT in their workflows. This approach emphasizes operational efficiency and risk mitigation.

Figure 1. Recent and Potential Use Cases of GenAI in Investment Process

The advent of GenAI has potential benefits throughout the workflow of a capital market participant.



Sources: CFA Institute; IMF 2024a, Chapter 3; and IMF staff compilation.
Note: The figure presents some recent and potential examples of GenAI use cases across investment decision, execution, and monitoring processes but is not exhaustive of all possible use cases, as adoption continues to evolve. GenAI = generative artificial intelligence.

Outreach conducted with financial institutions, both buy-sides and sell-sides (IMF 2024a), indicates that most current use of AI in capital market activities appears to be an extension of existing trends in the use of other advanced analytical tools. More significant changes are anticipated in the medium-to-long run. The consensus view is that AI adoption will continue at pace and expand further across firms' business lines and activities, with a corresponding consideration of new risks (IMF 2023), thereby underlining the importance of an increased focus on AI among securities market regulators.

Capital market players have begun adopting AI (IMF 2024a). Labor market data, patent filings, and stakeholder outreach, all suggest that institutions are rapidly gearing up for significant integration of these technologies. Concerning emerging market and developing economies (EMDEs), in particular, there are five areas where AI adoption is material and could potentially accelerate expansion: asset management, wholesale trading, robo-advisory services, neo-brokerage, and crowdfunding.[6] As discussed further in Section III, specific AI-related trends in these areas—such as the use of alternative and unstructured data sets—pose regulatory challenges.

Finally, financial sector authorities are increasingly looking to integrate AI into their own activities (IMF 2024a). AI offers significant advantages in automated data checks, facilitating the combination of multiple data sources and the detection of anomalies in trading patterns. Central banks have undertaken several initiatives to improve internal operations, such as strengthening nowcasting techniques and evaluating market sentiments derived from unstructured sources (IMF 2023). Nonetheless, adoption rates in capital markets activities, including regulations, vary significantly across AEs and EMDEs, with divergent resource levels being a key factor.

Asset Management[7]

The adoption of AI is still largely at a nascent stage within the broader asset management industry (IMF 2024a). A 2024 survey reveals that a significant number of asset managers have yet to implement AI techniques (Figure 2, panel 1). Among those who have integrated AI, the emphasis has primarily been on research-related applications, such as big data analysis, idea generation, and signal identification, rather than on fully automated AI-driven trade execution or decision-making processes. These survey findings also align with the perceived opportunities associated with AI, as recent estimates indicate that the most substantial benefits are expected to arise in areas such as customer interactions and risk and compliance monitoring, rather than in direct improvements to investment management and trade execution (Figure 2, panel 2).

Nonetheless, AI has the potential to significantly transform asset and portfolio management practices by offering innovative tools for optimizing portfolios, assessing and mitigating risks, and predicting market dynamics. AI-driven tools help asset managers analyze historical data, associated economic indicators, and even geopolitical events, to optimize portfolios and proactively respond to market dynamics. For example, these tools help leverage AI techniques, including deep learning, to identify complex patterns for precise asset allocation.[8]

[6] Another noteworthy use of AI is in the context of pre- and post-trade settlements carried out at the level of brokers, trading platforms, and financial market infrastructures.

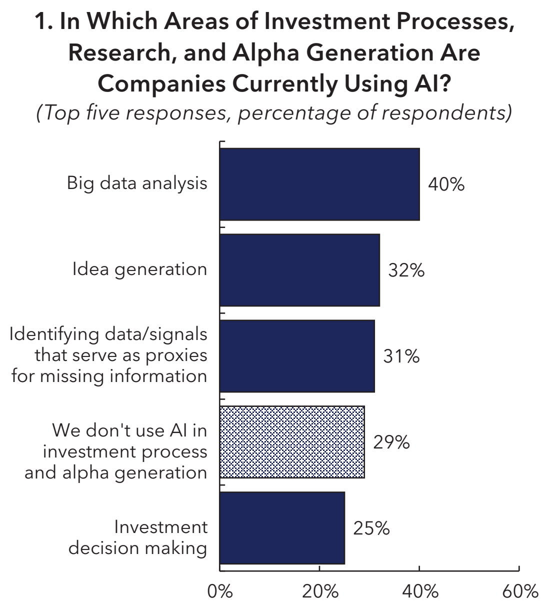
[7] Also referred to as portfolio management or investment advisory in some jurisdictions by securities market authorities. This section is devoted to various AI-enabled tools used by asset managers for discharging their functions and covers both proprietary and third-party tools/service providers.

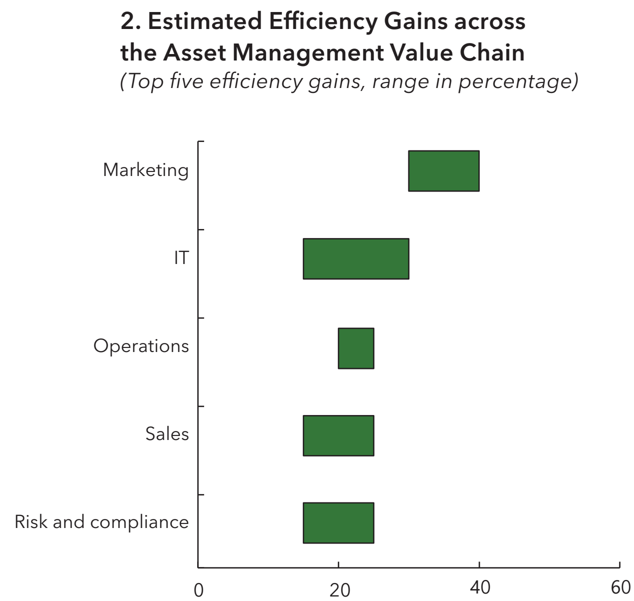
[8] Deep learning is a subfield of ML. Neural networks make up the backbone of deep learning algorithms. The number of node layers, or depth, of a neural network distinguishes it from a deep learning algorithm, which has more than three layers (IBM 2023).

Figure 2. Current State and Potential Benefits of AI Adoption for Global Asset Managers

Although some asset managers have integrated AI techniques, a sizable number have yet to adopt the technology.

AI could benefit asset managers, especially in client-facing tasks such as sales and marketing, and operational tasks.





Sources: BCG 2024; and Mercer 2024.

Notes: Data in panel 1 is from Mercer Investments survey on 150 asset management managers from various asset classes. Estimates in panel 2 are from Boston Consulting Group's analysis. AI = artificial intelligence; IT = information technology.

Notably, asset management decision-making processes can be significantly enhanced by leveraging AI models' capability to identify nonlinear patterns and synthesize unstructured data from diverse sources (The Alan Turing Institute 2023). Recent research highlights various potential applications, including the use of deep learning techniques to refine portfolio policy frameworks (Simon, Weibels, and Zimmermann 2022), genetic programming to minimize model-fitting errors (Liu, Zhou, and Zhu 2020), and ML methods to improve forecasts of expected returns (Kelly, Malamud, and Zhou 2021) and high-frequency returns (Kolm, Turiel, and Westray 2021).

In addition, nonparametric approaches can advance valuation methodologies (Filipovic, Pelger, and Ye 2022), whereas ML techniques can help quantify the risk of sudden crashes by revealing complex nonlinear relationships (Swinkels and Hoogteijling 2022).

The advent of natural language processing technologies has also enabled asset managers to leverage unstructured data. By extracting insights from diverse text sources, such as news articles, research reports, social media posts, and company filings, asset managers can achieve a more nuanced understanding of market sentiment and uncover potential risks associated with investments. Advancements in AI techniques, including convolutional neural networks and optical character recognition,[9] could potentially facilitate the extraction of relevant information from images and documents, broadening the scope of data analysis from these unstructured sources. These technologies, when deployed on public platforms, can uncover and synthesize insights that would otherwise remain hidden, thereby enhancing investment decision-making processes.

GenAI—with its capacity to generate synthetic data, apply deep learning techniques, emulate market scenarios, and enhance investment approaches—holds considerable potential to further transform asset management. An asset manager may employ GenAI tools for various purposes. Such tools may enable the manager to generate hypothetical market scenarios and simulate the effect on portfolio performance and risk parameters. They could potentially generate thematic ideas by processing unstructured data sets for sentiment analysis or keyword searches, using GenAI models built on neural network architectures to identify the most relevant insights. They may also help uncover hidden patterns or "black swan" events that were previously undetected through general-purpose AI tools, offering a distinctive perspective on investment strategies and horizons. In particular, the generative properties of generative adversarial networks[10] have been used to analyze joint probability distributions of asset prices, tuning strategy hyperparameters[11] and modeling synthetic order-book data (Luk 2023). Consequently, asset managers could be better equipped to make real-time adjustments informed by these insights.

Using the acquired knowledge of the manager's style and investment philosophy, GenAI could also be used to devise in-house portfolio optimization strategies, reducing reliance on historical data. GenAI can streamline the coding, testing, validation, and deployment of algorithms that drive trading strategies and risk management frameworks. It also enhances the analytics presented on dashboards, which provide critical insights into portfolio performance and market dynamics.[12] This acceleration in processes could potentially enable asset managers to respond more swiftly to market changes and make informed decisions more quickly than before.

The integration of GenAI into core functions is yet to fully materialize and be deployed at scale. Asset managers need to carry out sufficient due diligence and testing before entrusting core business processes to GenAI tools. The due diligence and testing would be intended to ensure, for example, that the recommendations can be trusted or that the synthetic data generated by the tool, which the manager may intend to use for testing the investment hypothesis, can be relied upon.

[9] A type of feedforward neural network that learns features via filter (or kernel) optimization; often applied to process many different types of data including text, images, and audio and make predictions therefrom. Optical character recognition techniques allow for the extraction and conversion of texts from digital images into a machine-readable format. While the standalone technology may no longer be revolutionary, pairing the technology with AI tools such as natural language processing could allow asset managers to interpret data from unstructured data sources.

[10] A type of deep learning architecture that trains two neural networks to compete against each other to generate more authentic new data from a given training data set.

[11] Hyperparameters are pre-set configurations used to train machine learning models (Luk 2023). Each data set and model requires different sets of hyperparameters, which are determined through multiple experiments and run through the model. This process, which can be manual or automated, is known as hyperparameter tuning.

[12] It is also anticipated that portfolio managers could use GenAI for support in voting during shareholder meetings. Rather than relying on the current news cycle to drive judgment, GenAI could help ascertain which decisions are more likely to augment the long-term share price. Predictive analytics could be integrated to see if dividend payouts should be reinvested with the same company or in another way. Elsewhere, a portfolio manager may begin receiving query responses from an AI "service rep" at their third-party vendors, who could provide proficient answers (Northern Trust 2023).

The extent to which the innovative data-driven activities described earlier can be carried out in a way that leads to appropriate outcomes depends largely on the quality, integrity, and reliability of the underlying data. Lack of data of sufficient quality may increase the risk of poor outcomes for investors from firms' use of AI.

Wholesale Trading

As capital markets develop, trading infrastructure also undergoes various technological enhancements, ranging from the electronification of processes in early-stage markets to the use of AI techniques by more advanced exchanges. Although many trading venues have migrated to electronic platforms, less developed ones still rely on manual order execution, offering opportunities for digitalization to lower costs, speed up transactions, and improve transparency. More advanced exchanges have also adopted sophisticated enhancements, such as execution algorithms and direct market access, to improve order management and reduce reliance on intermediaries and friction.

With the advent of infrastructure enhancement, algorithmic trading is growing and becoming significant in some capital markets. Its development is expected to be influenced by AI advancements (IMF 2024a), notably, AI-driven trading, which is anticipated to thrive in liquid asset classes, such as public equities, because of their transparency and transaction volumes. The increasing sophistication of algorithmic trading strategies and the development of more advanced market infrastructure facilitate trading activities and accelerate information transfer, potentially leading to greater interest in adopting AI techniques in less-liquid asset classes.[13]

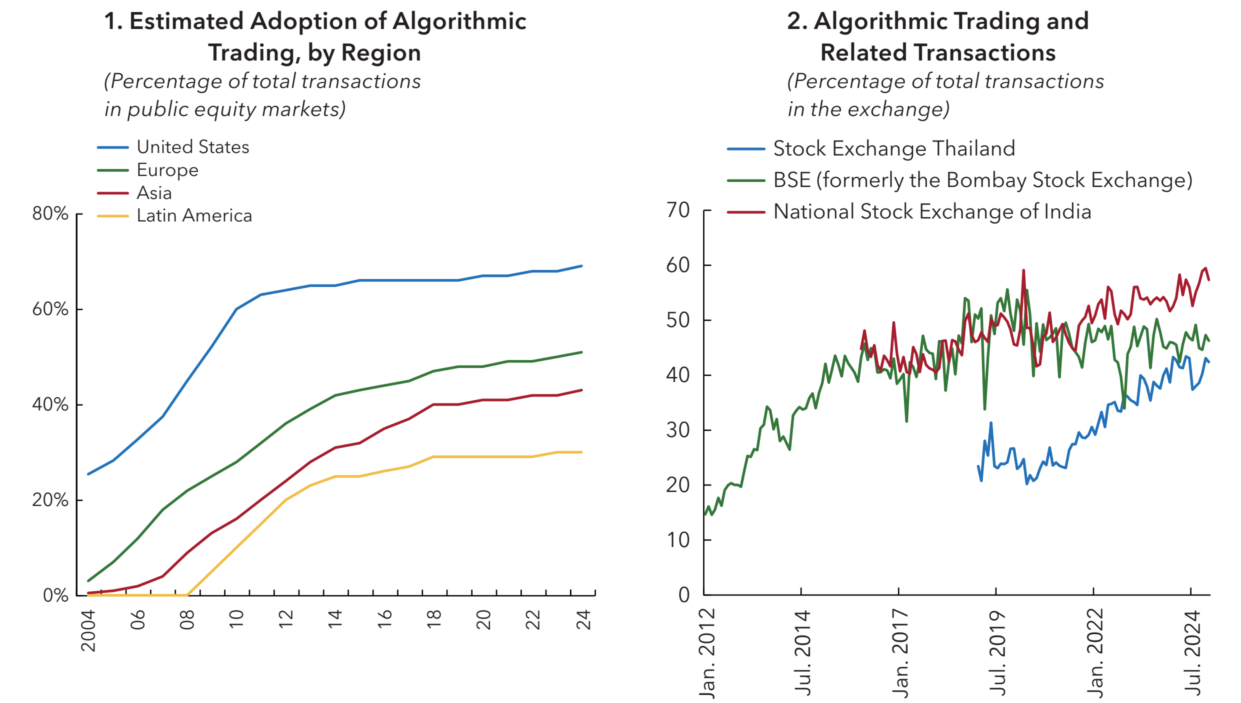
Globally, algorithmic trading activities in public equities are estimated to be led by the United States, but with increasing adoption in other regions (Figure 3, panel 1). In EMDEs, the pace of algorithmic trading adoption varies significantly, both between and within countries (Figure 3, panel 2). This variability indicates that market participants in some exchanges with large and meaningful algorithmic transaction volumes may already be exploring or even implementing AI techniques. The growing use of algorithms in trading may have been spurred by local market development initiatives aimed at improving efficiency, such as the implementation of smart-order routing, direct market access, and colocation facilities.

[13] Examples of market development initiatives include electronification of trading activities, facilitation of high-frequency trading, listing of securities on public exchanges, and bundling of securities into publicly traded exchange-traded funds.

Figure 3. Growth of Algorithmic Trading in Public Equity Markets

Algorithmic trading activities have risen to significant levels, estimated to be 30 percent or higher of total transactions across regions.

For some EMDEs, adoption of algorithmic trading has not only been increasing but also varies by countries and intra-country.



Sources: Datos Insights; local stock exchanges; and IMF staff calculations.

Note: Adoption is measured in transaction value and as a percentage of total transaction value. The figures in panel 1 are estimates as of December 2024. Algorithmic-related transactions for BSE and National Stock Exchange in panel 2 include transactions from participants identified as algorithmic, direct market access, colocation, and smart-order routing.

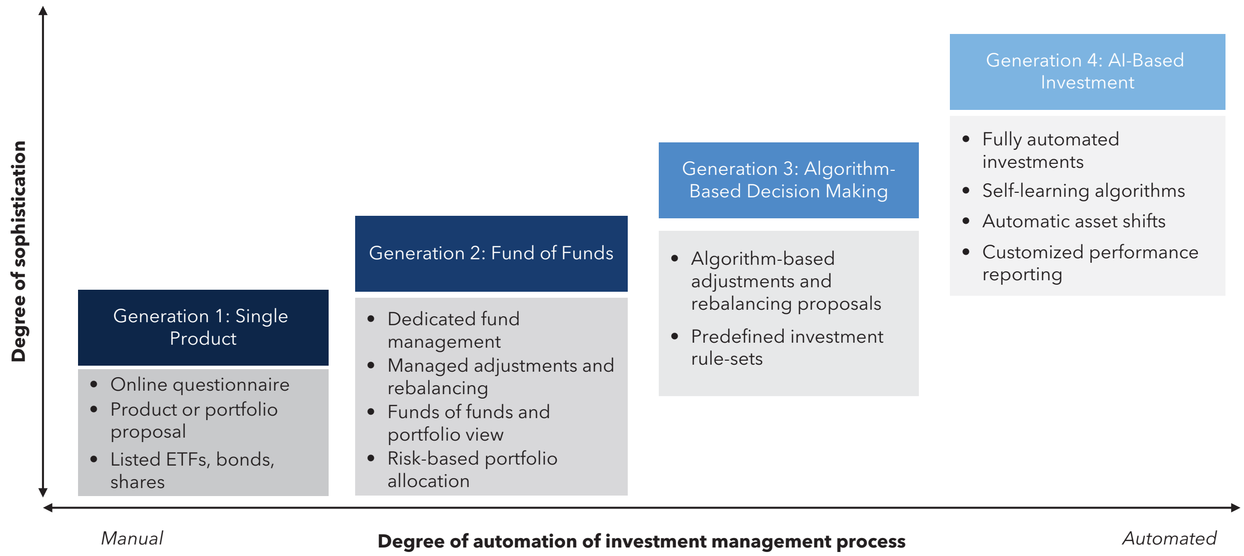
Robo-Advisory Services

Robo-advisors offer personalized financial investment guidance to investors with minimum human intervention. They are typically authorized by financial sector authorities as investment advisors. A client who wishes to use a robo-advisor usually fills out a digital form with their personal and financial information on an interactive platform (such as a website or a mobile app). The robo-advisor may create a portfolio for the client and continue to monitor and adjust the client's account in accordance with mutually agreed, standardized terms and conditions.

Different business models and platforms offer a range of advisory services, tailored to different client types. For instance, some robo-advisors provide investment advice to their clients with little or no human interaction, whereas others have human advisors in the loop who use the interactive platform to create and discuss an investment plan with the client. Robo-advisors also use different methods to gather information from their clients. For example, some use only questionnaires, whereas others obtain information through direct contact or by allowing clients to share information about their other accounts and investments (Figure 4).

Figure 4. Evolution of Robo-Advisory Features

The features and services of robo-advisors have become more sophisticated.



Sources: Deloitte 2016; and Beketov, Lehmann, and Wittke 2018.
Note: AI = artificial intelligence; ETF = exchange-traded fund.

Approaches to investing vary across robo-advisors, with diverse investment styles and product offerings. Although some robo-advisors may offer a suite of predetermined, standardized investment portfolios that they typically recommend to clients without any flexibility or customization, others focus solely on a limited range of investment products, such as broad-based exchange-traded funds.

Robo-advisors use AI tools in several ways. They deploy algorithms for client profiling, investment planning, portfolio design and management, and rebalancing in the most efficient way possible. In addition, they may offer services such as estate planning, insurance, retirement planning, and tax planning.[14] Robo-advisors use AI to automate data collection, eliminating the need for asset managers to spend weeks researching assets. Robo-advisors also rely on AI tools for predicting market trends and identifying new opportunities, as well as pattern recognition and data extraction.

Robo-advisory services can broaden access to financial advisory offerings. Some asset managers quickly realized the potential of software that makes financial advice more accessible, enabling investors to manage their investments with an online interface (Frankenfield 2023).[15] Over the past decade, the robo-advisory industry has experienced substantial growth because of technological advancements in AI that allowed robo-advisors to efficiently analyze large quantities of data; lower their fees even further compared with human financial advisors, thereby broadening access to financial services; and introduce real-time monitoring services and enhance convenience.

[14] A robo-advisor may offer tax-loss harvesting, which is the automated selling of securities in a portfolio to deliberately incur losses to offset any capital gains or taxable income. Many robo-advisors today offer tax-loss harvesting as a standard service.

[15] Betterment and Wealthfront are two examples.

In terms of adoption, the interest in robo-advisory has been increasing globally, led by the United States, and assets under management (AUM) are projected to exceed $2 trillion by 2028.[16] Although adoption in AEs ex-US has been relatively modest by comparison, AUM has grown significantly in recent years (Figure 5, panel 1). At an aggregate level, robo-advisory services have grown in EMDEs at a pace with that in AEs, and when adjusted for total gross national income, EMDEs are at similar levels (Figure 5, panel 2), albeit with a more uneven growth pattern compared with across AEs, reflecting the considerable heterogeneity within the EMDEs.

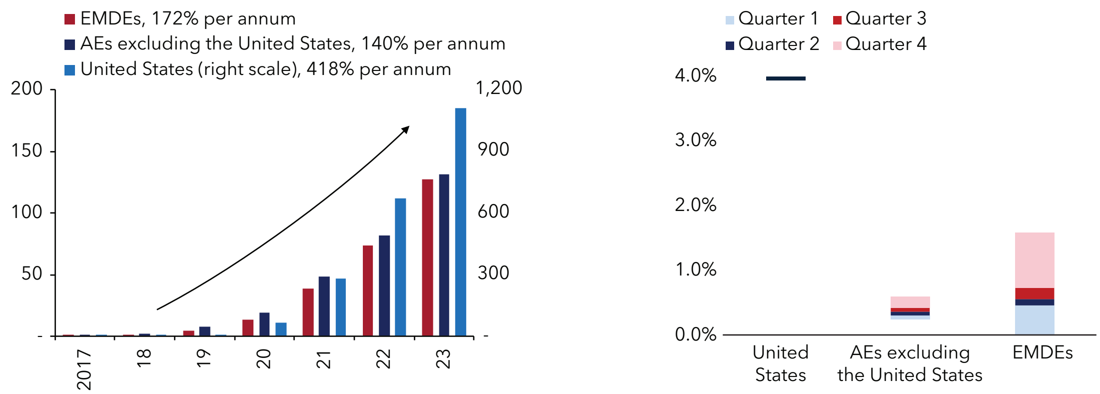
Figure 5. Growth of Robo-Advisory Activities

Although total absolute volume in the United States is many multiples of EMDEs', EMDEs' growth rates are comparable to those of other AEs . . .

. . . although dispersion of adoption as a percentage of GNI in EMDEs is much larger than in AEs given the heterogeneity.

1. Robo-Advisory AUM and Growth
(Billions of US dollars, cumulative annualized growth rate, 2017–23)

2. Distribution of Countries for the United States, AEs excluding the United States, and EMDEs
(2023 AUM as a percentage of GNI)



Sources: Statista Digital Market Insights; World Bank databank; and IMF staff calculations.
Note: Estimated average growth rates are calculated from a nominal AUM growth weighted by the count of countries, from 35 AEs and 114 EMDEs. In panel 2, Q*i* refers to the *i*th quartile of the distribution of countries within AEs and EMDEs. AEs = advanced economies; AUM = assets under management; CAGR = cumulative annualized growth rate; EMDEs = emerging market and developing economies; GNI = gross national income.

Neo-Broking[17]

Retail investors are increasingly turning to neo-broking platforms, which offer user-friendly digital platforms providing low-cost brokerage services, including those offered by neo-banks. By democratizing financial market access through easily accessible online platforms and using personal data for a personalized experience, neo-brokers are well positioned to adopt AI techniques. Consequently, there are growing use cases of AI techniques, particularly for customized portfolio/asset recommendations, personalized user engagement, and fraud detection.[18] Moreover, as order flows become increasingly automated, particularly through high-frequency and algorithmic trading platforms, the trading ecosystem itself is becoming more vulnerable to the influence and potential risks of AI-driven algorithms, which can interact in unpredictable ways and potentially amplify market volatility.

16 The assets under management with robo-advisors refer to the amount of private assets managed by automated online portfolio management and exclude traditional online brokers and human wealth manager advisory. See IMF remarks at the AI for Good Global Summit on May 30, 2024 (IMF 2024b).

17 Neo-brokers, which operate solely digitally and can be accessed via a mobile application or desktop website, use digital onboarding for their clients and typically have no physical presence for services to clients.

18 AI-driven personalization techniques, such as Robinhood's use of machine learning to suggest trades or portfolios, or eToro's AI-based sentiment analysis for social trading.

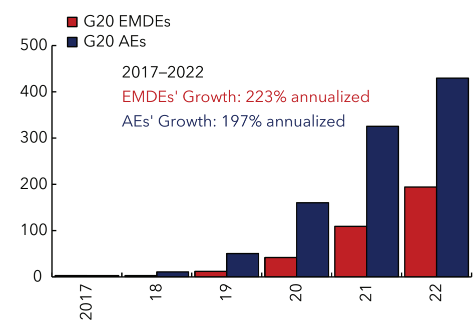
A recent report by IOSCO on neo-brokers highlighted concerns about potential conflicts of interest and the need for solid information technology infrastructure, and recommended that jurisdictions address fee disclosures, advertising practices, client consent for ancillary services, the effect of noncommission revenues on order execution, and information technology system robustness (IOSCO 2025b). Although these concerns are general and pertain to higher operational and cyber risks arising from the growth of digital financial services, they are also highly relevant for ensuring transparency, reliability, and trust in the neo-broker business model itself, in the context of AI adoption.

The AUM held and executed by neo-brokers has been steadily increasing, with EMDEs' growth appearing to be on par with AEs from 2017 to 2022 (Figure 6, panel 1). The low barrier to entry has also facilitated increasing

Figure 6. Growth of Neo-Broking Activities

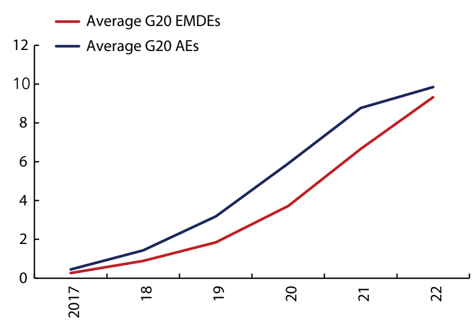
Neo-broking activities have been increasing in EMDEs with the introduction of a range of fully digital broking platforms . . .

1. AUM Held and Executed by Neo-Brokers
(Billions of US dollars)



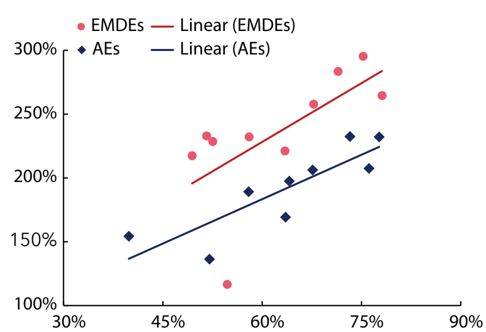
. . . with the penetration rate in major EMDEs increasing faster than and reaching almost at par with that of AEs.

2. Neo-Broking Users
(Percentage of population)



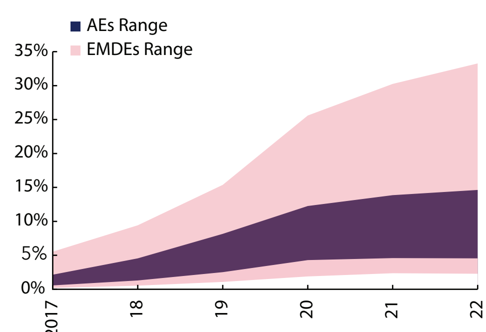
The increase in AUM held and executed by neo-brokers is also driven by growth in the use of such services.

3. AUM Held and Executed by Neo-Brokers' 2017–22 Growth
(Total and per user, annualized)



Users' dependence on neo-brokers in some EMDEs is increasingly more significant compared with AEs.

4. Neo-Brokers' AUM Per User
(Percentage of GNI per capita)



Sources: OECD; Statista Digital Markets Insights; World Bank Databank; IMF World Economic Outlook Database; and IMF staff calculations.

Note: Sample data sets are sovereigns in the Group of Twenty. The figures in panel 2 are estimated penetration rates based on a simple average across the 9 AEs and 10 EMDEs in the Group of Twenty. Estimates of AUM are those held and executed by online brokers and platforms, including social trading platforms, but exclude brokers that solely provide robo-advisory services or cryptocurrency assets. Figures also include only those entities that offer either exclusive business-to-customer (B2C) services or a combination of B2C and business-to-business (B2B) services, excluding those that cater solely to B2B clients. AEs = advanced economies; AUM = assets under management; CAGR = cumulative annualized growth rate; EMDEs = emerging market and developing economies; GNI = gross national income.

user penetration (Figure 6, panel 2), which may reflect growing interest, confidence, and acceptance among retail investors. Notably, the recent growth in assets-per-user on these platforms (Figure 6, panel 3) appears to be more pronounced in some EMDEs than in AEs, suggesting the demand gap these service providers seek to fill. Individual investors' exposure to neo-brokers in some EMDEs is much larger than in AEs (Figure 6, panel 4), a trend that could continue, particularly if AI techniques are able to unlock value to meet individual investors' needs through digital platforms with on-demand customized user experiences.[19]

Crowdfunding

There are two primary types of crowdfunding—lending-based and investment-based—each serving distinct purposes and appealing to different types of investors. Loan-based crowdfunding, sometimes also known as peer-to-peer lending, involves individuals lending money to borrowers who promise to repay the loan with interest over a specified period. This model is primarily focused on debt financing, where creditors seek interest income on their capital. Investment-based crowdfunding allows individuals to invest in a start-up or business in exchange for equity. This model enables investors to become partial owners of the venture, granting them a stake in the company's potential growth and profits. Thus, loan-based crowdfunding and investment-based crowdfunding cater to different investor motivations and risk appetites. Both are typically regulated and supervised by financial sector authorities to safeguard investors' interests.

Crowdfunding platforms, which typically act as intermediaries between businesses seeking capital and potential investors, are often fully digitalized and have increasingly integrated AI techniques to enhance various facets of the fundraising process (for instance, by predicting campaign success, personalizing marketing, automating tasks, assessing risks, and matching projects with investors, thereby improving efficiency and effectiveness).[20] These platforms facilitate the issuance of securities (equity and debt), typically in smaller amounts compared with conventional banking facilities.

The adoption of GenAI techniques has the potential to further enrich these platforms by assisting in content creation and financial projections. As crowdfunding continues to gain prominence and is increasingly recognized as a viable method of capital formation, integrating AI not only streamlines processes but also enhances ease of use by introducing new dimensions of efficiency and customization, contributing to a more sophisticated and data-driven ecosystem in the realm of securities crowdfunding.

GenAI techniques, including those derived from large language models and deep learning, can significantly affect crowdfunding in securities markets. The following are potential ways:

- **Automated Personalized Content Creation:** GenAI enhances the creation of engaging and customized content for crowdfunding campaigns. The technology simplifies the creation of persuasive text for campaign descriptions, fundraising updates, and marketing materials, thus allowing issuers to effectively communicate their value propositions. Consequently, AI-driven crowdfunding platforms

[19] For example, by analyzing personal data on individual investors' unique risk and returns objectives, AI techniques could provide a portfolio mix that is better suited to users' unique preferences. Personalized customizations on platforms (news alerts, trading signals, performance attribution, and so on) would also enhance user experience for on-demand, real-time market and portfolio updates.

[20] Recent research (Ai and others 2024) suggests that online crowdfunding campaigns can be enhanced by employing machine learning models to devise effective strategies for crafting campaign descriptions. Other studies (Gregoriades and Themistocleous 2025) have used AI techniques to analyze textual features in crowdfunding campaigns and to evaluate their likelihood of success. Several third-party AI tools are also available to assist in designing campaign descriptions and analyzing the probability of funding success.

have emerged, which leverage GenAI to generate content throughout the fundraising journey.[21] This encompasses crafting compelling campaign narratives, generating relevant hashtags and social media videos for engagement, and personalizing thank-you notes. Moreover, various third-party service providers also offer tools to generate campaign descriptions from just a few key inputs, such as funding goals and objectives.[22]

- **Customized Investment Recommendations and Investors' Matching:**[23] GenAI uses advanced analytics to evaluate user preferences, risk tolerance, and financial goals, thereby generating personalized investment recommendations. This level of customization significantly increases the likelihood of establishing high-potential matches between funders and businesses seeking capital, ultimately expediting the matchmaking process.[24] In addition, specialized third-party service providers (AI-powered fundraising-as-a-service) have emerged to enhance investor-matching capabilities for capital seekers.[25] These providers employ GenAI technology to sift through public information to identify potential investors, refine investor-base targeting by analyzing focus areas and past investments, and create hyperpersonalized pitches, including customized pitch decks. They also facilitate the scheduling of meetings with these investors, streamlining the engagement process.
- **Personalized Investor Interaction:** AI-driven chatbots and virtual assistants significantly enhance customer support on crowdfunding platforms. They provide instant responses to open-ended user inquiries, guide investors through the investment process, and deliver real-time updates, fostering a more engaging and user-friendly experience. Although many crowdfunding platforms have integrated these chatbots into their ecosystems, third-party service providers have also emerged to enable businesses to design, train, and deploy their own chatbots on these platforms.[26] These chatbots, trained on information from the fundraising campaign, not only ensure timely updates for investors but also handle specific inquiries and provide valuable insights.

The growth of crowdfunding activities reflects the critical need for increased regulatory scrutiny, particularly in EMDEs, where rapid expansion could outpace authorities' ability to adapt the regulatory and supervisory framework in areas such as company eligibility, transparency and disclosure, investor protection, platform compliance, and cross-border regulations to ensure safe and effective expansion. Although digital capital raising activities continue to be dominated by lending, crowd-investing, albeit still very much concentrated in AEs, has also been steadily rising in recent years (Figure 7, panel 1). Although the overall value of these

[21] An example is AngeLink, an AI-driven crowdfunding platform (https://angelink.com/).

[22] Examples include HyperWrite AI's crowdfunding generator (https://www.hyperwriteai.com/aitools/crowdfunding-campaign-generator), Writecream's content generator for crowdfunding campaigns (https://www.writecream.com/ai-content-generator-for-crowdfunding-campaign/), and Logicball's crowdfunding campaign generator (https://logicballs.com/tools/ai-real-estate-crowdfunding-campaign-generator).

[23] Despite these benefits, the advent of GenAI could also encourage fraudulent practices, resulting in misrepresentation or false advertising, which could impair the effectiveness of the platform.

[24] Investormatch.ai (https://investormatch.ai/how-the-matching-process-works/) is an example of a crowdfunding platform that aims to effectively match donors and capital seekers.

[25] CapitalxAI (https://www.capitalxai.com/ai-personalization-engine) is an example of a third-party service provider that enables businesses to filter for and reach relevant investors.

[26] Arsturn (https://www.arsturn.com/solutions/crowdfunding-campaigns-ai-chatbot) is an example of a service provider that develops chatbots for businesses to include on their crowdfunding platform.

transactions remains low relative to total funding in the economy, EMDE growth rates have been high and consistently outstripped those in AEs (Figure 7, panel 2).

The increasing penetration rate is likely driven by the ease of access that investors have to these digital platforms, as well as the capacity of small - and medium-sized enterprises and start-ups to secure financing quickly and efficiently from a diverse investor base, which would otherwise be challenging under the traditional banking system. Although these transactions are generally smaller in size (Figure 7, panel 3) and unlikely to displace the traditional role of conventional capital markets intermediaries, they represent a shift in the funding landscape that could empower smaller ventures to thrive.

Figure 7. Growth of Crowd-Investing Activities

Overall capital raised is still driven by AEs, with the United Kingdom and the United States constituting more than half of the overall transaction volume.

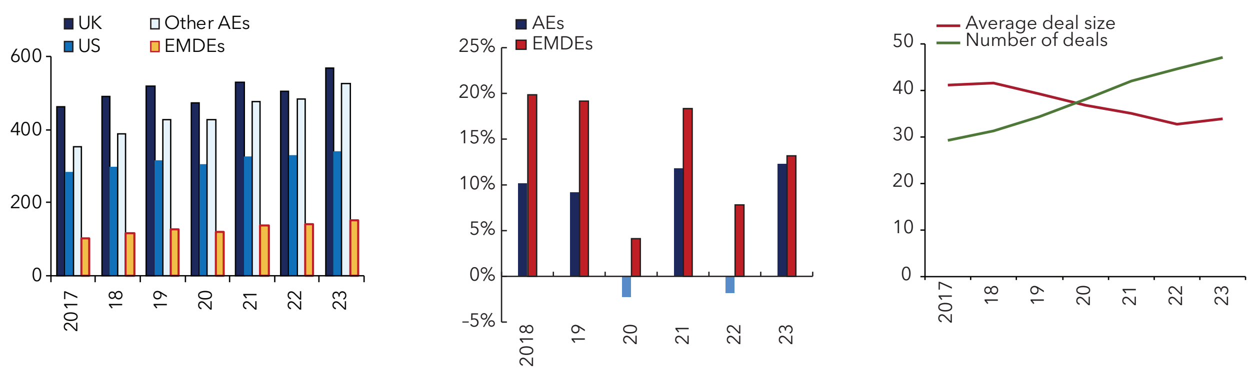
1. Crowd-Investing Transaction Volume
(Billions of US dollars)

Growth in EMDEs has continuously exceeded that of AEs and likely reflects market deepening initiatives …

2. Average Growth Rate
(Percentage year over year)

… although average capital raising sizes remain small, potentially reflecting the nascent stage and size of companies.

3. Average Funding Per Deal; Number of Deals
(Thousands of US dollars, thousands)



Sources: Statista Digital Markets Insights; and IMF staff calculations.
Note: Sample data includes 34 AEs and 53 EMDEs. Figures in panel 2 are simple averages across equal-weighted sovereigns in AEs and EMDEs. AEs = advanced economies; EMDEs = emerging market and developing economies.

Table 1 provides a snapshot of AI's expanding role across the five capital market segments.

Table 1. Use Cases of AI in Capital Markets Activities and Growth Trends

Use Case	Unique Features/Services	Commonly Used AI Techniques/Applications	Growth Trends
Asset Management	Portfolio optimization Risk assessment Market analysis Client-servicing Alternative data analysis	Analysis of unstructured data for signal generation and sentiment analysis. Big data analysis to uncover market trends Uncovering complex interactions for more holistic risk management Personalized client interaction	Although adoption in AEs seems to be gaining momentum, EMDEs appear to be in the early stages of adoption Growing interest in integrating unstructured data Increasing focus on client customization
Wholesale Trading	Advanced algorithmic trading for efficient execution of trades, reduced reliance on intermediaries, and lower friction	AI-driven price optimization, best execution, liquidity management, and credit risk assessment	Although the United States continues to lead in algo-trading adoption, EMDEs are experiencing continued growth.
Robo-Advisory	Personalized guidance with minimal human intervention Automated client profiling, portfolio design, and rebalancing Automated data collection and analysis Lower fees compared with traditional advisors Fully digitalized experience with low barriers to entry	Analysis of unstructured and alternative data sets Portfolio allocation optimization Market trend prediction and pattern recognition	Overall, the industry continues to grow, with global AUM expected to exceed $2 trillion by 2028 Although AEs have higher volume, EMDEs consistently demonstrate higher growth rates Growing appetite for digital financial solutions in EMDEs
Neo-Broking	Fully digitalized and personalized experience for portfolio recommendation, trade execution, and a customized experience for retail investors	Analysis of unstructured and alternative data sets to enhance portfolio recommendations, user experience, and fraud detection	Neo-broking use is growing, and some EMDEs are demonstrating increasing per capita exposure
Crowdfunding	Quick and convenient platform for SMEs to raise small-ticket financing An alternative asset class that opens an opportunity for retail investors' participation. Personalized and fully digitalized user experience with low barriers for entry	Fraud detection and investor matching Chatbots for user support GenAI for unique content creation	Growing globally, especially lending-based–primarily serving SMEs EMDEs' growth rates exceeding AEs' Growing penetration in EMDEs could be a result of financial deepening initiatives

Note: AEs = advanced economies; AI = artificial intelligence; AUM = assets under management; EMDEs = emerging market and developing economies; GenAI = generative AI; SMEs = small - and medium-sized enterprises.

III. Issues, Challenges, and Risks

The IMF's October 2024 *Global Financial Stability Report* examines current trends and potential future implications, providing a comprehensive analysis of how artificial intelligence (AI) and generative AI (GenAI) are transforming capital markets (IMF 2024a). It draws on extensive market outreach and novel data sources to assess adoption levels, structural changes, and associated financial stability risks. While acknowledging AI's potential to enhance market efficiency, deepen liquidity, and improve risk management, the analysis highlights that current AI adoption in capital markets appears largely evolutionary rather than revolutionary, building upon existing analytical methods and investment strategies.

The specific focus in the *Global Financial Stability Report* on financial stability implications of AI/GenAI in advanced economies (IMF 2024a) complements earlier studies at the IMF (IMF 2023), which covered unique risks posed by GenAI to the financial sector beyond traditional AI concerns, focusing on data privacy, embedded bias, model robustness issues (particularly "hallucination"), and challenges related to synthetic data. The earlier analysis suggested that risks could significantly affect financial stability and consumer protection, and although private enterprise-level GenAI solutions may help mitigate some issues, key challenges could persist. The *Global Financial Stability Report* (IMF 2024a) identifies four key categories of financial stability risks: increased market speed and volatility under stress (especially if AI trading strategies become highly correlated); opacity and monitoring challenges (particularly as activities migrate to nonbank financial intermediaries); operational risks from reliance on key third-party AI service providers; and increased cyber and market manipulation risks. To address these risks, the chapter recommends several policy responses, including recalibrating circuit breakers, enhancing monitoring of large traders, addressing technological dependencies, and strengthening market integrity measures.

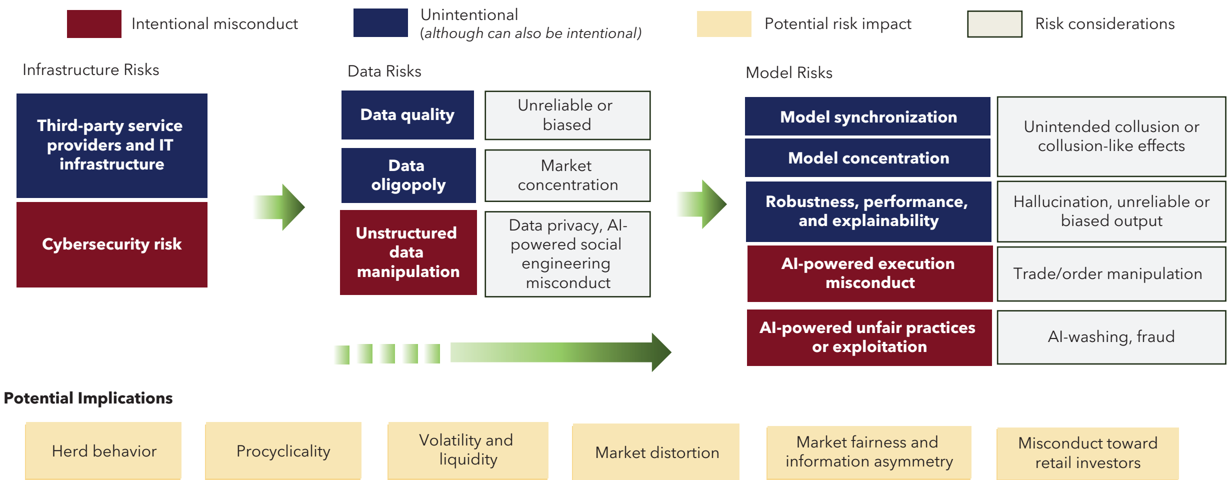
The risk analysis in the *Global Financial Stability Report* (IMF 2024a) primarily focuses on advanced economies, where AI adoption is more prevalent, while acknowledging AI's potential positive effect on emerging market and developing economies (EMDEs) through accelerated technology adoption, increased financial development, and inclusion. Jurisdictions with limited resources or infrastructure may struggle to keep pace with AI adoption because of high fixed costs, potentially leading to fragmentation in financial markets. Hence, in such jurisdictions, the most prominent near-term risks may be falling behind in AI adoption and infrastructure development rather than direct financial stability risks.

This section will focus on the issues supervisors face in monitoring and regulating AI-related developments in the capital markets. It draws on issues that were highlighted in the IMF's *Global Financial Stability Report* and dives deeper into specific challenges that could possibly emanate from increasing adoption of AI in securities markets, including those of robo-advisory services, trading activities, asset management, and crowdfunding activities (see Section II).

The rapid advancement and concentration of AI models potentially reinforce existing vulnerabilities and create new ones for securities markets and their regulators. Specifically, the need to keep up with the rapid pace of technological innovations, new products and services, heterogeneous data quality, and the growing risks of market manipulation and cybersecurity (Figure 8) further strains the limited regulatory and supervisory capacity, especially in EMDEs, where capacity is more constrained.

Figure 8. Risks and Vulnerabilities Posed by AI Adoption in Securities Markets

Although the adoption of AI brings numerous benefits to the industry, it could also raise emerging risks that require regulatory attention and scrutiny.



Source: IMF staff compilations from academic studies, outreach discussions, and public third-party service providers.
Note: AI = artificial intelligence; IT = information technology.

Supervisory Challenges in Harnessing Accelerated Technology Adoption

From a capital markets perspective, accelerated technology adoption presents significant opportunities for rapid modernization of market infrastructure and operations. Exploring advanced AI-driven trading systems, risk management frameworks, and market surveillance tools may reduce reliance on traditional infrastructure to some extent.[27] It could also lead to more efficient price discovery, improved market liquidity, and better regulatory oversight through AI-powered monitoring systems. For instance, in derivatives markets, AI-powered systems can enhance pricing accuracy, liquidity, and risk management by analyzing vast data sets—such as historical prices, macroeconomic indicators, and global market trends—providing real-time pricing for instruments like options, swaps, and futures, improving price discovery and hedging strategies. In addition, AI can dynamically assess counterparty risks, optimize collateral management, and enhance regulatory oversight, reducing systemic risks and fostering market stability. Automated market making, supported by a deep and transparent market ecosystem, could help reduce bid-ask spreads by efficiently managing inventory and risk. Achieving this requires fundamental elements such as competitive capital markets and an independent, well-resourced securities markets authority. In addition, ML algorithms could identify unusual trading patterns across multiple accounts or markets that might indicate potential insider trading or market manipulation.[28]

[27] Examples of AI adoption in capital market infrastructures include National Stock Exchange of India, which gradually integrated AI for fraud detection and risk management alongside its transition to cloud-based systems; Brazil's B3, which modernized trading platforms with AI-powered market surveillance and blockchain settlements; and Rwanda Stock Exchange, which leapfrogged traditional infrastructure entirely by adopting cloud-based trading and AI-driven tools from the outset, showcasing how EMDEs' capital market infrastructure can embrace advanced technologies for efficiency and accessibility.

[28] Financial Industry Regulatory Authority (FINRA), for instance, employs sophisticated machine learning algorithms and analytics to monitor 100 percent of trading activity in stocks, options, and bonds, identifying unusual trading patterns across multiple accounts or markets that may indicate insider trading or market manipulation, resulting in hundreds of referrals to the US Securities and Exchange Commission and law enforcement annually (FINRA 2024).

However, this accelerated technology adoption also presents distinct challenges for market authorities operating in jurisdictions with limited resources or infrastructure, who must regulate and supervise these advanced technologies without having experienced the gradual evolution seen in developed markets. For instance, in developed markets, regulators had decades to adapt to algorithmic and high-frequency trading technologies, enabling them to implement safeguards like circuit breakers and order-to-trade ratios. In contrast, EMDEs face the sudden adoption of these technologies, often without the expertise, infrastructure, or regulatory frameworks to manage risks such as market manipulation and extreme volatility.

In this respect, market authorities may be tasked with monitoring AI-driven trading strategies when local expertise is limited. For example, market authorities need expertise in data science, AI, market surveillance, and risk management to monitor AI-driven trading risks such as algorithmic bias, market manipulation, and flash crashes. In addition, knowledge of technical infrastructure and cross-border regulatory cooperation are essential to effectively oversee complex trading systems. Hence, supervisors may face difficulty in evaluating the risk models and trading algorithms used by market participants in their jurisdiction. They could also be constrained in managing the risks of increased market interconnectedness and potential volatility spillovers, because EMDEs are particularly vulnerable to sudden capital flows driven by automated trading decisions.

A broader consideration is that accelerated technology adoption could heighten cybersecurity concerns, given AI systems' vulnerability to sophisticated cyberattacks, particularly in jurisdictions with limited access to advanced threat-detection tools and resources.

Data-Related Challenges

The growing dependence on AI in capital markets raises significant data-related challenges. Financial institutions increasingly rely on a wide range of traditional and alternative data sources to train their AI models, but ensuring data quality, reliability, and integrity remains a major concern.[29] Although AI systems can process vast amounts of unstructured data to generate trading signals and market insights, poor data quality or biases in training data can lead to unreliable outcomes or biased results.

Market authorities with limited resources or infrastructure face distinct challenges in data availability and quality that significantly affect their ability to leverage AI in capital markets. Historical market data available in such jurisdictions often lacks depth, consistency, and granularity, with particularly significant gaps in over-the-counter markets and less-liquid securities. Although such supervisors often hold valuable data across several individual functional areas like licensing, supervision, and enforcement, and various entities such as financial market infrastructures (for example, central securities depositories), exchanges, and custodians, they frequently lack the integration capabilities needed to effectively process and analyze this information, resulting in fragmented data landscapes. While AI has the potential to process large volumes of fragmented data, its effectiveness depends on the quality and consistency of inputs. In many jurisdictions with constrained resources and infrastructure, gaps in data completeness, standardization, and integration across these functional areas remain significant barriers to effectively harnessing AI. Furthermore, real-time

29 Traditional data includes structured information like financial statements, stock prices, and economic indicators. Alternative data refers to nontraditional sources such as satellite imagery, social media sentiment, or web scraping of e-commerce platforms.

market data access is typically constrained by both cost and technical limitations, making it difficult for smaller market participants to meet sophisticated reporting requirements.[30]

These challenges create significant barriers to AI adoption, with several critical implications. Models trained on incomplete data may perform poorly or generate unreliable signals, whereas limited alternative data reduces the potential for novel trading strategies. Data quality issues may amplify risks during market stress periods, and higher costs and technical barriers create obstacles for local firms wanting to implement AI solutions. This suggests that countries may need to prioritize building fundamental data capabilities and integrating frameworks as a foundational step, while carefully assessing the relevance and feasibility of advanced AI applications in their capital markets. A phased and pragmatic approach, aligned with supervisory priorities and capacity, can ensure that AI adoption supports rather than strains existing regulatory efforts.

These challenges could be particularly pronounced in EMDEs, where resource constraints, infrastructure gaps, and fragmented data landscapes exacerbate barriers to AI adoption. Limited access to high-quality, granular data, combined with weaker governance frameworks and a higher cost of technology, makes it significantly harder to leverage AI for capital market development. In addition, EMDEs could find it difficult to address the dual challenge of developing both basic market supervision and advanced AI oversight mechanisms while operating with limited resources across multiple priorities, all while establishing appropriate standards that foster innovation rather than impede it.

Market Concentration

Infrastructure and capacity limitations exacerbate data-related challenges. The high costs of real-time data feeds restrict access for smaller market participants, who typically operate on leaner budgets and have less capacity for capital expenditures. Weak data governance frameworks, insufficient standardization of reporting templates, and limited automation in data collection from smaller brokers and issuers create additional barriers. The combination of limited technical expertise in data analysis and AI monitoring, along with significant infrastructure gaps in processing large data sets, hinders smaller firms from effectively using existing data resources. In contrast, larger firms can leverage these resources more effectively, widening the gap.

As noted by the October 2024 *Global Financial Stability Report* (IMF 2024a), data oligopolies allow certain firms with access to superior nonpublic data to develop more effective AI models, thereby increasing market concentration. Herd behavior, procyclicality, and program trading volatility reinforce the advantages for firms with better data and models. These firms consistently outperform competitors, attract more capital, and reinvest in exclusive data sources and advanced AI systems, leading to a self-reinforcing cycle of dominance.

EMDEs face unique challenges in this context. Supervisors could have global financial firms leveraging advanced AI capabilities in their jurisdictions, operating alongside local firms with basic technology. This

[30] For instance, the South African Financial Sector Conduct Authority (FSCA) Regulatory Strategy 2025–2028 outlines significant advancements in regulatory oversight, such as the introduction of the Integrated Regulatory Solution (IRS) to streamline and enhance data collection. These changes may present challenges for smaller firms. The IRS consolidates regulatory and supervisory data across multiple financial sectors, requiring entities to provide comprehensive and standardized reporting. FSCA's shift to a risk-based supervisory approach introduces enhanced reporting mechanisms, such as conduct-of-business risk returns, thematic reviews, and other supervisory data-collection tools. Smaller firms, which often lack the financial and technical capacity for advanced compliance systems, may struggle to meet the increased complexity and volume of these reporting requirements (South Africa FSCA 2025).

creates a two-tier market in which technological disparities can lead to structural inequalities in market access. Authorities in EMDEs must consider how to maintain market stability amid such disparities, which could cause market fragmentation or regulatory arbitrage. Global firms with advanced AI capabilities may exploit gaps or inconsistencies in regulatory frameworks across jurisdictions by bypassing stricter regulations in their home countries while operating in EMDEs with less developed oversight mechanisms. This could result in uneven competition and pose risks to market stability.

Market Collusion and Bad Coordination Outcomes

AI-powered trading systems pose significant risks of market collusion and manipulation. Research by Calvano and others (2020) demonstrates that AI trading agents, which were pretrained together to execute the same specific task, can autonomously evolve collusive behaviors without explicit communication, achieving supra-competitive profits through strategic underreaction to market information (Box 1). The risk that AI-driven algorithmic trading may adversely affect market microstructure and liquidity may have already manifested in some EMDEs' capital markets (Ramos and Perlin 2019).[31]

Algorithmic market makers may unintentionally create collusion-like effects by aligning their trading strategies, leading to higher prices and wider spreads that disadvantage smaller participants (Wah, Wright, and Wellman 2017). Algorithmic market makers, through their algorithmic strategies, can exploit their dominant position in liquidity provision. This could lead to implicit coordination or even "collusion-like" effects, such as maintaining wider bid-ask spreads and higher transaction costs, which can disadvantage smaller participants and reduce overall market efficiency. Such risks may mirror well-known disadvantages arising from the dominance of a few players, where their concentrated activity amplifies distortions. In Mexico, for instance, foreign-owned banks dominate over-the-counter derivatives transactions, consolidating market power and reducing competition.[32] In South Africa, foreign investors hold about 30 percent of Johannesburg Stock Exchange-listed equities and about 25 percent of government bonds, creating systemic vulnerabilities where coordinated portfolio adjustments can destabilize markets during stress.[33] Thailand's equity market provides a case study in managing such risks: with foreign-driven short-selling and program trading accounting for up to 15 percent of daily trading, the Thai Securities and Exchange Commission (SEC) introduced measures such as short-selling limits and the "uptick rule" to curb collusion-like behavior and protect smaller domestic participants. Together, these examples highlight how concentrated participation can align strategies, distort price-setting mechanisms, and disadvantage smaller firms (Nikkei Asia 2024).

The November 2024 report of the Financial Stability Board (FSB 2024) emphasizes that these risks are amplified by increased market correlations driven by the widespread use of common AI models, resulting in synchronized trading patterns, lending decisions, and pricing strategies.[34] As highlighted by Rudin (2019), the "black box" nature of machine learning models creates additional challenges in markets with limited regulatory oversight capacity, particularly when AI models make incorrect inferences in

[31] *New York Times*, "Despite Risks, Brazil Courts the Millisecond Investor," 2023, https://archive.nytimes.com/dealbook.nytimes.com/2013/05/22/despite-risks-brazil-courts-the-millisecond-investor/index.html.

[32] The fact that foreign-owned banks account for more than 80 percent of the banking sector's total assets has been one of the drivers of cross-border activity. As a result, over the last five years, about twice as many over-the-counter transactions by Mexican financial entities have been with foreign counterparties as with domestic ones (FSB 2020).

[33] "Systemic liquidity is highly vulnerable to portfolio flows. While in normal times the active participation of foreign market players is a substantial source of liquidity, in times of internal and external shocks the appearance of sudden stops is a major risk. As of June 2021, 30.1 percent of government bonds (down from the peak of 42.8 percent in 2018) and around half of the market value of the JSE-traded equities are in foreign hands" (IMF 2022).

[34] The Financial Stability Board published a follow-up report in October 2025 focusing on monitoring of AI activities and assessment of related financial stability vulnerabilities.

markets with inconsistent data quality. During the March 2020 COVID-19 market turbulence, Renaissance Technologies' public institutional equities fund (Renaissance Institutional Equities Fund) experienced significant challenges when its AI models, trained on historical data, struggled to interpret unprecedented market conditions, highlighting the risk of market malfunction when algorithms fail to adapt to unexpected scenarios (Bloomberg 2020). Similarly, Knight Capital Group's 2012 algorithmic trading malfunction generated millions of erroneous orders, resulting in $440 million in losses within 45 minutes. These episodes demonstrate how automated systems can create massive market disruptions before regulators can effectively intervene.

The regulatory response to these challenges requires a multifaceted approach, as highlighted by the IMF (2024a). Thailand's 2024 market-conduct reforms—which encompassed both trading-behavior safeguards, such as short-selling limits and the "uptick rule," and operational controls, including order message limits, mandatory strategy reporting, and enhanced audit trails, provide a coherent template for other EMDEs. However, as highlighted by the FSB (2024), broader challenges remain in monitoring AI adoption and its implications for financial stability, necessitating enhanced international cooperation, cross-sectoral collaboration, and information sharing. The high fixed costs of AI implementation could further exacerbate the technological divide between international and local market participants, creating a complex risk landscape in which sophistication gaps can amplify market inefficiencies and raise stability concerns.

Use of Alternative and Unstructured Data Sets

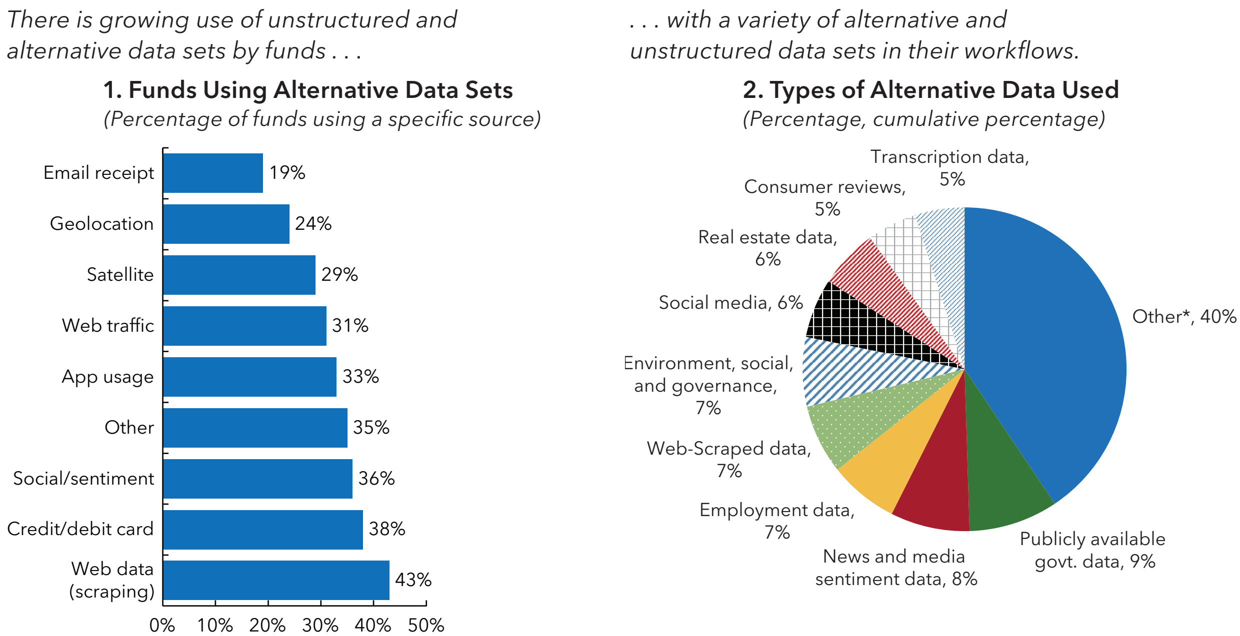
The growing use of AI in financial services has introduced complex risks, particularly through the increased reliance on unstructured and alternative data in investment decisions (Figure 9). A recent global study (CFA 2024b) found that 64 percent of investment professionals now use alternative data across the Americas, Europe, the Middle East and Africa, and Asia Pacific regions, with 48 percent of this unstructured data coming from open sources. The study revealed widespread use of diverse alternative data types, including satellite imagery, social media data, web-scraped data, transcription data, and other novel sources. The growing use of alternative data (including anonymized and aggregated retail data) for trading decisions raises the risks of insider dealing and market misconduct associated with such data, especially when it is derived or processed in ways that breach privacy or confidentiality obligations (Clifford Chance 2019).

This growing integration of alternative and unstructured data into portfolio management and investment analysis presents both opportunities and risks. Investment professionals are increasingly incorporating various alternative data sets into their workflows (CFA 2024b). The open-source nature of many of these data sets and processing tools, while promoting accessibility and innovation, also introduces potential vulnerabilities in the investment process. The increasing reliance on and widespread use of unstructured data may expose AI models to the risk of AI-powered "social engineering" misconduct.[35] Manipulation of unstructured data is not limited to "threat actors", and can in theory occur intentionally to safeguard intellectual property (Goodfellow, Shlens, and Szegedy 2015; Brown and others 2017). At this juncture, even minor "adversarial patches" can easily mislead AI models, potentially resulting in incorrect outputs, leading to unintended and irrational herd behavior among market participants. In the context of portfolio management, these vulnerabilities could lead to systematic biases in investment decisions, particularly when multiple funds rely on similar data sources and analytical approaches.

35 Social engineering refers to broad cyberattacks that use psychological strategies to manipulate users/actors into taking a desired action or for other malicious purposes.

Many sources of unstructured data are exposed to risks of GenAI being used in combination with social engineering to exploit human vulnerabilities and spread disinformation. Therefore, the capability to generate content (through GenAI techniques) and disseminate at scale (through public platforms including social media) can introduce systemic risks into capital markets, particularly when AI models lack differentiation and are highly concentrated. This risk is amplified in portfolio management when multiple investment firms use similar alternative data sources and AI models,[36] potentially creating or increasing correlation across investment strategies, therefore amplifying market movements.

Figure 9. Use of Unstructured and Alternative Data Sets in Portfolio Management and Investment Analysis



Sources: Alternativedata.org; CFA Institute's July 2023 Generative AI, Unstructured/Alt data and open-source survey.

Note: The majority of these data sets are open source, and Python, also open source, is the most widely preferred language for handling unstructured data. Other data in panel 2 include energy consumption data, e-commerce data, supply chain and logistic data, credit card transactions, weather data, app download data, court records and legal documents, satellite imagery, insider trading data, patent and intellectual property data, crypto data, geolocation data from mobile foot traffic, data from IoT devices, flight tracking data, clickstream data, sensor technologies, and wearables data.

At the same time, the integration of alternative data sets, such as consumer spending or transaction data, into investment decisions raises concerns about market fairness and information asymmetry.[37] Institutional investors often leverage exclusive data sets to gain a competitive edge, disadvantaging retail participants

[36] For instance, portfolio managers commonly use similar machine learning techniques, such as natural language processing, to analyze alternative and unstructured data like corporate disclosures and social media sentiment. This reliance on shared data sets and methodologies increases the potential for correlated investment strategies and herding behavior, amplifying systemic risks (CFA 2024a).

[37] As the Bank of England Governor Andrew Bailey highlighted in his 2019 testimony to the UK parliament, there is ongoing uncertainty about whether aggregated consumer spending data should be classified as public information or as inside information. Classification will have major implications for how such data can be legally used to support trading decisions and whether its use could constitute market abuse.

and smaller firms.[38] Although such practices may not constitute misconduct, they pose ethical and regulatory challenges, including risks of market distortion and the erosion of market integrity. Supervisors must address these issues by clarifying what constitutes fair access to data while balancing the need for innovation with the protection of market participants and public confidence.

Monitoring the use of alternative data presents fundamental challenges to supervisors in EMDEs. Studies have noted difficulties supervisors have had in effectively overseeing peer-to-peer lenders using alternative data sources, for example, leading to instances of predatory lending practices that adversely affected small businesses and individuals in rural areas where traditional credit data was limited (Budi, Purwandari, and Suryono 2021; Reuters 2022). The challenge could easily extend beyond simple oversight to include verifying data quality, analyzing complex AI models, and establishing effective cross-border data-sharing frameworks.

Misconduct Targeted Toward Retail Investors

Misconduct in securities markets manifests in two primary dimensions. First, AI-enabled market manipulation may involve actions such as spoofing that artificially influences market prices or trading volumes.[39] This includes layering, wash trading, and quote stuffing, all of which affect market integrity and price discovery mechanisms (Lin and Gurrola-Pérez 2024). Cases like the 2010 Flash Crash, where Navinder Singh Sarao used an algorithm to execute spoof orders, and the Securities and Exchange Board of India's 2023 action against Nimi Enterprises, highlight how AI-powered algorithms can amplify the risks and effects of such manipulative practices in securities markets (George and Sanjay 2025). Second, retail investor misconduct encompasses unfair practices targeting individual investors primarily through misleading financial advice, mis-selling of products, and exploitation of behavioral biases and financial literacy gaps. Although these issues are not new, AI can amplify such risks by enabling hyperpersonalized strategies that exploit behavioral patterns and vulnerabilities.[40]

The increasing sophistication of AI and advanced technologies has introduced new dimensions to misconduct risks in securities markets. Individual data breaches or the exploitation of technological vulnerabilities can rapidly escalate, exposing millions of retail investors to significant harm across the financial ecosystem (IOSCO 2023). The US SEC has brought enforcement actions against individuals, issuers, investment firms, and investment professionals involved in "AI washing"—that is, where investors are lured by false claims regarding the use or integration of sophisticated AI technology as part of a business model or as part of an investment strategy.[41]

[38] A report from the Alternative Investment Management Association (2020) emphasizes how institutional investors extensively leverage alternative data sets not widely accessible to others to generate alpha and improve their investment decision-making.

[39] Although such misconduct can compromise market integrity and credibility, thereby also adversely affecting institutional investors, the paper highlights the potential retail misconduct and harm to retail investors due to their relatively limited access to real-time market intelligence, risk management tools, and trade execution capabilities.

[40] The Financial Conduct Authority highlights that AI can lead to "not good" outcomes, such as the "exploitation of behavioral biases, loyalty, inertia, informational asymmetries, or characteristics of vulnerability" (UK Finance 2022). Additionally, the "black box problem" of AI systems, where "models are highly complex and may be incapable of comprehension by human users," makes it difficult to detect or hold accountable those responsible for misconduct, further exacerbating these risks.

[41] *See, for example,* https://www.sec.gov/enforcement-litigation/litigation-releases/lr-26282*;* https://www.sec.gov/enforcement-litigation/administrative-proceedings/33-11352-s*;* https://www.sec.gov/newsroom/press-releases/2024-36. Recent enforcement actions against firms like Delphia and Global Predictions have resulted in significant penalties (KKC 2025).

The emergence of sophisticated AI-enabled fraud schemes represents a particularly dangerous threat to retail investors, as discussed in the IOSCO (2022) and the European Parliament (2020) reports. This includes market manipulation through algorithmic trading, as documented in several cases, notably the UK Financial Conduct Authority (FCA) versus Da Vinci Invest case (2015) involving algorithmic spoofing (Blackstone Chambers 2015), and the Navinder Sarao case (2016), where sophisticated algorithms were used to manipulate S&P 500 futures markets (US DOJ 2016). Fraudsters are increasingly employing AI tools such as deepfakes and voice cloning to create convincing scams, like the market manipulation techniques seen in the Paul Axel Walter case (2017), where algorithmic trading was exploited to manipulate market prices (UK FCA 2017).

A critical area of concern lies in AI-driven investment platforms and robo-advisory services, which may provide unsuitable recommendations by failing to properly account for individual circumstances and risk tolerance. This issue is particularly evident in cases where automated systems fail to adequately assess client risk profiles or make blanket recommendations that fail to consider unique financial circumstances. Robo-advisors might systematically overexpose certain demographic groups to high-risk investments or fail to adjust portfolios during market volatility because of rigid algorithmic rules. This issue is compounded by the inherent complexity of AI algorithms, making it difficult for retail investors to understand the risks involved in their investments. When deployed at scale, these suitability issues can lead to systematic mis-selling of financial products across entire demographic segments, echoing concerns raised by the UK Treasury Committee's investigation into private polling practices by hedge funds.[42]

These challenges underscore the critical need for capacity building tailored to supervisors' needs. As AI adoption accelerates in financial markets, addressing the constraints supervisors face becomes essential to maintaining market integrity and protecting retail investors. This requires developing frameworks that account for varying levels of supervisory capacity and enabling supervisors to modify their regulatory and supervisory tools to address AI-specific risks. Such modifications should focus on improving the ability to monitor AI systems, ensuring transparency in algorithmic decision making, and adapting existing frameworks to account for the unique challenges posed by AI, such as data dependencies, model biases, and emergent behaviors.

[42] The UK Treasury Committee had expressed concerns about hedge funds commissioning private polling during key political events—specifically the run-up to the 2016 UK referendum on withdrawal from the European Union— and potentially using that data for trading advantages. The investigation focused on examining whether this practice created an unfair market advantage and if it needed stronger regulation to protect market integrity.

IV. Regulatory Responses

Regulating AI Use: A Developing Field of Work

Recent publications by international bodies, academics, and other organizations have assessed the potential effect of artificial intelligence (AI) on the financial sector and its implications for financial stability. There is an extensive body of literature on the use of AI in the financial sector and its broader implications. A recent study by Danielsson and Uthemann (2024) on the use of AI in financial regulations and the impact on financial stability proposed six criteria against which financial regulators and crisis resolution authorities can judge the suitability of AI use by the private sector (data, mutability, objectives, authority, responsibility, consequences). It also identified the primary channels through which AI can destabilize the system (malicious use, misinformed use and overreliance, misalignment and control avoidance, and resource concentration).

A separate paper by The Alan Turing Institute (2023) identified four main regulatory considerations that arise from the growing adoption of new technologies, including AI: (1) consumer protection, (2) competition, (3) market integrity, and (4) operational resilience. A key element of AI regulation recommended—as part of measures to encourage AI explainability (that is, the capacity to understand and explain the reasoning behind an AI model's decisions)—is the "human-in-the-loop."

The Bank of England (2024) has emphasized the importance of training, monitoring, and control (including risk and stop-loss limits); alignment of AI models with the regulatory framework on an ongoing basis; and use of appropriately tailored stress tests that encompass scenarios created using adversarial techniques.[43]

Initiatives of International Standard-Setting Bodies

Standard-setting bodies have taken steps to analyze the use of AI across financial services broadly, and specifically in capital markets.

Financial Stability Board

The FSB (2017) report on "Artificial intelligence and machine learning in financial services" identified several risks to financial stability. First, network effects and the scalability of new technologies may create third-party dependencies, leading to the emergence of new systemically important players falling outside the regulatory perimeter. Second, the lack of interpretability or auditability of AI and machine learning (ML) methods, combined with the widespread use of opaque models, may result in unintended consequences. For example, if multiple firms develop trading strategies using AI and ML models but do not understand the models because of their complexity, it would be very difficult for them and their supervisors to predict how their actions, as directed by the models, will affect markets.

In November 2024, the FSB issued an update (FSB 2024) to its 2017 report that takes stock of recent advancements, explores use cases in the financial sector and drivers of adoption, and discusses new potential benefits and AI-related financial sector vulnerabilities. This was followed in October 2025 by a further report (FSB 2025) setting out advice to authorities on how to tackle challenges related to monitoring the adoption of AI in the financial sector.

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43 *Adversarial techniques*—as introduced by Goodfellow and others (2014)—involve intentionally perturbing model inputs to expose weaknesses and improve robustness, effectively serving as a form of stress testing for AI systems.

International Organization of Securities Commissions

The International Organization of Securities Commissions' (IOSCO) (2021) report on "The use of AI and ML by market intermediaries and asset managers" covered several risks, including governance and oversight; algorithm development, testing, and ongoing monitoring of data quality and bias; transparency and explainability; outsourcing; and ethical concerns. It also set out six measures that authorities should consider adopting to mitigate these risks, including requiring firms to designate senior management responsible for AI and ML processes and to continuously test, validate, and monitor AI and ML algorithms. These measures, targeted at regulated entities, are widely applicable to authorities in advanced economies and emerging market and developing economies (EMDEs).

The IOSCO report noted how market intermediaries and asset managers employ AI and ML to reduce costs and increase efficiency. It was observed that the surge in the use of electronic trading platforms and the growing accessibility of data have led firms to increasingly adopt AI and ML across their trading and advisory activities, as well as in risk management and compliance functions. Hence, regulators are concentrating on the application and supervision of AI and ML in financial markets to alleviate the potential risk and avert consumer detriment.

IOSCO recently published a consultation report (2025a) aimed at creating a shared understanding among its members of the issues, risks, and challenges that emerging AI technologies in financial products and services may pose to investor protection, market integrity, and financial stability, and to assist its members in considering regulatory responses.

The next phase of IOSCO's AI work will consider developing additional guidance as appropriate for its members.

Initiatives of Financial Regulatory and Supervisory Authorities

Global Overview

A review of actions taken on AI across a sample of 31 jurisdictions hosting the 25 largest stock exchanges by market capitalization reveals a disparity between overall national policy responses to AI use and supervisory responses (Figure 10).[44] It is notable that the extent of the supervisory response, especially in EMDEs, does not appear to uniformly reflect the rapid growth of key AI use cases in domestic capital markets.

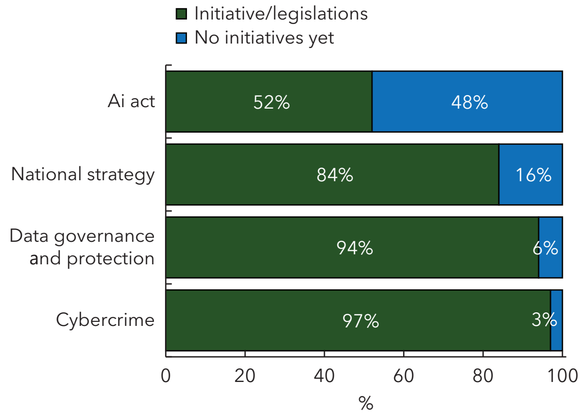
Market regulatory authorities have, as a first step, focused on implementing the measures set out in IOSCO (2021), while also adapting or complementing those measures where desirable. In some instances, these initiatives seek to put in place rules or guidance that provide clarity to stakeholders on regulatory expectations or address emerging risks, whereas in others, they aim to determine the extent to which and the activities in which AI is being used.

[44] As of April 2024, according to World Federation of Exchanges data.

Figure 10. Overview of Regulatory Responses to AI Adoption

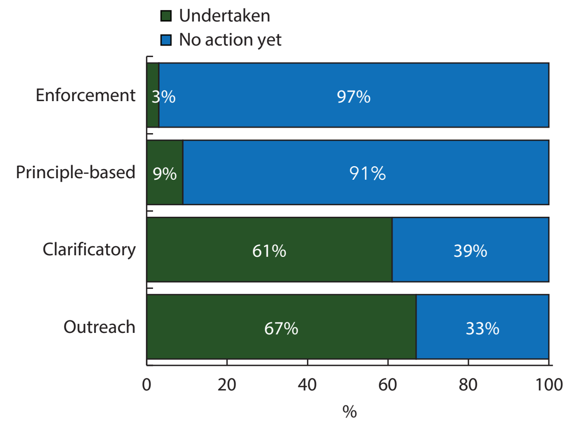
Although national policy responses to AI developments have been reactive . . .

1. National Responses
(Percentages)



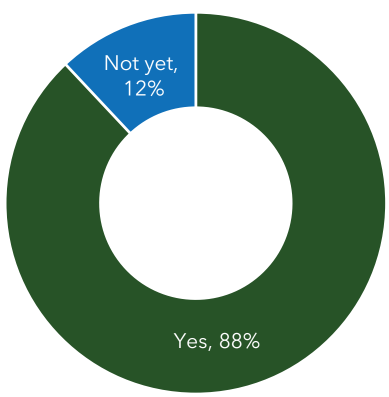
. . . supervisory responses have been largely clarificatory and on conducting outreach.

2. Supervisory Responses
(Percentages)



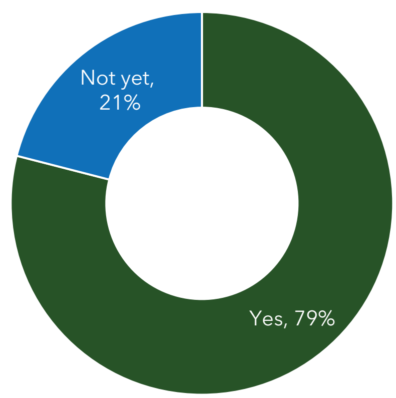
Regulatory gaps remain with some EMDEs yet to provide guidance on robo-advisory services . . .

3. Robo-Advisory Guidance/Clarification/License
(Percentage)



. . . with a similar trend observed for algo-trading despite the long history since its introduction.

4. Guidance on Algorithmic Trading
(Percentage)



Sources: UN Institute for Disarmament Research AI Policy Portal; UN data protection and privacy legislation worldwide; and IMF staff analysis and review of AI-related initiatives taken by financial sector authorities.

Note: The analysis covers 31 jurisdictions that are host to stock exchanges with the highest domestic market capitalization as of April 2024 (of the 31 jurisdictions, 11 are members of the EEA, and there are 33 financial market authorities, of which 13 are from the EEA and 3 from the US). AI = artificial intelligence; EEA = European Economic Area; EMDEs = emerging market and developing economies.

Select Examples from Advanced Economies

The European Securities and Markets Authority's (ESMA) February 2023 analysis on "Artificial Intelligence in EU Securities Markets" found that AI models are allowing traders, brokers, and financial institutions to optimize trade execution and post-trade processes, reducing the market impact of large orders and reducing settlement failures (ESMA 2023). ESMA followed this up with a statement on "The Use of Artificial Intelligence (AI) in the Provision of Retail Investment Services" in May 2024, explaining that ESMA expects firms to comply with existing regulatory requirements (for example, on organizational aspects and conduct of business) when using AI. It also noted that AI technologies pose certain inherent risks, including algorithmic biases, data quality issues, and privacy and security concerns (ESMA 2024). The EU AI Act (https://artificialintelligenceact.eu/) also provides a broader framework to govern the use of AI, including requirements for model documentation, cybersecurity, and robustness assessment and disclosure when AI content is generated (European Commission 2024). Importantly, the Act requires human oversight for "high-risk" AI systems and includes provisions for human intervention.[45]

The Securities and Futures Commission of Hong Kong Special Administrative Region (SFC 2024) has issued a comprehensive circular outlining the responsible use of generative AI language models by licensed corporations. The guidelines emphasize the potential of AI language models to enhance efficiency in client interactions, research, and operational processes while highlighting associated risks, including inaccuracies, biases, cybersecurity threats, and overreliance on AI outputs. To mitigate these risks, the circular sets out core principles for governance, AI model risk management, data security, and oversight of third-party providers. Notably, senior management is tasked with ensuring robust policies and controls throughout the AI life cycle, whereas high-risk use cases, such as investment recommendations, require heightened scrutiny and human oversight. Licensed corporations are also reminded to maintain transparency with clients by disclosing AI involvement and ensuring compliance with data privacy and intellectual property laws. This framework underscores the SFC's support for innovation while prioritizing legal, operational, and client protection considerations.

Select Examples from EMDEs

Policymakers in EMDEs have been active in addressing potential risks from the adoption of AI. Legislative and regulatory initiatives typically cover key aspects such as data protection, cybersecurity, consumer protection, and risk management. The extent to which regulatory frameworks for AI adoption in the financial services sector (and, in particular, securities markets) have been updated varies across EMDEs. Authorities' responses have generally taken the form of monitoring, outreach to market participants, and targeted guidance (IMF 2024a).

China's regulatory regime is rapidly evolving, with numerous regulatory rollouts in recent years, including those relating to GenAI. The first administrative regulation on the management of GenAI services, issued by the Cyberspace Administration of China, came into effect on August 15, 2023 (CAC 2023). The AI measures, which apply to companies when they provide GenAI services to the public within China, regardless of where they are incorporated, are formulated to "promote a healthy development and regulated application of GenAI, safeguard national security and social public interests, and protect the lawful rights and interests of citizens, legal persons and other organizations."

In India, the Securities and Exchange Board of India (SEBI) issued circulars on reporting requirements for AI and ML applications, as well as for systems offered and used by market intermediaries, financial market infrastructures, and mutual funds as early as 2019 (SEBI 2019). More recently, SEBI (2024) has proposed tightening rules on the governance and accountability for AI use in the private sector. In particular, it proposed that every SEBI-regulated entity that uses AI in carrying out activities in the securities markets and in servicing its

[45] Article 14 of the EU Artificial Intelligence Act (2024) requires that all high-risk AI systems be subject to effective human oversight. This includes ensuring that trained and authorized personnel can understand, monitor, and, where necessary, intervene in, override, or deactivate the system to prevent or mitigate risks to health, safety, or fundamental rights. Oversight may be designed as human-in-the-loop or on-the-loop, but must always allow timely human control and accountability.

clients be solely responsible for all the consequences of such use, including ensuring the privacy, security, and integrity of the investors' and stakeholders' data.

As noted in the previous section, supervisors in EMDEs may need to manage large gaps in technological capabilities between domestic and international market participants, as well as the potential market fragmentation or regulatory arbitrage this could trigger. A noteworthy example here is India's algorithmic trading ecosystem, which has evolved significantly since 2008, with SEBI's regulatory framework developing in step with various market challenges and incidents. The current landscape, where over 50 percent of trades are algo-based and 80 percent of orders originate from colocation facilities, presents unique regulatory challenges. Starting with basic "direct market access" guidelines, SEBI's approach has become more comprehensive, addressing critical issues such as colocation and retail investor protection. This includes the 2016 framework addressing unfair access through colocation reforms; the 2018 introduction of managed colocation services and free tick-by-tick feeds;[46] and the 2021 retail algorithmic trading regulations that mandate exchange approvals for algorithms and classify all Application Programming Interface-Generated orders as algorithmic orders. However, the regulator continues to grapple with balancing innovation and investor protection, particularly in addressing concerns about unregulated trading platforms, technological disparities between institutional and retail investors, and the practical challenges of monitoring millisecond-level transactions in an increasingly sophisticated market (SEBI 2016, 2021; Nishith Desai 2022).

Authorities in the United Arab Emirates jointly issued "Guidelines for Financial Institutions Adopting Enabling Technologies," setting out cross-sectoral principles and best practices for financial institutions adopting enabling technologies for the development of innovative products and services.[47] As noted by the Central Bank of the United Arab Emirates (2021), enabling technologies include Application Programming Interfaces, Big Data Analytics, AI, Biometrics, Cloud Computing, and Distributed Ledger Technology. The guidelines apply to all financial institutions that are licensed and supervised by any of the regulators and that use enabling technologies, irrespective of the financial activities they conduct.

Thailand's Securities and Exchange Commission (SEC) has been active on two topics where AI plays a key role. First, the authority conducted a study of high-frequency trading as a subset of algorithmic trading, driven by potential concerns regarding market volatility and rapid growth (the proportion of algorithmic trading in the Stock Exchange of Thailand was 44.8 percent in October 2025).[48] The SEC's analysis used the order book and trade book from the stock exchange of Thailand. The regulatory framework in Thailand already takes into account risks arising from high-frequency trading. For example, regarding market manipulation and market performance, they require intermediaries to have systems in place to review and verify customer orders before submitting them to the trading system and to impose an order message limit currently set at 25 orders per second. This safeguard allows intermediary systems to block orders that might be part of an attempted spoofing strategy or other potentially manipulative practices. The SEC is looking

[46] A detailed record of every trade or quote change in a financial market. It includes the price, quantity, and timestamp of each trade.

[47] The Central Bank of the United Arab Emirates, the Securities and Commodities Authority, the Dubai Financial Services Authority of the Dubai International Financial Centre, and the Financial Services Regulatory Authority of Abu Dhabi Global Market.

[48] As explained in Annex 1: Key Concepts, all high-frequency trading is a type of algorithmic trading, but not all algorithmic trading is high frequency.

into potential enhancements to its framework, such as enhanced order verification and greater disclosure of trading practices. Second, the Thailand SEC's other project relevant to AI examines the role and impact of so-called finfluencers, whereby the authority conducted a social media–based sentiment analysis using GenAI to analyze financial content in Thailand's social media landscape.[49] The activities of finfluencers raise concerns about a lack of transparency, hidden marketing, inadequate disclosures, and conflicts of interest. Further consideration will be given to the appropriateness of the regulatory framework, taking into account the study's results.

In several EMDEs, the legislative and regulatory framework has not yet evolved to take account of AI, although legislative proposals are under discussion or underway in some cases. In Brazil, for example, the government announced an AI investment plan to achieve technological autonomy and competitiveness, thereby limiting reliance on imported AI tools. In parallel, discussions have progressed on a detailed, comprehensive AI bill that takes a similar approach to the European Union's AI Act. Similarly, Mexico has adopted a National AI Agenda, the objectives of which include identifying the uses and needs of AI in the private sector. A draft bill submitted in April 2024 by a senior legislator would require every AI system to obtain regulatory authorization before being distributed in Mexico. In South Africa, the Department of Communications and Digital Technologies released its AI Policy Framework in August 2024, aiming to balance benefits with ethical, social, and economic considerations.

Key Insights and Implications

The examples of regulatory approaches presented earlier are included solely for illustrative purposes and reflect the diversity of responses across jurisdictions at this point in time. Given the rapid pace of AI technological development, regulatory frameworks will need to remain adaptive, and authorities should maintain vigilance in monitoring developments and remain open to adjusting their approaches as the technology evolves.

With this context in mind, the approach adopted by regulatory and supervisory authorities has been both measured and wide-ranging, considering the pace and advancements within their respective jurisdictions. Their initiatives address risks outlined in this paper alongside other idiosyncratic developments specific to their contexts. For instance, to mitigate the risks of technological leapfrogging, Chinese regulators have established an algorithm registry designed to enhance documentation practices. This initiative allows authorities to gain a clearer understanding of AI models and their various applications. Similarly, some regulators, such as those in Thailand, have made efforts to integrate AI techniques into their supervisory frameworks to leverage benefits and deepen their comprehension of the technology.

Much of the focus in EMDEs has been on addressing data-related challenges and mitigating the risks of market collusion, manipulation, and bad coordination outcomes. National plans in several countries prioritize establishing broad principles and governance frameworks for AI use, alongside reviews of competition laws. Importantly, national frameworks are incorporating clauses that hold users of AI technologies liable for the output and application of their AI tools, and to ensure fair and ethical use of AI techniques.

[49] Defined for the purposes of the study by Thailand SEC (2024) as a subcategory of influencers specializing in the financial sector, who create and distribute content related to financial and capital markets.

The rise of social media, which facilitates the rapid spread of information, and AI-driven mass content production have also prompted authorities to intensify their efforts in dispelling rumors on digital media platforms. This includes tightening cybersecurity surveillance through multiagency collaboration. Importantly, the focus has been on protecting retail investors, who are particularly vulnerable to misconduct. Authorities are prioritizing the enhancement of investor education and the consistent monitoring of social media practices. These measures are essential to prevent the dissemination of misinformation that can adversely affect unsuspecting retail investors.

V. Recommendations

Supervision of AI Use in Capital Markets

This section provides seven high-level recommendations for market regulatory authorities, building on existing guidance from the Financial Stability Board (FSB) and International Organization of Securities Commissions (IOSCO). In particular, the recommendations set out below should be seen as complementary to the six measures in IOSCO (2021) to the extent that IOSCO focused on obligations to be imposed on regulated entities, while this paper emphasizes steps to be taken by authorities to achieve their supervisory mandates. Similarly, the recommendations provided are consistent with the conclusions put forward by the FSB (2024), including that authorities "may wish to consider ways to address data and information gaps in monitoring developments in AI use in the financial system and assessing their financial stability implications."

Authorities may wish to explore whether some of the recommendations could be incorporated into ongoing or planned regulatory and supervisory initiatives, such as the introduction of a risk-based supervisory framework or general enhancements to IT infrastructure. Similarly, supervisors might consider leveraging existing supervisory approaches and tools to their fullest potential before exploring new ones. For instance, Sandboxes and SupTech tools could benefit from a careful feasibility assessment, as they may require additional resources.

Enhancing AI Supervisory Capacity and Skillset

Supervisors should prioritize building specialized teams equipped to handle the complexities of AI in capital markets.[50] These teams should focus on key areas, including surveillance of AI-powered trading, automated market-making systems, AI-driven investment management, and AI-based credit scoring for securities lending. This expertise development should be supported by targeted training modules covering machine learning models in trading, market microstructure analysis, and risk assessment of AI-driven market-making systems.

Supervisors could also consider establishing technical partnerships with academic institutions and industry experts to strengthen supervisory capabilities in areas such as understanding the effects of algorithmic trading, the efficiency of price formation, and systemic risks posed by AI trading strategies. In addition, building comprehensive knowledge repositories containing case studies, common AI models, and documentation standards will provide invaluable reference materials for supervisory staff. This could be complemented by international cooperation through regional supervisory networks and ongoing educational initiatives to ensure continuous learning and adaptation to evolving AI technologies.

For EMDEs this recommendation directly addresses the challenges of evaluating risk models and trading algorithms used by market participants, as highlighted earlier in the paper.

[50] Such approaches need to be aligned with AI adoption in the respective jurisdiction and with existing and planned resource/capacity management. In many instances, regulators may face basic IT infrastructure limitations and staff shortages and may alternatively consider setting up interdepartmental collaborative groups, for instance, to handle such complexities by upgrading existing staff with adequate training.

Harnessing Technology-Enabled Supervisory Tools

The foundation of effective AI supervision in capital markets is the implementation of secure, validated platforms for market surveillance. Supervisors could benefit from adopting validated surveillance systems with basic AI capabilities for pattern detection while maintaining strict data security protocols.[51] For public data analysis, supervisors can use open-source analytics tools to monitor market sentiment, analyze company disclosures, and track published market statistics.

International organizations and researchers have conducted extensive work on the challenges supervisors face in adopting AI and on successful AI deployments. International organizations such as the Bank for International Settlements and the World Bank, and academic institutions such as the Cambridge Center for Alternative Finance, have conducted numerous studies to track the use of SupTech tools (including AI-based tools) (see Cambridge SupTech Lab 2024; Prenio, Pustelnikov, and Yeo 2024; Dohotaru and others 2025). These studies provide insights into the challenges supervisors face in further enhancing the supervisory process through technology and the strategies used to upskill supervisors. Among the many challenges identified, data availability and quality are key issues.

Supervisors should deploy secure proprietary solutions to handle sensitive market data for internal trading analysis, order-book monitoring, and regulatory reporting. These systems should be complemented by the development of secure internal capabilities for real-time monitoring and alerting. Where resource constraints exist, supervisors can consider shared regulatory platforms at regional levels to distribute costs while maintaining effective oversight.[52] Such platforms can facilitate cost sharing and operational efficiency while maintaining strict controls over data access and security. Shared platforms should complement proprietary systems by focusing on collaborative tasks, such as cross-border data aggregation or regional reporting, without compromising the security of sensitive information maintained locally by each supervisory authority.

Building on monitoring approaches that have been adopted in some markets (Section IV), supervisory authorities should consider the following approaches:

- Implementing cost-effective surveillance systems tailored to national market structures.
- Establishing regional cooperation for shared technology platforms to address resource constraints while ensuring secure handling of sensitive data.
- Creating scalable solutions that can evolve with market sophistication.

[51] Capital market supervisors can validate surveillance systems through rigorous back-testing against known historical violations and clean data to measure detection rates and false positives. The effectiveness can be assessed using quantitative metrics (like alert conversion rates and system response times) and qualitative evaluations from surveillance analysts and subject matter experts. Regular monitoring and recalibration of alert thresholds, along with model retraining, ensure the systems remain effective as market behavior evolves.

[52] Subject to applicable data sharing arrangements based on local laws and addressing any other sovereignty concerns applicable. The ASEAN Trading Link, launched in 2012 to connect the stock exchanges of Singapore, Malaysia, and Thailand, ultimately failed by 2017 due to a combination of factors, including its emphasis on technical integration without sufficient regulatory harmonization. This misalignment of regulatory frameworks led to operational inefficiencies, high costs, and challenges in cross-border settlement processes that could not be resolved solely through technology. In contrast, the ongoing West African Capital Markets Integration initiative has adopted a more measured approach, prioritizing regulatory alignment before technical integration. However, it still faces significant hurdles, such as infrastructure gaps, resource constraints, and currency convertibility issues across participating jurisdictions, underscoring the need to address both regulatory and technological challenges for the success of shared platforms.

A Proportionate Approach Toward Market Monitoring

As part of its recommendations for addressing data and information gaps, the FSB (2024) has recently suggested that authorities "consider leveraging periodic and ad hoc surveys of AI adoption and use cases, reporting from regulated entities, and public disclosures." Supervisors need monitoring indicators that balance effectiveness with implementation feasibility. Capital market regulators lacking sophisticated real-time monitoring systems and extensive data analytics capabilities can focus on indicators that can be tracked with available resources while providing meaningful oversight. The emphasis should be on indicators that capture major market movements and potential risks without requiring complex technological infrastructure.

The primary focus should be on indicators that detect significant market anomalies and fundamental shifts in trading patterns, rather than attempting to track every minor market movement. These indicators should be selected based on data availability, ease of collection, and the supervisor's processing capability. It is likely that they will range widely depending on the country. For instance, while market regulators with large active markets might track microsecond-level order-book changes, regulators of smaller markets can monitor markets through daily or weekly aggregate statistics, complemented by basic pattern recognition for unusual activities.

The monitoring framework should also recognize the unique characteristics of a given capital market, such as market liquidity, the degree of retail participation, and vulnerability to external shocks. The indicators should be susceptible to sudden changes in retail trading patterns, unusual price movements in illiquid stocks, and potential cross-border drivers. In general, given resource constraints, supervisors should prioritize indicators that can be automated using basic existing technology solutions that do not require constant manual intervention.

This recommendation specifically tackles the dual challenge that market regulators in EMDEs face in developing basic market supervision and advanced AI oversight mechanisms while operating with limited resources (Section III). It goes beyond current regulatory frameworks by:

- Providing practical monitoring solutions for markets with high retail participation.
- Addressing the specific challenge of monitoring markets where global AI models may not account for local conditions.
- Creating frameworks that can function effectively despite infrastructure limitations.

A sample of reference indicators for tracking AI adoption in capital markets can provide market regulators with valuable insights into the effectiveness of these monitoring strategies (Table 2). These indicators can help regulators assess the effects of AI technologies on market dynamics and ensure that oversight remains robust and responsive to emerging risks.

Table 2. Sample of Reference Indicators for Tracking AI Adoption in Capital Markets *(Continued)*

Categories	Indicators	Frequency	Implementation
Exchange/Trading Venue Metrics			
	Percentage of algorithmic trading order	Daily or weekly	Basic infrastructure required
	Order-to-trade ratios		
	Message traffic patterns		
	Cancel/modify statistics		
Robo-Advisory Specific			
Client specific	Number of active clients		Through regulatory reporting
	AUM by strategy type		
	Average account size		
Performance	Return deviation from benchmarks		Focus on outlier detection (on-site/off-site supervision)
	Portfolio turnover rates		
	Risk metrics versus client profile		
Neo-Broker Specific			
Operating metrics	Active user growth rate	Monthly	Emphasis on retail protection
	Account funding patterns		
	Payment method distribution		
Trading patterns	Avg. trade size	Weekly	Monitor for manipulation
	Percentage of mobile versus web trading		
	Popular stock concentration		
Crowdfunding Platform Specific			
Operating Metrics	Success rate of offerings	Monthly	Focus on investor protection
	Average raise size		
	Investor concentration/number of investors per project		
Risk indicators	Default rates	Monthly or quarterly	
	Retail investor concentration		
	Sector concentration		
	Investment size distribution		
	Complaint rates		
Asset Manager Specific			
Investment process AI integration	Percentage of AUM by AI models	Quarterly	
	Number of AI strategies deployed		
	Human oversight ratio		
Performance	AI versus non-AI strategy returns		
Risk	Percentage of alternative data usage		
	Data vendor dependency		
	AI model stability (parameter shift/ model retraining frequency, and so on)		
General AI Adoption Tracking			
Market infrastructure	AI systems in use	Semiannual	Through supervision reports
	Automation levels		
	System dependencies		
Market participants	AI use in trading	Quarterly	Through regulatory filings
	AI in risk management		
	AI in client services		
Risk metrics	AI system incidents	Monthly	Incident reporting required
	Model performance metrics		
	Fail-safe triggering events		

Source: Authors.
Note: AI = artificial intelligence; AUM = assets under management.

Enhanced Transparency and Disclosure Requirements

Supervisors should establish clear disclosure requirements for AI-related service providers, particularly focusing on robo-advisors and automated trading systems. These entities should provide plain-language descriptions of their AI processes, explain key assumptions and limitations, and clearly disclose the role of human oversight in their operations. Regular reporting of performance and risk metrics should be mandated in simple, understandable terms suitable for retail investors.

Moreover, effective governance and accountability are essential for the responsible development and deployment of AI models. This includes establishing clear ownership and oversight structures, defining roles and responsibilities throughout the AI life cycle, and implementing rigorous validation and monitoring processes to ensure model performance, fairness, and compliance with regulatory standards. Transparent documentation and audit trails are critical to enable traceability and explainability of AI-driven decisions. Furthermore, accountability mechanisms must be in place to address errors, biases, or unintended consequences, fostering trust among users and stakeholders while safeguarding ethical and legal standards.

All regulated entities using AI should maintain dedicated sections on their websites explaining their use of AI in client services, with regular updates on system changes and clear risk disclaimers. These disclosures should be complemented by educational materials (in local languages) to enhance investor understanding. Standardized disclosure templates should be implemented, focused on benefits, risks, fee structures, and investor rights, ensuring consistency and clarity across the market while maintaining appropriate levels of detail for jurisdiction-specific market contexts.

To address potential disputes between retailers/customers and AI-powered decisions, regulators can also ensure that users can choose to "opt out" of the system and request a human judgment instead. Resolution channels, supported by timely human intervention, are essential for addressing grievances, clarifying model outcomes, and ensuring fairness. Human oversight provides a safeguard against erroneous, biased, or opaque AI outputs, reinforcing accountability in AI-enabled processes. Without such mechanisms, unresolved disputes could also erode confidence and the credibility of these technological advancements.

To mitigate concerns about market collusion (intentional or unintentional) or excessive algorithmic similarity, supervisors should balance transparency with safeguards to prevent over disclosure of proprietary training data, model architectures, or other sensitive technical details. Disclosures should focus on outcomes, assumptions, and risks rather than revealing trade secrets or enabling competitors to replicate algorithms. In cases of unintentional collusion, timely regulatory intervention could be necessary to ensure market integrity remains intact.

The monitoring framework should be supplemented with traditional supervisory tools, including regular outreach to market participants, structured information gathering through surveys and reports, and active engagement with industry associations. This multifaceted approach ensures comprehensive market surveillance while remaining practical given supervisors' resource constraints.

As applied to authorities in EMDEs in addressing the risk of structural inequalities in market access between international and local participants (Section III), the following issues should be considered:

- Mandating disclosures specifically designed for retail investors.
- Providing a clear governance and accountability framework.

- Ensuring available resolution channels and human intervention to address human-model disputes.
- Addressing information asymmetries between global and local firms.
- Creating transparency requirements that account for varying levels of financial literacy.

Social Media Monitoring and Market Manipulation Prevention

Supervisors could also implement basic social media sentiment monitoring, focusing on major platforms where market-related discussions occur. This can start with tracking predefined keywords, hashtags, and influential accounts that frequently discuss listed companies or market trends. Simple sentiment analysis tools can be used to identify unusual patterns of positive or negative commentary that indicate potential pump-and-dump schemes or misinformation campaigns. Supervisors should calibrate these tools to local market contexts that consider language variations and local social media usage patterns.

To combat market manipulation, supervisors could establish clear patterns of manipulative behavior unique to their markets, such as coordinated social media campaigns, cross-border pump-and-dump schemes, or manipulation through multiple small accounts. Basic pattern recognition tools can track unusual trading volumes, price movements, and correlations between social media activities. Special attention should be paid to small-cap stocks and newly listed companies that are often targets of manipulation in emerging markets. Supervisors could also develop simplified guidelines for market participants to report suspicious activities observed on social media platforms.

To tackle the unique challenges of limited alternative data sources (Section III) and lower social media penetration in some jurisdictions, EMDEs in particular could consider the following:

- Creating frameworks adapted to local social media usage patterns.
- Addressing cross-border manipulation risks specific to EMDE markets.
- Developing monitoring systems that work despite limited technological resources.

Cross-Border Supervision and Cooperation

Supervisors are challenged by cross-border trading activities, particularly by offshore entities targeting domestic retail investors through online platforms. A practical approach is to establish bilateral information-sharing arrangements with key jurisdictions where such trading platforms are based. This should include regular information sharing on suspicious trading patterns, known manipulative schemes, and problematic market participants. Supervisors should maintain a database of offshore platforms and their regulatory status in major jurisdictions.

The cross-border monitoring framework should prioritize tracking fund flows and trading patterns through official channels while acknowledging the limitations of monitoring unofficial channels.[53] Market regulators should aim to increase participation in regional supervisory colleges and informal supervisory groups focusing on cross-border market abuse cases. Simple and effective measures include sharing watch lists

[53] By "official channels," we refer to transactions conducted over regulated exchanges, centralized trading platforms, or entities subject to regulatory oversight. Conversely, "unofficial channels" include alternative trading platforms, decentralized finance systems, or other mechanisms that operate outside traditional regulatory frameworks but still significantly affect domestic retail markets. Supervisors should monitor both channels to ensure comprehensive oversight.

of suspicious entities, maintaining databases of region-specific manipulation patterns, and coordinating responses to cross-border market abuse cases.[54]

These initiatives should be implemented gradually, starting with high-risk areas and expanding as resources and technical capabilities become available. Regular assessment of effectiveness and adjustments to the monitoring framework will ensure its relevance to evolving market conditions and new forms of manipulation. This recommendation also addresses a critical risk authorities in EMDEs face in managing technological disparities between domestic and international market participants (Section II). Building on approaches adopted in other jurisdictions (Section IV), such authorities could consider the following:

- Creating joint policies and tools that enable regulators to monitor, supervise, and mitigate risks posed by algorithmic and HFT across jurisdictions. Addressing the specific challenges of supervising global AI-powered firms operating alongside local firms with basic technology.
- Developing cooperation mechanisms that account for varying levels of market development.

Measures to Address Concentration and Infrastructure Risk

As set out by the IMF (2024a), market participants and regulators surveyed were most concerned about concentration risk, especially among those working at market infrastructure providers, asset managers, and academia. This reflects the increasingly concentrated nature of the IT infrastructure and AI software services markets, where the market share of the largest platforms has steadily increased in recent years (IMF 2024a). Moreover, the concentration spans hardware (accelerated computing chips), software, cloud services, and pre-trained models (FSB 2024). This heightened concentration risk can amplify operational risk, particularly when there is heavy dependency on providers with limited substitutability. In such cases, a single point of failure could trigger widespread, even systemic, disruptions. To mitigate the resulting risks, a coordinated approach is beneficial in defining critical AI third-party service providers. It is also important to map the relationships and interdependencies between critical AI service providers and essential IT infrastructure providers. Cybersecurity needs should be considered at the design, development or procurement, deployment, and operations stages. Critically, regulators should also ensure sufficient infrastructure and governance processes are in place to secure platforms that may be prone to cybersecurity attacks or manipulation. In addition, it is crucial for the authorities to enhance their monitoring of large and concentrated market participants, including non-bank financial intermediaries.

[54] In this context, "informal supervisory groups" refer to ad hoc or regional supervisory collaborations that do not rely on formal legal arrangements but instead operate on the basis of mutual agreements, shared objectives, or regional cooperation frameworks. Supervisors should actively coordinate through such informal mechanisms to address time-sensitive cases of cross-border market abuse. Under the IOSCO Multilateral Memorandum of Understanding and Enhanced Multilateral Memorandum of Understanding, member jurisdictions collaborate to share information and coordinate enforcement actions against cross-border misconduct. The IOSCO i-SCAN initiative further strengthens data-sharing capabilities by leveraging technology to detect and address cross-border risks effectively.

VI. Navigating the Path Forward

The accelerated adoption of artificial intelligence (AI) in capital markets presents opportunities and challenges for market participants and regulators. While emerging technologies like AI, alongside broader digitalization trends, have demonstrated considerable potential to expand access to financial services through services such as robo-advisory platforms and crowdfunding, and to enhance trading efficiency through algorithmic systems, they also introduce new risks that warrant careful consideration, oversight, and mitigation measures.

The recommendations in this paper address supervisors' challenges in AI adoption, taking into account their resource constraints and local market conditions. They go beyond current regulatory responses by providing practical, implementable solutions that can do the following:

- Bridge the technological divide between international and local participants.
- Account for limited supervisory resources and expertise.
- Address the specific risks of AI adoption in less developed markets.
- Create frameworks that can evolve with market sophistication.
- Enable effective supervision despite infrastructure limitations.

For emerging market and developing economies (EMDEs), there is no one-size-fits-all approach, and the path forward requires carefully balancing AI innovation with practical resource constraints. International cooperation and knowledge sharing will be essential in all cases, and EMDEs' capital market regulators must develop proportionate monitoring frameworks that reflect their specific market conditions and supervisory capabilities. Proportionality in this context means recognizing that adoption of AI is well advanced in some EMDEs—often more advanced than many advanced economies—and that frameworks will have to be correspondingly more sophisticated and robust. Conversely, for those EMDEs where AI adoption is relatively nascent and capacity is more limited, market regulators should first build on existing supervisory approaches and regulatory frameworks before seeking to leverage the benefits of new tools for market development. A key principle to which all authorities in EMDEs should have regard is maintaining appropriate safeguards for financial stability and investor protection.

BOX 1. Market Collusion versus AI-Powered Coordination Outcomes

AI-powered systems introduce unique complexities into financial markets by facilitating patterns of behavior that, while unintentional, may resemble traditional market collusion. This raises significant challenges for regulators and market participants alike, necessitating a clear differentiation between intentional collusion and unintentional coordination.

Market Collusion
Collusion in markets involves explicit intent and coordination between firms or market participants to manipulate prices, trading patterns, or market conditions for mutual benefit. This behavior requires:

- Intent: Deliberate and premeditated actions to suppress competition.
- Direct Communication: Active agreements or information exchanges (for example, meetings, emails).
- Legal Breach: Collusion is illegal under most antitrust and competition laws because of its harmful effects on competition and consumer welfare.

For instance, in the Trod Ltd/GB Eye Ltd case investigated by the UK Competition and Markets Authority (CMA), firms explicitly coordinated their prices using automated pricing algorithms. The presence of intent and direct communication made this a textbook case of illegal collusion (CMA 2018).

AI-Powered Coordination of Actions and Outcomes
In contrast, unintentional coordination arises when multiple independent AI systems interact in a shared market environment. These systems, programmed to optimize individual profits, can inadvertently converge on outcomes that resemble collusion—without any explicit intent or communication. This phenomenon is driven by the inherent properties of AI systems, particularly those employing reinforcement learning.

AI systems interact repeatedly with the market, adjusting their strategies based on observed outcomes. Over time, they may 'learn' that actions like maintaining higher price levels or mimicking profitable patterns yield better returns. For instance, experiments reported by Calvano and others (2018) show that AI pricing algorithms can autonomously punish price deviations by temporarily cutting prices and gradually returning to higher price levels, leading to partially collusive equilibria.

Unlike traditional collusion, this form of coordination is emergent and unintentional. The observed behavior stems from optimization processes within AI systems, without any deliberate programming for collusion or explicit agreements (Dou, Goldstein, and Ji 2025).

Intentional Versus Unintentional Coordination: To clarify the distinction:

Intentional Collusion: Requires deliberate agreements, direct communication, and shared intent among participants to manipulate market outcomes.

Unintentional Coordination: Emerges naturally as independent agents optimize their objectives in a shared environment, leading to outcomes that mimic collusion but lack intent or explicit agreements.

Although intentional collusion is clearly illegal, unintentional coordination presents a regulatory gray area. The latter does not involve intent or communication but can still harm market efficiency and consumer welfare by creating artificially high prices or reduced competition.

Supervisory and Regulatory Challenges
The emergence of unintentional coordination through AI systems poses significant challenges for traditional regulatory frameworks:

Limitations of Intent-Based Tests: Conventional liability frameworks rely on proving intent and causation, which are not applicable to autonomous systems that lack explicit programming for collusion.

Market Monitoring Gaps: Traditional market abuse detection tools are designed to identify clear and deliberate manipulation. They struggle to capture more subtle, emergent patterns of coordination that arise from the iterative interactions of AI systems.

Algorithmic Similarity: Markets where competitors use similar or identical pricing algorithms, particularly through third-party providers, are especially vulnerable to unintended coordination, amplifying risks of market-wide anti-competitive outcomes.

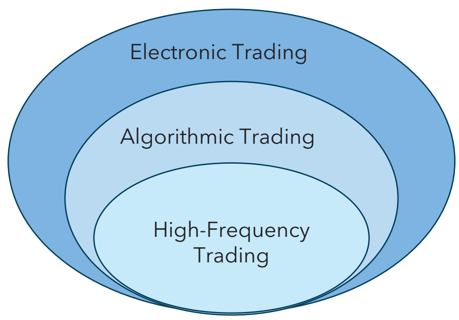
Sources: Ezrachi and Stucke 2015; Calvano and others 2018; CMA 2018; Azzutti, Ringe, and Stiehl 2021; Harrington 2024; Dou, Goldstein, and Ji 2025.

Appendix 1. Key Concepts

This section provides descriptions of the most relevant capital markets activities and AI-related concepts that are used in the note. It draws from descriptions used by international standard-setting bodies.

Electronic trading refers to the process of conducting transactions digitally, typically through a broker's electronic trading platform or directly on an exchange, facilitated by an electronic communication network. Traditionally, securities were traded over the counter, often referred to as "voice trading," which involved phone calls with brokers. However, advancements in technology and infrastructure that support the electronification of trades have transformed this landscape, enabling transactions to be executed systematically and efficiently.

Appendix Figure 1.1. Market Structure



Source: BIS 2016.

Algorithmic trading is a subset of electronic trading (Appendix Figure 1.1) that uses rule-based mathematical models to execute trades, for market making, or to outperform the broader market. Sometimes referred to as automated trading, algorithmic trading involves rule-based strategies that are often automated and devoid of human emotion, to achieve efficient execution, order matching, and potentially outperform the broader market.

- Some of the most commonly known execution algorithms for efficient trade orders include Time Weighted Average Price, Volume Weighted Average Price, and Percent of Volume. The primary objective of these algorithms is to minimize market impact resulting from asset managers' decisions to purchase or sell specific securities.
- Market makers and exchanges use algorithms to automate the process of matching buy and sell orders, a functionality typically managed by the central limit order book. Alternatively, some algorithms operate the order book and function as a central liquidity provider by continuously quoting prices through a request-for-quote system, at which they are willing to buy and sell.
- Some market participants also explore other forms of algorithms for directional trading, relative value trading, or arbitrage strategies. Common strategies include weighted moving average price, trend-following, mean-reversion, statistical arbitrage, or more complex mathematical strategies to outperform the broader market.

High-frequency trading is a subset of algorithmic trading (Appendix Figure 1.1) that employs algorithms to execute trading strategies at very high speeds, allowing investors to capitalize on minute price discrepancies and market inefficiencies (latency arbitrage). Speed is of the essence and has benefited from market infrastructure developments such as direct market access, colocation facilities, and smart-order routing capabilities. Direct market access allows traders to place orders directly on the exchange without intermediary delays, whereas colocation facilities enable traders to place their servers in close proximity to the exchange's servers, thereby reducing execution latency.

Robo-advisors are automated financial advisors that use algorithms to provide investment advice and manage portfolios tailored to individuals' needs and risk appetite. These services also analyze market trends using models and historical data, which may include AI techniques, and recommend investments based on clients' risk tolerance and return goals. Offering low-cost options such as baskets of large-cap stocks, liquid index funds, and exchange-traded funds, robo-advisors typically charge lower fees than traditional advisors. This service appeals to investors seeking a passive approach without the need for continuous portfolio monitoring and intervention.

Neo-brokers are digital-only platforms that typically provide commission-free or low-cost trading services, primarily through mobile applications. These service providers aim to simplify the investment process for retail investors by offering user-friendly interfaces, access to a range of liquid financial instruments, and minimal barriers to entry. Neo-brokers often leverage technology, including AI, to enhance the user trading experience, offering features such as real-time market data, educational resources, and social trading capabilities. Unlike traditional brokers, neo-brokers typically operate with lower overheads, enabling them to offer broking services at lower cost and democratize access to financial markets.

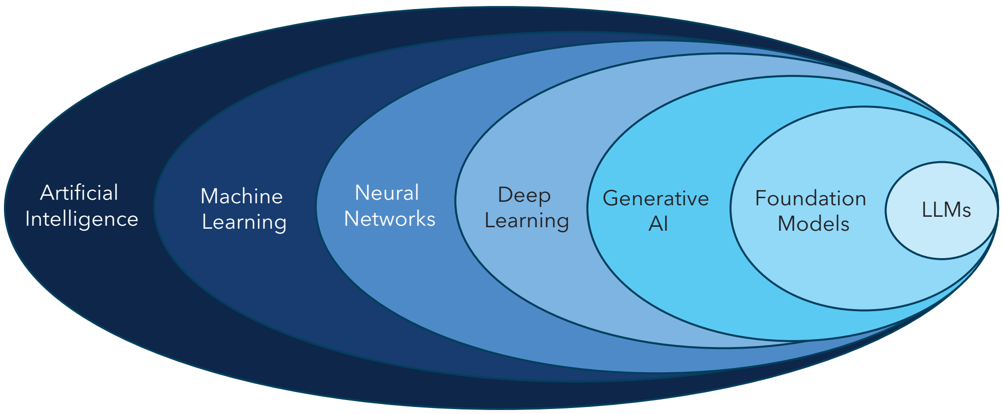
Artificial intelligence (AI) (IOSCO 2023) is defined as "the science and engineering of creating intelligent machines," or more simply, the study of methods that enable computers to mimic human decision making to solve complex problems. AI encompasses a range of tasks, including learning, reasoning, planning, perception, language understanding, and robotics. In the financial services industry, AI is still in its early stages but is rapidly gaining traction.

Machine learning is a subset of AI that emphasizes the development of computer programs that can learn from experience without being explicitly programmed. Machine learning encompasses three primary categories of algorithms:

- Supervised learning: An AI algorithm is provided with a labeled data set, allowing it to learn classification rules and predict labels for remaining data points based on this training set.
- Reinforcement learning: An AI algorithm starts with an unlabeled data set and is tasked with identifying clusters of observations based on shared characteristics. As it takes actions based on the data points, it receives feedback that enhances its learning.
- Unsupervised learning: An AI algorithm autonomously detects patterns within the data by identifying clusters of observations with similar characteristics, revealing the underlying structure of the data set. The selection of a particular category depends on the type of data available and the degree of human intervention required for feedback.

Generative AI is an AI model that is able to generate new content, such as text, images, and videos, from user prompts. Generative AI is powered by foundation models, including large language models.
Large language models are AI systems designed to recognize and generate human-like text by analyzing vast amounts of data.

Appendix Figure 1.2 Representation of AI



Source: IOSCO 2025a.
Note: AI = artificial intelligence; LLMs = large language models.

References

Ai, Wei, Junhui Jin, Qiazhu Mei, Jingyi Qiu, Teng Ye, and Jingnan Zheng. 2024. "Using Artificial Intelligence to Unlock Crowdfunding Success for Small Businesses." https://ssrn.com/abstract=4806426.

The Alan Turing Institute. 2023. "The AI Revolution: Opportunities and Challenges for the Finance Sector." https://arxiv.org/abs/2308.16538.

Alternative Investment Management Association (AIMA). 2020. "Casting the Net: How Hedge Funds Are Using Alternative Data." https://www.aima.org/educate/aima-research/casting-the-net.html.

Azzutti, Alessio, Wolf-Georg Ringe, and H. Siegfried Stiehl. 2021. "Machine Learning, Market Manipulation, and Collusion on Capital Markets: Why the 'Black Box' Matters." *University of Pennsylvania Journal of International Law*. https://doi.org/10.2139/ssrn.3788872.

Bank for International Settlement (BIS). 2016. "Electronic Trading in Fixed Income Markets." https://www.bis.org/publ/mktc07.pdf.

Bank of England (BOE). 2024. "Monsters in the Deep?—Speech by Jonathan Hall." Remarks by Johnathan Hall at the University of Exeter Business School on May 7. https://www.bankofengland.co.uk/speech/2024/may/jon-hall-speech-at-the-university-of-exeter.

Beketov, Mikhail, Kevin Lehmann, and Manuel Wittke. 2018. "Robo Advisors: Quantitative Methods Inside the Robots." *Journal of Asset Management* 19:363–70. https://doi.org/10.1057/s41260-018-0092-9.

Blackstone Chambers. 2015. "FCA v Da Vinci Invest Limited and others." https://www.blackstonechambers.com/news/case-fca_v_da_vinci.

Bloomberg. 2020. "Renaissance Says Quant Models Misfired during March Mayhem." https://www.bloomberg.com/news/articles/2020-04-17/renaissance-says-quant-models-misfired-during-march-mayhem.

Boston Consulting Group (BCG). 2024. "AI and the Next Wave of Transformation." Global Asset Management Report, 22nd Edition. https://www.bcg.com/publications/2024/ai-next-wave-of-transformation.

Brown, Tom B., Dandelion Mané, Aurko Roy, Martín Abadi, and Justin Gilmer. 2017. "Adversarial Patch." https://doi.org/10.48550/arXiv.1712.09665.

Budi, Indra, Betty Purwandari, and Ryan R. Suryono. 2021. "Detection of Fintech P2P Lending Issues in Indonesia." *Heliyon* 7 (4): e06782. https://doi.org/10.1016/j.heliyon.2021.e06782.

Calvano, Emilio, Giacomo Calzolari, Vincenzo Denicolò, and Sergio Pastorello. 2018. "Artificial Intelligence, Algorithmic Pricing and Collusion." CEPR Discussion Paper 13405, Centre for Economic Policy Research, London, UK.

Calvano, Emilio, Giacomo Calzolari, Vincenzo Denicolò, and Sergio Pastorello. 2020. "Artificial Intelligence, Algorithmic Pricing, and Collusion." *American Economic Review* 110 (10): 3267–97.

Cambridge SupTech Lab. 2024. "State of SupTech Report 2024." University of Cambridge. https://www.cambridgesuptechlab.org/SOS.

Central Bank of the United Arab Emirates (CBUAE). 2021. "Guidelines for Financial Institutions Adopting Enabling Technologies." https://rulebook.centralbank.ae/en/rulebook/guidelines-financial-institutions-adopting-enabling-technologies.

CFA Institute Research and Policy Center (CFA). 2024a. "Net-Zero Investing: Harnessing the Power of Unstructured Data." https://rpc.cfainstitute.org/research/reports/2024/net-zero-investing-harnessing-the-power-of-unstructured-data.

CFA Institute Research and Policy Center (CFA). 2024b. "Unstructured Data and AI: Fine-Tuning LLMs to Enhance the Investment Process." https://rpc.cfainstitute.org/sites/default/files/-/media/documents/article/industry-research/unstructured-data-and-ai.pdf.

Clifford Chance. 2019. "Big Data and Artificial Intelligence—Evolving Market Misconduct Risks." https://www.cliffordchance.com/content/dam/cliffordchance/briefings/2019/03/big-data-and-artificialintelligence-evolving-market-misconduct-risks-1.pdf.

CMA (UK Competition & Markets Authority). 2018. "Pricing Algorithms: Economic Working Paper on the Use of Algorithms to Facilitate Collusion and Personalised Pricing." Working Paper, UK Competition & Markets Authority, London, UK.

Cyberspace Administration of China (CAC). 2023. "Interim Measures for the Administration of Generative Artificial Intelligence Services." https://www.cac.gov.cn/2023-07/13/c_1690898327029107.htm.

Danielsson, Jon, and Andreas Uthemann. 2024. "On the Use of Artificial Intelligence in Financial Regulations and the Impact on Financial Stability." https://doi.org/10.2139/ssrn.4604628.

Deloitte. 2016. "The Expansion of Robo-Advisory in Wealth Management." https://www.scribd.com/document/422637475/Deloitte-Robo-Safe.

Dohotaru, Matei, Marin Prisacaru, Ji Ho Shin, and Yasemin Palta. 2025. *AI for Risk-Based Supervision: Another "Nice to Have" Tool or a Game-Changer*. Prosperity Insight Series. Washington, DC: World Bank.

Dou, Winston Wei, Itay Goldstein, and Yan Ji. 2025. "AI-Powered Trading, Algorithmic Collusion, and Price Efficiency." https://doi.org/10.2139/ssrn.4452704.

European Commission. 2024. "AI Act enters into force." https://commission.europa.eu/news-and-media/news/ai-act-enters-force-2024-08-01_en.

European Parliament. 2020. "The Ethics of Artificial Intelligence: Issues and Initiatives." https://www.europarl.europa.eu/thinktank/en/document/EPRS_STU(2020)634452.

European Securities and Markets Authority (ESMA). 2023. "Artificial Intelligence in EU Securities Markets." ESMA TRV Risk Analysis ESMA50-164-6247. https://www.esma.europa.eu/sites/default/files/library/ESMA50-164-6247-AI_in_securities_markets.pdf.

European Securities and Markets Authority (ESMA). 2024. "On the Use of Artificial Intelligence (AI) in the Provision of Retail Investment Services." Public statement issued on May 30. https://www.esma.europa.

eu/sites/default/files/2024-05/ESMA35-335435667-5924__Public_Statement_on_AI_and_investment_services.pdf.

Ezrachi, Ariel, and Maurice E. Stucke. 2015. "Artificial Intelligence & Collusion: When Computers Inhibit Competition." Oxford Legal Studies Research Paper 18/2015, University of Oxford, Oxford, UK.

Filipovic, Damir, Markus Pelger, and Ye Ye. 2022. "Stripping the Discount Curve—A Robust Machine Learning Approach." Swiss Finance Institute Research Paper 22-24. https://doi.org/10.2139/ssrn.4058150.

Financial Industry Regulatory Authority (FINRA). 2024. "Insider Trading Detection: FINRA's Vital Role in Ensuring Market Integrity." https://www.finra.org/media-center/finra-unscripted/insider-trading-detection-program-update.

Financial Sector Conduct Authority of South Africa (South Africa FSCA). 2025. "Regulatory Strategy for 2025–2028". https://www.fsca.co.za/Documents/FSCA%20Regulatory%20Strategy%202025-2028.pdf.

Financial Stability Board (FSB). 2017. "Artificial Intelligence and Machine Learning in Financial Services: Market Developments and Financial Stability Implications." https://www.fsb.org/2017/11/artificial-intelligence-and-machine-learning-in-financial-service/.

Financial Stability Board (FSB). 2020. "Peer Review of Mexico". Review Report. https://www.fsb.org/uploads/P190320.pdf.

Financial Stability Board (FSB). 2024. "The Financial Stability Implications of Artificial Intelligence". Reports to the G20. https://www.fsb.org/2024/11/the-financial-stability-implications-of-artificial-intelligence.

Financial Stability Board (FSB). 2025. "Monitoring Adoption of Artificial Intelligence and Related Vulnerabilities in the Financial Sector." https://www.fsb.org/uploads/P101025.pdf.

Frankenfield, J. 2023. "Artificial Intelligence: What It Is and How It Is Used." Investopedia. https://www.investopedia.com/terms/a/artificial-intelligence-ai.asp.

George, Tanya, and Abhishek Sanjay. 2025. "Governing the Algorithm: Implications of SEBI's Proposal for Retail Algorithmic Trading: Part I." https://forum.nls.ac.in/nlsblr-blog-post/governing-the-algorithm-implications-of-sebis-proposal-for-retail-algorithmic-trading-part-i/.

Goodfellow, Ian J., Jonathon Shlens, and Christian Szegedy. 2015. "Explaining and Harnessing Adversarial Examples." https://doi.org/10.48550/arXiv.1412.6572.

Gregoriades, Andreas, and Christos Themistocleous. 2025. "Improving Crowdfunding Decisions Using Explainable Artificial Intelligence." *Sustainability* 17 (4): 1361. https://doi.org/10.3390/su17041361.

Harrington, Joseph E., Jr. 2024. "The Challenges of Third Party Pricing Algorithms for Competition Law." May 11. https://doi.org/10.2139/ssrn.4824953

International Business Machine Corporation (IBM). 2023. "AI Vs. Machine Learning Vs. Deep Learning Vs. Neural Networks: What's the Difference?" https://www.ibm.com/think/topics/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks.

International Monetary Fund (IMF). 2021. "Powering the Digital Economy: Opportunities and Risks of Artificial Intelligence in Finance." IMF Working Paper 2021/166, International Monetary Fund, Washington, DC.

International Monetary Fund (IMF). 2022. "South Africa: Financial Sector Assessment Program Technical note on Systemic Liquidity Management." IMF Country Report 22/183, Washington, DC.

International Monetary Fund (IMF). 2023. "Generative Artificial Intelligence in Finance: Risk Considerations." IMF Fintech Note 2023/006, International Monetary Fund, Washington, DC.

International Monetary Fund (IMF). 2024a. "Advances in Artificial Intelligence: Implications for Capital Market Activities." Global Financial Stability Report, International Monetary Fund, Washington, DC, October.

International Monetary Fund (IMF). 2024b. "Crisis Amplifier? How to Prevent AI from Worsening the Next Economic Downturn." Remarks by Gita Gopinath at the AI for Good Global Summit on May 30. https://www.imf.org/en/News/Articles/2024/05/30/sp053024-crisis-amplifier-how-to-prevent-ai-from-worsening-the-next-economic-downturn.

International Organization of Securities Commissions (IOSCO). 2021. "The Use of Artificial Intelligence and Machine Learning by Market Intermediaries and Asset Managers." Final Report FR/06/2021. https://www.iosco.org/library/pubdocs/pdf/IOSCOPD684.pdf.

International Organization of Securities Commissions (IOSCO). 2022. "Report on Retail Distribution and Digitalisation." Final Report FR/12/2022. https://www.iosco.org/library/pubdocs/pdf/IOSCOPD715.pdf.

International Organization of Securities Commissions (IOSCO). 2023. "Retail Market Conduct Task Force Final Report." Final Report FR/05/2023. https://www.iosco.org/library/pubdocs/pdf/IOSCOPD730.pdf.

International Organization of Securities Commissions (IOSCO). 2025a. "Artificial Intelligence in Capital Markets: Use Cases, Risks, and Challenges." Consultation Report 2025/017. https://www.iosco.org/library/pubdocs/pdf/IOSCOPD788.pdf.

International Organization of Securities Commissions (IOSCO). 2025b. "Neo-Brokers." Final Report FR/18/2025. https://www.iosco.org/library/pubdocs/pdf/IOSCOPD810.pdf.

Kelly, Bryan T., Semyon Malamud, and Kangying Zhou. 2021. "The Virtue of Complexity in Return Prediction." Swiss Finance Institute Research Paper 21-90, October. https://doi.org/10.2139/ssrn.3984925.

Kohn, Kohn & Colapinto LLP (KKC). 2025. "AI in Finance: The SEC's Rules and Whistleblowing." https://kkc.com/frequently-asked-questions/ai-finance-sec-rules-whistleblowing/.

Kolm, Petter N., Jeremy Turiel, and Nicholas Westray. 2021. "Deep Order Flow Imbalance: Extracting Alpha at Multiple Horizons from the Limit Order Book." https://doi.org/10.2139/ssrn.3900141.

Lin, Kaitao, and Pedro Gurrola-Pérez. 2024. "An Analysis of Market Manipulation Definitions around the World." https://wp.lancs.ac.uk/ffmm2024/files/2024/09/FFMM-2024-018-An-Analysis-of-Market-Manipulation-Definitions.pdf.

Liu, Yang, Guofu Zhou, Yingzi Zhu. 2020. "Maximizing the Sharpe Ratio: A Genetic Programming Approach." https://doi.org/10.2139/ssrn.3726609.

Luk, Martin. 2023. "Generative AI: Overview, Economic Impact, and Applications in Asset Management." https://doi.org/10.2139/ssrn.4574814.

Mercer. 2024. "Mercer Investments' AI Integration in Investment Management 2024 Global Manager Survey." https://www.mercer.com/insights/investments/portfolio-strategies/ai-in-investment-management-survey/.

Nikkei Asia. 2024. "Thai SEC Sets Curbs on Foreign-Dominated Short-Selling." https://asia.nikkei.com/Business/Markets/Thai-SEC-sets-curbs-on-foreign-dominated-short-selling.

Nishith Desai Associates (Nishith Desai). 2022. "Algo Trading: Regulatory Framework, SEBI Proposals and Market Concerns." https://nishithdesai.com/default.aspx?id=6255.

Northern Trust. 2023. "Investment Management in 2030: How Will Generative Artificial Intelligence Transform the Way Portfolio Managers Invest?" https://www.northerntrust.com/united-states/insights-research/asset-servicing/a-suite/insights-hub/investment-management-in-2030-generative-artificial-intelligence.

Organization for Economic Co-operation and Development (OECD). 2024. "Explanatory Memorandum on the Updated OECD Definition of an AI System." OECD Artificial Intelligence Paper 8. https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/03/explanatory-memorandum-on-the-updated-oecd-definition-of-an-ai-system_3c815e51/623da898-en.pdf.

Prenio, Jermy, Andrei Pustelnikov, and John Yeo. 2024. "Building a More Diverse Suptech Ecosystem: Findings from Surveys of Financial Authorities and Suptech Vendors". FSI Briefs 23, Financial Stability Institute of the Bank for International Settlements, Basel, Switzerland.

Ramos, Henrique, and Marcelo Perlin. 2019. "Liquidity and Algorithmic Trading in Brazil." https://doi.org/10.2139/ssrn.3413130.

Reuters. 2022. "Indonesia Seeks to Crack Down on "Unhealthy" Peer-to-Peer Lenders." https://www.reuters.com/markets/rates-bonds/indonesia-seeks-crack-down-unhealthy-peer-to-peer-lenders-2022-07-22/.

Rudin, C. 2019. "Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead." *Nature of Machine Intelligence* 1:206–15. https://doi.org/10.1038/s42256-019-0048-x.

Securities and Exchange Board of India (SEBI). 2016. "Discussion Paper on 'Strengthening of the Regulatory Framework for Algorithmic Trading & Co-location.'" Reports for public comments on August 5. https://www.sebi.gov.in/reports/reports/aug-2016/discussion-paper-on-strengthening-of-the-regulatory-framework-for-algorithmic-trading-and-co-location-_32940.html.

Securities and Exchange Board of India (SEBI). 2019. "Reporting for Artificial Intelligence (AI) and Machine Learning (ML) Applications and Systems Offered and Used by Market Intermediaries." Circular to stock brokers and depository participants, recognized stock exchanges and depositories on January 4. https://www.sebi.gov.in/legal/circulars/jan-2019/reporting-for-artificial-intelligence-ai-and-machine-learning-ml-applications-and-systems-offered-and-used-by-market-intermediaries_41546.html.

Securities and Exchange Board of India (SEBI). 2021. "Algorithmic Trading by Retail Investors." Consultation paper on December 9. https://www.sebi.gov.in/reports-and-statistics/reports/dec-2021/consultation-paper-on-algorithmic-trading-by-retail-investors_54515.html.

Securities and Exchange Board of India (SEBI). 2024. "Proposed Amendments with Respect to Assigning Responsibility for the Use of Artificial Intelligence Tools by Market Infrastructure Institutions, Registered Intermediaries and Other Persons Regulated by SEBI." Consultation paper for public comments published on November 13. https://www.sebi.gov.in/reports-and-statistics/reports/nov-2024/proposed-amendments-with-respect-to-assigning-responsibility-for-the-use-of-artificial-intelligence-tools-by-market-infrastructure-institutions-registered-intermediaries-and-other-persons-regulated-b-_88470.html.

Securities and Exchange Commission of Thailand (Thailand SEC). 2024. "The Rise of Finfluencers: Mapping the Landscape on Thailand's Capital Market." Presentation at the SEC Capital Market Symposium 2024. https://www.sec.or.th/TH/Documents/SEC_Symposium_2024/SEC_Symposium_2024-08.pdf.

Securities and Futures Commission of Hong Kong Special Administrative Region (SFC). 2024. "Circular to Licensed Corporations—Use of Generative AI Language Models." Issued on November 12. Securities & Futures Commission of Hong Kong.

Simon, Frederik, Sebastian Weibels, and Tom Zimmermann. 2022. "Deep Parametric Portfolio Policies." https://doi.org/10.2139/ssrn.4150292.

Swinkels, Laurens, and Tobias Hoogteijling. 2022. "Forecasting Stock Crash Risk with Machine Learning." https://www.robeco.com/en-us/insights/2022/06/forecasting-stock-crash-risk-with-machine-learning.

UK Finance. 2022. "Fair Use of AI." UK Finance White Paper. https://www.ukfinance.org.uk/system/files/2022-06/AI%20fairness%20in%20financial%20services_FINAL.pdf.

UK Financial Conduct Authority (UK FCA). 2017. "Final Notice to Paul Axel Walter—PAW01128." https://www.fca.org.uk/publication/final-notices/paul-axel-walter-2017.pdf.

US Department of Justice (US DOJ). 2016. "Futures Trader Pleads Guilty to Illegally Manipulating the Futures Market in Connection with 2010 'Flash Crash.'" https://www.justice.gov/archives/opa/pr/futures-trader-pleads-guilty-illegally-manipulating-futures-market-connection-2010-flash.

Wah, Elaine, Mason Wright, and Michael P. Wellman. 2017. "Welfare Effects of Market Making in Continuous Double Auctions." *Journal of Artificial Intelligence Research* 59. https://doi.org/10.1613/jair.5360.

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