Artificial intelligence enabled solutions in capital markets

Discussion paper

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AGENDA

AI in capital markets report prepared in collaboration between the OSC and EY

We invite the reader to refer to a report on AI in capital markets prepared in collaboration between the OSC and EY: Artificial intelligence (AI) | OSC Innovation Office. The report explores current AI use cases, value drivers and challenges. By exploring these use cases, OSC and EY aim to raise awareness of the many ways in which AI is starting to transform capital markets and help Ontario's market participants, innovators and policy makers as they grapple with the transformative potential of AI.

1

Overview of AI in capital markets

AI promise in capital markets (CM)

AI adoption in CM

- Over the last few years, AI solutions have been increasingly used to address various use cases in capital markets.
- This large gain in popularity of AI in capital markets is driven by the ability of these methods to generate new benefits and efficiencies within organizations through:
  - ✓ Process automations which reduce manual and repetitive works (reduce costs, increase productivity and improve efficiency)
  - ✓ Their ability to process a large variety and volume of data (big data) to improve market decision processes (e.g., gains from improvements in risk management by enhanced predictions of liquidity risk)
  - ✓ Their strong ability to handle some limitations of the traditional methods (e.g.: mean-variance investment method, liquidity risk prediction through sentiment analysis as suggested by academic works, etc.) and produce performance improvement.
- These models (including reinforcement learning (RL) and deep learning (DL)) have been used in different areas of the capital market (e.g., asset management, market manipulation, trading insights, and data quality management) for three different functions: revenue generation, efficiency improvement, and risk management.
- The degree of maturity of AI use cases varies significantly across domains.

The challenges

- Despite the range of advantages offered by AI to organizations in the CM, their adoption in CM comes with risks and challenges that need to be addressed and managed.
- These challenges can be categorized into the following major areas: explainability, data-related challenges, effective governance, ethics, and regulatory challenges.
- To ensure that an AI system is effective within the CM, its adoption in any area of the CM should be developed with appropriate risk management strategies and regulatory guidelines.
  - ✓ A robust governance framework is essential for fostering a culture of responsibility and accountability in the utilization 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.

AI adoption in capital markets functions

Back office | Middle office | Front office

Industry importance | Scale of AI adoption

1 — **Revenue generation** — **2**

Capital markets participants aim to generate revenue by engaging in activities that drive profits and growth of the firm. Such activities include trading, asset allocation, and generating sales strategy.

2 — **Efficiency Improvement** — **1**

Capital markets participants strive to enhance efficiency in their operations to achieve cost savings, improve processes, and optimize performance. This results in better allocation of resources, improved execution speed, and enhanced customer/employee satisfaction.

3 — **Risk management** — **3**

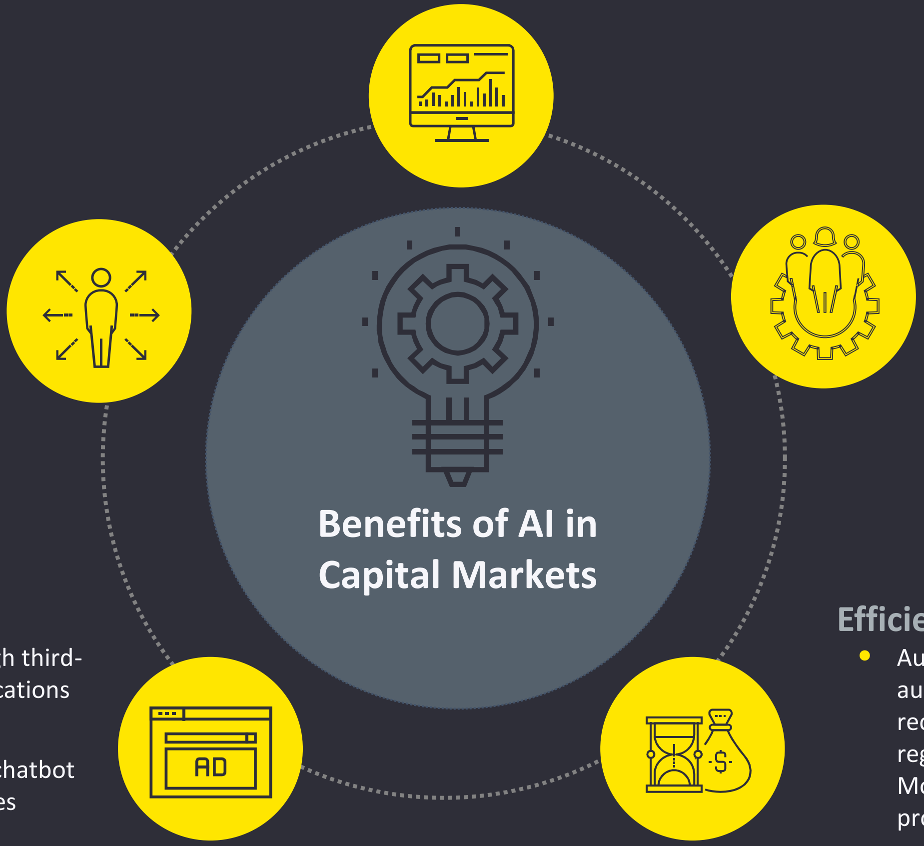
Capital markets participants face various risks inherent in their operations, such as market volatility, credit risk, liquidity risk, or operational risk. AI may be used in risk mitigation activities such as diversification, hedging strategies, risk assessment models, regulatory compliance, and internal control systems.

2 The Benefits of AI adoption in capital markets

Benefits of using AI in capital markets

Performance enhancement (revenue generation)

- AI models are observed to have consistently better predictive performance compared to most traditional models because of their ability to analyze vast volumes and diverse types of data from various sources
- Greater predictive performance results in greater economic gains (confirmed by academia and industry) as these models can process both structured and unstructured datasets, providing more useful information than most statistical models



New ways of working

- AI algorithms enable the analysis and use of volumes and types of data not feasible for other models (e.g.: AI can process both unstructured and structured data unlike most of the statistical models)
- This results in improvements to strategies, risk management capability, and optimization of human effort

Better risk management

- Advanced AI techniques improve risk management. For example, financial service providers may reduce liquidity-related risks effectively by precise market liquidity forecasting enabled by the strong ability of these models to process a variety of datasets under realistic economic conditions
- Reinforcement Learning methods may provide added value in dynamic hedging in P&L and standard deviation when compared with traditional methods

Improved customer service

- Improving customer service excellence through third-party AI tools is a prominent realm of AI applications
- Within this domain, a broad spectrum of AI applications can be observed, spanning from chatbot functionalities to personalized advisory services

Efficiency gain (improvement)

- Automation: This encompasses, but is not limited to, the automation of back-office tasks such as data management, reconciliation, and report generation, as well as ensuring regulatory compliance through measures such as Anti-Money Laundering (AML) and Know Your Customer (KYC) procedures
- Significantly reduced manual and repetitive tasks

AI-enabled revenue generation in capital markets

Revenue Generation

	ASSET ALLOCATION	TRADING INSIGHTS	ASSET PRICE FORECASTING	HIGH FREQUENCY TRADING	SALES AND MARKETING
OVERVIEW	Leveraging AI capabilities, improving the allocation of resources among different asset classes to maximize return on investment.	Utilize Natural Language Processing (NLP) and other AI methods to extract information from news and other diverse data sources, enabling valuable trading insights.	Leverage AI to predict asset prices using historical and cross-sectional data, uncovering non-linear interactions among numerous variables.	Utilize AI capabilities in high-frequency trading to enhance prediction accuracy, where trades are executed at extremely fast speeds.	AI enables efficient and effective marketing, including customer segmentation, lead generation, predictive analytics, and chatbot assistance.
BENEFITS	▸ Develop dynamic asset allocation strategies ▸ More consistent returns than traditional method	▸ Extract valuable insights from unstructured data sources ▸ Overcome accessibility limitations to analyze unstructured data	▸ Extract valuable insights from untapped unstructured data sources expanding the scope of knowledge	▸ Enhance prediction accuracy ▸ Capture intricate dependencies present in Financial Time Series (FTS)	▸ Leverage insights derived from unstructured and alternative data sources ▸ Enhanced comprehension of sales and marketing dynamics
ADOPTION	Medium	Medium	Medium	Medium	Medium
SAMPLE AI TECHNIQUE [1]	Reinforcement Learning, Deep Learning	Natural Language Processing	Natural Language Processing, Deep Learning	Transformers, Long Short-Term Memory	NLP, Other Generative AI methods

Low Medium High

Adoption Levels

1. **Exploratory:** Potential of AI is acknowledged and its utility is tested through proof-of-concept.
2. **Intermediate:** AI is used tactically and additional use cases are explored.
3. **Advanced:** AI is strategically included in business processes.

[1]Note: Refer to Appendix A for explanations on AI methods

AI-enabled efficiency improvement in capital markets

Efficiency Improvement

	AUTOMATION OF TRADE PROCESSES	EXECUTION QUALITY IMPROVEMENT	LEVERAGING INSIGHTS FROM TEXT/DOCUMENT	CUSTOMER SERVICES AND SUPPORT
OVERVIEW	Integrate an AI system with a trade execution platform to automate the process such as generating trade reports and submitting them to regulatory authorities.	Minimizing losses in trade execution relies on capitalizing on favourable liquidity conditions. Precise liquidity forecasting helps in improving trade execution.	NLP models are used to extract information from documents – for example, ingesting information from regulatory documents and mapping to regulatory requirements.	Various benefits by leveraging advanced AI technologies to enhance customer interactions, streamline processes, and improve overall customer experience.
BENEFITS	▸ Reduced back-office workload ▸ Improved Execution	▸ Extract information from text data, ▸ Better liquidity prediction than traditional methods	▸ Reduced workload ▸ Greater throughput ▸ Informed decision-making	▸ Reduced workload ▸ Greater speed ▸ Informed decision-making
ADOPTION				
SAMPLE AI TECHNIQUE[1]	NLP and third-party tools	Convolutional Neural Network, Reinforcement Learning, NLP	NLP and third-party tools	NLP and third-party tools

Low Medium High

Adoption Levels			
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AI-enabled risk management in capital markets

Risk Management ●●○

	FUTURES MARKET CLASSIFIER	DATA QUALITY IMPROVEMENT	HEDGING	TRADE SURVEILLANCE
OVERVIEW	AI based framework is explored to analyze and categorize market conditions in the futures market in order to optimize slippage in futures trading.	In capital markets, data quality plays a vital role for AI users. Accurate and reliable data is essential for training AI models and generating valuable insights.	AI is being explored to develop strategies that can help in maintaining desired risk-return profile by taking the opposite position of portfolio.	Market manipulation is a fraudulent activity perpetrated by individuals or organizations. AI is being used to detect such market manipulations.
BENEFITS	▸ Optimize trade execution which resulted in minimized slippage	▸ Identify anomalies in the data ▸ Improved model performance	▸ Hedging strategies are upgraded by integrating realistic market conditions, encompassing transaction costs	▸ AI methods are observed to result in fewer false positives than rule-based approaches
ADOPTION	●○○	●●○	●○○	●●○
SAMPLE AI TECHNIQUE[1]	Clustering and semi-supervised AI methods	Clustering	Reinforcement Learning	Vendor supported AI tools based on transfer learning, deep learning, and other machine learning methods

●○○ Low ●●○ Medium ●●● High

Adoption Levels

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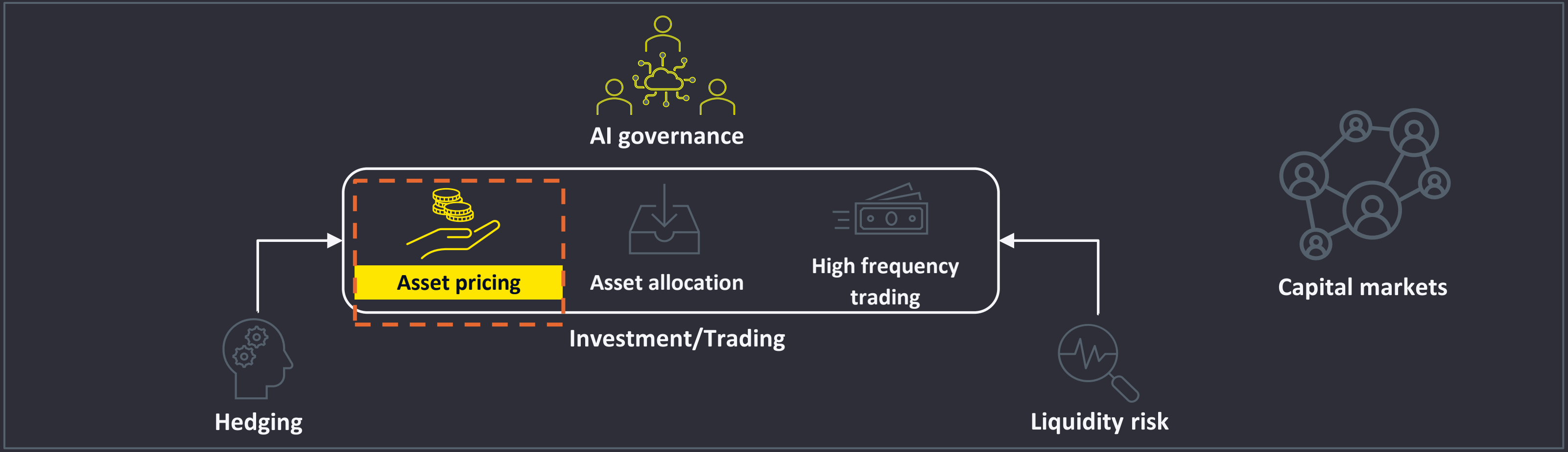
3 AI use cases in capital markets

Asset price forecasting

AI use case



Target application

- Asset price forecasting is one of the most important topics in the financial market
- The idea is to use available information to predict future asset price patterns by utilizing an abundance of data that is available
- Traditionally, Capital Asset Price Models-like factor models utilizing statistical methods were used for this purpose
- Rapid progress in AI (new time series forecasting models) and increased availability of large volumes of structured and unstructured data has catalysed the adoption of AI in asset price forecasting

Current pain points

- With a constant increase of the prediction factors (**high dimensional** data), most of the standard statistical methods perform poorly
- **Unstructured** data cannot be processed by traditional statistical methods
- Combining financial market data with firm-wide financial variables causes challenges for statistical analysis. AI algorithms pave the way to combine the two distinctive datasets model-free for price prediction
- AI algorithms allow the incorporation of subjective information in price prediction

Objective

- Leverage advancements in AI algorithms to improve the performance of price prediction models. The advantage primarily stems from the ability of AI models to efficiently learn from high-dimensional data
- Use AI solutions to develop new prediction factors from unstructured data. There is greater availability of unstructured data such as textual data, satellite imagery, social media data, web scrapping (e.g., product reviews), etc.

Approach and challenges

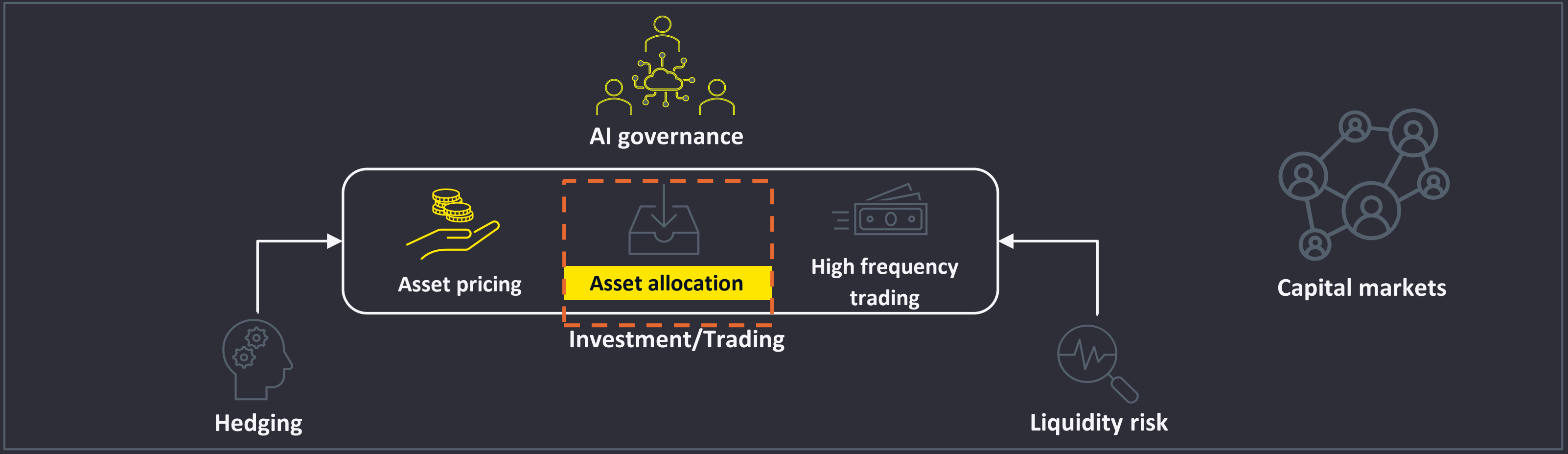
- Wide range of **Neural Network** based models (as well as random forests, other regression models) are used to replace traditional methods. They are opaque and can be difficult to interpret. However, some very sophisticated models are proving to have strong predictive power (e.g., TFT from Google)
- **Advanced NLP models** (e.g., BloombergGPT / GPT-4) are being used to derive prediction factors (embeddings) from financial news and other available online text data to predict asset prices

Risk management

- Poor data quality could lead to inaccurate return predictions with AI solutions. Therefore, data quality should be checked using approaches such as DL models to detect issues in the dataset
- Insignificant factors in asset price models reduce the prediction ability in any model. As a result, insignificant factor detection methods (i.e., statistical tests) should be used along with AI models

Asset allocation

AI use case



Target application

- Asset allocation consists of finding the best way to allocate resources in a set of assets (as stocks, bonds, and cash) to maximize the return on the investment
- Since the seminal work of Markowitz (1952 with Mean Variance (MV)-principle) several investment strategies have been proposed including **global minimum variance, naïve strategy, most diversified strategy, target strategy (max Sharpe ratio),** etc.
- AI solutions can be widely used to improve the performance of those strategies or propose new strategies.

Current pain points

- The estimation of the investment opportunity parameters (**assets correlations and expected returns**) remains a difficult task for individuals in both academia and industry
- **High dimensional** datasets in asset allocation remain a fundamental challenge for capital markets participants. As an example, in mean-variance optimization problems, the maximum likelihood method fails to provide an effective solution
- Asset managers add practical restrictions preventing corner solutions in AI algorithms

Objective

- Use AI models (e.g., Reinforcement Learning models) to provide investment strategy replacing traditional methods that rely on asset correlations estimation
- Use AI models (e.g., Neural Network models) to search for effective investment strategies in high dimensional investment problems

Approach and challenges

- RL is used to select an optimal action (investment strategy) maximizing a reward function (e.g., MV-objective or cumulative return)
- NN based models are used for initial stocks selection and to assist in hyperparameter selection (e.g., in Lasso-MV strategy)

Risk management

- Maintain efforts to improve the explainability of AI models by using appropriate AI solutions depending on the investment objective (e.g., in continuous MV-framework RL provides interpretable solution)
- Poor data quality could lead to the selection of a strategy with poor performance. Hence, data quality should be checked, using traditional and advanced DL methods to detect issues in the dataset

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High frequency trading

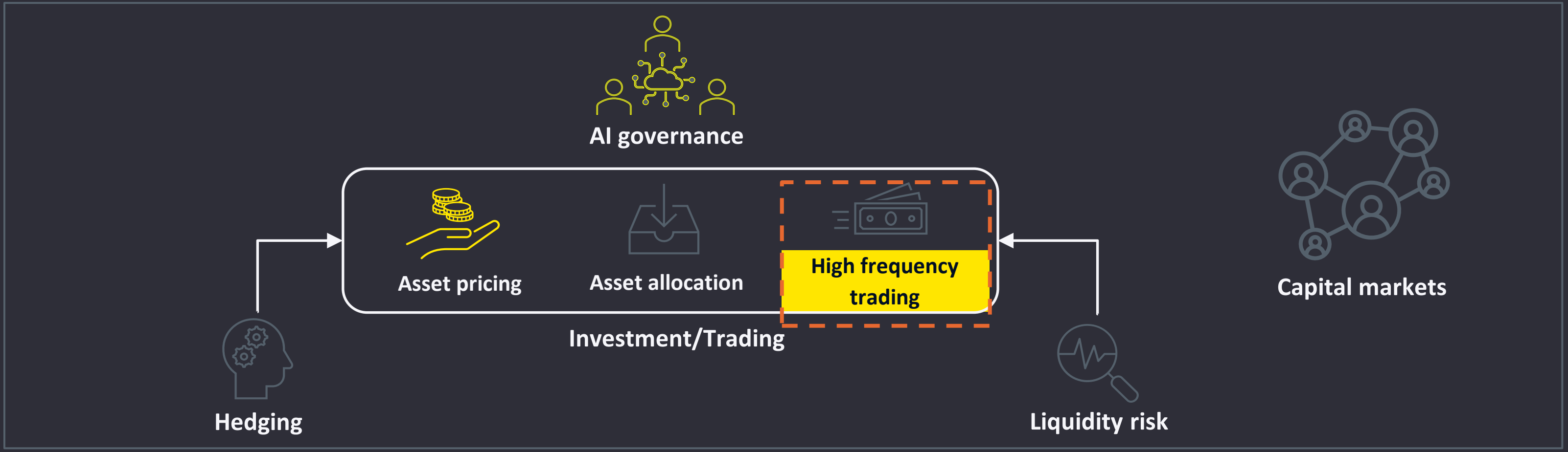
AI use case

Target application

- High-frequency time series forecasting is an area of active AI development. There have been various stochastic, and time-series based deep learning methods, that have been deployed successfully
- High-frequency forecasting is reliant on various data inputs as they are non-stationary and exhibit seasonality at different scales, while considering factors such as trends, drift, auto-correlation, and heteroskedasticity

Current pain points

- Current approaches for forecasting financial time series use stochastic and regression-based deep learning models
- Low-latency trading strategies require efficient models that consider market complexities while maintaining computational efficiency
- Many stochastic models may oversimplify the complexity of financial markets, while other sequential time-series based deep learning models are difficult to parallelize making it challenging to use with millisecond executions



Objective

- A family of deep learning models called Transformers, that can capture long-term dependencies and are inherently parallelizable making it a good candidate for low-latency trading strategies
- AI models that are optimized for high-frequency time-series have the potential to attain better forecasting, when compared to traditional stochastic methods or sequential deep learning models as the size of the training increases

Approach and challenges

- Utilize a variety of deep learning architectures to perform high-frequency time series forecasting on data with varied frequencies
- The transformer models have shown superior results due to their ability to process large amounts of data and parallelized architecture
- Simplifying the evaluation environment is a challenge as they may not account for various market factors such as impact, actual price, and available quantities

Risk management

- Algorithmic trading may result in capital loss and requires continuous risk monitoring. The strategies should be paper traded initially before live trading while assessing risks such as price, liquidity, compliance, and regulatory risks
- Rigorous back-testing with realistic market factors is required, as the trading environment is simplified and model performance is evaluated using model-based metrics, rather than mathematical reasoning

Forecasting liquidity risk

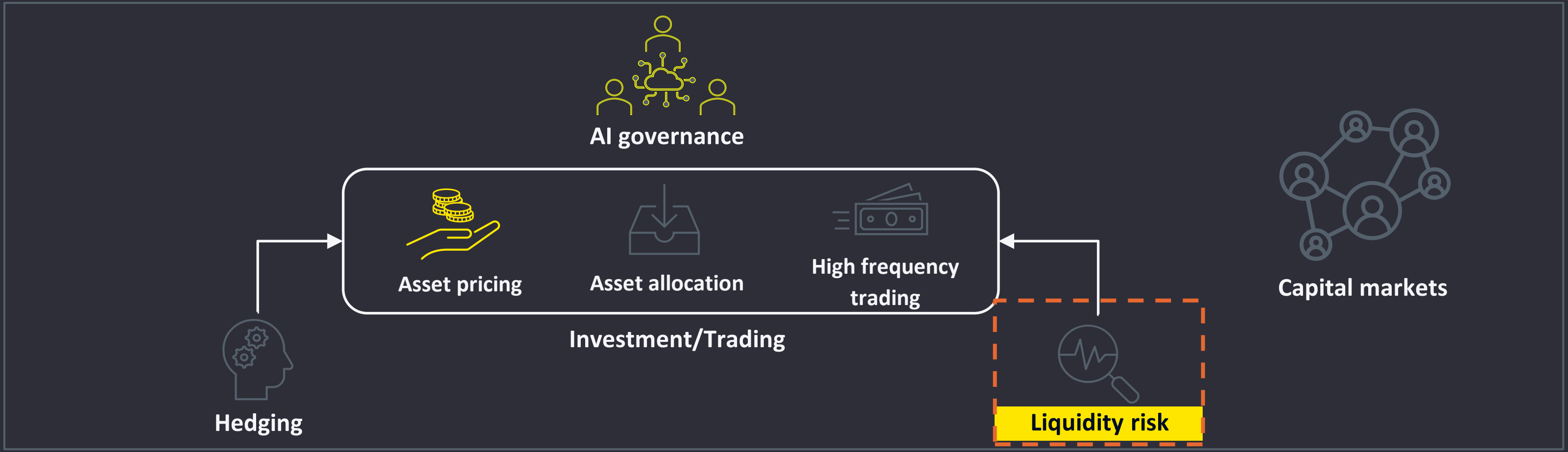
AI use case

Target application

- Liquidity risk arises when an asset cannot be traded quickly enough to prevent or minimize losses
- It is one of the most important risks in financial markets and has a direct effect on almost all financial decisions (e.g. investment decision: can increase loss)
- AI models constitute promising methods to improve liquidity prediction performance by taking advantage of nonlinear interactions and learning through news data

Current pain points

- Market liquidity assessment under extreme market outlook (financial crisis periods, Covid-19) is a challenge and traditional methods were not able to correctly predict this risk during the 2007-09 financial crisis
- Microblogging services, that are generally ignored by statistics methods, can enrich the information investors use to make financial decisions on the stock markets



Objective

- Leveraging advancement in AI algorithms to improve the performance of liquidity risk prediction models by taking advantage of the ability of AI models to learn from alternative datasets (e.g., unstructured data including social media) to more accurately predict liquidity
- Use AI models to assess market liquidity risk during bad economic periods

Approach and challenges

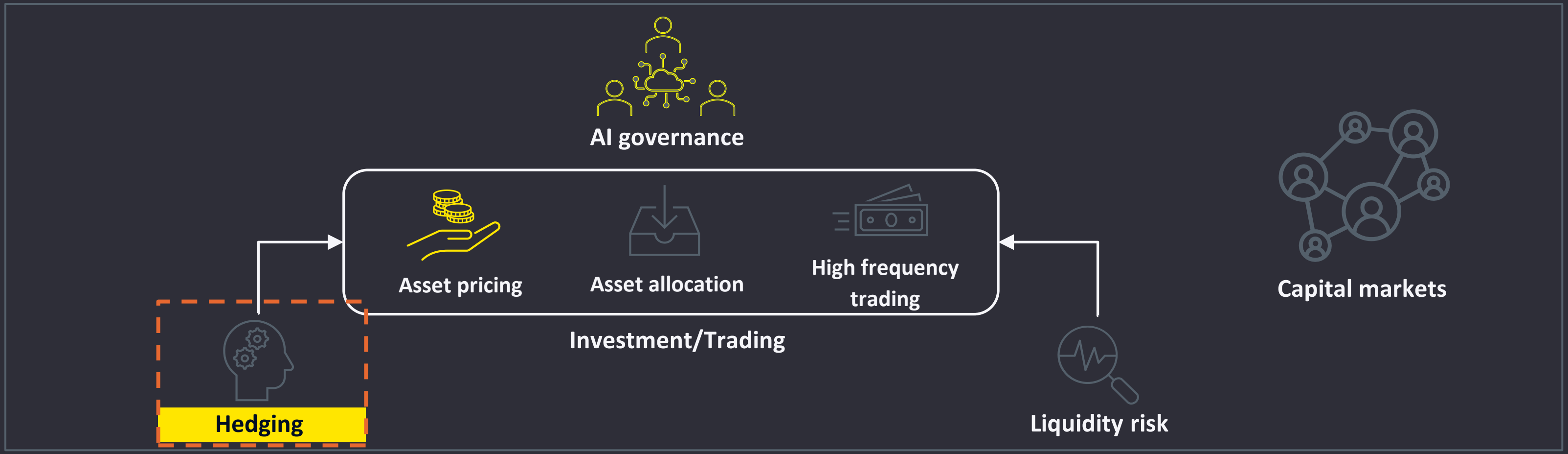
- NLP is used to extract sentiment from social media to predict liquidity risk. It is also used to predict liquidity risk based on financial index and historical trade volume
- RL is used during an extreme economic outlook to learn from data to select optimal action (predicted liquidity risk) that minimizes a loss function (Mean Squared Error)

Risk management

- Several liquidity measures are available (e.g. **quoted spread and effective spread**), and the prediction performance could depend on the selected measure. Users should check the robustness of AI models with different liquidity measures
- Liquidity risk measures are highly volatile variables and combined with their dynamic character make them difficult to model. AI models should be used with an appropriate model specification to guarantee prediction performance improvement

Hedging

AI use case



Target application

- Hedging is an important function of capital markets. Recent research has focused on utilizing advanced reinforcement learning models
- The dynamic nature of hedging strategies makes using reinforcement learning models a logical choice, as they can learn various strategies
- Much of this work is still in its infancy and testing of strategies is required

Current pain points

- Financial inventory management heavily relies on human decision making and heuristic adjustments
- Non-analytic hedging approximations add more operational risk
- Sharp payoff change of new barriers for structural products pose challenges in hedging strategy

Objective

- The growing popularity of RL models is also due to their nature of getting trained on simulated data, which allows the model to be refined until the desired performance is achieved
- RL-based hedging methods introduce a model-agnostic, data-driven framework for scalable decision making in financial inventory management
- RL hedging models are also used to dynamically test and modify various hedging parameters depending on the volatility requirements and risk appetite

Approach and challenges

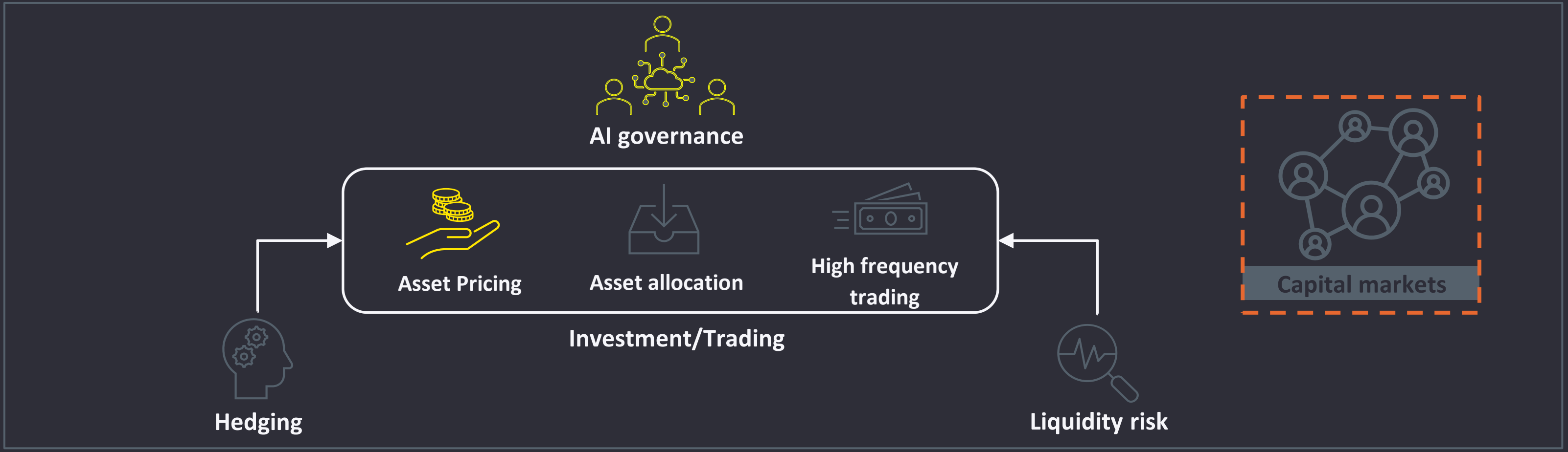
- Utilize RL-based methods to model various hedging strategies such as mean-variance, option, and Gamma & Vega hedging
- RL agents are trained on simulated data, which enables generation of large volumes of synthetic data to train the RL agents
- RL agents are trained on multiple risk-aversion factors to generate multiple risk strategies while focusing on overall returns
- There are various challenges around ensuring the simulated data behaviour correlates well with real market conditions, which would require monitoring and understanding of the model

Risk management

- Interpreting RL models is challenging, and something to consider while deploying these models in real market conditions
- Since RL agents' behaviour can be challenging, creating a test (sandbox) environment is useful to perform sensitivity and robustness testing
- There are potential model risk aspects with deploying RL models, which would require a well-defined model risk management framework
- A key is to test the robustness of the assumptions and then undertake testing on real world historical data

Market manipulation

AI use case



Target application

- Market manipulation is a critical aspect to monitoring malicious activities that could disrupt the market or impact capital formation
- There are two major focus areas in which AI can impact market manipulation: 1. Detecting market manipulation and 2. Causing market manipulation
- Another aspect is the consideration of AI agents making automated trade decisions based on optimized policies, which leverages reinforcement learning models

Current pain points

Manipulation Detection:

- Market manipulation detection relies on rule-based approaches, and the securities market demands scalable AI algorithms to support identification of market manipulation activities

Causing Manipulation:

- AI trading agents tend to learn based on the optimal strategies which could eventually lead to market collusions between agents

Objective

Manipulation Detection:

- There are various models explored within market manipulation detection, spurred by the growth of available open-source data: supervised ML and unsupervised anomaly detection

Approach and challenges

Manipulation Detection:

- Supervised models trained on public data are used to detect manipulation in securities. Deep learning based anomaly detection methods can be used for the same purpose

Causing Manipulation:

- The growth of AI trading agents is also a cause for concern, as they have the potential to learn from each other and result in automated market manipulation
- With increased model complexities, monitoring the model's predictions and behaviour patterns becomes challenging

Risk management

- The risks of market collusion could be intentional (human enforced algorithmic collusion) or unintentional (AI agents learn similar policies leading to collusion). This could be a potential risk depending on technology maturity
- Maintaining "human-in-the-loop" systems within all AI decision processes to guarantee responsibility and accountability
- Ensuring trustworthy AI development and implementation by affirming well-designed model risk management, data governance, and fundamental AI principles

AI governance

AI use case

Target application

- Effective governance of strong AI can help to mitigate a range of risks, including those related to bias, reliability, accountability, and transparency in AI models
- AI governance also plays a critical role in ensuring compliance with legal and regulatory frameworks

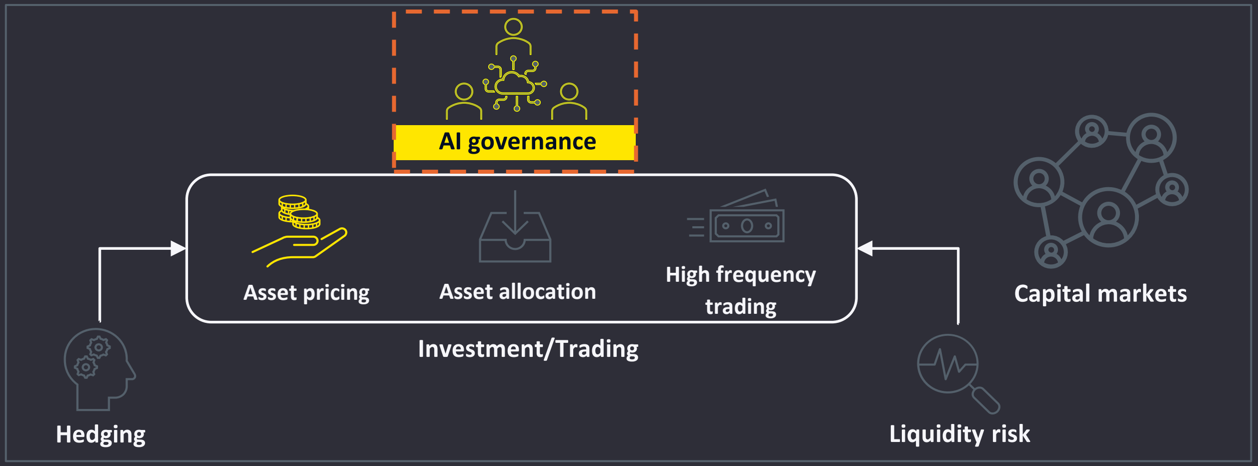
Current pain points

The risks posed by AI systems are unique vis-à-vis traditional systems. Examples are:

- Model Bias: Non-representative data used in AI model training can result in bias in model prediction. Bias can also result from inaccurate model specification
- Non-Explainable: Lack of explainability in AI models reduces confidence in AI systems as there could be unknown risks in the model
- Non-interpretable: Lack of interpretability reduces the significance output of the model

Objective

AI governance aims to address the risks posed by AI systems that are not currently covered by governance standards designed for traditional systems.



Approach and challenges

- Risk Measurement: Not well defined and less understood risks are difficult to measure such as reliable metrics construction or risks related to third parties.
- Risk Tolerance is very contextual to specific organizations and use cases
- Risk Prioritization: Mitigating risk completely is resource intensive. However, risk prioritization is challenging
- Residual risks are those risks that remain after risk treatment, e.g., human error
- Lack of Explainability: Inability to explain an AI system makes it appear opaque
- Lack of Interpretability: Interpreting the output of an AI system is a challenging task
- Fairness: Testing an AI system for any discrimination that it can cause

Risk management

Organization Level:

- Maintain **Independent risk function**
- Use **integrated risk mitigation** approach and prioritize risk based on the likelihood of occurrence and impact
- **Human oversight** and ongoing monitoring system in place
- Integrate **bias mitigation strategy**
- Reconsider **technology neutrality**

Model Level:

- **Assess the level of interpretability and explainability needed** and design the system accordingly
- **Modify the loss function** by putting financial constraints to gain more interpretability. For example, incorporate no-arbitrage pricing theory in estimating asset pricing
- **Feature reduction techniques** can improve the model's inherent explainability, besides using conventional AI model explainability tools
- Document methodology, including limitations

Blockchain-based finance (future direction)

Applications of distributed ledger technologies (DLT), such as the blockchain, have proliferated in recent years in finance. The rapid growth of blockchain-based applications is supported by the purported benefits of speed, efficiency and transparency[1] that such innovative technologies could offer, driven by automation and disintermediation.

Widespread adoption of DLTs in finance may be driven by efforts to increase efficiencies from disintermediation, including in:

1. Securities Markets (issuance and post-trade/ clearing and settlement)
2. Payments (central bank digital currencies)
3. Tokenisation of Assets (e.g. securities, commodities, and other non-financial assets)

The implementation of AI in DLT/blockchain based finance can help:

- reduce security susceptibilities and protect against compromising of the network (e.g. in payment applications)
- detect fraudulent or irregular activity
- Anti-Money Laundering/Combating the Financing of Terrorism (AML/CFT) checks
- assist in compliance processes and risk management

[1] For example, tokenisation could enhance transparency in transactional data and information around the issuer and the asset characteristics through enhanced information recording and sharing mechanisms. In addition, DLT-based security registries may provide increased transparency through a clear record of beneficial ownership with certainty at any point in time. Increased transparency may also be achieved in terms of regulatory compliance and interactions with regulators: as programmed regulatory restrictions are automatically enforced, the regulator may be automatically notified through smart contracts when restrictions are modified or turned-off. Regulators may also have quasi-real-time information about specific on-chain events of interest to them.

4

EY credentials

EY credentials along with maturity level

Asset allocation	●●○○
Trading insights with news	●●○○
Dynamic hedging	●●○○
Futures markets classifier	●●○○
Market data quality improvement	●●○○
Trusted AI framework	●●○○
Capability activation using Large Language Models (LLMs)	●●○○
Customer segmentation	●●○○
Anti-Money Laundering with AI model	●●○○
Model documentation automation using generative AI	●●○○

Maturity level	Potential use case	Work in progress	Ready for production	In production
	●○○○	●●○○	●●●○	●●●●

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Asset allocation

AI use case

Target application

- Develop a framework to optimize its allocation of assets across asset types (Government Bonds, Corporate Bonds, Equities, Alternative Small Cap Public Equity, and Cash).
- Cash is used to meet solvency requirements and for liabilities.

Current pain points

- It is challenging to identify an optimal asset allocation, especially in a volatile macroeconomic environment.
- Asset allocation is a multi-step optimization problem with short-term and long-term optimization goals.

EY maturity

HISTORICAL DATA

Historical data for the DJIA, which is composed of 30 stocks and index is price weighted

BASELINE MODEL

Define the baseline model and the key performance metrics, which include: Sharpe ratio and min-variance portfolio allocation

FUNCTION APPROXIMATION

Train an RL agent on the historical data to maximize risk adjusted return using *Actor-Critic* methods

PERFORMANCE

Compare the performance between modern portfolio theory benchmark and the reinforcement learning agent

Objective

- Allocate assets dynamically to provide stable returns in a volatile environment.
- Use a multi-step optimization model (Reinforcement Learning) which maximizes risk-adjusted returns measured by Sharpe Ratio
- The data used is the open source DJIA.
- A 10-year simulation window is utilized by the model.
- Provide cVAR, Expected Shortfall, and Return estimates for wide variety of economic scenarios.

EY teams’ approach

- The multi-step optimization model takes these parameters as inputs at each timestep: asset prices, macroeconomic factors, and VIX. These are then used to update the model for the next timestep.
- Cash requirement (solvency + liabilities) and return on assets are calculated for the timestep. The model is rewarded based on the previous actions taken on: return, reallocation costs, and penalty for insufficient cash.
- The model incorporates and adapts its strategy based on features of the updated timestep, where the assets are allocated. The model is rewarded based on the asset allocation performed in the previous timestep.

Results & Benefits

- A model yielding higher returns (a higher surplus) without violating solvency requirements.
- Due to the nature of reinforcement learning, the asset allocation will produce a more stable return across macroeconomic environments.

Challenge:

- Expanding the scope of the data to a larger range of stocks and market behaviour could impact the model behaviour. Therefore, this would require testing in a sandbox environment before deploying to real market conditions.

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Trading insights with news

AI use case

Target application

- The extraction of information from news is a manual process which can be time consuming and costly.
- This process can be optimized by leveraging Natural Language Processing (NLP) and Machine learning to activate automated insights and sentiment extraction leveraged for trading strategies.

Current pain points

- Consuming, interpreting, and extracting information from news is time-consuming and it occupies resources.
- Relying on human resources to read the news may result in insight latency and likelihood of missed news/insights that could potentially impact capital markets.

EY maturity

Method 1

Inputs
- News data
- List of words for a topic

Intermediary Steps
- Data cleaning
- Descriptive statistics
- Abstract article summarization
- Key-phrase extraction using text rank

Output
- States about news count and word count
- List of topic words extracted from the body which can be used to refine the list

Method 2

Inputs
- News data
- List of words for a topic

Intermediary Steps
- Data cleaning
- Finding basic sentiment score using lexicon
- Use of word-embedding to further enhance the lexicon
- Finding the sentiment on the sentence level by using supervised learning algorithms

Output
- Sentiment score of article using lexicon
- List of semantically closer words to modify the lexicon
- Advance Sentiment score using sentences

Method 3

Inputs
- News data
- List of words for a topic

Intermediary Steps
- Data cleaning
- Use of semi-supervised clustering techniques to find the topics words
- Use of word-embedding to find topic-probabilities per article
- Finding emerging and retired topics over a time period

Output
- List of top sub-topics for a given topic
- Ability to derive topic probability per article
- List of emerging, retiring and continuing topic over a time period

Objective

- Identify key financial insights such as polarity characteristics and summary of themes or topics, from unstructured data such as news articles using language models.

EY teams’ approach

- Generate descriptive statistics and extract key-phrases using the list of key-words and phrases given by the business. (Method 1)
- Using a lexicon given by the business, derive a basic sentiment score of articles. (Method 2)
- Given a set of topics, use semi-supervised methods to find the top words for a topic and use them to find the topic probability distribution of an article. (Method 3)

Results & Benefits

- Descriptive statistics about news and key topics.
- Sentiment score on topics selected by stakeholders.
- Identification of emerging, continuing and retired topics.

Challenge:

- Dynamic nature of news data requires close and continuous monitoring.

Dynamic hedging

AI use case

Target application

- Delta hedging is optimal for the hedging of options if no market friction and trading costs are considered.
- The objective is to design an automated hedging approach that accounts for realistic market conditions.

Current pain points

- Hedging is a multi-step optimization problem, that carries trading costs, and has the potential to result in market friction

EY maturity

ENVIRONMENT INTERACTION*

For each episode and each state, obtain an action from the epsilon-greedy policy, and the subsequent states'

Q-LEARNING*

Given a pair X=(s,a), obtain Y as the reward plus the maximum q-value of the next state

FUNCTION APPROXIMATION*

Given the pairs (X,Y) for a batch of episodes, use supervised learning techniques for non-linear regression to estimate Y as a function of X

ITERATION*

Iterate the full process with the updated approximation of the q-function (i.e., updated epsilon greedy policy), and updated exploration rate epsilon

Objective

- Build a multi-step optimization model (Reinforcement Learning) for efficient hedging of a portfolio of options.
- The model incorporates realistic market constraints such as discrete trading decisions, nonlinear trading costs, and liquidity restrictions.

EY teams' approach

- Simulate market scenarios and trading costs using Brownian motion and Black Scholes.
- Determine the baseline and success criteria, based on the delta hedging strategy.
- Train the RL model on the simulation environment.
- Run the RL model on a validation window.
- Compare the performance of RL and the baseline model, based on the "profit and loss (PnL)" and volatility metrics.

Results & Benefits

- RL using Neural Networks results in a profit and loss (P&L) improvement compared to baseline but the Standard Deviation increases compared to baseline.

Challenge:

- Modelling the reward function for the dynamic hedging use-case can be challenging, as the benchmarking is performed against a highly risk-averse delta-hedging strategy.

Futures markets classifier

AI use case

Target application

- Optimize slippage by mapping optimal execution style to market conditions.
- Monitor trade cost performance intraday and change trading styles according to market dynamics.

Current pain points

- High slippage for certain asset mixes
- Limited insight into slippage per asset class, region, and contract

EY maturity

FUTURES SELECTION

Perform initial clustering on the list of futures, to identify similarities between them

DATA ENGINEERING

Perform data engineering on key features that are required for guided clustering and classification

GUIDED CLUSTERING

Semi-supervised clustering performed for each of the initial futures selected, to gain insights on market conditions

CLASSIFICATION & VISUALIZATION

Classification model trained for each initial future that recommends an execution type and incorporates guided clustering results. Interactive dashboard allows for exploration of model results

Objective

- Train an AI model on historical market and order data to cluster current market conditions that would inform different trade execution styles.
- In the future, combining the identification of current market conditions with real-time order status creates the opportunity to further reduce slippage by changing order execution style for poorly performing orders on an intraday basis.

EY teams' approach

- The external data sources used are categorized into three components: Standard futures data, Market depth data, and Underlying data.
- Internal data used pertain to the volume, price, execution type, date, and time.
- The features used for the classification model are bid-ask volume imbalance, signed transaction volume, immediate market order cost, bid-ask spread, and cross-spread volume. This approach is used to improve the segmentation.
- Lastly, the labelled order data contains a slippage indicator and magnitude of slippage consideration, with the final output defining the clusters of market conditions that contain information on execution type and slippage rate.

Results & Benefits

- Ability to monitor trade cost performance intraday and being able to change trading styles according to market dynamics.
- Scale and utilize various market clusters as these vary by contract and instrument type.

Challenge:

- Requires strong collaboration across analytics and capital market participants.

Market data quality improvement

AI use case

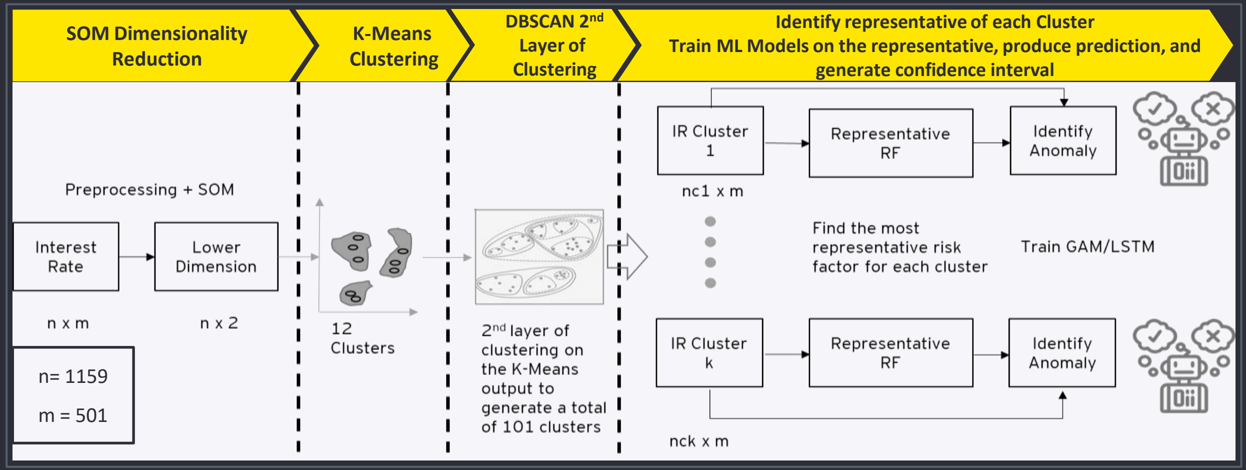
Target application

- Capital efficiency can be improved for better return on equity (RoE), through data quality enhancements.
- By leveraging AI techniques to identify and remediate data quality issues, data quality can be improved using the minimal manual intervention.

Current pain points

- Anomalous data points are currently monitored using statistical baseline models that make a number of parametric assumptions
- Data remediation is still being performed based on business judgment.

EY maturity



Objective

- Build a clustering model that detects anomalies in market time series data, with this approach intended to compliment existing statistical methods.
- Utilize clustering models, along with deep learning models to replace or to compliment existing back filling approaches.

EY teams' approach

Anomaly detection:

- Investigate data quality, identify preprocessing techniques and unsupervised outlier detection methods based on available computing power.
- Implement a voting model using both the baseline and AI models to increase efficiency.

Time series back/gap filling:

- Identify unsupervised clustering methods with proper history for training, using time series forecasting deep learning methods.

Results & Benefits

- Better accuracy and risk sensitivity due to improved model performance.
- Increased RoE resulting from higher capital efficiency.
- Flexible solution, capable of being implemented alongside existing solutions rather than replacing them.
- 50% reduced manual labor on monitoring, enabling more resources on analytics.

Challenge:

- Interpreting analytics from the clustering analysis and the business reasoning.

EY

Trusted AI framework

AI use case

Target application

- The increased usage of AI models in recent times has caught the attention of regulators. Formal supervisory guidance on a recommended mechanism to manage the use of AI applications in financial institutions is defined.
- AI model comes with new risks owing to lack of transparency, high reliance on data and its quality, and bias in model selection.

Current pain points

- Absence of a formal governance structure.
- Absence of adequate controls around fairness and privacy aspects of AI applications.

EY maturity

AI RISK MANAGEMENT COMPONENTS

Ethics risk aassessment
pperformed by Analytical Tool Developer
and reviewed by AI Risk team

Privacy Impact Assessment
Performed by Privacy Designate
and reviewed by AI Risk team

Performance Testing
Performed by the Analytics Teams
and reviewed by AI Risk team

Implementation and Deployment Testing
Performed by the Analytics Teams
and reviewed by AI Risk team

Objective

- EY's AI governance framework which encompasses four key risk components: Ethics Risk, Privacy Impact Assessment, Performance Testing, and Implementation and Deployment Testing.
- These elements play a critical role within the implementation of compliant AI methodologies. These are deployed within the big 5 banks in Canada.

EY teams' approach

- Ensure business purpose, governance, and stakeholder engagement are properly identified and aligned.
- Review and identify sources of risk specific to AI applications.
- Institute processes to address idiosyncratic risks posed by AI applications.
- Ensure AI governance solution is scalable and deployable with the right tech infrastructure, and continuously monitored.

Results & Benefits

- Definition of AI tools and tiering based on complexity and business impact.
- Identification of AI Risk Management component activities.
- Distribution of ownership using the RACI (responsible, accountable, consult, inform) matrix.

Challenge:

- Trusted AI demands should be agile, to ensure that frameworks are aligned with the evolving technology.

Capability activation using Large Language Models (LLMs)

AI use case

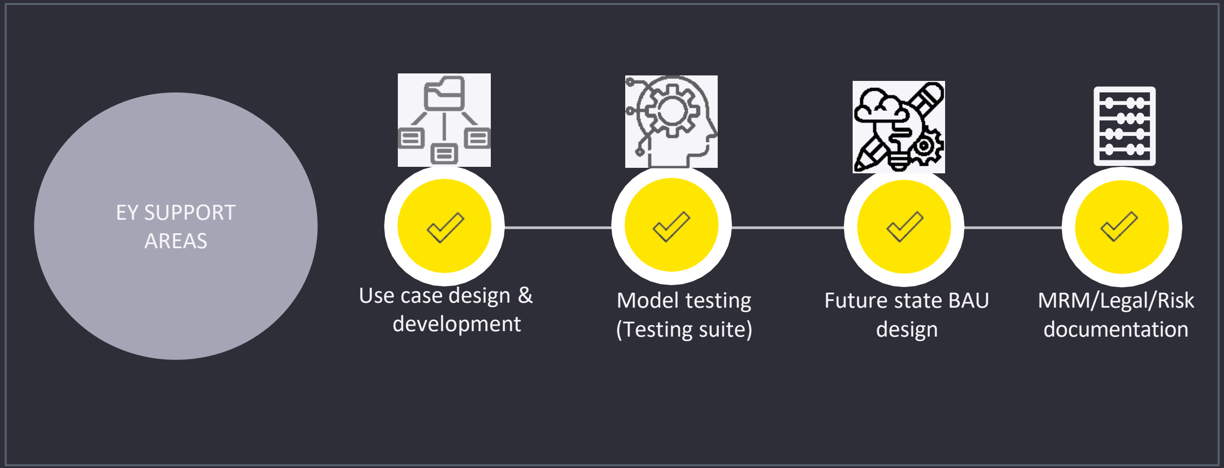
Target application

- A large Wealth Manager is executing a program to integrate OpenAI into core platforms with the intent of (i) improving access to internal content by employees (Financial Advisors, Service Associates), (ii) enhance employee productivity, and (iii) improve client experience.
- LLMs can be used within capital markets for tasks such as market analysis, portfolio management, and trading. These are particularly useful for asset and wealth management entities.

Current pain points

- Search is limited to a keyword search and creates inefficiencies when searching on query context.
- Content metadata lacks consistently and often faces completeness and accuracy issues.
- Chatbots are built on a set of predetermined FAQs so answers are limited to those content areas.

EY maturity



Objective

- Internal Knowledge Management: Improve access and retrievability of the organization's knowledge base through Virtual Assistant, enhanced search, and creating quality metadata (Summarization, Taxonomy, FAQs).
- Call Center Analytics: Increase agent productivity and client experience by deriving interaction insights for CRM logging, flagging opportunities and risks in conversations, and better workforce training.

EY teams' approach

- LLMs can enhance search by creating richer embeddings for contextual search and accommodating natural language querying.
- LLMs can be used for automating metadata generation that can be reviewed and subsequently published by authors.
- LLM powered internal chatbots can be leveraged to analyze content, find / synthesize the correct answer to user queries.

Results & Benefits

- Lower effort & higher productivity: Accessing/Searching for information, tagging content, etc.
- High quality & consistent content: New content generated e.g., knowledge - title, keywords, FAQs, notes, etc.
- Better service & client engagement: Understanding user needs and experiences (sentiment, etc.)
- Reusable assets for LLM adoption and scaling: testing/ evaluation suite and enhanced LRC governance, etc.

Challenge:

- Requires various application specific safety measures and assessments to ensure a safe system is deployed.

Customer segmentation

AI use case

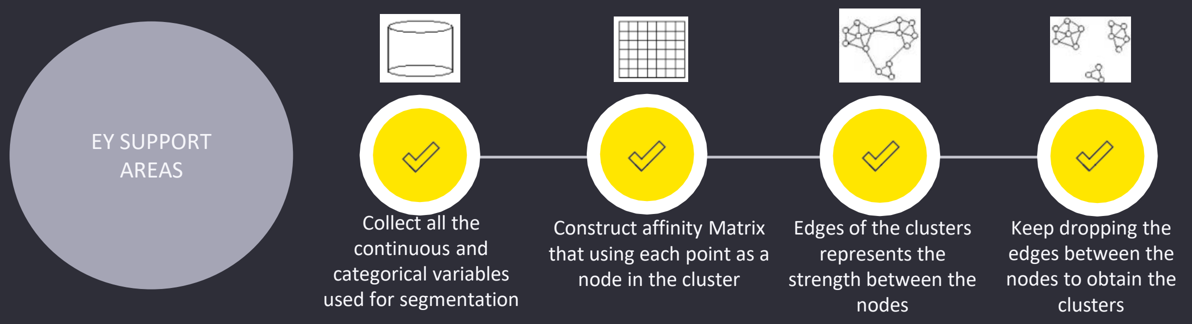
Target application

- To effectively recommend a product to a new customer or upsell to an existing customer, it is important for a business to understand the customer's preferences. However, customers may not always reveal their preferences directly, and a business may not have direct information about them.
- Right recommendations can be useful in business because they help to improve the customer experience, increase engagement, and ultimately drive sales.
- Additionally, personalized recommendations can also help to increase the average order value by encouraging customers to purchase more items or higher-priced items.
- Providing the right recommendations can help businesses to improve their bottom line and stay competitive in the marketplace.

Current pain points

- Traditional clustering algorithms are not effective in handling very high-dimensional, complex, and sparse data.
- Creating clusters based on business judgement is time-consuming and inefficient given the dynamic nature of customer base.

EY maturity



Objective

- Implement a recommendation system to enhance the personalization of product recommendations, which would result in improved customer satisfaction.
- Additionally, providing tailored product recommendations would result in increases in sales.

EY teams’ approach

- Pairwise distance is computed using a suitable distance metric to find similarity measure.
- Choice of distance metrics is a critical decision and it can vary depending on data
- Graph cluster algorithm is used on the data with number of clusters specified
- Required number of clusters are obtained either from business intuition, eigenvalue method, minimizing total variance, from previous work, etc.
- Suggest recommendation of the most popular in the cluster to cluster members
- Discussion with business team, identify the problem in the clusters formation, and suggest recommendation
- Change distance metrics or number of clusters or apply additional logic from business standpoint to make clusters meaningful

Results & Benefits

Graph clustering algorithm provides clusters which unlike traditional clustering methodologies have the following benefits:

1. **Large number of clusters,** which would enable more targeted recommendations.
2. **Uniform cluster sizes,** which result in robust recommendation.

Anti-Money Laundering with AI model

AI use case

Target application

- In the capital markets, the AML rules are used to detect and report suspicious activity potentially related to money laundering and terrorist financing, such as securities fraud and market manipulation. The objective of this approach to protect the integrity of the financial system.
- With the rapid progress in AI (e.g., new time series forecasting models) and increased availability of large volumes of structured and unstructured data, one can use various AI models to provide new AML rules.

Current pain points

- The traditional rule format and historical biases fail to detect changing/new laundering patterns
- Reliance on traditional data sources and money laundering rules leads to an excess of false positives
- The current approach relies heavily on costly and time-consuming human investigation.

EY maturity

Objective

- Leverage AI system capability to improve the AML process by incorporating different data.

EY teams' approach

- An AI model is trained using active learning, continuously adapting to new data
- The AI model generates alerts scored according to their priority level and categorizes them automatically based on important features
- NLP is implemented before the manual triage phase to screen for adverse media prior to human investigation
- The model is initially trained on historical labels produced by FIU. To optimize training and minimize noise, the training subset consists of instances chosen for their informational value
- Cost sensitive learning is used to minimize cost rather than to minimize misclassifications (as false negatives are more costly than false positives)
- Named entity recognition, topic modelling, and sentiment analysis are used to automate adverse media screening
- Dashboard is created in client's BI tool, providing user with summary stats, alert categorization, and alert prioritization

Results & Benefits

Data Driven & Adaptative

- Using artificial intelligence allows for the identification of new money laundering patterns that have not been identified yet
- Rerouting new data into the model allows for continuous learning and adaptation of the model to changing customer behaviour and macroeconomic situations
- Using a model approach is less exploitable by money launderers than using a rule based one

Prioritized Alerts

- Prediction results in the form of likelihood of escalation allow for prioritization of alerts based on level of risk
- Visualization of prioritized alerts through a dashboard interface leads to increased investigation efficiency
- Data-driven categorization of alerts based on their risk signature / risk profile allows for easier and more directed classification

Model documentation automation using generative AI

AI use case

Target application

- Model documentation is very important during model development process to help all the stakeholders including the model validation team and model users understand the model development process, the underlying assumptions, and the potential limitations. To avoid some repetitive and difficult tasks related to the model documentation process, EY uses Gen AI to automate this process.

Current pain points

- Currently, the model documentation process involves different repetitive tasks which may sometime be time consuming.
  - Read guidelines to kickstart documentation
  - Capture information from different sources
  - Run tests and write minimal analysis results
  - Format document with generated results and table insights

EY maturity

●●●○

Objective

- The objective is to use Gen AI to automate the different steps of the model documentation
  - Generate document template based on guidelines
  - Standardise input collection
  - Derive detailed insights from raw analysis outputs
  - Automatically synthesize results and format document artifacts (tables, graphs, etc.)
  - Document draft generated in minutes.

EY teams' approach

- Use Gen AI model to automate credit risk model documentation for a large Canadian Bank.
- **Retail development/re-development AIRB PD models is selected, as retail** model development is more systematic compared to wholesale portfolios and is a better suited as a starting point.
- The following steps are used:

#1: Template & Narrative Generation

- Generates document template based on historic reports and narratives that leverage existing data
- Incorporates tables (csv) and image diagrams as a part of the template creation
- Formats text into a pre-defined table template

#2: Table Insights Generation

- Generates insights for correlation matrices and threshold tables as well as modeling documentation specific table templates
- Asset can be extended to other table types with similar patterns by adjusting instruction-based prompt.

Results & Benefits

Accelerated model lifecycle

- Streamlines documentation process by combining human expertise with AI capabilities
- Allows for real-time adjustments and fine-tuning of content based on expert understanding

Optimization of Resources

- Reduces the manual workload for documentation experts, allowing for higher productivity
- Consumes business insights to train and improve AI documentation automation

Consistency of Documentation

- Minimizes errors and inconsistencies in documentation by standardizing documents
- Delivers accurate and relevant content that meets organizational goals and standards

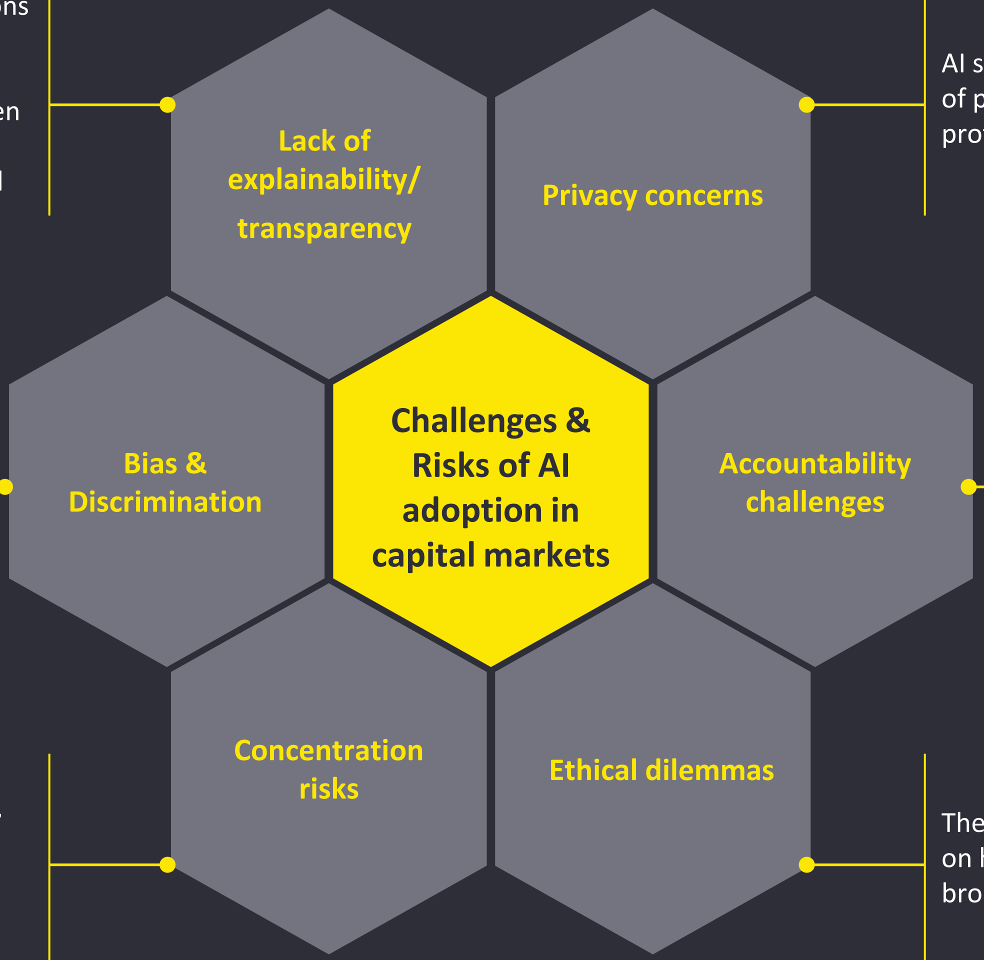
5

Challenges and risks associated with AI adoption in capital markets

AI in CM challenges & risks

AI systems can be complex and opaque, making it difficult to understand how they work and how decisions are made. This can create transparency challenges. In this context, AI outputs are complex and explanations are not always readily apparent, with AI processes often impossible for lay users to understand. Hence, it becomes difficult for end users to have knowledge and control on what data is being captured and how it is used.

AI systems can collect, store, and process large amounts of personal data, raising concerns about privacy and data protection.



The inadequate use of data or the use of poor quality data could lead to biases and discriminatory results, ultimately harming financial consumers.

It can be difficult to assign responsibility when something goes wrong with an AI system, especially if it involves multiple parties.

The use of AI gives an advantage to large players, potentially limiting smaller financial services providers' ability to compete due to resource constraints and unequal access to data.

The use of AI raises ethical questions about the impact on human autonomy, dignity, and well-being, as well as broader societal implications such as job displacement.

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Regulatory considerations in adopting AI in capital markets

Regulatory consideration

- Given the rapid evolution, potential benefits and potential risks of widespread AI adoption, international and national regulatory bodies are seeking to promote responsible adoption of AI technologies.
- This requires that appropriate measures be put in place to identify, assess, and mitigate risks of harm or biased output prior to a AI system being made available for use.
- These consist primarily of rigorous testing of the algorithms used before they are deployed in the market, and continuous monitoring of their performance throughout their lifecycle.
- Although many countries have several existing regulations, some advanced AI techniques may not be compatible with these regulatory requirements.
  - ✓ The lack of transparency and explainability of some AI models and the dynamic nature of continuously adapting deep learning models are prime examples of such potential incompatibility.
  - ✓ The technology-neutral approach that is being applied by most jurisdictions to regulate financial market products (in relation to risk management, governance, and controls over the use of algorithms) may be challenged by the rising complexity of some innovative use-cases

Regulations in Canada

- The government has introduced the Artificial Intelligence and Data Act (AIDA) as part of the Digital Charter Implementation Act, 2022.
- The AIDA proposes new requirements for businesses to ensure the safety and fairness of high-impact AI systems throughout the entire AI lifecycle, encompassing Design, Development, and Deployment stages (AIDA 2022).
- Under AIDA, businesses engaged in regulated AI activities will be held accountable for the risks associated with high-impact AI systems based on their involvement in the AI system lifecycle.

Regulations in Europe

- The European Union has proposed the Artificial Intelligence Act, a new legal framework for AI.
- It classifies AI systems into four risk tiers: unacceptable, high, limited, and minimal.
  - ✓ Each tier has specific requirements for development and use.
  - ✓ Systems with limited and minimal risk have fewer obligations, focusing on transparency.
  - ✓ Unacceptable risk systems are prohibited, while high-risk systems undergo rigorous testing, data documentation, and human oversight (European Commission AI Act, 2021).
- Additionally, the European Union has implemented the General Data Protection Regulation (GDPR) that outlines responsibilities for privacy protection, grants data subjects' certain rights, and empowers regulators to enforce accountability and impose fines for non-compliance with GDPR requirements (European Commission AI Act, 2021).

Regulations in USA

- In the USA, there is no comprehensive federal legislation on AI.
- Instead, the U.S. has a patchwork of various current and proposed AI regulatory frameworks
  - ✓ The implementation of the Automated Employment Decision Tools (AEDTs) Act mandates regular fairness audits for firms utilizing AI in employee recruitment and promotion processes (AEDT, 2023).
  - ✓ Similarly, the Equal Opportunity Employment Commission (EEOC) launched an initiative on "algorithmic fairness" in employment.
- The National Institute for Standards and Technology (NIST) has begun work to standardize AI risks and an approach to managing them in a "trustworthy" manner.
  - ✓ It focusses on valid and reliable, safe, fair, explainable and interpretable, transparent and accountable AI systems

Note: Refer to Appendix B for details about regulations in different regions

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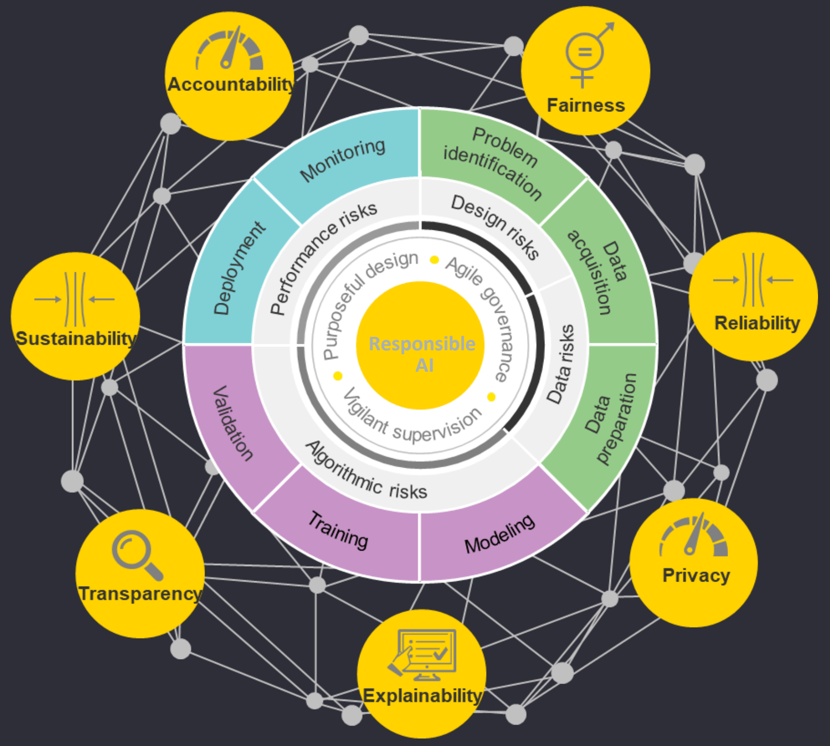
EY teams' approach to responsible AI

The Responsible AI framework developed by EY teams facilitate clients to reduce AI risks while complying with emerging AI regulations. It can evaluate AI risks and build controls across seven trust attributes, four risk categories and three governance domains.

Accountability: there is unambiguous ownership over AI systems and their impacts across the AI development lifecycle.

Sustainability: the design and deployment of AI systems are compatible with the goals of sustaining physical safety, social well-being, and planetary health.

Transparency: appropriate levels of openness regarding the purpose, design, and impact of AI systems is provided so that end users and system designers can understand, evaluate, and correctly employ AI outputs.



Fairness: AI systems are designed with consideration for the need of all impacted stakeholders and to promote inclusiveness and positive societal impact.

Reliability: outcomes of AI systems are aligned with stakeholder expectations and performed at a desired level of precision and consistency, while being secured from unauthorized access, corruption, and/or adversarial attack.

Privacy: AI systems are designed with consideration to data rights regarding how personal information is collected, stored, and used.

Explainability: appropriate levels of explanation are enabled so that the decision criteria of AI systems can be reasonably understood, challenged, and/or validated by human operators.

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