ONTARIO SECURITIES COMMISSION

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Artificial Intelligence in Capital Markets

EXPLORING USE CASES IN ONTARIO

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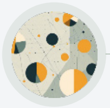

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EXECUTIVE SUMMARY

Artificial intelligence (AI) is a transformative technology that is reshaping the conversation on technological innovation.

For most, AI has become synonymous with chatbots, image generators and other creative tools like ChatGPT and DALL-E. With this report, we aim to raise awareness of the many ways in which AI is starting to transform our capital markets.

AI systems can streamline complex tasks, optimize processes and uncover hidden insights and trends, all while learning and refining their capabilities. At the same time, the disruptive nature of AI systems has raised important questions about the role of regulation and governance in managing risks as well as the potential for its malicious use.

Understanding current use cases, value drivers and challenges can help Ontario's market participants and innovators as they grapple with this technology's transformative potential. As market participants embrace AI innovation, its potential benefits will need to be balanced with a sensible approach to its implementation to protect investors and the integrity of our markets.

Regulators like the Ontario Securities Commission (OSC) are considering how oversight, regulation or guidance can facilitate responsible AI innovation and adoption in Canada.

By engaging with market participants and collaborating with national and international partners, we can continue to foster innovative and globally competitive capital markets in Ontario that put investors first, help innovative businesses succeed and attract investments from around the world.

Key themes

1

Capital market participants are currently using AI to enhance their existing products and services rather than creating new ones. AI is supporting a diverse range of capital market processes, including asset allocation, price and liquidity forecasting, hedging, trade order execution and surveillance, high-frequency trading, futures market analysis, and sales and marketing. Currently, AI is being used to improve the efficiency and, in some cases, effectiveness of these processes. This includes improving the quality of data available by detecting patterns, trends and anomalies with greater precision.

2

AI is at an intermediate stage of adoption in Ontario's capital markets. More advanced and sophisticated applications of natural language processing (NLP) are being actively explored but challenges remain. Issues related to data quality, privacy, fairness, explainability and interpretability as well as staffing challenges, retention of developers and changes to cultural and operating models will need to be thoughtfully addressed to fully benefit from AI.

3

The key value drivers of AI adoption in capital markets include:

- Enhanced capacity to extract information and insights from enormous volumes of structured and unstructured data.
- Greater automation of manual processes that involve handling and managing data.
- More precise predictive analytics.
- Better liquidity forecasting and hedging.
- Increased end-user satisfaction through more personalized service.

4

The most mature use of AI in capital markets is focused on three principal areas: (i) improving the efficiency and accuracy of operational processes; (ii) trade surveillance and detection of market manipulation; and (iii) supporting advisory and customer service. There are tools to automate processes such as reconciliation, trade surveillance and detection of potential market manipulation, client onboarding, determining whether counterparties are eligible to trade and trade reporting. Firms are also using AI to provide automated customer support functions and support client-facing advisors with information, analysis and recommendations.

5

Areas such as asset allocation and risk management show less maturity in Canada. While large hedge funds are using AI for research, economic analysis and order execution, its use for trading and asset allocation are otherwise limited. Risk management shows varying degrees of AI adoption.

6

Scale is important for the development of AI models: larger firms appear to be developing in-house solutions and using AI in areas with financial risk more than smaller firms. The significant investment required to build AI solutions for economic research and investment allocation means that development has been concentrated among larger firms, while small players lag due to concerns over return on investment (ROI).

7

AI development primarily occurs in-house in Ontario. In the development of these AI models, firms tend to use data from different sources including structured, unstructured (such as text and image data), time series, cross-sectional, public and proprietary data. At the same time, the easiest path to implementation is via third-party tools that use AI models. AI-supported third-party tools are driving AI adoption for operational and market surveillance use cases.

8

While capital market participants continue to employ and explore a range of AI techniques, NLP is the most commonly used. Capital market participants are showing significant interest in leveraging NLP to analyze large amounts of structured and unstructured data. The development of these solutions benefits from a low cost of failure, meaning the cost to market participants is relatively low should the solutions perform poorly.

9

Major challenges remain for AI adoption. Adopters must grapple with a number of issues relating to the development or procurement of AI systems including data constraints, accessing skilled labour and corporate culture. Data constraints can be a significant hurdle whether from a lack of available data or changes in the distribution or characteristics of data over time (data shifts). Attracting and retaining AI talent can also be challenging due to competition from technology vendors. Market participants also need to face their own internal challenges in adapting operating models and culture to benefit from AI. Issues related to privacy, bias, fairness, explainability and interpretability need to be addressed when developing or procuring an AI system.

1

INTRODUCTION

AI has captivated the public since the release of tools that generate text, images and music in ways previously thought only possible by a human.

Tools like ChatGPT and DALL-E have come to symbolize technological innovation. On a global scale, both consumers and businesses are recognizing the potential of large language models (LLMs) to enhance productivity and augment knowledge.

The **AI systems**[1] that support these well-known tools are only part of the story. **Capital market participants are already developing, testing and implementing AI systems** to support front, middle and back-office functions using a variety of AI models.

The disruptive nature of AI systems and their increased use has also brought attention to some of the risks, such as those related to bias, privacy and the potential for its malicious use. Important questions have been raised regarding regulation and the development of governance frameworks and controls.

This report is an exploration of AI in capital markets. In it you will find a detailed catalogue of current applications of AI in Ontario's capital markets along with a discussion on value drivers, challenges, and related considerations. By exploring these use cases, we aim to raise awareness of the many ways in which AI is starting to transform capital markets.

[1] An AI system "is a machine-based system that is capable of influencing the environment by producing an output (predictions, recommendations or decisions) for a given set of objectives. It uses machine and/or human-based data and inputs to (i) perceive real and/or virtual environments; (ii) abstract these perceptions into models through analysis in an automated manner (e.g., with ML), or manually; and (iii) make use of model inference to formulate options for outcomes. AI systems are designed to operate with varying levels of autonomy" (OECD, 2021)

2

THE ROLE REGULATORS CAN PLAY

AI has the potential to impact processes and stakeholders throughout our capital markets from investors to businesses, professionals, intermediaries, and marketplaces.

Given the transformative potential of AI, the Ontario Securities Commission (OSC) has undertaken this research to better understand current and future applications of AI in capital markets. **Understanding these use cases provides a foundation for us to consider how to best support responsible innovation and adoption** in Ontario's markets including the extent to which oversight, regulation or guidance can support this objective.

The OSC's vision is to be an effective and responsive securities regulator – fostering a culture of integrity and compliance and instilling investor confidence in the capital markets. The OSC Innovation Office helps the OSC be agile in its approach to regulating our markets and respond to emerging trends, new technologies, and novel business models and is our central hub in this process.

Through a proactive approach to technological innovation and the building and sharing of knowledge, we can continue to **foster innovative and globally competitive capital markets in Ontario that put investors first**, help innovative businesses succeed and attract investments from around the world. As we do so, collaborating with other regulators and governments is key to implementing consistent and effective regulation of this space.

AI innovation may offer significant efficiencies for markets and market participants, enable new solutions and new entrants, and attract investment to Ontario's AI businesses. These gains to productivity, competition and capital formation can ultimately contribute to economic growth for Ontario. **At the same time, the disruptive nature of AI systems has raised important questions about the role of regulation and governance in managing risks as well as the potential for its malicious use.**

While AI can be a meaningful asset to the extent it is used to prevent, detect, and deter unfair and fraudulent practices, it is essential for regulators to consider how to best protect investors from its dishonest use by unscrupulous actors. Likewise, it is important for both regulators and market participants to understand the potential for AI to impact markets to ensure that appropriate safeguards are in place to maintain the continued stability of our financial system.

We view this report as an important first step. Through this introductory glance into AI adoption and the associated challenges, we hope this report will serve as a bedrock for further collaboration between capital market participants, innovators, and regulators to support responsible AI innovation and adoption for capital markets.

3

AI IN ONTARIO'S CAPITAL MARKETS

A. Current landscape

Canada's leadership in AI is highlighted for example in Tortoise's Global AI Index report that ranks Canada as the fifth position after the United States, China, Singapore and the United Kingdom. Canada scores well in areas such as government AI strategy, talent, commercial aspects of AI and the overall operating environment, while there is potential for enhancements in AI infrastructure.

Ontario itself is a significant hub for AI and a destination for capital looking to invest in this sector. According to Ontario's world-renowned Vector Institute in its 2022 and 2023 reports:

- An estimated 22,458 AI jobs were created in Ontario in 2021-22 and the number of actively engaged AI professionals in Canada has risen 29% in 2022-23.
- $1.08 billion was spent on Ontario AI research and development in 2022-23.
- $2.86 billion in venture capital (VC) investment flowed into Ontario's AI ecosystem in 2021-22, and total VC AI investment in Canada reached $8.64 billion in 2022-23, ranked third among G7 countries in per capita VC investment in AI.
- Forty-six new AI companies were founded in Canada in 2022-23, more than half of which (27) were founded in Ontario.

This data suggests that supporting the responsible development of AI systems can be a significant contributor to economic growth in Ontario. Increased investments in AI solutions by Ontario's financial industry can further support this trend and pave the way for the industry to be a leader in responsible AI adoption, while taking advantage of the ways it drives value for adopters.

The adoption of AI in capital markets is currently driven by its ability to offer incremental operational efficiencies and resource optimization improvements, higher revenue generation and improved risk management.

This adoption is supported by the increasing availability of a larger volume of structured and unstructured data, increased computational power and advancements in AI techniques, alongside the availability of enterprise-grade AI tools and the integration of AI methods into third-party solutions. Efficiency improvements drive a great deal of AI adoption, benefiting from internal data accessibility and lower failure costs.

Revenue generation, including trading and tailored sales strategies, follows closely as the incentive for AI adoption, facilitating the analysis of large volumes of structured and unstructured data to provide useable insights. AI adoption relating to risk management is mixed, with restricted use in highly regulated areas but greater prevalence in areas like anti-money laundering (AML) and collateral optimization.

While AI has become more prevalent in capital markets, the level of adoption varies across functions due to the availability of data, cost of failure, and regulatory constraints.

Other factors that impact adoption of AI are an organization's size, culture, willingness to invest in new technologies, existing IT infrastructure, level of technical expertise, cost of implementation and potential ROI.

Increasing interest in AI has led to significant investment in the field, accelerating innovation of advanced AI products for business applications.

While these developments contribute to the accessibility and adoption of AI solutions, commercial AI solution providers tend to keep the proprietary details of their models strictly confidential, in contrast to the past trend of open-source frameworks in traditional AI research. This lack of transparency makes it difficult for firms to manage AI-related risks. As adoption of these solutions grows, so does the level of market-wide risk related to opaque AI models.

B. Perspectives from capital market participants

Interviews with market participants for this report provided unique insight into how AI is being used and thought about in Ontario's capital markets. We heard a range of perspectives from a variety of participants including investment dealers, fund managers, financial institutions, alternative trading systems and exchanges in Ontario.

AI is an evolving field and the use of technology to enhance business operations is often treated as confidential, particularly in experiments, proofs of concept and pilots. In the interviews, participants were open about the fact their firms were using AI, but many were reluctant to share specifics for competitive reasons. Most notably, in the area of custom AI development, especially for revenue generating business lines such as trading and asset allocation, firms were unwilling to share details they viewed as valuable intellectual property.

Capital market participants are using AI to enhance their current products and services rather than create new ones.

At the moment, AI is principally being used to do things faster, better, cheaper – rather than to generate new sources of revenue, develop new products, or otherwise innovate in the marketplace. One expert went as far as to say there were no use cases that are entirely dependent on AI; instead, AI serves to improve efficiency and effectiveness in various areas.

Large financial institutions appear to be adopting AI systems, including in their capital markets functions, focusing specifically on NLP.

These institutions leverage NLP tools to extract insights from unstructured data sources, including text and image data to gain a competitive advantage through better-informed decision making. The extent of NLP tool adoption varies among organizations, with some exploring advanced LLMs, while others rely on traditional NLP models. At the same time, one expert emphasized that LLM output is not sufficiently stable for some purposes, restricting its application primarily to automating processes in middle or back office.

AI models are being adopted to provide insights for advisory and sales purposes, automate customer service operations, streamline back-office processes and support economic forecasting.

The adoption of AI in these areas is driven mainly by enhanced efficiency, as well as provides more insights for advisory and sales and trading functions. For example, firms can use AI to conduct a revenue and profitability analysis of clients and segment them into "high-touch" and "low-touch" categories.

Once this segmentation has been completed, AI can be used to generate customized reports and recommendations for low-touch clients, providing tailored services at a lower cost. AI can also be used to process information about high-touch clients from multiple sources and types of data to generate insights about client profiles, activity and preferences to provide insights for advisors[2] and individuals in sales and trading.

Furthermore, large hedge funds rely on AI for comprehensive research including economic forecasting, optimizing order execution processes, and managing and mitigating risks in investment strategies.

Most organizations reported conducting custom AI development in-house, primarily in Ontario.

At the same time, interview participants also recognized the value of collaboration with third-party providers when economically and strategically feasible. Many organizations already take advantage of third-party solutions that apply AI models and integrate into their existing software to automate processes for customer service and back-office functions.

[2] The term advisor is used broadly and intended to refer to individuals who are registered with a self-regulatory organization, salespeople, portfolio managers, etc.

Organizations also reported using diverse data sources to fuel their AI initiatives.

The data employed to power AI systems encompasses both proprietary and public sources, drawn from exchanges or social media platforms as well as synthetic data (e.g., data generated by algorithms). Organizations use both historical and real-time data, which can be structured or unstructured (such as text and image data). However, ensuring data quality poses a significant challenge due to the diverse types and multitude of data sources involved.

Most interview participants who reported using AI also reported having formal risk oversight policies, procedures and accountabilities in place to ensure responsible AI practices.

These measures are aimed at addressing some of the challenges arising from AI adoption which include an evolving regulatory landscape (e.g., regarding privacy), mitigating bias in AI systems, ensuring explainability and interpretability while managing data availability, coping with data distribution shifts, attracting and retaining technical talent, and competing with tech vendors for skilled AI professionals.

4

AI USE CASES IN CAPITAL MARKETS

Capital market participants are adopting AI systems for three overarching purposes: (A) efficiency improvements, (B) revenue generation and (C) risk mitigation.

In this section, AI's use cases in capital markets are presented and categorized according to their intended purpose. They provide a compelling view into the diverse applications that are supported by the technology as well as the breadth of market participants who can rely on them.

A. Efficiency improvement

Currently, the most widespread adoption of AI in capital markets is for efficiency improvement. This can be attributed to the ease of obtaining internal datasets, lower cost of failure, fewer regulatory requirements, and the availability of third-party software applications that incorporate machine learning (ML) and AI models.

USE CASES

I. Pre- and post-trade processes automation

USER CATEGORY	Asset management, institutional investors, market intermediaries.
OVERVIEW	Integrate an AI system with a marketplace or dealer to automate pre- and post-trade processes such as trade validation, generating trade reports and submitting them to regulatory authorities.
BENEFITS	Reduced back-office workload; improved execution.
ADOPTION	Intermediate to advanced.

What is pre-and post-trade process automation?
Pre- and post-trade process automation involves using sophisticated technological methods and tools to simplify and speed up different phases of trade operations, reducing manual errors and costs and streamlining the trade lifecycle. Automation includes pre-trade operations such as order and trade validation and post-trade operations such as reconciliations and trade reporting.

Market insights:
AI systems can quickly evaluate the details of a proposed trade and determine if the trade meets the relevant risk and regulatory criteria, and if the counterparties involved are eligible to complete the trade. By automating this process, trade support services can be streamlined, reducing manual effort, and improving efficiency while ensuring compliance with regulatory standards.

AI is also being used to automate post-trade processes such as trade reporting. For example, a financial institution may employ an AI system that is integrated with the platform the trade was executed on and other relevant data sources. This AI system can process trade data in real-time, extract relevant information, generate accurate and comprehensive trade reports, and submit the reports to regulatory authorities or trade repositories.

Technical aspects:
AI techniques are instrumental in enhancing trade operations automation capabilities. Machine learning algorithms enable predictive analytics, aiding in demand forecasting and inventory management. NLP facilitates automated extraction of insights from unstructured data sources, such as contracts, regulations and internal controls and frameworks.

Current state of adoption:
Considering the scope and scale of adoption, AI appears to be at an **intermediate to advanced** stage of adoption in customer services and support.

II. Execution quality improvement: Liquidity forecasting

USER CATEGORY	Capital market activities of financial institutions.
OVERVIEW	Minimizing losses in order execution relies on capitalizing on favourable liquidity conditions. Precise liquidity forecasting helps in improving order execution.
BENEFITS	Extract information from text data; better liquidity prediction than traditional methods.
ADOPTION	Intermediate.

What is liquidity forecasting?
Market liquidity forecasting plays a critical role in capital markets by providing predictions into the availability and movement of financial assets. It helps investors and traders make informed decisions by providing insights into the market's capacity to absorb and facilitate the buying and selling of assets. Accurate liquidity prediction can help to minimize transaction costs and reduce the risk of price slippage.

Market insights:
EY's experience with financial service firms suggests that market participants primarily rely on simple statistical techniques, such as moving averages, when forecasting liquidity. That being said, the CFA Institute highlighted the use of deep learning models for forecasting trading volume in a 2019 report.

Technical aspects:
In the CFA Institute's report, a two-step approach was adopted. First, intuitive market segments of securities (e.g., stocks of pharmaceutical companies) were created based on variables such as market indices, historical trading volume data and calendar days. Subsequently, a multi-layered convolutional neural network (CNN) was developed for each market segment that would forecast liquidity. Reinforcement learning (RL) and NLP techniques could be used for liquidity forecasting. Liquidity prediction based on RL could demonstrate superior performance compared to other methods, particularly in extreme market conditions (Janabi, 2022). Additionally, traders, investors and financial analysts

can use NLP models to maximize the insights gained from textual data, aiding in the mitigation of liquidity risk (Andrawos, 2022).

While AI can bring benefits to liquidity forecasting, there are challenges associated with its adoption. There is a range of liquidity measures available, such as quoted spread and effective spread, and the predictive performance may vary depending on the chosen measure. Assessing the robustness of AI models requires a comprehensive examination of these liquidity measures, which calls for deep domain expertise in both liquidity and AI. Liquidity risk measures are inherently volatile, and their dynamic nature adds complexity to the modeling process.

Current state of adoption: Based on the limited levels of tactical deployment and ongoing research interest, our evaluation indicates that AI is at an **intermediate** stage of adoption in asset allocation.

III. Customer services and support

USER CATEGORY	Wealth management, capital market activities of financial institutions, dealers.
OVERVIEW	Various benefits by leveraging advanced AI technologies to enhance customer interactions, streamline processes and improve overall customer experience.
BENEFITS	Reduced workload; greater speed and throughput; informed decision-making.
ADOPTION	Advanced.

How does AI impact customer services and support?
Given the recent interest and advancements in LLMs, a prevalent strategy among businesses is to engage in experimentation in lower-risk LLM use cases like customer support chatbots.

Market insights:
Significant efforts are underway to adequately process the input and output of these models, mitigating the production of unsafe content. Additionally, there is an increasing focus on prompt engineering to align the outputs generated by LLMs with the desired results specific to each use case.

Wealth management firms indicated they are using AI in customer service tools. For example, financial advisors are using a GPT-4 powered chatbot trained on their internal library – greatly reducing the amount of time needed to conduct research in response to client queries (OpenAI, 2023).

Technical aspects: Despite the low-risk and cost-effective nature of customer services and support use cases, leading to the rapid integration of AI in this domain, there are several challenges that accompany its adoption. A key challenge lies in the heavy reliance on substantial amounts of diverse and unstructured data for effective training of AI models. Additionally, the proper storage and transformation of such data present significant hurdles to overcome.

Current state of adoption:
Considering the scope and scale of adoption, AI appears to be at an **advanced** stage of adoption in customer services and support.

B. Revenue generation

Another reason capital market participants are adopting AI systems is for revenue generation. This is due to the capability to extract insights from previously untapped datasets, AI's ability to capture intricate dependencies in datasets, the functionality to provide greater insights to advisors about their clients and the availability of tools for the development of sales strategies and marketing materials. However, bespoke models for trading and price forecasting are costly and complex to build, which increases the financial risk associated with developing these solutions.

USE CASES

I. Sales and marketing

USER CATEGORY	Wealth management, capital market activities of financial institutions, dealers.
OVERVIEW	AI enables efficient and effective marketing, including customer segmentation, lead generation, predictive analytics and chatbot assistance.
BENEFITS	Leverage insights derived from unstructured and alternative data sources; enhanced comprehension of sales and marketing dynamics.
ADOPTION	Advanced.

How does AI impact sales and marketing?
AI has the potential to revolutionize sales and marketing in capital markets by reshaping the way financial products and services are marketed, distributed and sold. With its ability to process vast amounts of data, extract insights and automate tasks, AI empowers capital market participants to enhance their marketing strategies by targeting customers and delivering personalized experiences.

Market insights:
Market participants interviewed suggest that there is widespread adoption of AI in sales and marketing. This trend can be attributed to several factors, including the ease of accessing internal datasets, lower risk of failure and fewer regulatory constraints. The implementation of AI offers tangible benefits such as cost reduction and improved operational efficiency.

AI is used to analyze customer data to generate personalized product recommendations, including potential investment opportunities. This can be done through the automatic segmentation of customers into high-touch and low-touch clients. Customized materials are generated using AI for low-touch clients providing enhanced services at a lower cost. For high-touch clients, AI can be used to process information about clients from multiple sources and types of data to generate insights about client profiles, activity and preferences.

Similarly, BloombergGPT is trained on financial data to support various tasks including sentiment analysis and Q&A. (Wu et al., 2023).
It was developed to automate customer-facing interactions currently performed by relationship managers. AI models serve as supportive tools in sales and advisory roles, functioning as co-pilots to advisors to enhance performance.

Notably, a dealer commented that ChatGPT is being used to create marketing material. LLMs enable the generation of content for various marketing purposes, including advertisements, social media posts, product descriptions and complete marketing campaigns.

Technical aspects:
According to research papers and industry reports, generative AI has emerged as a prominent technology used in sales and marketing (Deveau, Griffin, & Reis, 2023). Additionally, Deveau et al.'s report features the use of generative AI in real-time negotiation guidance and the provision of predictive insights based on thorough analyses of historical transaction data, customer behaviour and competitive pricing. However, market participants have expressed concerns regarding the limited availability of data and the technological requirements, which pose challenges in adopting AI for their sales and marketing endeavours.

Risks associated with this use case are also magnified as the level of automation increases. Even where AI tools are used to provide guidance to advisors, there is a fear that advisors may become reliant on these tools to the point where they are unable to recognize that poor or biased advice is being recommended based on flawed data. The extent to which consumers understand these risks is also an important factor to consider.

Current state of adoption:
Considering the scope and scale of adoption, AI appears to be at an **advanced** stage of adoption in sales and marketing.

II. Asset allocation

USER CATEGORY	Insurance companies, portfolio managers, fund managers.
OVERVIEW	Employ AI capabilities, optimizing the allocation of resources among different asset classes to maximize return on investment.
BENEFITS	Develop dynamic asset allocation strategies; more consistent returns than traditional methods.
ADOPTION	Intermediate.

What is asset allocation?
Asset allocation is the process of determining the optimal distribution of resources among different asset classes, such as stocks, bonds and cash, with the objective of maximizing investment returns. It is similar to solving a dynamic optimization problem, as it involves making frequent adjustments to the asset mix in a portfolio based on market conditions to achieve long-term returns. The aim is to effectively respond to current risks and market downturns while capitalizing on trends to outperform a targeted benchmark. Moreover, asset allocation becomes particularly challenging in volatile macroeconomic environments, making it difficult to identify the optimal asset distribution. Over the years, several investments strategies have been proposed following Markowitz's influential work in 1952 (i.e., risk minimization through diversification), including global minimum variance,

naïve strategy, most diversified strategy, and target strategy (maximizing the Sharpe ratio). The integration of AI solutions holds the potential to significantly enhance the performance of these strategies or even introduce novel approaches (Bartram, Branke, & Motahari, 2020).

Market insights:
Market participants interviewed expressed that there is limited adoption of AI in asset allocation, without providing any specific applications. However, portfolio managers demonstrate an ongoing interest in applying AI's capabilities. It was observed that the level of investment in AI by fund managers is directly proportional to the size of the fund. Larger funds persist in allocating resources to AI research, whereas smaller funds exercise caution due to concerns regarding ROI in AI research.

EY applied RL for asset allocation including in the development of a framework for a large financial institution:

EXAMPLE 1

Development of a reinforcement learning-based asset allocation framework for a large financial institution

The purpose of this use case is to demonstrate the dynamic allocation of assets in a volatile environment in a way that generates stable returns, while maximizing risk-adjusted returns measured by the Sharpe ratio. The approach uses a reinforcement learning (RL) model, which is trained on open-source data from the Dow Jones Industrial Average (DJIA), consisting of 30 stocks over a 10-year simulation period.
Input parameters such as asset price, macroeconomic factors and VIX (volatility index) are considered during the model training. Actions by the RL agent are taken based on calculated returns, reallocation costs and solvency requirements. However, expanding the scope of data to a more diverse selection of stocks and market behaviours could potentially impact the model's behaviour. To mitigate this risk, models can be run in testing environments before deploying them to real markets.

Technical aspects:
In addition to RL, neural networks (NN) also show promising results in the field of asset allocation.

NNs have proven to be valuable in hyperparameter selection for simpler asset allocation methods (Haoran & Yu, 2020).
Traditional statistical approaches, such as the maximum likelihood estimation method, struggle to handle high-dimensional datasets.

It is difficult to provide accurate estimations of asset correlations and returns with traditional methods using high-dimensional data. In contrast, a well-trained neural network can effectively handle these higher-dimensional datasets used in asset allocation (Wang et al., 2020).

Both RL and NN models are known for their complexity, making it challenging to provide clear explanations of their decision-making processes. This is because outputs generated by these models are not always interpretable and/or explainable, limiting their application in asset allocation decisions.

Furthermore, the use of these AI methods necessitates the exclusion of insignificant factors[3] as input variables, as their inclusion may compromise the models. To eliminate these insignificant factors, the application of both statistical tests and domain knowledge becomes imperative. Therefore, to effectively harness AI in asset allocation, a comprehensive understanding of statistics and domain knowledge is essential in addition to expertise in AI.

Current state of adoption:
Based on the levels of tactical deployment and ongoing research, our evaluation indicates that AI is at the **intermediate** stage of adoption in asset allocation.

[3] Insignificant factors are very context specific variables that may not have a significant impact on asset allocation. For example, short term market news that may cause short-term fluctuation in the market may become an insignificant factor for a specific asset allocation that has a long-term investment objective.

III. Asset price forecasting

USER CATEGORY	Sales and trading.
OVERVIEW	Use AI to predict asset prices using historical and cross-sectional data, uncovering non-linear interactions among numerous variables.
BENEFITS	Extract insights from untapped unstructured data sources expanding the scope of knowledge.
ADOPTION	Intermediate.

What is asset price forecasting?
Asset price forecasting involves predicting the future value of an asset using historical data and other relevant information. Traditional models use statistical methods, focusing on time series and cross-sectional approaches (Drobetz & Otto, 2021). AI techniques have gained popularity in asset price forecasting due to their ability to handle time series data more effectively, as well as extract and process meaningful information about a stock from unstructured data.

Market insights:
Only a small number of market participants reported explicitly using AI for asset pricing, without providing details as to specific applications. However, the majority of these market participants acknowledged the use of NLP models to generate signals/alerts from text data such as analyst reports, earnings call transcripts, news and social media data. These signals/alerts are then used as input variables in traditional asset price forecasting models.
There appear to be few, if any, use cases that are entirely reliant on AI. The use of AI to augment, rather than displace, current processes is in line with global trends – a 2023 report from the European Securities and Market Authority (ESMA) on the use of AI in EU securities markets remarked that very few investment funds have developed a fully end-to-end AI-based investment process (ESMA, 2023).

Technical aspects:
Traditional models exhibit limitations in asset pricing because they rely on a restricted set of explanatory variables for predicting asset prices[4] and assume a linear relationship between explanatory variables and asset prices, disregarding the potential non-linear relationships that exist[5].

The existing body of literature indicates that traditional models are inadequate in handling high-dimensional data, especially in the presence of irrelevant data. ML models can be used to address the challenge posed by high dimensionality, in addition to offering improved precision in predicting asset prices (Drobetz & Otto, 2021.

The analysis of existing literature further highlights that the adoption of AI/ML models in asset price forecasting can yield considerable positive returns (Gu, Kelly, & Xiu, 2020). The substantial improvement in forecasting accuracy achieved by AI/ML models is attributed to their ability to capture the non-linear interactions among explanatory variables (Gu, Kelly, & Xiu, 2020).

This capability to model non-linear interactions is challenging in traditional statistical models, thereby underscoring the advantage of employing AI/ML approaches in asset price prediction. Furthermore, traditional models have limited applicability when it comes to extracting information from unstructured data, such as using news data for asset price forecasting. In contrast, NLP models are specifically developed to extract information from unstructured data. For example, an NLP model trained on financial news is shown to have significantly better predictive power than the Fama-French 5-factor model (Liao, Wu, & Wells, 2021).

Despite the numerous advantages offered by AI techniques in asset pricing, their implementation poses challenges. In addition to requiring a data scientist responsible for designing and adjusting the model, building a forecasting model generally also requires the expertise of an economist to provide an underlying structure for the estimation problem (Jafar et al., 2023). This further complicates hiring and retaining the appropriate personnel, which is already difficult due to

[4] For instance, in the capital asset pricing model (CAPM), an asset's expected return is simply the sum of the risk-free rate and the market risk premium. Computation of the market risk premium only requires two factors: historical returns of the asset under consideration and the return of a suitable market index. While other models, such as the Fama and French Three-factor/Five-factor models, incorporate a greater number of factors, and unlike AI methods, they still struggle to effectively leverage the predictive information available from simultaneously processing many other available factors.

[5] In the CAPM model, for instance, the mathematical relationship between a stock's expected return and market risk is assumed to be linear. However, in practice, the relationship between various factors could be non-linear.

competition with big tech companies and proprietary AI firms. AI/ML models also exhibit significant variation in their statistical predictive performance, resulting in noticeable disparities in economic profitability (Drobetz & Otto, 2021). Moreover, in interviews with subject matter experts, it was observed that AI/ML models lack an upper bound on their predictive error[6], which slows down their adoption in asset pricing. There are additional inherent challenges related to AI/ML, such as explainability, data privacy and bias. These factors could be the reason for limited adoption of AI by capital market practitioners, despite promising results highlighted in academic literature.

Current state of adoption:
Based on apparent levels of deployment, potential benefits and ongoing research, our evaluation indicates that AI is at an **intermediate** stage of adoption in asset price forecasting.

IV. Trading insights

USER CATEGORY	Pension funds, asset managers.
OVERVIEW	Utilize NLP and other AI methods to extract information from news and other diverse data sources, enabling valuable trading insights.
BENEFITS	Extract insights from unstructured data sources; overcome accessibility limitations to analyze unstructured data.
ADOPTION	Advanced.

What are trading insights?
In the realm of financial markets, extracting valuable information from news sources is a crucial yet time-consuming and costly task. Traditional statistical methods have been unable to effectively extract insights from unstructured data, such as text or video data. However, recent advancements in AI development present an opportunity to optimize this process by leveraging NLP and ML

[6] Confidence interval construction is a well-known concept in statistical models, but it is an active area of research AI models.

techniques to automate the extraction of insights and sentiments from news articles, streamlining the information-gathering process for trading strategies.

Market insights:
The interviews revealed the application of AI, specifically NLP, in generating trading insights. One respondent reported they are using AI to understand market microstructure, which they may combine with other relevant information to optimize order execution across multiple trading venues. Others are employing NLP for summarizing documents and collecting data from social media and web scraping.
Interviews with the subject matter experts indicated that AI, particularly NLP, is being used to prepare research report synopses and optimal order execution. A literature review also suggests significant use of AI in generating market insights. For example, AI asset managers also use AI tools to evaluate big data obtained from web scraping and social media to generate further market insights (Novick, et al., 2019).

EY deployed AI in an application that generates descriptive statistics, sentiment scores and identifying emerging topics from publicly available news data:

EXAMPLE 2

NLP signals development for a large financial institution to use in downstream trading models

This project employed language models to identify key financial insights from unstructured data such as news articles, polarity characteristics (positive/negative/neutral sentiment) and a summary of themes. Signals are extracted through three approaches. The first approach generates descriptive statistics and extracts key phrases based on a provided list of keywords. These descriptive statistics include measures like average sentiment scores, frequency counts of specific key phrases, or trends in sentiment over time.

For example, key phrases extracted from news articles include "rising inflation rates," "merger and acquisition activity" or "technology advancements in renewable energy." The second approach uses business-provided lexicons to derive sentiment scores from financial articles. For example, after reviewing a given batch of articles for market confidence, the solution generates a positive or negative score to express whether there is positive or negative investment sentiment in the market. The third approach uses semi-supervised techniques to identify words that contribute significantly to topics, generating topic probability distributions for financial articles. Examples of topic probability distributions could include high probabilities for topics like "cryptocurrency regulation," "global trade tensions" or "sustainable investing." Hence, the "topic probability distributions for financial articles" is used to identify the prevalence and importance of specific topics within the analyzed news articles.

The benefits of these approaches include generating descriptive statistics on key topics, identifying sentiment scores on selected topics, and identifying emerging, continuing, and retiring topics. However, a challenge to consider is the dynamic and high-frequency nature of news data, which requires continuous and close monitoring.

Technical aspects:
It is important to acknowledge that this use case can also be implemented using advanced LLM models. However, during interviews with subject matter experts, it was indicated that these LLMs have not yet demonstrated sufficient stability. Consequently, they do not consistently outperform traditional NLP models.

There are ongoing efforts to tackle common challenges associated with NLP models, including enhancing their explainability. One subject matter expert indicated that there is a significant risk that inadequately trained and partially understood NLP models can contribute to share price volatility by generating random trading signals.

Current state of adoption:
Based on the reported levels of deployment among capital market participants, our evaluation indicates that AI is at the **advanced** stage of adoption in generating trading insights.

V. High-frequency trading (HFT)

USER CATEGORY	Hedge funds, capital market activities of financial institutions.
OVERVIEW	Utilize AI capabilities in high-frequency trading to enhance prediction accuracy, where orders are executed at extremely fast speeds.
BENEFITS	Enhance prediction accuracy; capture intricate dependencies present in financial time series (FTS).
ADOPTION	Intermediate.

What is high-frequency trading?
HFT in financial markets refers to trading strategies where computers use algorithms to enter, change and cancel orders at extremely fast speeds. These algorithms analyze market data and make buying or selling decisions within fractions of a second. HFT takes advantage of small spreads or price movements, which may be caused by temporary market inefficiencies[7].
To seize these transient opportunities of price movement, HFT relies on cutting-edge technology, rapid data processing capabilities and an ability to send an order into the marketplace's trading book almost instantaneously.

Market insights:
HFT firms are very secretive regarding their technology and strategies. There appears to be a general perception that HFT firms are adopting AI, but feedback from a subject matter expert indicates that the use of AI in generating signals for HFT is challenged by the time required for AI models to analyze data and generate signals. Speed is the quintessential requirement for HFT. Latency in AI models contributes to “tick to trade latency,” which hampers HFT’s ability to profit from small price differences.

[7] In an efficient market, there are no opportunities for price arbitrage. An example of price differences resulting from market inefficiency is when a stock is listed on multiple exchanges. At a given moment, the stock may be priced at $50 on one exchange and $50.10 on another exchange. The HFT algorithms can quickly buy the stock at $50 on one exchange and simultaneously sell it at $50.10 on the other exchange, making a profit of $0.10 per share in just a matter of seconds.

Technical aspects:
Literature reviews suggest that AI techniques are being actively explored for their potential application in HFT. One notable example is the use of deep learning models, which have demonstrated promising results in HFT (Kolm, Turiel, & Nicholas, 2021). Additionally, transformer models, which are a variation of deep learning models used in NLP, are also being used in HFT (Barez, Bilokon, Gervais, & Lisitsyn, 2023). Transformers can use a mechanism called multi-head attention to capture long-term dependencies in the data.[8]
Furthermore, transformers possess a natural parallelizability feature, allowing for efficient and high-speed execution of computations.[9]

The literature review also highlighted challenges related to using AI techniques in HFT. One key challenge with transformers is that they are not specifically designed for local sequential structures (Barez, Bilokon, Gervais, & Lisitsyn, 2023).

However, in HFT, where financial time series (FTS) data is timestamped, capturing local sequential patterns is crucial. Additionally, modeling short and long-term dependencies while considering FTS properties like seasonality and auto-correlation is still a question to be addressed (Barez, Bilokon, Gervais, & Lisitsyn, 2023).

Adapting common AI techniques used in FTS forecasting to the unique requirements of HFT poses challenges. For example, long short-term memory (LSTM) models, widely used in deep learning for FTS forecasting (Sezer, Gudelek, & Ozbayoglu, 2020), face limitations when applied to HFT due to their sequential structure, hindering efficient parallelization of computations.

Current state of adoption:
Based on our impression of the levels of tactical deployment, reported challenges and ongoing research, our evaluation indicates that AI is at an **intermediate** stage of adoption in high-frequency trading.

[8] By employing Multi-Head Attention, the transformer can simultaneously consider various aspects of the data, enabling it to capture complex dependencies between different elements in the financial time series.

[9] This parallelization capability greatly reduces the data processing time, making transformers particularly suitable for low-latency trading strategies, which is a key requirement for HFT (Barez, Bilokon, Gervais, & Lisitsyn, 2023).

C. Risk management

AI adoption in capital markets for risk management purposes is varied. While AI use is low in certain highly regulated areas such as the calculation of regulatory capital requirements, it is more prevalent in areas like AML, surveillance and onboarding processes where the analysis of unstructured data is required due to the availability of third-party tools to carry out these functions. For instance, AI can be used to automatically extract information from know-your-client documents and unstructured public data to potentially identify profiles of concern, as well as to verify the identity of individuals via video calls using facial recognition techniques.

AI is also being used in collateral and liquidity optimization to provide insights into various financial operations. It assists in determining when and how to move collateral to support trading and settlement, forecasts liquidity requirements and offers guidance on the selection of eligible collateral. Third-party solutions using AI are also available to automate trade reconciliation.

In addition, AI is used in the realm of derivative pricing. For instance, it is being gradually used to model volatility surfaces for illiquid products, where volatility is an essential input for derivative pricing. AI is also used to approximate traditional models used for pricing derivatives, enabling faster computation, which is critical for calculating x-value adjustment (XVA), including credit value adjustment and funding value adjustment.[10]

Additionally, for end-of-day risk computation, multiple runs of the pricers across the firm's entire trading book are required. Currently, substantial computational power, coupled with parallelization, is used for this purpose. However, if AI models are employed to obtain the results of simulation-based models, the need for extensive computation during the inference time of the AI models is greatly reduced.[11]

[10] Conventional pricing models necessitate significant computational power due to their reliance on executing a high number of Monte Carlo simulations in a single pricing run.

[11] It should be noted, though, that achieving the same level of accuracy as conventional simulation-based pricing models is not feasible when using AI, which has a faster computation time. Nevertheless, when it comes to risk management, as opposed to the front office utilization of pricing models, there is greater flexibility to accept a certain level of reduction in accuracy.

AI is also being used to improve the distribution of derivative pricing on a large compute grid, whether on-premises or in the cloud, thereby reducing time and cost[12]. In addition, financial service firms are actively exploring the application of AI for dynamic hedging of complex portfolios. AI is also being tested for optimal order execution in illiquid markets.[13] Furthermore, in the context of HFT, AI implementation has reached the production stage in some large firms for strategy development and accurate prediction.

Adoption in this category remains limited due to the regulatory and governance concerns surrounding explainability, regulatory approvals required for dynamic model changes and the requirement for continued human supervision given the regulated nature of these systems.

Overall, capital market participants are implementing AI solutions in a phased approach, prioritizing low-risk applications such as the synthesis of news and policy insights for production, while higher risk applications, such as those related to risk management and revenue generation, are used with a human-in-the-loop or as a benchmark.

[12] The faster and more precise calculation of derivative pricing models is crucial for managing the risk profile of a portfolio comprising complex derivative products.

[13] JP Morgan also announced a deep RL based equity execution system called LOXM for trade execution (Noonan, 2017).

USE CASES

I. Hedging

USER CATEGORY	Portfolio managers, capital market activities of financial institutions.
OVERVIEW	AI is being explored to develop strategies that can help maintain a desired risk-return profile by taking positions opposite to those in the portfolio.
BENEFITS	Hedging strategies are upgraded by integrating realistic market conditions, encompassing transaction costs.
ADOPTION	Exploratory.

What is hedging?
Hedging is a risk management strategy employed to offset losses in investments from adverse market movement by taking an opposite position to one's portfolio. By having this offsetting position, hedging helps minimize potential losses and maintain a desired risk-return profile. Hedging strategies can be particularly important for institutional investors, such as mutual funds or pension funds, which often have large portfolios and lower risk appetites.

Market insights:
A subject matter expert stated when interviewed that AI is being used to manage risk in portfolio management.

EY has developed an application for deep hedging using reinforcement learning for consideration by a large financial institution:

EXAMPLE 3

Deep hedging using reinforcement learning for derivatives portfolio

The objective of this use case is to develop an efficient hedging strategy for a portfolio of options by incorporating realistic market constraints such as discrete trading decisions (academic models assume continuous-time decision-making capability), nonlinear trading costs and liquidity restrictions. The approach employs an RL model, trained using simulated market scenarios generated with Brownian motion and the Black-Scholes pricing model, while considering trading cost constraints.
The trained RL model, which incorporates NN, is evaluated on the validation window, with performance compared against baseline delta hedging strategies. It shows significant improvements in profit and loss and standard deviation when compared to the baseline. However, a challenge encountered in this use case is the modeling process of the reward function, which benchmarks against a highly risk-averse delta-hedging strategy.

Technical aspects:
Traditional hedging techniques heavily rely on human decision-making and heuristic adjustments, which introduces an increased risk of error (Murray, et al., 2022). Additionally, traditional hedging models often rely on unrealistic assumptions, such as assuming the market is complete and that perfect information is available at all times, which does not accurately reflect real-world conditions (Murray, et al., 2022). Traditional hedging techniques are further challenged by investments in products like barrier derivatives, where the return depends on whether an underlying asset has met or exceeded a given threshold. The possibility of sharp payoff changes resulting from whether or not a threshold has been met increases the difficulty of managing the risk associated with these investments.

Hedging can be viewed as a dynamic optimization problem, as it involves continuously adjusting hedge positions to minimize risk or protect against potential losses. There is a perpetual need to make decisions in response to changing market conditions. The dynamic nature of hedging strategies calls for the use of RL models, which is a natural and well-suited technique for solving dynamic optimization problems.

A review of 17 research papers and industry reports also suggest that RL has great potential for developing optimal hedging strategies for derivatives portfolios (Cao, et al., 2022). RL-based hedging techniques can incorporate realistic market conditions, including transaction costs, discrete trading decisions, non-linear trading costs and liquidity restrictions. In contrast, these factors are often overlooked in traditional hedging approaches, such as delta-hedging.

Deploying RL for hedging presents certain challenges. One significant challenge is designing the reward function. Additionally, interpreting RL models can be complex, requiring careful consideration when deploying them in real market conditions. RL agents exhibit multifaceted and intricate behaviour, making it beneficial to establish a dedicated test or sandbox environment for conducting sensitivity and robustness testing.

It is important to acknowledge that the deployment of RL models introduces additional model risk, highlighting the need for a well-defined framework to manage such risks. To ensure reliability, it is essential to validate the robustness of assumptions and conduct thorough testing using historical data from real-world scenarios.

Current state of adoption:
Based on the indications of exploratory work and ongoing research, our evaluation indicates that AI is at the **exploratory** stage of adoption in hedging.

II. Futures market classifier

USER CATEGORY	Pension funds.
OVERVIEW	AI-based framework is explored to analyze and categorize market conditions in the futures market to optimize slippage in futures trading.
BENEFITS	Optimize trade execution which resulted in minimized slippage.
ADOPTION	Exploratory.

What is a futures market classifier?
A futures market classifier refers to a framework or model that is designed to analyze and categorize market conditions in futures markets. The purpose of this classifier is to provide insights and guidance on trade execution styles and slippage optimization in futures trading. Accurately estimating market impact using traditional modelling methods is notorious for being quite difficult, particularly for illiquid securities (ESMA, 2023).

Market insights:
A challenge specific to this use case is the scarcity of specific data on metadata and the inability to pool data without raising privacy concerns.

However, a futures market classifier framework has been developed by EY for a large financial institution with the aim of optimizing slippage and improving trade cost performance:

EXAMPLE 4

Futures market classifier for a large financial institution

This use case effectively reduces trade slippages and improves efficiency by providing insights into various trade execution styles. The approach consists of a three-step process.

First, it uses internal and external data sources to perform clustering analysis to generate the initial selection of similar futures.

Next, it defines the clusters based on market conditions, such as execution type and slippage rates, which is achieved through a semi-supervised approach.

Lastly, a trained classification method provides a recommendation based on comparing various execution types and selecting ones with the least probability of slippage.

This approach enables the monitoring of trade cost performance and adaptation of trading styles based on market dynamics. It also provides scalability and the ability to use various market clusters, which vary depending on the contract and instrument type. Success in these projects heavily relies on fostering robust collaboration between the analytics team and capital market participants.

Current state of adoption:
Based on the reported levels of tactical deployment and ongoing research, AI is currently at the **exploratory** stage of adoption in futures market classification.

III. Trade surveillance and detection of market manipulation

USER CATEGORY	Sales and trading.
OVERVIEW	Market manipulation is a fraudulent activity perpetrated by individuals or organizations. AI is being used to detect such market manipulations.
BENEFITS	AI methods are observed to result in fewer false positives than rule-based approaches.
ADOPTION	Intermediate to advanced.

What is trade surveillance and detection of market manipulation?
Market manipulation is a fraudulent activity perpetrated by individuals or organizations with the intention of artificially influencing the price or trading volume of financial instruments. It encompasses deceptive tactics that create false or misleading perceptions of supply, demand, or market conditions, all in pursuit of personal gains at the expense of other market participants.

Such manipulation undermines the fairness, transparency, and integrity of capital markets, eroding investor trust and distorting the mechanisms of price discovery. Market regulators play a crucial role in upholding the integrity of capital markets through their efforts in detecting, investigating and prosecuting individuals or entities engaged in market manipulation (Austin, 2015).

Market insights:
Industry reports and company marketing information indicate that significant vendors of trading surveillance systems, such as NASDAQ Trade Surveillance (SMARTS), Eventus Systems (Validus), NICE Actimize, Neurensic and Breaking Wave (Relativity Trace), have all implemented AI models in their platforms, including ML, transfer learning, deep learning and NLP (Infosys, 2021) (Moran, 2023).

Technical aspects:
Rule-based approaches are currently being used to identify manipulation activities but can struggle to detect unknown manipulative schemes and adapt to changing market conditions due to the exponential growth of transactional data (Golmohammadi, Zaiane, & Diaz, 2015).
When used for detecting market manipulation, rule-based systems have traditionally returned many false positives. They are further challenged by the complexity of markets, the volume of data, and the constant evolution of market behaviour and manipulative practices. To address these challenges, Golmohannadi et al. successfully employed AI models to identify manipulation in labelled datasets.

IV. Data quality improvement

USER CATEGORY	Capital market activities of financial institutions.
OVERVIEW	In capital markets, data quality plays a vital role for AI users. Accurate and reliable data is essential for training AI models and generating insights.
BENEFITS	Identify anomalies in the data; improved model performance.
ADOPTION	Intermediate.

What is data quality improvement?
In capital markets, data quality plays a vital role for AI users. Accurate and reliable data is essential for training AI models and generating insights. Inaccurate or incomplete data can lead to flawed analysis and unreliable predictions, which can have significant implications for investment decisions. High-quality data ensures that AI algorithms receive accurate inputs, enabling them to detect patterns, trends and anomalies with greater precision. Additionally, data quality is crucial for regulatory compliance and risk management.

Market insights:
A subject matter expert shared that AI is being used for the generation of synthetic data. Synthetic data serves various purposes, such as augmenting imbalanced datasets to enhance model training, enabling data sharing while complying with regulations, and creating stress scenarios to test the behaviour of models under extreme conditions. Apart from synthetic data generation, the subject matter expert also highlighted the use of AI in ensuring privacy protection for sensitive information through the implementation of differential privacy methods.

EY has implemented a use case aimed at improving the quality of market data for a large financial institution. These models have been specifically designed to improve upon earlier deployed statistical models, such as Gaussian mixture models (GMM), which are capable of detecting anomalies but rely on several parametric assumptions. Deployed AI methods are free from parametric assumptions, which results in improvement in model performance and a reduction in manual labour:

EXAMPLE 5

Market data quality enhancement for a large financial institution

The aim of this use case is to improve market data quality by implementing two applications that leverage AI techniques. The first application uses unsupervised anomaly detection methods to build a clustering model that can detect anomalies in the financial institution's historical risk factors data. A voting model is then implemented, combining both the baseline and forecasting methods.
Example: Suppose a market participant is analyzing historical stock market data to identify anomalies in risk factors. They apply unsupervised anomaly detection methods, e.g., a clustering algorithm. After clustering, they can identify data points that do not belong to any cluster. These identified data points are potential anomalies that could indicate data errors or unusual market behaviour. The market participant can investigate these anomalies further and take corrective actions.

The second application replaces existing statistical approaches to gap filling by using clustering and deep learning methods. The clustering algorithm is used to cluster the financial institution's risk factors, and time series forecasting is used to identify areas that require gap filling. These approaches result in improved accuracy and risk sensitivity, increased return on equity through higher capital efficiency, and can be implemented alongside existing solutions rather than replacing them entirely.
Example: Consider a market participant that needs to fill gaps in its FTS data, such as stock prices, for accurate analysis and reporting. Firstly, they apply a clustering algorithm to group similar stocks based on their historical price patterns. Next, for each cluster, they use a deep learning model like a LSTM network to forecast the missing values or gaps in the time series data. This can improve overall accuracy of financial analysis.

Technical aspects:

The literature review also highlights the use of AI in enhancing data quality and enriching complex data sets obtained from diverse sources (Novick, et al., 2019). Novick et al.'s report showcases how asset managers utilize AI in processing, cleaning, and analyzing vast amounts of data, including macroeconomic data and analyst reports. Asset managers employ AI techniques to process alternative data such as GPS and satellite imagery to geo-locate and evaluate operations of customers and businesses. Asset managers also use AI to evaluate big data obtained from web scraping and social media to generate further market insights. Although the report refers to AI in general, we believe that, based on the applications discussed, the majority of the models are deep learning models.

The use of AI models to improve data quality in capital markets data presents technical challenges that require careful consideration. Methods like random forest, K-nearest neighbours and gradient boosting are prone to overfitting, where the model becomes too specialized in the training data (Gu, Kelly, & Xiu, 2020). To address this, effective control of hyperparameter tuning is necessary when using these models for predictions in capital markets.

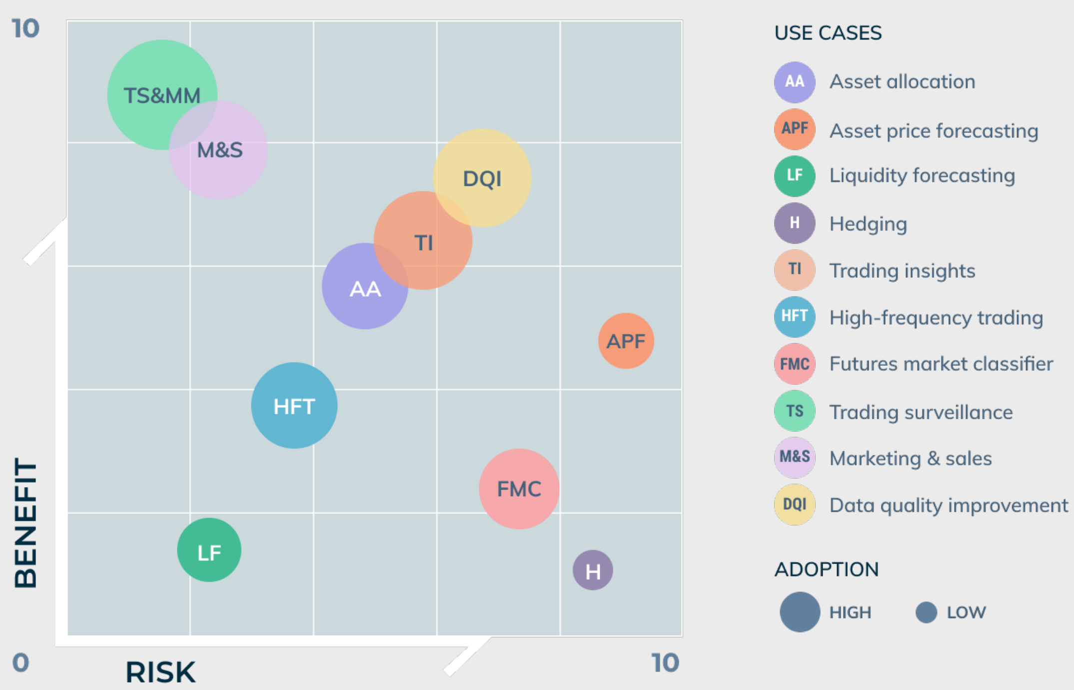
Current state of adoption:
In terms of maturity, AI applications in data quality improvement have reached an intermediate stage. However, continuous efforts are being made to develop more effective AI techniques that can further enhance data quality. Considering the scope and scale of adoption, AI deployment in data quality improvement appears to be at an **intermediate** level of adoption.

D. Use cases compared

The chart below compares the use cases included in this report based on their potential benefits, risks and adoption levels.[14]

The concept of risk is comprised of two aspects: **model risk**, which considers factors such as the accuracy and complexity of the AI model and **use case risk**, which considers the materiality associated with the AI application.
For instance, capital calculations may involve higher materiality risk, while a chatbot may have a lower materiality risk.

Similarly, the concept of benefit also encompasses two aspects: **efficiency**, which pertains to the AI system being faster and contributing to cost reduction and **capability**, which involves the AI system being more accurate and capable of performing a wider range of tasks that were previously done manually.



[14] The benefits displayed on the chart reflect the perception of subject matter experts regarding the realized benefits of each use case to date, the potential risks associated with AI usage, and the level of adoption in these particular use cases. The analysis of these use cases is based on a relative scale or ranking, meaning that the magnitude of the differences between use cases does not hold significant meaning in terms of benefits, risks, and adoption.

5

LOOKING AHEAD - AI ADOPTION: VALUE DRIVERS AND CHALLENGES

A. Value drivers

Market participants can improve their operations' efficiency and capacity by using AI. The implementation of AI in capital markets offers the potential to enhance various functions, including client interaction, risk management and reporting, compliance, and back-office processing (AFME, 2018).

I. Capacity enhancement: increases capacity to handle volume of data for more insights

One significant advantage of AI is its ability to assist in reviewing investment options, sell-side analysis, and documentation, manage sensitive client data, and extract insights about clients. **By employing AI systems, capital market participants can effectively analyze vast volumes and diverse types of data from various sources. This empowers them to make more informed and data-driven investment decisions.**

II. Precision enhancement: better predictive analytics

The substantial economic benefits that deep learning models can offer have been consistently highlighted in both academic papers and industry reports. A recent study demonstrated that NNs offer a substantial advantage in predicting equity risk premium compared to traditional methods (Gu, Kelly, & Xiu, 2020). This improvement in predictive accuracy was found to be consistent with a variety of AI models. Another study found that recurrent neural networks (RNN) exhibit a minimum of an 18% improvement in accuracy when forecasting stock prices in comparison to capital asset pricing models (CAPM) (Eliasy & Przychodzen, 2020). These findings highlight the superior performance of NN and RNN approaches in the respective domains of equity risk premium and stock price prediction.

III. Reduced manual work: NLP models to extract information from unstructured data

NLP models have numerous applications in the capital markets space. These models effectively extract valuable information from unstructured data. EY has developed NLP models for a pension fund, leveraging them to derive sentiment scores for specific topics identified by stakeholders and to identify emerging topics. Based on insights from interviewees, it is evident that LLMs are being actively explored despite their limitations in producing stable outcomes. **The primary driver behind this experimentation is the LLM's capability to reduce the human effort required in various processes.**

IV. Risk mitigation: liquidity forecasting and improved hedging

AI has also proven to be advantageous in the realm of risk management. Advancements in AI techniques can significantly enhance market liquidity prediction, showcasing superior performance relative to other methods, especially in extreme market conditions (Janabi, 2022). Financial services firms in North America have capitalized on AI's improved predictive capabilities for stock liquidity forecasting (Chartered Financial Analyst Institute, 2019). **In addition to NLP, RL has emerged as a prominent AI technique with extensive exploration, particularly in dynamic hedging**.

V. Customers and stakeholders: increase in customer and stakeholder satisfaction

Enhancing customer and stakeholder satisfaction through the development or integration of third-party AI tools is a significant area of AI application in capital markets. These applications encompass a wide range of functionalities, from the implementation of chatbots for improved customer support to the delivery of tailored advice and services as described in section 5.I.

A survey report published by the Economist Intelligence Unit highlights that financial services providers consider AI applications in customer and stakeholder engagement as their most effective use case (Kocourek, 2020).

In the context of capital markets, the evaluation of AI's benefits remains an ongoing and dynamic process. However, there has been a noticeable increase in the consideration and exploration of AI, particularly in use cases focused on enhancing efficiency. For example, market participants are particularly interested in leveraging LLMs to drive efficiency improvements by automating the manual text parsing.

B. Challenges

Based on the information gathered from interviews, EY's experience, and a review of research papers and industry reports, the challenges identified in AI adoption are largely consistent across all economic sectors, including capital markets.

These challenges are being identified and analysed through forums like the Financial Industry Forum on Artificial Intelligence (FIFAI) and can be categorized into five major areas: explainability, data-related challenges, effective governance, ethics and regulatory challenges (OSFI-GRI, 2023). At FIFAI, the OSC participated in discussions with thought leaders (academic, regulators, financial institutions, insurers, pension plans, fintech businesses and research centres) around appropriate safeguards and risk management in the use of AI at financial institutions.

I. Explainability: a concern in AI adoption

The growing availability of enterprise-grade AI applications has significantly enabled institutions to adopt AI systems. However, the lack of explainability of AI systems remains a key challenge that hinders broader adoption in capital markets. AI systems, in general, are highly complex and lack inherent explainability, which sets them apart from traditional mathematical/statistical models.

Explainability is crucial for establishing trust, but there is no settled definition of what constitutes explainability in the AI industry. For example, there is debate over whether a model can be considered explainable if its overall structure is understood but its weighing of variables is not (ESMA, 2023).

While there is no single solution to achieve explainability in AI models, there are two broad approaches to address the issue.

The first approach, **post-hoc explainability methods**, involves running explainability algorithms on a developed model to gain insights into its internal workings.

The second approach focuses on designing model architectures that possess **inherent explainability from the outset**. While the second method is considered better than the first, it is not always possible to design an architecture that is inherently explainable. Some ML models are difficult to explain and interpret, such as NNs.

As more advanced AI models are developed, researchers are actively working to address the growing challenges associated with explainability that these models present. It is essential to establish the importance of explainability throughout the model development lifecycle and within the organizational culture. This ensures that there is an effective framework for addressing the challenges associated with explainability and reinforces the need for adopting appropriate approaches. Additionally, it is important to note that developing advanced AI models while adequately addressing explainability concerns requires the expertise of individuals with a deep understanding of AI techniques**.**

Advancements in the explainability of AI systems are expected to have a significant impact on adoption rates. The ability to explain AI model outputs would enable stakeholders to facilitate more informed and sound business choices.

II. Diverse data sources: not easy to handle

The role of data in the development and implementation of AI is crucial. Challenges associated with data in AI adoption include data volume, variety, sources, privacy concerns, aggregation, and quality (OSFI-GRI, 2023). Market participants also mentioned that data availability, sparsity and frequent data drift pose challenges in AI modeling.

The diverse sources and formats of data create difficulties for organizations in terms of data aggregation, while also maintaining data quality and consistency. ML models often require significant adjustment and retraining, as FTS data possesses a low signal-to-noise ratio, thus differing greatly from the data typically used in other ML use cases (ESMA, 2023). For applications that require a large and diverse amount of consumer data from numerous sources, each source may have different associated terms and conditions, complicating usability if fresh consent is not obtained where the data is used for a new purpose (Martin-Bariteau & Scassa, 2021).

The use of AI systems also raises privacy concerns. As AI systems collect vast amounts of data from diverse sources, they have the potential to identify individuals directly or indirectly.

The European General Data Protection Regulation (GDPR) sets out regulations related to data protection and privacy that can limit the use of data in AI models. Regulators in other jurisdictions have also expressed their concerns regarding potential violations of data privacy. However, regulations that too stringently restrict the use of public datasets run the risk of entrenching market leaders that benefitted from training their models on this data prior to the establishment of regulation.

The budding use of AI to generate synthetic data may alleviate some of these challenges and will assist in training models where actual data is scarce, expensive to obtain in large quantities, or subject to privacy/confidentiality restrictions. Synthetic data refers to procedurally generated data that attempts to mimic real data.

Although generating synthetic data requires an existing, representative dataset, if this precondition is met, it can be produced cheaply and free of copyright or data privacy concerns (Zewe, 2022). **By augmenting AI training data sets, advancements in synthetic data generation will facilitate the development of better AI systems, lower development costs and increase compliance with data regulations.**

III. Governance approach: unique risks require change in governance approach

Currently, many organizations that implement AI and ML continue to rely on existing governance frameworks and compliance personnel (ESMA, 2023). **A robust, AI-specific governance framework can be an important tool to foster a culture of accountability in the responsible use of AI within an organization**. This framework enables financial institutions to fully capitalize on the benefits offered by AI while safeguarding customers and society at large from potential harm.

Risks associated with AI systems are distinct and require specific governance measures beyond traditional approaches. Several unique risks arise from the nature of data used in AI, including issues related to risk measurement, reliance on third-party models, use of open-source material, tracking emerging risks and the availability of reliable risk metrics (NIST, 2023).

Given the resource constraints and the human-intensive nature of effective governance, it is imperative to prioritize risks appropriately. Consequently, individuals possessing a blend of AI expertise and domain knowledge are crucial for establishing effective governance. These experts are better equipped to understand the trade-offs between bias and model performance and can provide valuable guidance moving forward (NIST, 2023). Governance models that are based on a thorough understanding of unique AI risks are essential, similar to models developed for credit and market risk.

Another barrier to enhanced accountability is the fact that trade secret law often protects the algorithms responsible for decisions made by AI systems (Martin-Bariteau & Scassa, 2021). In developing a regulatory framework, stakeholders should balance protecting trade secrets with meaningful disclosure.

IV. Ethics: a subjective point in AI adoption

Ethics in business encompasses the moral principles and values that guide an organization's decision-making process. The subjective nature of ethics poses challenges when addressing issues related to AI. For instance, **fairness is a significant concern in AI ethics**; however, there is no universally agreed-upon principle regarding fairness in the AI space (OSFI-GRI, 2023).

Our interview participants also identified fairness as a prominent challenge in AI adoption. They expressed difficulties in obtaining data related to sensitive attributes to assess the fairness of AI models. Additionally, they often lack clarity on which fairness metric is suitable for their specific use case.

V. Research and investment costs: a source of divergence in AI adoption

Implementing AI in capital markets requires substantial research and financial investment. Subject matter experts identified these costs as a barrier to AI adoption, especially for smaller players with concerns over ROI.

This challenge is largely tied to the difficulty of hiring and retaining technical specialists with sufficient ML expertise, which requires competing with large financial institutions, high-paying AI shops and major tech companies for talent.

The evolution of enterprise-grade AI solutions, as well as the continued incorporation of AI models into off-the-shelf solutions, will help address the challenge for smaller firms. However, increased reliance on third-party vendors further exacerbates risks relating to explainability and governance if the vendor maintains opaque systems that limit client oversight and control.

Investment costs are also causing differences in AI adoption across regions. Based on EY's experience and a review of research and industry publications, the use of AI in capital markets is overall more advanced in markets such as in the US and the UK. In contrast, Canadian market participants sometimes seem to lag in adopting these new technologies. This discrepancy is partly due to the smaller size and scale of some Canadian market participants compared to their US and UK counterparts. Where Canadian market participants can benefit from size and scale, they are competing effectively against their global peers. At the same time were according to the Evident AI Innovation Report, two large Canadian financial institutions were early movers in establishing in-house AI research teams and rank highly in the Evident AI Index. They are also global leaders in AI research as measured in number of research papers published, number of AI patents filed, number of AI investments made and number of active GitHub repositories.

VI. Market stability: a concern with automation

In addition to the challenges faced at the firm level, there are risks associated with AI that impact the overall financial market. **The dynamic adaptability and increased autonomy of AI models have the potential to contribute to procyclicality and systemic risks in the market** (OECD, 2021). A prominent researcher also confirmed the potential procyclicality generated by AI models.

In the case of AI, a potential convergence of AI models on leading industry practices (Danielsson, Macrae, & Andreas Uthemann, 2022) and the common use of previously unrelated data sets (Financial Stability Board, 2017) can lead to recommendations or decisions that can reinforce or amplify trends. Furthermore, as AI increasingly becomes an important productivity input across various sectors, major AI providers will likely enjoy substantial market power over other market participants, whether they compete directly with them or not (Martin-Bariteau & Scassa, 2021).

The high level of infrastructure, expertise and resources needed for AI development heightens the risk of procyclicality if the market for AI tools is dominated by a few major players with access to substantial datasets.

VII. Operating models and culture

Any major technological disruption challenges current operating models and organizational culture. The introduction of AI is a case in point. Where significant resources and teams have been developed to manage complex manual processes such as trade reconciliations, managing settlements, collateral and liquidity, and onboarding clients and counterparties, it can be a significant challenge to adapt entrenched processes and ways of working to new technology.

An example is found in the many blockchain proofs of concept that demonstrate operational efficiency but that are impeded by concerns over replacing processes that work, and the need for the development of industry-wide infrastructure.

Capital market participants need to be ready to apply these new models and ways of working. Furthermore, technological disruption necessitates changes in personnel and responsibilities. Currently held positions may become redundant, and some roles – such as those that represent the human-in-the-loop for decision-making and management – will have enhanced responsibility. Beyond the issues of organizational change, there exist strategic challenges of replacing core functions that are battle-tested and serve their purposes with new processes and tools that can potentially put those core functions at risk. **The resulting risk aversion can inhibit the adoption of new processes and functions.**

6

AI GOVERNANCE

As market participants increasingly rely on AI, they note that traditional governance approaches are insufficient in addressing its unique risks, such as lack of transparency, heavy reliance on different types of data, quality of data and bias in model selection.

These risks have prompted the development of AI governance frameworks that prioritize trusted AI principles such as unbiasedness, performance, transparency, explainability and resilience.

Additionally, financial institutions are expanding their third-party risk management frameworks to account for the increased reliance on third-party providers of AI solutions. EY's experience and observations indicate that larger financial institutions, including in Ontario, tend to be further along in this journey than other capital market participants.

The development and adoption of AI governance frameworks that emphasize trusted AI principles and the explainablility of models, as well as the incorporation of AI risks into risk management frameworks, are poised to promote broader responsible AI adoption in capital markets. These frameworks can be effective tools to prioritize and classify risks based on their impact on business operations and their complexity.

7

CONCLUSION

AI is an emerging trend in technological innovation. Its adoption in Ontario's capital markets is currently at an intermediate stage, with varying levels of maturity across different functions.

Right now, AI adoption is focused in areas that further operational efficiencies in functions with lower risk, cost and regulatory constraints.

While use cases in capital markets have been the focus of this report, the world is witnessing adoption of AI in many industries, including in other parts of financial services such as banking and insurance. Capital markets regulators are one of many bodies who can impact how responsible AI is adopted in Canada.

The all-encompassing and interdisciplinary nature of AI will require collaboration across different verticals and horizontals:

Insights from capital market participants

We welcome further engagement from market participants as they innovate in the AI space and encounter risks and challenges when deploying AI systems.
As regulators, we seek to understand where markets can benefit from the responsible use of AI systems and determine how best to support this important technological innovation, while ensuring that risks are properly mitigated.

Join the conversation
If you're innovating in the AI space, we want to hear from you.
Let us know how your firm is deploying AI as well as the risks and challenges you're encountering at OSC IdeaHub.

IDEAHUB

Collaboration between legislators and regulators

Continued collaboration between federal and provincial governments, securities regulators and financial services regulators is needed to develop consistent regulation. Many market participants offer a wide array of services that fall under different regulatory bodies. Therefore, dialogue and collaboration are critical to facilitate responsible AI adoption in Canada.

As noted, these conversations have already begun through initiatives like FIFAI, where discussions were furthered around appropriate safeguards and risk management in the use of AI at financial institutions. In addition, given that the use of AI systems easily transcends borders, international collaboration through global forums like the International Organization of Securities Commissions (IOSCO) is also critical in developing consistent standards that are applicable worldwide.

Continuously identifying and understanding the use of AI, its risks and potential in Ontario's capital markets is a key priority for the OSC. It will help us in the effective oversight of capital market participants that are adopting AI systems and its impacts on investors.

As the use of AI grows, so too does the risk that some actors will seek to exploit it for malevolent purposes. By understanding the current and future uses of AI prior to the wide-scale industry adoption, regulators can be better equipped to assess and mitigate these risks while supporting its responsible deployment.

8

APPENDIX

A. Overview table of AI use cases

EFFICIENCY IMPROVEMENT

USE CASE	OVERVIEW	BENEFITS	USER CATEGORY	AI TECHNIQUE	DATA INFORMATION	ADOPTION
Pre- and Post-Trade Processes Automation	Integrate an AI system with a marketplace or dealer to automate post-trade processes such as generating trade reports and submitting them to regulatory authorities.	Reduced back-office workload. Improved execution.	Asset Management, Institutional Investors, Market Intermediaries	NLP	Source: Internal systems, Market Data, Exchanges Data Access: Public, Proprietary Data Type: Structured, Unstructured	Intermediate to Advanced
Execution Quality Improvement: Liquidity Forecasting	Minimizing losses in order execution relies on capitalizing on favourable liquidity conditions. Precise liquidity forecasting helps in improving order execution.	Extract information from text data. Better liquidity prediction than traditional methods.	Capital Market Activities of Financial Institutions	CNN, NLP, RL	Source: Web, social media, Industry reports, Market data, exchanges Data Access: Public Data Type: Time Series, Cross Sectional, Unstructured	Intermediate
Customer Services and Support	Various benefits by leveraging advanced AI technologies to enhance customer interactions, streamline processes and improve overall customer experience.	Reduced workload. Greater speed and throughput. Informed decision-making.	Wealth Management, Capital Market Activities of Financial Institutions, Dealers	NLP, Generative	Source: Web, social media Data Access: Public, Proprietary Data Type: Unstructured	Advanced

REVENUE GENERATION

USE CASE	OVERVIEW	BENEFITS	USER CATEGORY	AI TECHNIQUE	DATA INFORMATION	ADOPTION
Sales and Marketing	AI enables efficient and effective marketing, including customer segmentation, lead generation, predictive analytics and chatbot assistance.	Leverage insights derived from unstructured and alternative data sources. Enhanced comprehension of sales and marketing dynamics.	Wealth Management, Capital Market Activities of Financial Institutions, Dealers	NLP, Generative	Source: Web, social media Data Access: Public, Proprietary Data Type: Unstructured	Advanced
Asset Allocation	Leveraging AI capabilities, optimizing the allocation of resources among different asset classes to maximize return on investment.	Develop dynamic asset allocation strategies. More consistent returns than traditional methods.	Insurance Companies, Portfolio Managers, Fund Managers	RL, NN	Source: Market Data Data Access: Public, Proprietary Data Type: Time Series	Intermediate

Asset Price Forecasting	Leverage AI to predict asset prices using historical and cross-sectional data, uncovering non-linear interactions among numerous variables.	Extract insights from untapped unstructured data sources expanding the scope of knowledge.	Sales and Trading	NLP	Source: Market Data, Macro-Economic Variables, Financial News Data Access: Public Data Type: Time Series, Cross Sectional, Unstructured	Intermediate
Trading Insights	Utilize NLP and other AI methods to extract information from news and other diverse data sources, enabling valuable trading insights.	Extract insights from unstructured data sources. Overcome accessibility limitations to analyze unstructured data.	Pension Funds, Asset Managers	NLP	Source: Web, Financial News, social media Data Access: Public Data Type: Unstructured	Advanced
High-Frequency Trading (HFT)	Utilize AI capabilities in high-frequency trading to enhance prediction accuracy, where orders are executed at extremely fast speeds.	Enhance prediction accuracy. Capture intricate dependencies present in financial time series (FTS).	Hedge Funds	Transformers	Source: Exchanges Data Access: Public Data Type: Time Series	Intermediate

RISK MANAGEMENT

USE CASE	OVERVIEW	BENEFITS	USER CATEGORY	AI TECHNIQUE	DATA INFORMATION	ADOPTION
Hedging	AI is being explored to develop strategies that can help in maintaining desired risk-return profile by taking the opposite position of portfolio.	Hedging strategies are upgraded by integrating realistic market conditions, encompassing transaction costs.	Portfolio Managers, Capital Market Activities of Financial Institutions	RL	Source: Market & Simulated Data Data Access: Public, Proprietary Data Type: Time Series	Exploratory
Futures Market Classifier	AI based framework is explored to analyze and categorize market conditions in the futures market to optimize slippage in futures trading.	Optimize trade execution which resulted in minimized slippage.	Pension Funds	Clustering	Source: Firm Risk Factors Data Data Access: Proprietary Data Type: Time Series	Exploratory
Trade Surveillance and Detection of Market Manipulation	Market manipulation is a fraudulent activity perpetrated by individuals or organizations. AI is being used to detect such market manipulations.	AI methods are observed to result in fewer false positives than rule-based approaches.	Sales and Trading	Various	Source: Exchanges Data Access: Public Data Type: Time Series	Intermediate to Advanced
Data Quality Improvement	In capital markets, data quality plays a vital role for AI users. Accurate and reliable data is essential for training AI models and generating insights.	Identify data anomalies. Improved model performance.	Capital Market Activities of Financial Institutions	Clustering	Source: Firm Risk Factors Data Data Access: Proprietary Data Type: Time Series	Intermediate

B. Glossary

Term	Description
AI governance	AI governance refers to the policies, processes, and frameworks that ensure responsible and ethical use of AI technologies, including compliance with regulations applicable to the firm's jurisdiction.
Auto-correlation	In time series data, "auto-correlation" refers to the relationship between a data point and previous data points within the same series. It measures the similarity or dependence between observations at different time points. Specifically, auto-correlation examines how a data point is related to its own past values.
Black-Scholes	Black-Scholes model is a mathematical model used to calculate the theoretical price of financial derivatives, particularly options. It assumes that financial markets are efficient and that the price of the underlying asset follows a geometric Brownian motion.
Bound in predictive error	Bound in predictive error statistically means confidence interval in prediction. This gives users confidence in the prediction of the model, because they know that probability of error larger than certain threshold is low.
Brownian motion	Brownian motion is a mathematical model that describes the random movement of particles in a fluid. In the context of financial markets, Brownian motion is used to simulate the unpredictable and continuous fluctuations in asset prices over time. It assumes that price changes are driven by random factors and that these changes are independent of past price movements. Brownian motion is a key component in models such as the Black-Scholes-Merton option pricing model and other derivative pricing models.
Cross-sectional	Cross-sectional models examine stock-level characteristics like size, value, and momentum to explain differences in expected returns.
Delta hedging	Delta hedging is a risk management strategy used in financial markets, particularly in options trading. It involves adjusting or rebalancing a portfolio to offset the potential price movements of an option contract. Delta refers to the sensitivity of an option's price to changes in the price of the underlying asset. Delta hedging aims to neutralize or minimize this sensitivity, thereby reducing the risk associated with the option position.
Differential privacy	Differential privacy is a method in AI that aims to protect the privacy of individuals when analysing or sharing sensitive data. It provides a mathematical framework for adding noise or randomness to the data analysis process to ensure that individual-level information remains private. Differential privacy guarantees that the output of a computation or analysis does not reveal specific information about any individual data point. By introducing controlled noise or perturbation, differential privacy prevents an adversary from linking specific data points to their corresponding outputs, thus safeguarding sensitive information.
Dynamic optimization problem	A dynamic optimization problem involves making sequential decisions over time to optimize an objective, while considering the changing variables and constraints. The goal is to find the best sequence of decisions that maximizes objective function while meeting the given constraints. This is exact requirement of asset allocation.
Explanatory variables	Explanatory variables, in the context of modelling, refer to the input features or factors that are used to explain or predict the outcome or target variable.
Gaussian mixture model	Gaussian mixture models (GMM) are probabilistic models that assume that the data is generated from a mixture of multiple Gaussian distributions. It represents the data as a combination of these Gaussian components, each having its own mean and covariance. GMM is used to estimate the underlying distribution of the data and can be used for various tasks such as clustering, density estimation, and anomaly detection.

Global minimum variance	Global minimum variance strategy aims to construct a portfolio with the lowest possible level of volatility or risk. It involves allocating investments in a way that minimizes the overall variance of returns.
High-dimensional data	High-dimensional data refers to simultaneously evaluating large number of financial assets for optimal portfolio allocation.
Hyperparameter	Hyperparameter refers to a configuration setting that is determined before the learning process begins. Unlike the parameters of a model, which are learned from the training data, hyperparameters are predefined choices that influence the behaviour and performance of the learning algorithm. Examples of hyperparameters include the learning rate, regularization strength, number of hidden layers in a neural network, size of the decision tree, and the number of clusters in a clustering algorithm.
Local sequential structures	Local sequential structures refer to the nuances that are present in the relationship between adjacent elements of a sequence.
Market microstructure	Market microstructure refers to the organizational structure and dynamics of financial markets, including the mechanisms and processes that determine the price formation and trading of financial assets. It involves studying the interactions between market participants, such as buyers and sellers, as well as the rules, regulations, and technological infrastructure that govern the trading environment. Market microstructure focuses on understanding how order flow, market liquidity, bid-ask spreads, trading volumes, and price discovery mechanisms influence the overall functioning and efficiency of the market. It helps explain the behaviour and patterns observed in the price movements and trading activity within a market.
Most diversified strategy	Most diversified strategy focuses on constructing a portfolio that maximizes diversification by investing in a wide range of assets or securities from different sectors or asset classes. The goal is to reduce risk by spreading investments across various sources.
Naïve Strategy	Naïve strategy is a simple approach that involves equally distributing investments across all available assets or securities in a portfolio, without considering their individual characteristics or performance.
Natural language processing	Natural Language Processing (NLP) methods encompass the study and development of computer systems that analyze and comprehend speech and text, emulating human language usage. These methods can be categorized as supervised or unsupervised learning algorithms.
Optimal order execution	Optimal order execution refers to the process of strategically placing and executing trades in financial markets to achieve the best possible outcome for an investor. It involves considering various factors, such as market conditions and microstructure, liquidity, trading costs, and timing, to minimize transaction costs and maximize the potential for favourable trade execution. The goal is to execute trades in a way that minimizes price impact and slippage, ensuring that the investor gets the most advantageous price for their orders.
Overfitting	Overfitting refers to the situations when a model becomes too specialized in the training data and fails to generalize well to new data.
Procyclicality	Procyclicality refers to the amplification of market cycles.
Prompt engineering	Prompt engineering is the process of carefully designing instructions or questions (“prompts”) given to an AI model to get the desired response. It helps guide the AI model's output by framing the input in a way that influences the generated results.
Reinforcement learning	Reinforcement learning (RL) is an AI method actively being explored for asset allocation. In RL, the agent functions akin to a fund manager, continuously making decisions on asset allocation within a dynamic market environment. This inherent similarity makes RL particularly well-suited for addressing the challenges of asset allocation.

Rule-based approach	A rule-based approach is a top-down approach that is based on a set of known patterns and predefined thresholds. Market data such as price and volume of securities (i.e., the number of shares or contracts that are traded in a security) are monitored using a set of rules and red flags trigger notifications.
Slippage	Slippage occurs when an order is executed at a price greater or lower than the quoted price, usually happening in periods when the market is highly volatile, or market liquidity is low. The exposure to slippage risk can be minimized by trading during hours of highest market activity and in low volatility markets.
Stability	Stability remains a crucial concern when considering the output of language models (LLMs) due to their inherent generative nature. Designed to be dynamic, these models generate diverse outputs upon each invocation, even when the inputs remain consistent. "Instability" of a model describes the phenomenon that identical inputs can result in different outputs when the model is run more than once.
Supervised learning	Supervised learning is a machine learning approach where an algorithm learns from labelled training data to make predictions or classify new, unseen data. In supervised learning, the training dataset consists of input data (features) along with their corresponding output labels or target values. The algorithm learns the relationship between the input features and the desired output by generalizing patterns from the labelled data. Once trained, the algorithm can make predictions or classify new instances based on the learned patterns. The goal of supervised learning is to minimize the difference between the predicted outputs and the actual target values, thereby achieving accurate predictions on unseen data.
Synthetic data	Synthetic data refers to artificially generated data that imitates real data but does not contain any personally identifiable information or confidential details. It is created using algorithms and statistical methods to replicate the statistical properties and patterns found in real data. Synthetic data is often used as a substitute for real data in various applications, such as research, testing, and machine learning, to address privacy concerns or data availability limitations.
Target strategy	Target strategy (maximizing Sharpe ratio) strategy aims to optimize the risk-return trade-off by maximizing the Sharpe ratio. The Sharpe ratio is a measure of risk-adjusted return, where higher values indicate a more favourable balance between risk and return. This strategy seeks to allocate investments in a way that maximizes the portfolio's risk-adjusted returns.
Tick-to-trade latency	Tick-to-trade latency refers to the time delay between the receipt of tick data, and the execution of a trade based on that data.
Time series	Time series models analyze portfolio returns with macroeconomic variables and technical indicators
Trend	Trend refers to the long-term pattern or direction in which the data points are changing over time. It represents the underlying tendency or movement of the data, regardless of short-term fluctuations or noise. A trend can be either upward (indicating growth or increase), downward (indicating decline or decrease), or even a flat line (indicating stability or no significant change).

C. Abbreviations

Abbreviation	Full Form
AI	artificial intelligence
AML	anti-money laundering
CAPM	capital asset pricing model
CNN	convolutional neural network
DJIA	Dow Jones Industrial Average
DL	deep learning
ESMA	European Securities and Market Authority
FIFAI	Financial Industry Forum on Artificial Intelligence
FTS	financial time series
GMM	Gaussian mixture model
HFT	high-frequency trading
IOSCO	International Organization of Securities Commissions
IP	intellectual property
LLM	large language models
LSTM	long short-term memory
ML	machine learning
NN	neural network
NLP	natural language processing
OSC	Ontario Securities Commission
RL	reinforcement learning
RNN	recurrent neural network
ROI	return on investment
VIX	volatility index
XVA	x-value adjustment

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