Artificial intelligence and machine learning in asset management

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Background

Technology has become ubiquitous. In 2014, we published a *ViewPoint* titled The Role of Technology within Asset Management, which documented how asset managers utilize technology in trading, risk management, operations and client services. As technology continues to evolve and computing power increases, new use cases are being identified and new applications are being developed. This applies broadly across sectors, including asset management. Artificial Intelligence (AI) and Machine Learning (ML) are the latest buzzwords in technology attracting attention. AI and ML reflect the natural evolution of technology as increased computing power enables computers to sort through large data sets and crunch numbers to identify patterns and outliers.

As we laid out in 2014, technology underpins many functions in asset management and has for decades. Virtually all asset managers utilize technology, either developing their own tools or outsourcing specific functions to a third party provider. Simply processing large quantities of data from portfolio managers, exchanges, custodians, rating agencies, and pricing services requires some level of automation to ensure efficiency and accuracy.

Today, AI and ML are being employed to improve the customer experience, increase the efficiency and accuracy of operational workflows, and enhance performance by supporting multiple aspects of the investment process. Consistent with our view that technology in general can improve the quality and analysis of data for decision-making and drive risk mitigation, we embrace technological advances, including AI and ML, that can help improve outcomes for our clients.

These technological tools are part of a larger ecosystem in which people make decisions using the information generated by computers in various aspects of asset management, where a myriad of regulations already apply. These regulations apply regardless of whether a process is performed manually or automated. Specifically, most regulatory regimes across the globe have standards of conduct for trading practices, safety and soundness rules governing electronic trading, information security regulations, disclosure requirements, regulatory reporting, and regulation regarding the provision of advice.

In this *ViewPoint*, we explore the uses of AI and ML in asset management. While these terms are used frequently, we find that there are many different understandings of AI and ML; therefore, we begin by defining some of the key terms. Using this foundation, we discuss use cases of AI and ML in the asset management industry, including some specific use cases at BlackRock. We suggest best practices for consideration by asset managers and regulators to factor into their operations and supervision of AI and ML.

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Summary: Best practices and key recommendations

Best Practices: Use of AI/ML in user experiences and interfaces

- The provision of investment advice is heavily regulated. Any new tools or digital advisors are subject to the same framework of regulation and supervision as traditional advisors, though the applicability and emphasis may vary.
- For AI and ML technologies that have access to client information and sensitive data, it is critical to ensure robust cybersecurity defenses, including data encryption, cybersecurity insurance, and business continuity management plans that include incident management frameworks.

Best Practices: Use of AI/ML for operational efficiency

- Investment, operations, and risk professionals should be closely involved in the creation and ongoing oversight of any model or system that leverages AI or ML, ensuring transparency into the underlying processes used by the technology.
- Asset managers rely on vast quantities of data, including from external data vendors. Thus, data quality and robust production monitoring should be of the utmost importance to reduce errors and mitigate operational risks.
- When asset managers choose to buy rather than build AI and ML services and capabilities, clarity on the respective responsibilities of the third party provider and the asset management firm using the service or tool is essential. Asset managers should conduct appropriate due diligence on the service providers including ensuring they have robust testing of the applications, business continuity management, technology disaster recovery planning, and cybersecurity.

Best Practices: Use of AI/ML in the investment process

- In the design of any model intended to augment human functions, it is critical that the appropriate investment and risk professionals be closely involved in the creation and ongoing oversight of the technology.
- All data inputs should be robustly tested to ensure models are performing analysis on accurate data sets, and periodic review procedures should be in place to ensure that no investment process is out-of-date.
- Portfolio managers and risk managers should be able to interpret both the inputs and outputs of the model to review any investment decision and adjust in new market environments. The more complex the ML technique used by the model, the higher the risk of obscuring the interpretability of results.
- When used for trading, the AI and ML processes should have appropriate pre-trade controls, development and release management processes, and real-time ability to monitor and shut off a system. More broadly, such robust controls should apply to any automated trading process, beyond AI and ML use cases, as electronic trading should be subject to prudent governance.

Regulatory approaches to the use of AI/ML

- Regulators should balance overseeing the development of new technologies with supporting innovations that may be beneficial for investors.
- Before pursuing new regulations, we recommend that policy makers consider the applicability of existing regulation to the uses of AI and ML technologies in asset management and provide additional guidance where appropriate.
- As the applications of new technologies evolve, policy makers should think about how regulation should similarly evolve and consider providing education and clarification on how existing regulations apply to the use of new technologies. Many applications of AI and ML are for research purposes only and are not tied to production processes. Production impact of specific use cases should be considered to determine the appropriate level of risk and oversight.
- Regulatory sandbox programs can allow for testing of new AI and ML innovations in a controlled environment, and we encourage regulators to engage with the industry to develop best practices and encourage ongoing innovations.
- Given the global nature of many AI and ML innovations and the financial system as a whole, we encourage regulators to work together to facilitate globally consistent regimes to ensure that these technologies can function across borders.

The proliferation of data

While AI has been around since the 1950s, certain trends have propelled it in the last five to ten years – the growth of computing processing power, storage, the cloud, and the proliferation of data. To frame the scale of how much data is now available to investors, consider a specific data set which is a key component of the modern investment process: detailed financial information about public companies. The Securities Act of 1933 and Securities Exchange Act of 1934 require all publicly traded companies in the U.S. to report universal and verifiable financial information, including quarterly to annual reports, 8-K filings, proxy statements, ownership filings and many other forms. For the Russell 3000 index, which is comprised of approximately 3,000 of the largest U.S. companies by market capitalization, quarterly and annual reports alone represent roughly 12,000 documents in a given fiscal year. Add to this the availability of transcripts from quarterly earnings calls and investor day presentations, and there is a trove of data about individual companies that can be aggregated to identify trends at the sector level.

The availability of information, such as a company's financials and a growing universe of less traditional data sets, combined with advances in modern computing, paved the way for what we refer to as "big data" and new technology tools to assess this data.

Defining artificial intelligence and machine learning

The terms "AI" and "ML" are often used interchangeably. While these terms are intertwined, AI is the broader umbrella term and ML is a subset of AI that reflects the evolution of AI.

AI is the use of machines to replicate human intelligence. This can be thought of on a spectrum ranging from "weak" or "narrow" AI to "strong" AI – with the goal of strong AI being replication of intelligence and reasoning. We view AI as being in a separate category and distinct from mechanical automation, which is a machine following a set of pre-defined instructions to accomplish a simple and repetitive task.

Spectrum of AI

At present, even the most advanced AI is considered "weak" by the computer science and academic community. However, weak AI is still quite powerful; it is used to perform tasks ranging from widget assembly on a conveyer belt, to more complex processes and decision making such as self-driving cars. Both widget assembly and self-driving cars follow a methodology that is common across all AI: machines process inputs which subsequently pass through functions to reach a computer-generated decision as an output. These functions can be logical (rules-based), mathematical, or a combination of both. Consider the example of a "smart home" system that regulates the temperature of a room. A user can manually set the logical parameters such as the desired temperature and the time of day to run. What makes the system "smart" is that it can be pre-programmed with capabilities that allow the system to change its output, such as automatically adjusting the temperature of the room according to the outside temperature, based on a user's past inputs. It does this without explicit instructions from the user. The data inputs in this example are specific and simple. As data sets have increased in size and complexity, mathematicians and computer scientists have developed new techniques to allow for systems to understand more complex inputs and generate more sophisticated outputs. These more advanced techniques and models used to analyze varying data sets are known today as ML, which we examine in more detail below.

ML is a specific data science approach to AI. ML programs learn to perform tasks by finding patterns in large data sets and making inferences instead of following explicit task-specific instructions that have already been programmed. Consider recent innovations with virtual assistants such as Apple's Siri or Amazon's Alexa that are already ubiquitous in millions of households. Based on the sounds a device receives (the input), an AI system using ML data science techniques attempts to determine what words have been spoken based on their similarity to a previously captured audio library. The AI system "learns" as inputs and outcomes, successful or not successful, are recorded and stored – large volumes of data allow the underlying models to recalibrate and better identify patterns. For example, if a user dictates "Search for spores near me", Siri will initially recognize the word "spores", before quickly modifying the query to "Search for stores near me". Apple's vast database of other user's queries has "taught" Siri that it is far more probable that the user is looking for a storefront rather than a collection of fungi. Siri uses statistical methods to determine and search a user's speech input. Instead of a programmer explicitly telling Siri to make this correction, Siri used vast amounts of data collected to make the rules by itself. It is important to note that data and models alone are not what allows AI programs like Siri to be successful – an entire system comprised of computing architecture, large data storage, mathematical solutions, and high-performance visualization tools must all work in tandem to realize the benefits of AI.

However, many AI/ML applications do not implement an action and make decisions autonomously like Siri. Rather, the underlying data science models drive a research process that enable users to make a more informed decision by identifying relationships and patterns in the data that were previously undiscoverable by human efforts alone. This is akin to GPS navigation applications, such as Google Maps or Waze, that consume large volumes of data such as street mappings, traffic areas, accident reports, etc. and make recommendations of how to get to the desired destination. The user makes the end decision of which path to follow or can choose to deviate from a recommended path as they see fit based on prior experience. The majority of use cases in asset management, which we explore throughout the rest of this paper, fall within research-oriented applications of AI/ML rather than production-oriented applications.

AI and ML in asset management

Technology has been integrated into asset management for decades with a variety of uses. Given the evolution of technology broadly in society, it is not surprising that there continue to be new technologies and use cases in asset management. The types of technologies being utilized today – including AI and ML – build on the existing systems and technology infrastructure.

Broadly speaking, we break asset management technology into three main categories:

- User experience and interfaces
- Operational efficiency
- Investment processes

In each of these areas, technology helps improve efficiency, manage risk, and enhance decision-making. Importantly, all of these technologies involve people and subject matter experts who provide oversight and consider the outputs of technologies for more informed decision-making. In the following sections, we take a closer look into each category, considering AI and ML techniques that can be applied in asset management broadly and how they are being deployed specifically within BlackRock.

The term *asset managers* refers to a broad group of firms and investment strategies. For purposes of this paper, we are focused on *traditional asset managers* which we differentiate from *nontraditional asset managers* (including hedge funds, private equity, and other alternative investment strategies). In our experience, traditional asset managers employ AI and ML to varying degrees. This paper focuses on common uses; this is not meant to be an exhaustive list.

User experience and interfaces

Historically, only the wealthy had the access and means to invest. In recent decades, technology has been the driving force in democratizing access to wealth management. For example, an individual investor would historically have to contact a stockbroker to facilitate stock transactions, often for high fees. They would need to consult with a tax specialist or accountant to consider tax implications and determine how to maximize the value of these investments.

Tools using AI and ML are now available for investors to better gain access to the financial markets and receive digital advice, including planning for retirement. Based on characteristics such as a user's age, income, risk tolerance, and desired income in retirement, model-based digital tools can help investors select the appropriate asset allocation mix to meet their goals. Digital advisors can incorporate these new tools and provide a way for individuals to get personalized investment advice at a lower cost than traditional advisory models. Digital advisors may also offer tax-loss harvesting, portfolio allocation rebalancing, and digital documentation delivery – features that previously would have been out of reach without technological advances like AI and ML.

Digital advice can be used to supplement traditional advisors, and most digital advisors offer multiple ways to engage with a human professional. While some digital advice firms offer a greater degree of human supervision of client services and trading systems than others, digital advisors have a fundamental obligation to oversee their systems and mitigate risks associated with digital processes. Rather than replacing human advisors, digital advisors can help them automate processes and more effectively provide advice at scale. As we outlined in our *ViewPoint* Digital Investment Advice: Robo Advisors Come of Age, digital advisors are subject to the same framework of regulation and supervision as traditional advisors, though the applicability and emphasis may vary.

Use at BlackRock: User interfaces

BlackRock utilizes user interfaces to interact with different audiences, ranging from large institutions to wealth managers. These capabilities are supported by over 2,500 experts dedicated to client service, data analytics & production, and technology development. These platforms are built to service the highly custom financial needs of advisors at scale to seek to create the best financial outcomes for clients. Currently, we are exploring the use of AI/ML in our tools with the aim of enhancing our ability to connect with clients and tailor solutions to help them achieve their financial goals.

Examples of BlackRock tools to improve the user experience and interfaces

Solution	Overview
aladdin Wealth	Aladdin Wealth provides an institutional-quality solution to wealth management firms and banks, including enterprise-wide business and risk oversight and portfolio analysis and construction capabilities
FutureAdvisor	FutureAdvisor digitizes the wealth management process for financial institutions and their advisors to onboard and serve new client segments in a scalable way
iRetire by BlackRock	iRetire helps financial professionals build plans that are focused on retirement saving, spending and income quickly and efficiently using a repeatable process – so they can focus on client service and asset acquisition
Advisor Center powered by aladdin	Advisor Center provides practice management capabilities, like scenario analysis and tax insights, powered by Aladdin, on the web

References to BlackRock's user interfaces are intended to illustrate how asset managers are able to use technology in various ways and are not intended to promote any specific BlackRock asset management service or technology solution.

Best Practices: Use of AI/ML in user experiences and interfaces

- The provision of investment advice is heavily regulated. Any new tools or digital advisors are subject to the same framework of regulation and supervision as traditional advisors, though the applicability and emphasis may vary.
- For AI and ML technologies that have access to client information and sensitive data, it is critical to ensure robust cybersecurity defenses, including data encryption, cybersecurity insurance, and business continuity management plans that include incident management frameworks.

Operational efficiency

Asset managers have a fiduciary duty to servicing clients at a lower cost. Technology has been a driving force to help streamline and manage the processing of internal data and external data feeds, and the post-trade operational processes from confirmation, settlement of trades to reconciliation of positions, cash balances, and net asset values (NAVs).

A key application of AI/ML to operational functions is the quality checking, monitoring, and exception handling of the vast quantities of data on financial instruments that asset managers rely on. Data quality is of the utmost importance as making fewer errors reduces operational risk and protects the end clients. Data may be missing, stale, or may contain other errors. To help alleviate this, machine learning techniques can be used to identify and flag outliers based on statistical assessments. For example, a model might be able to take known inputs such as the average price of a stock to determine if the latest price received from a vendor is erroneous.

Asset managers have always used technology to drive efficiencies and create better outcomes for investors, and newer technologies like AI and ML expand an asset manager's toolkit to do so even more effectively.

Use at BlackRock: Operational efficiency

Data scientists at BlackRock leverage AI and ML to scale data tasks for operational processes. Use cases include surveillance, data cleansing, and support functions. For example, we create and review over 1 million daily risk and exposure reports on portfolios through our system called Aladdin. These reports are generated from vast data sets. Because most data errors are systematic in nature (e.g., data is missing, out of date, or incorrect), data quality control (QC) and cleansing makes the process ideal for our data teams to use AI/ML models.

BlackRock's daily production process for report creation

Best Practices: Use of AI/ML for operational efficiency

- Investment, operations, and risk professionals should be closely involved in the creation and ongoing oversight of any model or system that leverages AI or ML, ensuring transparency into the underlying processes used by the technology.
- Asset managers rely on vast quantities of data, including from external data vendors. Thus, data quality and robust production monitoring should be of the utmost importance to reduce errors and mitigate operational risks.
- When asset managers choose to buy rather than build AI and ML services and capabilities, clarity on the respective responsibilities of the third party provider and the asset management firm using the service or tool is essential. Asset managers should conduct appropriate due diligence on the service providers including ensuring they have robust testing of the applications, business continuity management, technology disaster recovery planning, and cybersecurity.

Investment process

Technology is used to facilitate multiple aspects of the investment process including the data and research processes that drive the creation of alpha signals and models, pre-trade analysis, and understanding investment risks in a given portfolio.

Some examples of how technology is used by different investment strategies include:

- **Mathematical models** that can analyze datasets (both limited and large, traditional and "alternative") to identify patterns and insights as inputs to the investment decision-making process.
- **Smart beta portfolios** that can use various lenses to decide how to weight allocations within an index to favor certain characteristics, such as sustainable dividends or low volatility.
- **Index investing and ETFs** which facilitate efficient and accurate replication of an index and manage the mechanical trading processes that deliver index replication. Index funds and ETFs have been made possible by innovations in product structure supported by technology.

Research and alpha generation: seeking to generate superior returns for clients

To generate higher returns for actively managed portfolios, asset managers study and interpret the available data on the assets in which they invest on behalf of clients. In the case of equities, this process might begin with basic financial information provided by company filings. However, there is now a broad range of other information that can signal a company's future performance. Asset managers have developed AI and ML tools to compile, cleanse, and analyze the universe of data available, including analyst reports, macroeconomic data (e.g., GDP growth, unemployment) as well as newer "alternative" data sources. Examples of alternative data include GPS and satellite imagery to see where consumers are going, internet searches and tweets to see what people are researching and talking about, and employee satisfaction data, all of which can be accessed online today. These data points can help portfolio managers better assess individual companies and sectoral trends. As the volume of real-time data available increases beyond the capacity of individuals to analyze and understand it, the ability to compile, cleanse, and evaluate that data is increasingly important. AI and ML enable asset managers to find patterns in this data at scale, potentially identifying signals for generating returns for clients.

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Best Practices: Use of AI/ML in research and alpha generation

- In the design of any model intended to augment human functions, it is critical that the appropriate investment, trading and risk professionals be closely involved in the creation and ongoing oversight of the technology.
- All data inputs should be robustly tested to ensure models are performing analysis on accurate data sets, and periodic review procedures should be in place to ensure that no investment process is out-of-date.
- Portfolio managers and risk managers should be able to interpret both the inputs and outputs of the model to review any investment decision and adjust in new market environments. The more complex the ML technique used by the model, the higher the risk of obscuring the interpretability of results.

Use at BlackRock: Systematic Active Equity

BlackRock's Systematic Active Equity team leverages a rigorous research process that combines human insights with data, technology and mathematics to seek better returns for our clients. Each of the inputs and outputs of an investment model undergo a rigorous testing and approval process before the model is released into production.

The review process involves human oversight at every step, including peer reviews, research board approvals, production coding by an independent technology team and final sign off by a researcher. Once it is applied to a portfolio, the investment model is monitored by both the portfolio manager and an independent risk management team to ensure it is behaving as expected. Portfolio managers have ultimate visibility and control of their models, and they are able to perform "off-model overrides" if a particular investment does not make sense in the current market context.

Trading processes: minimizing transaction costs and market impact

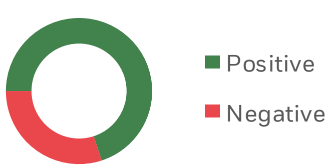
While analyzing data to generate investment ideas is a core part of the investment process, equally crucial is the implementation of the idea through efficient trade execution. Markets have experienced material transformation over the past few decades due to advances in technology and the adoption of new regulation. These drivers have increased the speed and automation of markets and fostered the emergence of new venues and market participants. As traditional over the counter execution has largely given way to electronic trading across primary asset classes, this has increased the breadth of digital touchpoints in the investment lifecycle, generating a vast dataset for trading teams to analyze in order to minimize costs. Consider the example of a basic trade order, illustrated on the next page.

Example of how we analyze large data sets to identify signals

Using text analysis techniques to anticipate future changes to company earnings guidance

Analyze

Use technology to analyze over 5,000 earnings call transcripts every quarter and more than 6,000 broker reports every day



Measure

Transform unstructured text into proprietary measures of trending analyst sentiment

Traditional approach:
Individual reports read by hand – or await analyst revision to occur

Basic order and trade execution

If a portfolio manager decides to buy 100 shares of Company XYZ and the trade is approved, it is up to the trading function to accomplish three goals:

1. Buy the shares at the lowest price possible;
2. Pay as little in facilitation fees as possible to minimize the cost of the transaction;
3. Minimize the market impact of the transaction.

AI and ML models can assist human traders in selecting the routing destination or execution methodology which optimizes for the three objectives above. For example, a trading model can analyze broker-dealer inventory, pricing data, and historical transactions to make recommendations on which counterparties or venues would result in better trading performance. These recommendations can then be incorporated using a programmed instruction set (typically not using AI and ML technology) within a tool called a "smart order router," which can display suggestions to traders or send orders out electronically.

Other parts of the trading process where AI/ML techniques may be applicable include external execution tools like broker-dealer execution algorithms. It is important to delineate the relevant responsibilities across the trading lifecycle, particularly as it relates to these third party processes where the asset manager does not develop the automated execution algorithms. In this case, the asset manager is submitting instructions to an external broker-dealer execution algorithm, which then facilitates the transaction for a fee. While it is important for the asset manager to understand the execution methodology of the third party, the actual implementation is managed externally.

Use at BlackRock: Trade execution

Our data scientists leverage AI and ML to analyze BlackRock's trading data captured electronically to help identify patterns in transaction costs. Based on these patterns, our traders can make more informed decisions on how to route trades for execution to reduce latency, cost, and market impact. BlackRock has a dedicated electronic trading and market structure team responsible for designing and overseeing the shift towards electronic trading and its integration into trading decisions to improve execution for clients (which we discuss in our *ViewPoint* titled U.S. Equity Market Structure: An Investor Perspective).

Best Practices: Use of AI/ML in trade execution

- In the design of any model intended to augment human functions, it is critical that the appropriate investment, trading and risk professionals be closely involved in the creation and ongoing oversight of the technology.
- When used for trading, the AI and ML processes should have appropriate pre-trade controls, building and release management processes, and real-time ability to monitor and shut off a system. As the primary usage of AI and ML in trading processes has been to conduct research, these controls should apply to automation of trading more broadly beyond AI and ML.

Use at BlackRock: Liquidity risk management

BlackRock has a financial modeling group that oversees developing investment risk models at the security and portfolio level. Last year, we developed a liquidity risk model that leverages ML techniques to estimate average daily volumes within the transaction cost framework. Another liquidity model still in a research phase can utilize ML to estimate redemption risk in our mutual funds.

Our financial modelers often choose to leverage more simplistic models in favor of more sophisticated ones that have higher interpretability – the ability to attribute the output of the model to the inputs. This gives us full control and understanding of how the model made forecasts. We believe that more complex ML techniques that are less interpretable should only be used after more interpretable models have been explored and the performance increase has business justifications.

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Risk management and oversight at BlackRock

BlackRock was founded on the principle that risk management is a key tenet of asset management. We take a multi-faceted approach to risk management embedding checks and balances and instilling a culture of risk management across portfolio management, trading and operations functions. As a first line of defense, the firm expects individual portfolio management, research and trading teams to take primary responsibility for managing the investment risks including liquidity risk management associated with the portfolios that they manage, and to ensure that they are following key controls, fund mandates, and regulations.

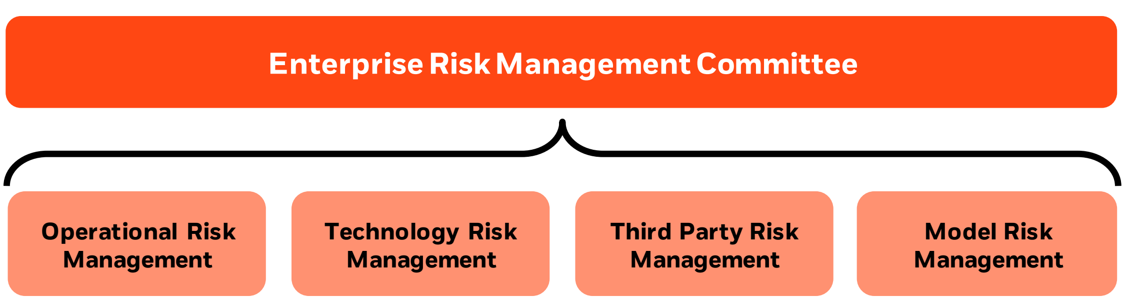
The second line of defense is our dedicated risk management group, called Risk and Quantitative Analysis (RQA), which monitors the risk profiles of portfolios managed on behalf of clients and regularly engages with the portfolio management teams to ensure risk positioning is deliberate, diversified, and scaled. BlackRock's RQA function is independent from the investment teams and monitors various aspects of the investment management process, including investment risks, operational risks, technology risks, third party risk and model risks. This helps to ensure that each of these risks is clearly identified, assessed, managed and monitored. These risk programs described below are inclusive of AI and ML applications and provide additional oversight as a supplement to the risk management undertaken within each applicable business function:

- **Operational risk**: RQA's Operational Risk team works with all operating and investment teams to proactively identify risk and assess the adequacy of controls. While more automated processes can reduce risk, consideration is given to the design and performance of such processes as part of operational risk assessment. The team is also engaged whenever operating events or errors occur in any investment or operational process, to ensure that root causes are quickly and clearly identified and controls improved.
- **Technology risk**: RQA's Technology Risk team works with all technology functions to help ensure technology controls are in place to protect clients and the firm, for example by monitoring system resilience and performance, or assessing software development and testing practices - aligning practices with industry and regulatory standards.
- **Third party risk**: RQA's Third Party risk team helps to identify and manage any risks that may arise from third party vendors by conducting due diligence on potential new vendors, validating the appropriateness of vendor controls and identifying potential risks prior to on-boarding and throughout the life of significant relationships. This includes any potential risks arising from the use, by third parties, of AI and ML applications in their provision of services to BlackRock.
- **Model risk**: RQA's model risk team has developed standards and policies for the design, implementation and use of quantitative models for investment, risk management, and valuation purposes. These include requirements for documentation and testing, independent model validation, release controls, performance monitoring and governance. Such requirements are readily applicable to, and can mitigate risk in, situations where models incorporate AI and ML.

The third line of defense is our internal audit function that independently validates investment businesses' adherence to key controls and policies and provides independent substantiation of control issues either self-identified by investment teams or flagged by independent risk management. Internal audit independently assesses and validates the scope and efficacy of RQA's risk management activities described above.

Finally, the Enterprise Risk Management Committee (ERMC), which includes leaders across the firm's risk management and technology functions as well as members of the Global Executive Committee, plays a key oversight role. The ERMC looks to identify the material risks of the firm, understand and define the firm's risk tolerance, assure each identified risk has an owner, review risk mitigation activities, and communicate individual, aggregated, and emerging risks to BlackRock's Board of Directors.

Enterprise risk oversight at BlackRock



Regulatory approaches to the use of AI/ML

Regulators across the globe are closely following the development and uses of technology in asset management while also considering how technology, including AI and ML, can improve regulatory functions. Before pursuing new regulations, we recommend that policy makers consider the applicability of existing regulation to new technologies and provide additional guidance where appropriate. The use and development of AI/ML is not stagnant, and policymakers should think about how regulation should similarly evolve. We recommend policy makers consider providing education and clarification on how existing regulations apply to use cases of these technologies.

Many applications of AI and ML are for research purposes only and not tied to production processes. Production impact of specific use cases should be considered to determine the appropriate level of risk and oversight. The use of regulatory sandbox programs can allow for testing of new AI and ML innovations in a controlled environment, and we encourage regulators to engage with the private sector to develop best practices and encourage ongoing innovations. Given the global nature of many AI and ML innovations and the financial system as a whole, we encourage regulators to work together to facilitate globally consistent regimes to ensure that these technologies can function across borders.

Conclusion

Technology will continue to play an integral role across various asset management functions as it has for decades. As new tools are developed, computing power becomes more affordable, and the availability of data continues to increase, additional use cases for AI and ML in asset management will emerge. We are already seeing tools that can help mitigate risk, reduce costs, generate better returns, and deliver products and services more efficiently for clients.

Appropriate controls and direct oversight by human professionals are critical to ensure the success of AI and ML applications. Some firms, including BlackRock, have implemented a governance structure that provides additional oversight. Regardless of the approach a firm deploys, human judgement, review, and robust testing are key. We encourage regulators and the industry to work together as these technologies evolve to provide better outcomes for investors.

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Remarks by Barbara Novick – The Future for Financial Services

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