



BACHELOR'S DEGREE IN BUSINESS
ADMINISTRATION AND MANAGEMENT

Final Degree Project

ANALYSIS OF ARTIFICIAL INTELLIGENCE
IN INVESTMENT MANAGEMENT

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Contents

1. Introduction	5
1.1 Context and relevance of AI in modern investment management.....	5
1.2 Objectives	5
1.3 Methodology	6
1.4 Structure	7
2. Theoretical Framework	8
2.1 Synergies between AI and investments	8
2.2 Investment Funds	8
2.2.1 Definition.....	8
2.2.2 Characteristics	9
2.3 Artificial Intelligence and Machine Learning	12
4. Framework, AI in Investment Management	14
4.1 AI applications for funds	14
4.2 Framework structure.....	14
3.1.1 First layer: strategic intent.....	16
3.1.2 Second layer: model architecture and ai tools	22
3.1.3 Third layer: ai model implementation and metrics	30
4.3 Evaluation and analysis.....	31
5. Case studies	34
5.1 Two Sigma	34
3.1.4 Analysis	34
3.1.5 Comparative Assessment.....	36
5.2 AIEQ ETF	37
3.1.6 Analysis	40
3.1.7 Comparative Assessment.....	42
6. Conclusions	46
Bibliography	48

Figure Index

Figure 1. Financial forecasting process for AI-powered investments	13
Figure 2. AI fund classification layer	18
Figure 3. AI management layer	19
Figure 4. Investment style layer	21
Figure 5. Scope layer	21
Figure 6. AI techniques	23
Figure 7. ML tools for investment strategies.....	26
Figure 8. Training process part 1	28
Figure 9. Training process part 2.....	30
Figure 10. Training process part 3.....	30
Figure 11. Fund metrics.....	31
Figure 12. Main considerations for investors when implementing AI.....	33
Figure 13. Top AI-Managed Investment Hedge Funds.....	36
Figure 14. AI Powered Equity ETF's Trailing Returns (%)	40
Figure 15. AI Powered Equity ETF's Annual Total Return (%).....	41
Figure 16. Historical Performance of the AI Powered Equity ETF	42
Figure 17. AI-ETFs key factors influencing returns: quality, volatility, growth and momentum.....	43
Figure 18. Top AI-Managed Investment Exchange Traded Funds	44

1. INTRODUCTION

This thesis provides a comprehensive and structured analysis of the applications of Artificial Intelligence (AI) in the financial sector, with a particular focus on its impact on investment funds. Therefore, its purpose is to explain the many ways in which investment management will be transformed and impacted by the fast-paced landscape and innovations of Artificial Intelligence and similar technologies simultaneously uncovering the threats and opportunities that arise from its implementations especially from the consumers, financial corporations and regulatory agencies' point of view.

1.1 CONTEXT AND RELEVANCE OF AI IN MODERN INVESTMENT MANAGEMENT

Artificial Intelligence, AI from now on, has made some impressive advancements in recent years marking a profound impact on the world of finance. One of the most noticeable advancements has without a doubt been the burgeoning of investment funds managed by AI.

These funds leverage machine learning, ML, (a key branch of AI) to analyse massive amounts of data and detect patterns and probable shifts in the financial markets with the objective of making investment decisions more efficiently and accurately than humans. As technology keeps rapidly evolving, the way investors manage their money also changes at great speed.

1.2 OBJECTIVES

The principal objective of this project is to develop a structured analytical framework for evaluating the integration and effectiveness of Artificial Intelligence in investment management.

This framework has the dual purpose of applying it to a comparative study of real-world case studies of leading AI-driven funds and platforms while also providing a foundation for future academic or professional analyses in the field. It will have a specific focus on AI's applications in portfolio optimization, trading strategies, risk management, and client advisory.

Some secondary objectives are:

1. To explore the types of AI technologies most relevant to investment management, such as machine learning, natural language processing, and reinforcement learning.
2. To assess how AI is currently applied across key functions like portfolio optimization, risk assessment, algorithmic trading.
3. To conduct a comparative analysis of leading investment firms using AI focusing on the proposed framework.
4. Draw conclusions from the study to evaluate whether AI-based strategies offer measurable advantages over traditional investment approaches and the best ways to implement AI in fund management.
5. To identify regulatory, ethical, and transparency challenges linked to AI deployment in finance.
6. To anticipate future developments, including trends in AI and the broader transformation of the financial asset management sector.

1.3 METHODOLOGY

This project adopts a qualitative and comparative methodology, centred on the design and application of a custom analytical framework. The tailored framework will then be used to assess the integration and effectiveness of Artificial Intelligence in investment management practices. It will be designed by drawing insights from industry reports, academic literature, and market examples to capture the most relevant factors ensuring it is practical and adaptable.

The assessment will be conducted with a comparative study of different cases of investment firms using AI and an evaluation of fund behaviour. The data collected will come from company publications, media reports, and publicly available performance metrics to apply the framework consistently. The goal is to produce a replicable tool for this and future analyses.

1.4 STRUCTURE

The project begins by understanding investment management and funds. This is followed by exploring the core AI technologies currently used in finance, such as machine learning, natural language processing, and reinforcement learning, to understand their potential applications and limitations. Chapter 4 will explain the evaluation model developed to assess different investment firms based on how they integrate AI into portfolio. It will also take a deep dive into some cases and their study to later compare them. The criteria will be based on AI techniques used, impact on investment performance, operational efficiency, transparency, and regulatory considerations. Lastly, chapters 5 and 6 will synthesize the findings and explain the conclusions drawn about the current state of AI in investment management, its benefits and challenges, and potential future trends. These will give a forward-looking perspective on AI adoption trends, sustainable investing, and the challenges that both investment firms and investors may face as AI continues to evolve.

2. THEORETICAL FRAMEWORK

2.1 SYNERGIES BETWEEN AI AND INVESTMENTS

One of the aspects radically modified by the integration of artificial intelligence in fund management has been the ability to make decisions, with a greater amount of data available. AI is capable of making decisions through the use of algorithms specialized in analysing data and making predictive models based on the information supplied.

Some of the revolutionary tools used in the financial field for decision-making are:

- credit scoring - a model used to assess the risk and solvency of credit applicants
- fraud control - a model that detects and prevents illegal activities
- virtual assistants - a model that helps customers in financial decisions and their needs
- and automated funds - a tool capable of analysing financial data to make predictions about where to invest

2.2 INVESTMENT FUNDS

2.2.1 DEFINITION

Investment funds are collective investment vehicles that lack independent legal personality and are classified in the broader category of institutional investors. Their governance structure is divided between two specialized entities.

- First, a Management Company is responsible for making investment decisions, executing the fund's strategy, and legally representing the fund, although it does not hold ownership of the underlying assets.
- Second, a Depositary safeguards the fund's assets, oversees cash flows, and ensures compliance with regulatory and operational requirements.

In contrast, Investment Companies are structured as public limited companies, possessing full legal personality and corporate governance frameworks. The distinction extends to how investors participate in each structure. In an investment fund, investors contribute capital to a common pool of assets and receive units or shares that represent a proportional interest in the fund's net asset value. Conversely, in an investment company, investors contribute directly to the company's share capital, acquiring equity shares that represent ownership in the corporate entity itself (Inverco, 2024).

Regulated investment funds are commonly defined as collective investment pools that are substantively regulated and structured as open-end investment vehicles. The type and size of eligible investors, the organizational structure, and the nature of the securities issued are all governed by their regulatory framework where funds can be classified into open-end and closed-end structures.

- Closed-end funds issue a **fixed** number of **non-redeemable** shares which can only be **traded on the secondary** market with other investors.
- Open-end funds, issue units or shares which are **redeemable** at any given point of time, each investor can **purchase or sell** their shares, and the fund will simply **increase or decrease the number** of shares (Mishkin, Eakins, 2018).

These are strictly and formally regulated. Transparent overview of the organizational structure of investment company, investment funds' management and custody fees, valuation of funds' assets and restrictions on investments including diversification across asset classes and limits on leverage. mutual funds and exchange traded funds (ETF), Undertakings for Collective Investment in Transferable Securities (UCITS) and Alternative Investment Funds (AIF).

2.2.2 CHARACTERISTICS

To understand how investment funds work in this section the principal factors of these financial instruments will be analysed and explained. The analysis of investment funds always considers their two main characteristics: profitability and risk.

1. Profitability

A fund's performance or profitability is based on the net asset value of the fund's holdings. The net asset value is the unit price of the share at a given time. It is calculated by dividing the investment fund's assets by the number of shares circulating at that time. Generally, it is the managing entity that calculates the daily net asset value. The net asset value can be calculated from the following equation:

$$NV_t = \frac{FVt}{\# \text{ shares}} = \frac{FVt - 1 + NR}{\# \text{ shares}}$$

NV_t : is the net asset value of a share at time t .

P_t : is the equity of the investment fund at time t .

t : is the number of shares outstanding at time t .

P_{t-1} : is the assets of the investment fund and

To calculate the value of the assets, the market price of the assets and transferable securities that make up the fund's portfolio at time t must be taken into account, subtracting associated expenses and commissions (CNMV).

2. Risk

Another factor to consider when evaluating an investment fund is the risk inherent in that investment. Risk is the sum of factors that can make the return on an investment different than expected (either higher or lower). The higher the return, the higher the level of risk to be assumed. Systematic and non-systematic risk can be differentiated.

- **Systematic**, also known as market risk, is risk that is not specific to an asset determined, depends on generic factors that affect the evolution of prices in the stock markets. This risk cannot be eliminated by simply diversifying the portfolio. To approximate it, the beta coefficient of its historical series is usually used.
- On the other hand, **non-systematic** risk is that which is specific to the asset and can be reduced by diversifying the portfolio (CNMV).

There are different measures to determine the risk of a financial asset: standard deviation, market beta, and Value at Risk (VaR).

The sample standard deviation is a statistic that measures the dispersion of observations with respect to the average of a series. It allows us to measure the volatility of the profitability of an investment fund as it determines how much prices vary with respect to its average.

$$\sigma = \sqrt{\frac{\sum_{i=1}^n (x - \mu)^2}{n}}$$

n : number of observations in the sample.

x : observed values.

μ : mean of the observed values.

On the other hand, the Sharpe ratio indicates the profitability of an investment considering its risk. This indicator shows us the excess return that we can obtain for each unit of volatility.

$$\text{Sharpe Ratio} = \frac{R_i - R_f}{\sigma_i}$$

R_i : is the average expected return of the financial asset.

R_f : is the risk-free return of the asset.

σ_i : is the standard deviation of the financial asset.

The beta coefficient, which measures the amount of systematic risk and how an asset's performance will vary relative to the market.

$$\beta = \rho_{im} \cdot \frac{\sigma_i}{\sigma_m}$$

ρ_{im} : is the coefficient of correlation between the return on the asset and the market return.

σ_i : is the standard deviation of the return on the asset.

σ_m : is the standard deviation on the market return.

With this indicator we can determine whether the price will vary along with the market ($\beta = 1$), will have greater volatility and vary more ($\beta > 1$) or will have less volatility and less systematic risk ($\beta < 1$).

Finally, VaR (Value at Risk) is used to measure the maximum potential loss that is expected to be observed with a degree of confidence over a period.

2.3 ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

This section delves into AI, with a specific focus on Machine Learning (ML) and predictive algorithms, which form the backbone of investment techniques. Artificial Intelligence is a field within computer science that focuses on the theoretical foundations, computational methodologies, and practical applications for emulating, augmenting, and extending human cognitive functions. It encompasses the development of algorithms and systems capable of acquiring, representing, and applying knowledge to perform tasks traditionally requiring human intelligence.

According to Russell and Norvig (2009) these tasks that AI is expected to achieve can be classified into four categories: Thinking and Acting Rationally and Thinking and Acting Humanly.

Thinking Rationally is related to the automation of manual and routine tasks from problems expressed in a logical way with no learning.

Acting Rationally, goes deeper, expecting the machine to be a rational agent operating autonomously and adapting to changes it perceives in the environment. It's not only solving a logically framed problem but acting independently and creating and pursuing goals (Russell and Norvig, 2009).

The cognitive modelling approaches, however, combine the algorithms with cognitive science, psychology and experimental techniques. This means that systems based on AI learn continuously when interacting with the environment and humans, augmenting the human decision-making process.

Lastly, Acting Humanly would encompass all the definitions of AI subcategories, machine learning (ML), natural language processing (NLP), knowledge representation, computer vision (CV), automated reasoning, etc. making systems autonomously intelligent by

adapting to different situations and acting completely without human intervention. To be fully classified with this quality, machines should fully pass the Turing Test, a benchmark for evaluating a machine's ability to exhibit human-like intelligence

ML is a branch of AI that allows computers to learn and improve with time without the need for reprogramming specifically to do so. Regarding investment funds, ML algorithms analyse vast amounts of financial data in a fast and precise way to predict future market trends and identify patterns and figures. This information includes not only historical information on asset prices, economic data, or financial reports but also news and political events. It has a significantly more powerful ability to process gather, clean and process data than analysts and can therefore identify may correlations and patterns that humans might miss.

One of the most powerful applications of ML has for investment funds is trend prediction since the algorithms can independently learn from historical data to anticipate how specific assets will likely behave in the future. A ML model can forecast has a high probability of appreciation based on its past price behaviour and present market indicators.

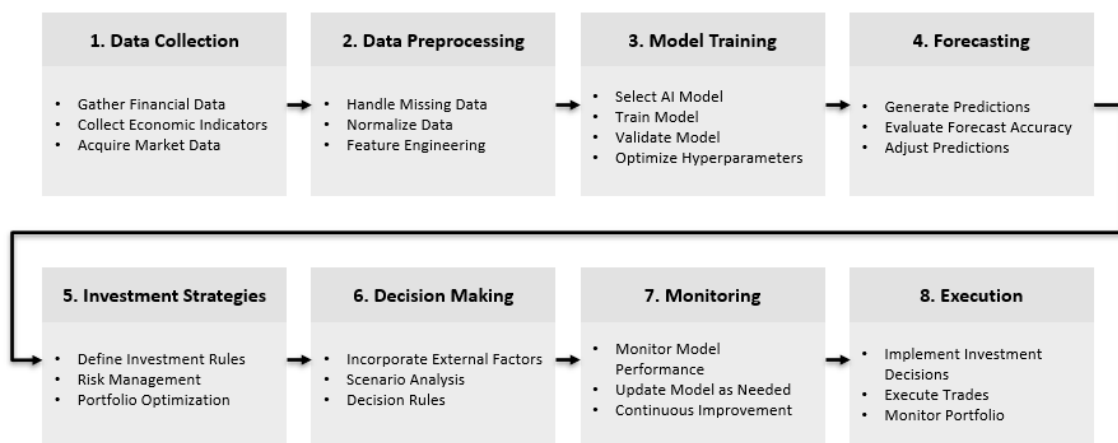


Figure 1. Financial forecasting process for AI-powered investments

4. FRAMEWORK, AI IN INVESTMENT MANAGEMENT

4.1 AI APPLICATIONS FOR FUNDS

The use of artificial intelligence and big data analytics is revolutionizing the way investment analysis and decision-making is done. AI tools can identify patterns and trends in financial markets more efficiently than traditional methods, which can give investors a competitive advantage.

According to Shah et al. (2019) within the price prediction itself, we find four categories: statistical predictions, pattern recognition, machine learning, and sentiment analysis. These categories can usually be grouped together within technical analysis.

4.2 FRAMEWORK STRUCTURE

There is no doubt that AI is rapidly reshaping investment management however, its adoption is usually fragmented, inconsistent, or poorly understood by investors. To tackle the lack of a unified way to classify, evaluate, and compare technology and solutions the following framework is proposed. A framework provides a systematic way of analysing problems, developing solutions and implementing and scaling them. It establishes a structured foundation by setting up the architecture, rules and components necessary for an analytical process.

The objective of this framework is to build a structure that provides a strategic and operational roadmap for classifying, analysing, and comparing AI solutions in relation to funds. It is designed to help both asset managers and investors:

- Understand how AI can interact with different fund strategies and structures.
- Evaluate the performance, risk, and operational robustness of AI-driven investment approaches.
- Compare AI powered funds using consistent criteria

- Identify and select the right AI enabled solutions for their investment goals
- Build a competitive advantage and stay ahead and of emerging innovations and regulatory expectations.

The framework is intentionally modular. It can be used to assess a single fund, compare multiple funds, or guide the design and implementation of new AI-driven strategies. It also supports scalability: from early-stage experimentation to full operational deployment.

To achieve this, the framework is organized into **three layers**, each addressing a different dimension of AI adoption:

1. Strategic Intent - Why AI is being used and what the fund aims to achieve
2. Model Architecture & AI Tools - How AI is built, trained, and integrated
3. Implementation & Metrics - How AI is deployed, monitored, and evaluated

Together these layers form a comprehensive blueprint for responsible, transparent, and effective AI adoption.

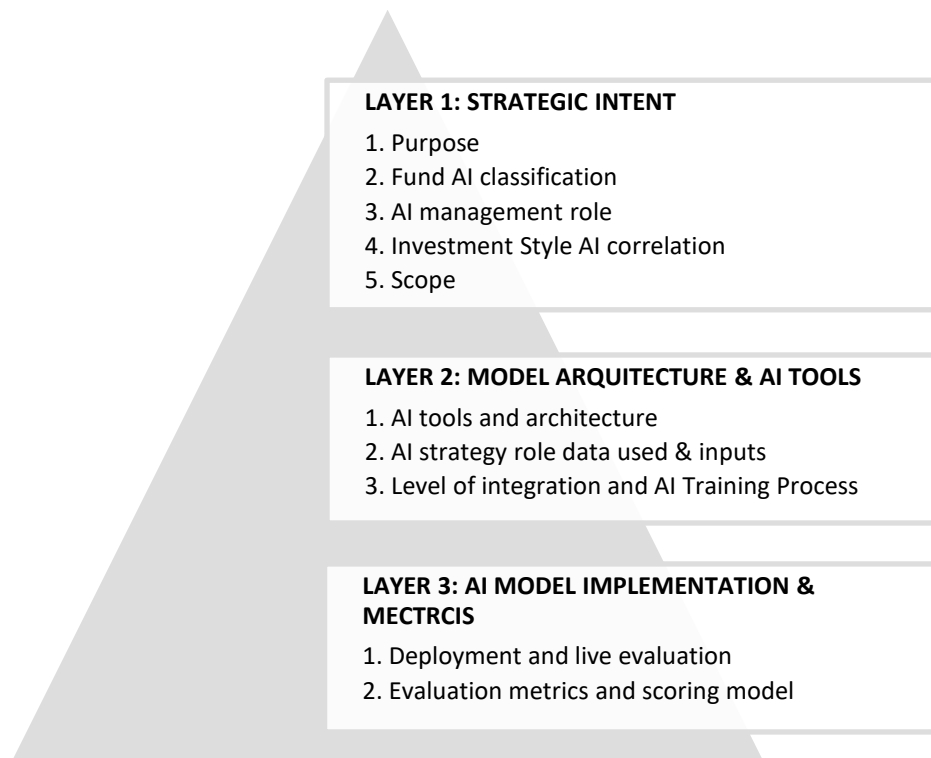


Figure 1. Framework structure

3.1.1 FIRST LAYER: STRATEGIC INTENT

This first layer answers to who and why AI is being used or needs to be implemented. It tackles investor type, strategic intent, and end use by establishing a clear business objective with defined KPIs. Among them would be improve alpha, reduce risk, automating and streamlining processes, reducing operational costs, or enhancing customer experience.

1. Sublayer - Purpose

In this first sublayer the most important thing is to define why AI must be used with a clear business objective. Additionally, to correctly set up a business strategy goal, key performance indicators (KPIs) should be defined in line with this target. Getting on the AI hype with no clear vision of the tools and end goals can lead to a waste of resources, risks and failure. In regard to the financial industry and more specifically investment funds some key objectives could be to improve alpha, reduce risk, process automation, operational cost reduction or client experience enhancement.

A robust purpose definition requires two components:

1. **A clearly articulated business objective**, grounded in the fund's investment philosophy, operational model, and investor expectations.
2. **A set of measurable Key Performance Indicators (KPIs)** that translate the objective into quantifiable outcomes.

In the context of investment funds, the purpose of AI adoption typically aligns with one or more of the following strategic goals:

<i>Goal</i>	<i>Possibilities</i>
Enhancing Investment Performance	<p>AI can support or automate tasks traditionally performed by portfolio managers and analysts to improve the fund's ability to outperform benchmarks or deliver superior risk-adjusted returns.</p> <ul style="list-style-type: none"> • Alpha generation through pattern recognition, predictive modelling, and cross-asset signal extraction. • Algorithmic and high-frequency trading, where machine-learning models identify micro-patterns invisible to human analysts. • Profit forecasting, using models that analyse financial statements, macroeconomic indicators, and alternative data to anticipate earnings changes.
Strengthening Risk Management	<p>Machine-learning-based risk systems can process far larger datasets than traditional models, enabling more granular and dynamic risk assessment.</p> <ul style="list-style-type: none"> • Detecting non-linear relationships and tail-risk exposures. • Identifying early warning signals through anomaly detection. • Stress-testing portfolios under simulated market regimes. • Improving credit scoring models for fixed-income or multi-asset funds.
Optimising Portfolio Construction and Allocation	<p>AI tools can help funds achieve more efficient allocations and reduce unintended exposures.</p> <ul style="list-style-type: none"> • Portfolio optimisation under complex constraints (liquidity, ESG, concentration limits). • Dynamic asset allocation, adjusting exposures based on market regimes. • Factor modelling, where ML identifies latent factors or improves factor timing.
Improving Execution Quality	<p>Execution is a major driver of performance leakage. Reinforcement learning and microstructure-aware models are increasingly used to minimise transaction costs.</p> <ul style="list-style-type: none"> • Predicting market impact and slippage. • Optimising order routing and execution timing. • Automating trade execution under predefined risk limits.
Automating Processes and Reducing Operational Costs	<p>Automation reduces manual errors, accelerates processes, and frees human capital for higher-value tasks.</p> <ul style="list-style-type: none"> • Data ingestion and cleaning • Report generation • Compliance monitoring • Reconciliation and operational workflows

Figure 2. AI fund main goals

2. Sublayer - Fund AI classification

<i>Fund Type</i>	<i>Can Be AI-Managed?</i>	<i>AI maturity</i>
Mutual Funds	Sometimes Mutual funds can only <u>sometimes</u> be managed by AI and only few are currently AI-managed. Some use quant strategies. An example is Fidelity's tech funds. Though AI-managed mutual funds do exist, most still combine human oversight, AI driven analytics and ML based decision support.	Medium
ETFs	Yes Exchange Traded funds are the <u>most common</u> AI-managed fund structure. Among the most noticeable ETFs are AIEQ and QRAFT. An ETF or mutual fund can be AI-managed if its investment decisions are made by algorithms.	High
Index Funds	Not usually Index funds are managed passively following set benchmarks, <u>rarely</u> using AI. However, while most passive index funds don't let AI fully run the fund, there are several mayor asset managers who use AI to enhance index construction, risk management, or product design. AI can contribute to how new index funds are conceived and optimized, even if day-to-day tracking remains traditional. For example,	
Hedge Funds	Often Hedge funds have been the <u>early adopters</u> of AI and may be <u>completely run by ML models</u> , for example, quant hedge funds. There are many leading quant or AI hedge funds who use ML models such as Two Sigma or Voleon.	High
Private Equity	Not directly Private equity is focused on ownership and buyouts, therefore is doesn't use AI in fund management but to support due diligence or risk analysis. It is typically used in deal sourcing for AI-driven scanning of companies, in due diligence for financial anomaly detection and NLP on documents and in portfolio monitoring for predictive KPIs.	Medium

Figure 3. AI fund classification layer

This analysis shows that despite almost all fund types can integrate some level of IA, the depth of automation varies among them. While AI-driven ETFs and quant funds are currently the most advanced, private markets and discretionary funds use AI techniques mainly to support decisions rather than to fully automate.

3. Sublayer - AI management role

<i>AI Management</i>	
Fully AI-driven	These are funds where AI autonomously executes trades and makes all the investment decisions. They are still uncommon with only a few existing. If the AI model is acting as the rule engine, they may qualify as quant funds.
Hybrid AI-assisted	These funds leverage AI to enhance human abilities in tasks such as sentiment analysis, analytics, filtering stocks, etc. However, the decisions are ultimately human driven. Managers make the final trade execution.
Quant-driven	These are funds that explicitly use quantitative trading models. Decisions are purely rule-based and lack human intervention.
* AI-themed funds	These funds don't have any AI management. However, they are often confused with AI-driven funds. These are merely funds investing in companies or sectors related to AI but lack AI models or technology in its management process. They are therefore completely controlled by human fund managers. Examples of these funds are RHB Global Artificial Intelligence Fund or Allianz Global Artificial Intelligence Fund, which despite being named "AI funds" don't use AI for actual trading decisions.

Figure 4. AI management layer

The key factors AI adoption come down to a handful of structural characteristics that either enable or limit automation determining whether a fund can be AI-managed or not.

- **Data richness** - AI needs large, clean, and frequent data so funds differ in how much usable data their asset class produces. A strategy producing more data better enables AI to automate signal generation, portfolio construction and execution. Hedge quant funds are more suited for AI since they navigate markets with millions of daily datapoints whereas private equity has sparse, irregular and qualitative data
- **Liquidity** - AI models thrive in situations where they can constantly adjust positions and identify short-lived opportunities. While highly liquid markets (equities, foreign exchanges or futures) allow AI to instantly execute trades at scale, illiquid markets (infrastructure, real estate or private credit) unable to trade algorithmically, limit AI to analysis nor execution, forcing human judgment and long-term decision cycles.
- **Regulation** - AI can further drive the end-to-end investment process with more flexible regulation since it limits how autonomous a fund can be. For example, the

required explainability and transparency in retail funds limit the use of black box models and the strict diversification, leverage and liquidity rules of UCITS funds (European Undertakings for Collective Investment in Transferable Securities) limits their operation within them. Hedge funds have far more flexibility.

- **Investment horizon** - AI learns from repetition improving and adapting faster the shorter the cycle, therefore performing best in environments where patterns repeat frequently. Long-term discretionary strategies rely on macro narratives, human judgment and qualitative interpretation. Short-term trading strategies with constant feedback loops are easier to automate ideal for ML.
- **Mandate flexibility** – AI integrates most naturally into strategies that already operate with rule-based structured decision frameworks like systematic funds. Others relying on human intuition, macro interpretation and dependent on portfolio managers or meetings with management like discretionary funds may only use AI to support research.

The sweet spot for AI managed funds is having clear flexible rules, liquid assets, and abundant data.

4. Sublayer - Investment Style AI correlation

<i>Investment style</i>	<i>Description</i>	<i>AI-Management</i>
Active	Active management is where a human manager, or in some cases AI, makes discretionary or model-driven decisions with the goal of outperforming the market (seeking alpha) in relation to a benchmark.	Fully AI-driven funds are most commonly active and quantitative. AI evolves from initial decision-support to semi or fully automated management where it works as signal generator, ensemble allocator, risk overlay and execution optimizer.
Passive	Passive management replicates indices or factor exposures through rule-based, transparent, mandates. AI models are therefore rarely used since management and decision-making is rule based.	In passive management, AI is limited to index construction and dynamic rebalancing to reduce tracking error and transaction costs. Index rule transparency is essential, and any ML adjustments must be auditable and disclosed to investors.
Long-only	Buy-and-hold equity or bond strategies with limited shorting.	AI augments research (NLP on filings, alternative data for early signals), improves risk budgeting (scenario analysis), and supports portfolio construction (risk-parity, factor tilts). Because horizons are longer, models emphasize explainability and robustness rather than ultra-low latency.
Market-neutral	Long/short strategies targeting low market beta.	AI can be used for pair selection, signal timing, portfolio construction, execution; models: statistical arbitrage, factor neutralisation, RL for execution.

Figure 5. Investment style layer

5. Sublayer - Scope

<i>Focus</i>	Sector or Industry orientation / Markets (emerging, small cap, etc.)
<i>Region</i>	Global vs. regional focus. Region (US, EU, Asia, etc)

Figure 6. Scope layer

3.1.2 SECOND LAYER: MODEL ARCHITECTURE AND AI TOOLS

This second layer answers to the use classification, the input data structure and AI tool analysis.

1. Sublayer - AI tools and architecture

AI cutting-edge technology is being integrated in the architectural design of leading funds shaping highly complex systems. This sublayer analyses the different technologies and tools to be used to build these models. Before trying to implement AI it is important to understand how it works and all the tools and possibilities it offers to better achieve a competitive advantage from its full potential.

AI algorithms perform statistical analysis as well as tactics to follow trends from historical information to identify market patterns and inefficiencies in prices. These approaches process vast quantities of data, unveil hidden patterns and adapt to market conditions.

These AI algorithms are all rooted in 3 types of model learning.

1. Supervised learning used for ML models forecasting stock price in relation to specific factors.
2. Unsupervised learning to help, cluster stocks and assets into groups based on similar traits and detect anomalies like market manipulation or other strange behaviours which are useful for portfolio management and risk evaluation.
3. Reinforcement learning which fine tunes investment decisions to correct previous errors. The model learns by trial and error and through interactions with its environment.

The findings these ML investment algorithm unveil however may be complemented with technical and fundamental analysis as well as subject-matter knowledge to fully improve investment performance and higher risk-adjusted returns. This is the reason to go deeper into AI techniques detailed in Figure 7 each encompassing the ones below by using more complex structures of the ones above.

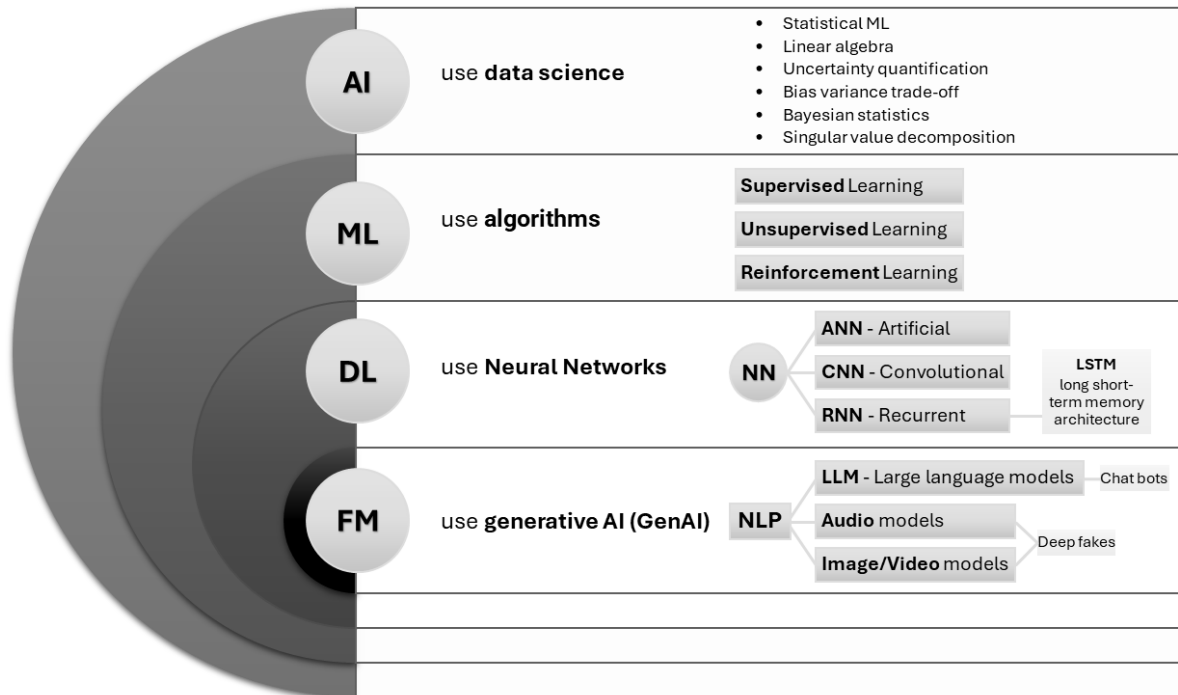


Figure 7. AI techniques

AI-driven financial large investment models are usually complex systems rooted in deep learning frameworks for accurate market predictions and trading decisions. They do so by combining time-series analysis, natural language processing (NLP) and reinforcement learning (RL).

- **RL** is gaining interest for investment decisions as it provides a system for automated trading navigating complex financial markets by tailoring its decision making to the most appropriate tactics learnt through trial and error. It offers high adaptability to the models by dynamically adjusting their strategies with market feedback. In spite of issues like unstable financial or high dimensional data, advanced NN and the combination of reinforcement learning with other methods result in higher efficiency. In portfolio optimization and automated trading, reinforcement learning is useful as it enhances how the model allocates resources and interprets market signals to send sell or purchase orders. Present hurdles are managing the interpretability of the methods learnt by the model as well as biases and overfitting.

- **Deep Neural Networks (DNNs)** lay the foundation by building multi layered (deep) AI models or neural networks. These autonomously process vast amounts of structured data like fundamental factors, technical indicators and detect non-linear complex features in the data or interactions hard for humans to identify offering more precise return prediction.

Deep learning is still limited to the black box nature of its results especially in highly regulated fields like the financial sector. **Explainable AI** or XAI is gaining traction as it counter acts the lack of transparency of model decision making, strengthens investor confidence and facilitates regulatory requirements through counterfactual reasoning, SHAP value analysis and attention mechanism visualization. Another challenge is the large requirement of computing power resulting in big infrastructure costs for the large TPU clusters.

- **Recurrent Neural Networks (RNNs)** have a specific internal recurrent architecture with loops designed to process and predict sequential data and detect temporal dependencies typical in financial time series data with historic and memory attributes. Simple RNNs have both long-term memory with weights that slowly change when training and short-term memory with ephemeral activations among nodes. The back propagation process uncovers the exploding gradient problem in when training. Long short-term memory architecture (LSTM) is a more powerful type of RNN that involves a gate mechanism to resolve the long-term memory dependency. LSTMs are very suitable for natural language processing (NLP) and time series analysis or forecasting future values in sequential data (stock prices, macroeconomic indicators or other time-series variables).
- **Transformer models** have been a recent breakthrough in **NLP** with self-attention mechanisms to weigh the relevance of parts or elements of the input sequence. It is highly influential in financial markets as this architecture can sort through a stock price sequence, a single company's financial reports, important news reports, analyst audios and videos and macroeconomic data all simultaneously. These models learn how data points from very diverse sources correlate to deliver board-based verdicts and provide general market understanding.

- Generative AI** (most known for the GPT series) are sophisticated ML models that simulate a brain by learning, decision-making and creating original content in response to a users' natural language request, prompt or question. It not only provides profound semantic understanding but also sentiment analysis of massive financial news, research reports, and social media comments with an accuracy that surpasses common linguistic statistics and provides an unprecedented surge in productivity. **Generative adversarial networks (GANs), diffusion models** and other **adversarial algorithms** push the model to generate incremental high-quality outputs by evaluating the accuracy and quality of self-generated data or adding noise to the training data and iteratively training the algorithm to diffuse it. These models are convenient for stress testing plausible market scenarios based on current economic conditions and their possible impact on the market for funds to evaluate critical risks.

2. **Sublayer** - AI strategy role data used & inputs

<p>Limits for funds</p>	<p>The accuracy is often limited by stock value characteristics.</p>	<p>Compared to supervised learning, decision making and interpretation could be limited or challenged by the lack of explicit target variables. Additionally, it needs subject matter expertise to bring forth clear insights and actionable orders.</p>	<p>The clustering algorithm may not capture some key features that could be overlooked.</p>	<p>These algorithms may have false positives and negatives that might need reviewing.</p>	<p>To accurately interpret and analyse it is crucial to consider other factors that influence investment decisions and subject matter expertise.</p>
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<i>AI ML method</i>	<i>Description</i>	<i>Examples</i>	<i>Purpose and Fund Application</i>
Supervised learning	It is a task driven ML technique used to train AI where the input data used is labelled (features) and corresponds to a specific output. With it the model identifies underlying patterns or relationships with internal parameters that are adjusted to minimize errors guided by a loss function and optimization techniques like gradient descent.	Supervised learning can be divided into regressions to predict a continuous numeric target variable or classification to predict a discrete categorical variable label or class. E.g. linear regressions, logistic regressions, KNN, support vector machine, decision trees, naive bayes classifiers and NN and DL.	It is used to improve decision making and identifying buying and selling opportunities based on price fluctuations. - Generation of trading signals - Prediction of stock prices - Analysis of trends
Unsupervised learning	Is a data driven type of ML where algorithms learn patterns, analyse and cluster data without any prior knowledge of its meaning, categories or outcomes, i.e. unlabelled. It is used for exploratory data analysis to understand the underlying structure of the data.	Key techniques are clustering, association rule learning (to uncover relationships between dataset variables) and dimensionality reduction (to reduce dataset features preserving maximum information possible). It has a wide range of applications such as customer segmentation, fraud detection or NLP tasks like modelling. E.g. clustering, anomaly detection, apriori and FP-growth algorithms, PCA, SVD and auto encoders.	It is used to diversify portfolios, find opportunities in specific sector investing and for risk evaluation by detecting outliers. - Portfolio diversification - Detection of anomalies - Risk assessment
	Clustering algorithms	E.g. K-means clustering, hierarchical clustering and Density-Based Clustering (DBSCAN)	Clustering groups unlabelled data by differences or similarities. It is useful for risk management and sector specific investments.
	Anomaly detection algorithms It is the identification of unusual or rare observations or events deviating from the majority datapoints.	E.g. Isolation forest, local outlier factor, robust covariance, one-class support vector machine	- Monitoring markets - Risk assessment - Fraud detection
Data driven investing strategies	It is not specifically a ML technique but rather investment strategies that use data to make informed decisions. Differing from the previous two, rather than learning from data, it focuses on interpreting data and analysis to derive investment decisions.	These strategies are rooted in the idea that data can generate insights about asset performance, market trends and comprehensive investment opportunities. Reinforcement learning involves E.g. random forest, reinforcement learning algorithms and DL models.	They not only uncover hidden patterns but also enable investment decisions and add-on to technical and fundamental analysis methods. - Optimization of investment strategies. - Performance evaluation

Figure 8. ML tools for investment strategies

data used	sentiment, price, macro
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inputs	Trading frequency, frequency of rebalancing, interpretability
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3. **Sublayer** - Level of integration and AI Training Process

The level of integration of AI in the system can be high, medium or low, it will be determined by... and will be mainly determined by the AI management layer.

Data Engineering	<i>Most often the biggest hurdle when it comes to implementing AI models is not designing and building the model but training it and having high-quality proprietary datasets to do so, giving them a competitive advantage over other models.</i>
Data Collection	<p>The starting point to implement and train an AI financial model after having determined all the previous sublayers is acquiring diverse and high-quality data and information. The data may be collected through multiple sources and should ideally be proprietary (owned exclusively by the company) and accumulated through the years. Some sources are:</p> <ul style="list-style-type: none"> - Corporate financial reports. - Macroeconomic indicators such as GDP, interest rates or CPI. - Markets data from exchanges in real time like trading volumes, stock prices or depth of market. - News and media or even supply chain data and satellite images.
Data Cleaning	<p>Raw datasets always contain noise, missing or invalid values. outliers and other that must be cleaned and corrected. The data collected must therefore be processed with automated code and statistical methods like sliding window detection for flash crashes (sudden rapid decline in the price of securities, followed by a quick recovery) or interpolation for abnormal gaps in values.</p> <p>NLP techniques should be used to process text data to extract key parameters such as financial indicators or company names, remove unnecessary irrelevant content and standardize terminology.</p> <p>Finally in relation to financial data, it is crucial to guarantee time alignment and non-data duplication with consistent timestamps to evade biases from different time zones or delays.</p>
Feature Engineering	<p>Before the model can be trained and after the data has been cleaned and processed feature engineering must be conducted to draw out the most valuable information to train it. In contrast to traditional methods (quantitative) with factors designed by hand like value, momentum or volatility, AI models use automated processes to obtain multi-dimensional features.</p>
Data Augmentation	<p>These techniques are used to deepen the ability of the AI model to generalize. Funds should use methods of generating synthetic data to enlarge the training set especially when the financial historical data is limited like in extreme events or financial crises.</p>

Figure 9. Training process part 1

Model Training and Validation	<i>With the data and features prepared the next step is training the model and minimising errors in predictions of future returns, negative value of the Sharpe ratio or the maximum drawdown in simulated trading, among others. The process takes form weeks to months and requires large tensor processing units (TPU) for the model to make continuous adjustments of internal parameters with backward propagation.</i>
Distributed Computing	Due to the large and complex need of computing to train the model and handle vast sums of data training should be carried out with distributed computing systems. Data storage and processing is distributed across multiple devices or platforms, each with its own processing capabilities, who work together and share resources to perform tasks. This architecture provides scalability, reliability and flexibility and is used in finance for high-speed economic simulations, predict market movements and assess portfolio risks.
Overfitting	<p>For funds, overfitting is usually avoided or prevented through regularization, careful validation, and respecting the temporal structure of market data. Financial data is nonstationary, noisy and has low signal to noise ratio so models that are closely fitted to the past will fail out of sample. Some of the core regularization techniques used by funds are:</p> <ul style="list-style-type: none"> • Dropout that forces NN to learn redundant, generalizable representations and deactivates neurons randomly during training. • L1 that encourages sparsity and is advantageous for feature selection among thousands of signals. • L2 that penalizes large weights, stabilizes models and reduces noise sensitivity. • Early stopping during training when validation loss worsens and models begin memorizing historical behaviour. • Ensembling that combines multiple weak models to reduce variance and improve robustness. <p>Random k-fold cross-validation fails in finance because financial time series violate the assumptions that datapoints are independent and identically distributed and shuffling does not break structure leading to optimistic but misleading performance estimates. Instead, funds use time-series cross-validation (TSCV) to always test the model on future, unseen data preserving chronological order with training, validation, and test sets, and simulating real-world forecasting. Institutional funds additionally often apply regime-based validation, stress testing or paper trading / shadow portfolios.</p>
Optimization	Large financial AI-driven models require continuous parameter updates remain aligned with rapidly evolving market conditions. To mitigate model drift and preserve predictive accuracy, funds can use incremental parameter updates through online learning, real-time monitoring, recursive estimation techniques and adaptative feature pipelines.

Additionally, continuous optimization must be coupled with real-time monitoring systems and safeguards that track prediction errors, execution quality, profit/loss patterns and alpha decay and risk exposures relative to predefined limits. If degradation is detected, these systems have to trigger corrective actions such as partial retraining, full model refresh, or rollback to a stable prior version.

Figure 10. Training process part 2

<p>Simulation and Risk Management</p>	<p><i>Traditional risk management frameworks must be embedded directly into AI models, which by design optimize an objective function and are therefore risk-neutral unless explicitly constrained. Some constraints to limit trading behaviour in AI models are value at risk, VaR, conditional value at risk, CvaR and factor exposure of key macroeconomic drivers.</i></p> <p><i>Model robustness may be evaluated using adversarial perturbations with small, targeted modifications to input features to test whether the model produces unstable or erroneous decisions exposing vulnerabilities and highlighting sensitivity.</i></p> <p><i>In parallel, funds can conduct large scale Monte Carlo simulations to generate many hypothetical market trajectories, including extreme but plausible stress scenarios to assess the model's behaviour under volatility spikes, liquidity shocks, and structural breaks.</i></p>
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Figure 11. Training process part 3

3.1.3 THIRD LAYER: AI MODEL IMPLEMENTATION AND METRICS

1. Sublayer - Deployment and live evaluation

Once trained, models should be introduced into production trading environments through pilot deployments that operate with limited capital to observe live performance, execution behaviour and risk exposures under real market conditions while minimizing financial impact.

Usually quantitative funds have closed-loop learning architecture where real time trading outcomes feed directly back into model development and research. This way, model iterations use online performance metrics like realized profit/loss, error distributions or regime specific behaviour as training signals.

Through this iterative deployment and monitoring AI driven financial systems not only achieve, high predictive accuracy, low latency, and strong adaptability but also become

robust and scalable enough to support real time investment decisions and operate across diverse asset classes and trading horizons.

2. Sublayer - Evaluation metrics and scoring model

<i>Metrics</i>	
Performance	Total return, annualized return (1Y, 3Y, 5Y) 1-year, 3-year, 5-year CAGR; Alpha, Beta, Sharpe ratio
Risk	Volatility (std dev), Max drawdown, Sortino ratio, VaR
Costs and size	investor base, AUM- Assets Under Management, Expense ratio, Minimum investment, Management fee, expense ratio, turnover rate
Qualitative	Transparency, explainability, track record, ESG alignment, Access to holdings, rebalancing policy, AI methodology disclosures Investor Suitability Risk appetite, time horizon, accessibility (institutional/retail)

Figure 12. Fund metrics

In some cases, it might be interesting to set up a scoring model for objective comparison by establishing Dimension – Weight – Score Criteria – Score to get to a Final Score = Weighted sum. E.g., performance 30%, risk 25%, AI quality 20%, transparency 15%, cost 10%.

Additional interesting initiatives are to set up benchmarks (e.g., outperforming S&P 500, peers in same category), create an AI evaluation layer that measures the rate of the **sophistication of the AI used** (e.g., NLP, deep learning, reinforcement learning) or defining metric thresholds (high volatility, strong AI).

4.3 EVALUATION AND ANALYSIS

Ultimately, this framework should be understood as an inherently iterative process. Since AI technologies evolve at a rapid rate, a sustained assessment and periodic updates of both the model and the supporting tools are necessary to ensure ongoing relevance, accuracy, and effectiveness.

Fund comparison tables, Risk–return scatter plots, AI-tech maturity matrix (AI depth vs fund performance)

Rank funds by scenario (e.g. “Low risk/long-term growth” or “High alpha/tech-savvy”)

cluster analysis or PCA to find similar strategy profiles Compare AI-managed vs human-managed peers (control group).

<p><i>Strategic approach for organizational implementation</i></p>	<ul style="list-style-type: none"> • As the first layer focuses on, funds must first spot both the key goals and mayor pain points for AI to optimize and enhance. • Funds should also constantly uncover and seek out emerging business opportunities enabled by AI capabilities. • Lastly, establishing governance structures that oversee how AI influences productivity and investment outcomes is interesting to truly measure the return on AI implementation.
<p><i>Security and data privacy</i></p>	<ul style="list-style-type: none"> • Data privacy and security must always be placed at the heart of all AL deployment efforts by embedding them as foundational principles in every stage of the implementation.
<p><i>Guiding innovation while defining the boundaries of AI models</i></p>	<ul style="list-style-type: none"> • To enhance investment processes and decision-making funds should identify opportunities and potential use cases for generative and predictive AI to collaborate. • On one hand, predictive AI initiatives deepen the understanding of model drivers, ensure data quality, and rigorously evaluate predictive performance. • On the other, generative AI should focus on strengthening prompt-engineering practices and refining models to minimise hallucinations and improve reliability.
<p><i>Expense oversight</i></p>	<ul style="list-style-type: none"> • The full cost structure associated with AI should be identified before the implementation of any AI model or initiative. This includes model-training and fine-tuning expenses, dataset sourcing and maintenance costs, and model-development requirements. • Additionally, it is interesting to carry out an assessment on which models can be efficiently developed in-house and which components are more cost-effective to outsource.

<i>Talent structure</i>	<ul style="list-style-type: none">• The potential long-term impact of AI on the funds people strategy indicates the need for a plan of the specific skill sets required to sustain and scale AI-enabled models and positions.
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Figure 13. Main considerations for investors when implementing AI

5. CASE STUDIES

<i>Fund Type</i>	<i>AI Role</i>
ETFs: AIEQ, QRAFT, THINK	AI directly selects and weights stocks based on financial and alternative data.
Community-Driven: Numerai	Unique case where data scientists train models anonymously and AI aggregates them for trading decisions.
Quant Hedge Funds: Two Sigma, Voleon, Rebellion	Use AI for predictive modelling, risk control, and algorithmic trading.

5.1 TWO SIGMA

This use case study will be focused on the integration of AI within hedge-fund investment processes, focusing on Two Sigma a paradigmatic example of how it can be embedded into the full lifecycle of investment management, from predictive modelling (alpha discovery) to risk control and execution (algorithmic trading).

Two Sigma is one of the most successful quant hedge funds focused on big data and technology by intensely working on machine learning and AI creating a corporate culture more aligned with Silicon Valley's tech companies than financial institutions. It was founded by David Siegel and John Overdeck, both previously executives from D. E. Shaw & Co., multinational investment management firm. Today, Two Sigma manages over \$60 billion in assets, positioning itself as one of the largest and most influential AI-driven hedge funds globally.

3.1.4 ANALYSIS

Focusing on the first layer of the framework, the company's model aims to pinpoint and authenticate new trading alpha signals through crowdsourcing and a competitive open process. It does so with data science challenges (through Kaggle) that attract elite worldwide talent to solve and tackle complex predictive problems.

The firm's objective is to identify weakly correlated alpha sources that diversify away from conventional factors such as value, momentum, or quality.

Two sigma covers a vast array of investment strategies going from high frequency trading all the way to long term investment while also controlling a hefty volume of assets. To streamline its research and development process the company has developed and invested in its Alpha Studio platform for collaboration, testing and big data access. Two sigma's key to building robust and diversified portfolios is enabling AI models to discover new alpha sources through alternative data processing with weak correlation with traditional factors (value, momentum, etc.).

Two Sigma's research pipeline integrates traditional financial data with alternative datasets, including web-scraped sentiment, corporate metadata and supply-chain networks, credit-card transaction flows, satellite imagery and geospatial mobility patterns.

For its feature engineering, Two Sigma's model employs deep autoencoders to compress high-dimensional price sequences and notice potential market states. Additionally, it uses CNNs (convolutional neural networks) to obtain predictive signals from satellite images and mobility patterns at stores. Earnings calls, regulatory filings and news sentiment are also analysed with NLP while reinforcement learning agents optimize execution strategies and adapt to evolving markets. Lastly, thousands of predictive models are combined through ensemble-model frameworks to limit specific model risk and raise robustness.

Two Sigma's AI platform is based on distributed computing and built on Apache Spark, TensorFlow, and large-scale GPU clusters. This means it is able to train its DNNs (deep neural networks) in parallel on thousands of GPU servers. The training process incorporates small batch gradient descent algorithms for optimization in combination with adaptive learning-rate optimizers such as Adam to accelerate convergence. Bayesian hyperparameter tuning is also used in the training process. Finally, to ensure adaptability to structural market changes Two Sigma has continuous retraining pipelines.

This computational scale allows Two Sigma to test millions of hypotheses, run extensive back tests, and deploy models that remain resilient even during periods of market stress.

3.1.5 COMPARATIVE ASSESSMENT

Two Sigma stands out for its scale, infrastructure and wide range of modelling techniques; however, other AI-driven hedge funds offer distinct approaches that show off the vast spectrum of ML applications for asset management. Among these hedge funds are Rebellion Research, Voleon Group, and Numerai. Both Rebellion Research and Voleon Group are pioneers in AI fund management but are not publicly traded or widely accessible.

<i>Fund Name</i>	<i>Type</i>	<i>Returns</i>	<i>Key Features</i>
<i>Rebellion Research Managed Accounts</i>	Quant Hedge Fund	Varies	It is closed to new retail investors and uses Bayesian AI algorithms for long-term equity investing.
<i>Voleon Group Funds</i>	Quant Hedge Fund	Undisclosed (private)	It is known for strong, consistent performance and is fully machine-learning driven.
<i>Two Sigma Absolute Return Fund</i>	Quant Hedge Fund	High historical returns	It is one of the most successful quant hedge funds with focus on AI and big data.
<i>Numerai Meta Model Fund</i>	Community based Hedge Fund	10–20% annually	Uses crowdsourced ML models from data scientists worldwide.

Figure 14. Top AI-Managed Investment Hedge Funds

Voleon is a pioneer in applying Bayesian ML and probabilistic graphical models for financial prediction as its core strength is being able to capture subtle nonlinear relationships in stable environments. However, Bayesian priors can become unreliable in macroeconomic regime shifts so its strategy is more fragile than Two Sigma’s ensemble approach.

In contrast, Rebellion Research is good at detecting long-term macroeconomic patterns and market dynamics driven by policies but is less effective in high-frequency short-term scenarios where Two Sigma’s microstructure also dominates. Rebellion focuses on NN’s (neural networks) and RL (reinforcement learning) particularly good in global macro and equity selection as seen in the framework.

Lastly, Numerai represents a radically different model it is crowdsourced and powered by encrypted datasets and global data-science competitions incentivising participants through the Numeraire (NMR) cryptocurrency. Its meta model aggregates thousands of users

submitted ML models taking advantage through this extremely diverse ensemble to reduce overfitting and single-model bias. Despite this, its dependence on anonymized data limits the use of alternative datasets and real-world signals limiting its predictions in relation to Two Sigma.

Therefore, Two Sigma emerges as the most institutionally mature, technically diversified, and computationally advanced of the four hedge funds. Voleon and Rebellion excel in specific ML paradigms but show higher sensitivity to regime shifts, while Numerai provides an innovative crowdsourced method that prioritizes model diversity over data richness.

Two Sigma's ensemble-model architecture, alternative-data pipelines, and large-scale distributed computing infrastructure provide a level of robustness and adaptability unmatched by more specialized competitors.

From this analysis and comparison, it can be concluded that long-term success in AI-driven asset management depends not only on algorithmic sophistication but on data range, computational scale, research infrastructure, and the ability to adjust to structural market changes.

5.2 AIEQ ETF

AI Powered Equity ETF (AIEQ) is a great example of the compatibility among investment methods and the most innovative technology. Since its launch on October 17th, 2017, in partnership with ETF Managers Group, it has represented a pivotal milestone in the evolution of AI-managed funds, establishing a benchmark for how machine learning can be effectively applied to financial decision-making (Rothney, 2021).

AIEQ is arguably the most widely recognized AI-powered investment fund attracting the most of analyst attention despite not being the top performer in its category. It is the most visible AI-driven asset management to assess both the current capabilities and the limitations of this growing class of funds.

In relation to the first layer of the frameworks, this fund is managed entirely by artificial intelligence, leveraging IBM Watson's extensive data platform. Its system is designed to replicate the analytical capacity of roughly 1,000 market analysts, traders, and quantitative researchers, generating predictive models. It identifies investment opportunities and selects assets by analysing news, social networks, analyst reports and financial statements from more than 6,000 U.S. companies using highly diverse data sources. From this universe, the algorithm ultimately selects between 30 and 200 stocks that it forecasts will deliver outperform over the following year. The algorithm chooses exclusively financially healthy companies and has a great capacity to understand future macroeconomic factors (for example, investing in low-cost food companies when it seems that the economy is going to enter a recession).

As it is listed as an ETF, it maintains characteristics and advantages such as lower rates and no minimum investment capital requirement. It is particularly noteworthy how an ETF can now replicate analytical functions of analysts traditionally associated with hedge funds, potentially reshaping competitive dynamics in the asset-management industry (Valens Research, 2023). AI Powered Equity ETF seeks long-term capital appreciation and aims for maximum risk-adjusted returns against the U.S. stock market (AIEQ, 2024).

Many of the investments made by the AEIQ algorithm may seem of low quality, since following GAAP accounting principles the return on assets (ROA) is 7%, while the average of companies in the S&P500 is 12%. Therefore, the fund may seem like a worse investment, since the analysis is too reduced to the final return generated by an asset while not considering productivity and other important factors. In the GAAP (Generally Accepted Accounting Principles), there is a poor accounting of investment in R+D, intangible assets like goodwill or the value provided by synergies from acquisitions.

Making a re-adjustment through a systematic process called "Embedded Expectations Analysis" and analysing AIEQ's investments, the ROA of these assets including hidden values of the companies reached 16% (above average).

Moving on to the second layer, the ETF invests directly in equities listed on the US stock exchange, taking as a reference the results of its own quantitative model that was developed by the deputy director of the EquBot fund with the Watson AI platform. This platform allows you to build models using natural language processing, machine learning, and semantic networks.

The fund is fulfilling what it promised, replicating the work of many analysts without having a large expenditure on salaries while still being at an early stage of the process.

IBM Watson AI is a calculation platform engineered to respond to natural language questions through the combination of large data sets, pattern recognition and progressive learning from each analysis to improve accuracy as it analyses more data. This platform offers some technologies AIEQ leans on like Watson Studio²⁵ for the identification and reduction of inaccuracies or Watson Discovery²⁶ for natural language understanding.

EquBot's model evaluates and ranks the companies by their estimated ability to capitalize on prevailing macroeconomic trends and broader global conditions. It finds those with the highest projected potential for appreciation, assigning portfolio weights in proportion to both their relative ranking and their expected contribution to overall returns.

It stands out in the collection and interpretation of unstructured data, specifically the one with formats that are more difficult for analysts to interpret like social networks or blogs rather than conventional financial statements and others.

Through this process it aims to optimize risk-adjusted performance relative to the U.S. equity market. While portfolio managers count on the models ranking to select the securities to incorporate or remove from the ETF, the fund's deputy director retains discretion to execute additional buy or sell decisions informed by the model's outputs, while systematically considering liquidity constraints and the tax implications of each transaction.

The AIEQ's continuous buying and selling activity stems from the frequent adjustments to the portfolio brought on by its investment strategy and performance objectives.

3.1.6 ANALYSIS

Building on this operational overview, the following analysis evaluates how AIEQ's AI investment methodology has actually translated into actual market performance over the last years. The fund's historical returns allow us to assess the effectiveness of its AI-driven decision-making framework and its capacity to generate superior risk-adjusted outcomes in comparison to traditional benchmarks.

Looking at its performance trajectory from 2019 through 2025 Figure 15 and Figure 16 clearly illustrate a pattern of pronounced variability which in part reflect both the potential and the constraints of AI-driven investment strategies as well as general market variability.

Trailing Returns (%) Vs. Benchmarks

<i>Monthly Total Returns</i>	<i>AIEQ</i>	<i>Category</i>
YTD	1.40%	7.17%
1-Month	0.10%	3.30%
3-Month	1.93%	7.26%
1-Year	16.26%	16.20%
3-Year	15.36%	13.73%
5-Year	4.37%	9.12%
10-Year	0.00%	11.70%

Figure 15. AI Powered Equity ETF's Trailing Returns (%)

(Data: Yahoo Finance & Vanguard)

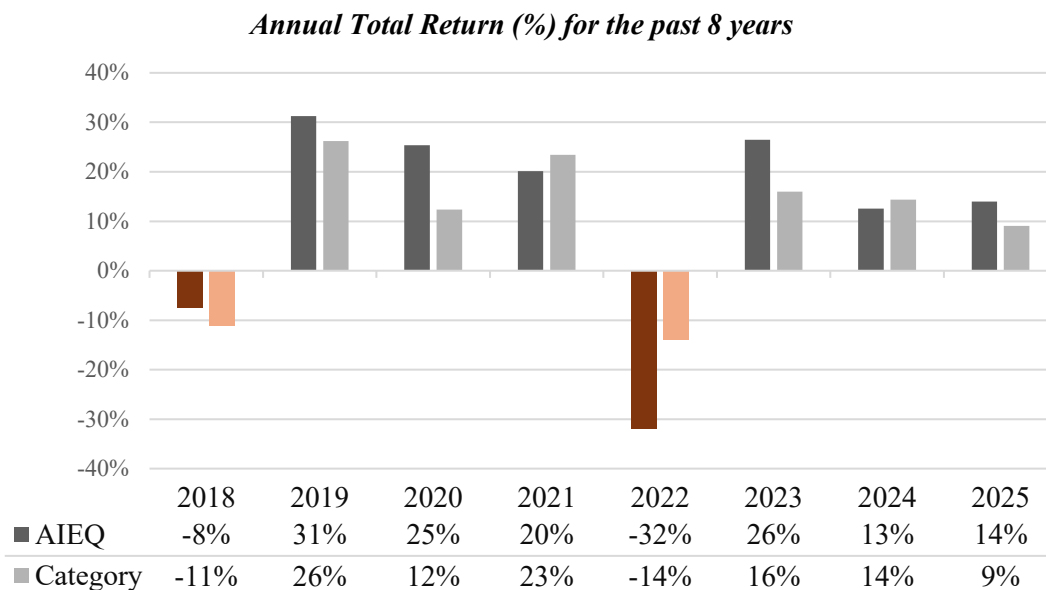


Figure 16. AI Powered Equity ETF's Annual Total Return (%)

(Data: Yahoo Finance & Vanguard)

- In 2019 the fund achieved an exceptional 29,7% return, by benefiting from its tendency to overweigh high-growth and defensive values during a favourable US macroeconomic environment.
- AIEQ maintained strong average annual returns of approximately 21% during 2020 and 2021 outperforming the S&P during the COVID-19 pandemic due to its rapid identification of opportunities in pharmaceutical and technological firms.
- In contrast, 2022 marked the fund's weakest year significantly underperforming the benchmark with a -31% decline as it struggled to adapt to rising interest rates, geopolitical tensions and the dominance of energy stocks. These factors challenged many quantitative strategies.
- The following year it managed to rebound with a 25,7% return though it again lagged the S&P 500 driven disproportionately by the magnificent seven¹, a concentration the model did not fully capture. This year was clearly marked by very few companies where these main seven represented 27% of the index and a 74% return.

¹ Apple, Microsoft, Amazon, Tesla, Meta, Nvidia and Alphabet

- During 2024 and 2025, AIEQ has continued to trail the broader U.S. equity market, with the ETF remaining below its 2021 peak in contrast to the S&P 500 who has advanced to new highs.

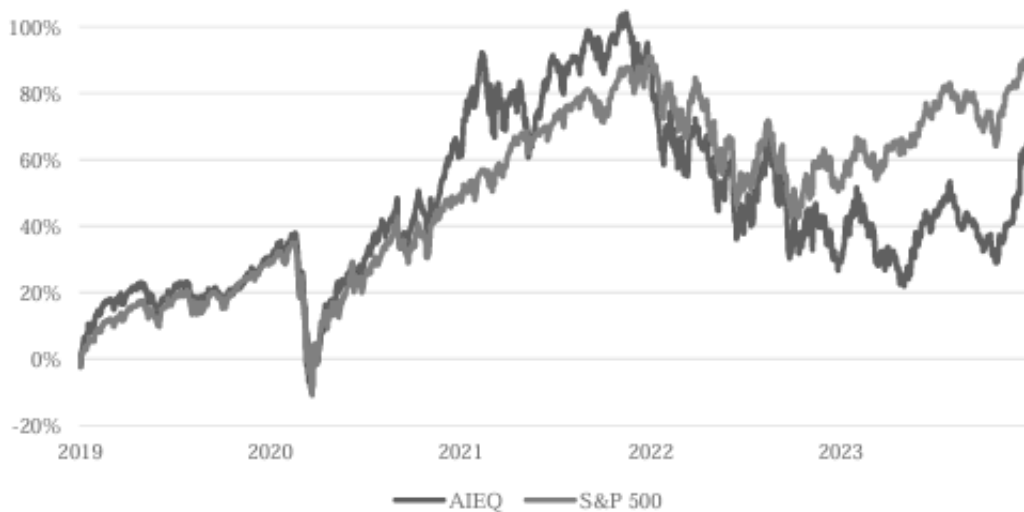


Figure 17. Historical Performance of the AI Powered Equity ETF

(Data: Yahoo Finance & Vanguard)

3.1.7 COMPARATIVE ASSESSMENT

This underperformance contrasts with other AI-enhanced ETFs such as QRFT and NVQ, who employ hybrid AI-factor models and have demonstrated more stable alignment with large cap market trends. Likewise, Canada's THINK ETF has also been more consistent than AIEQ in tracking the benchmark and has shown less volatility.

Comparing AIEQ (EquBot) to QRFT (Qraft) and BUZZ (VanEck) detailed in Figure 19, despite all being AI-powered they have surprisingly low overlap which indicates that each AI system selects very different stocks. In terms of factor exposure analysis, from a holding's perspective, the underlying portfolios compared to the S&P are quite dispersed on the quality, volatility, growth and momentum metrics shown in Figure 18 (S&P-Purple, AIEQ-Blue, QRFT-yellow and BUZZ-green).

From a valuation perspective they are not necessarily more expensive than the S&P except BUZZ, but they certainly are different in size (market cap). In relation to growth, they are

fairly similar to the S&P, but they are much more volatile while there is not much differentiation from a quality perspective.

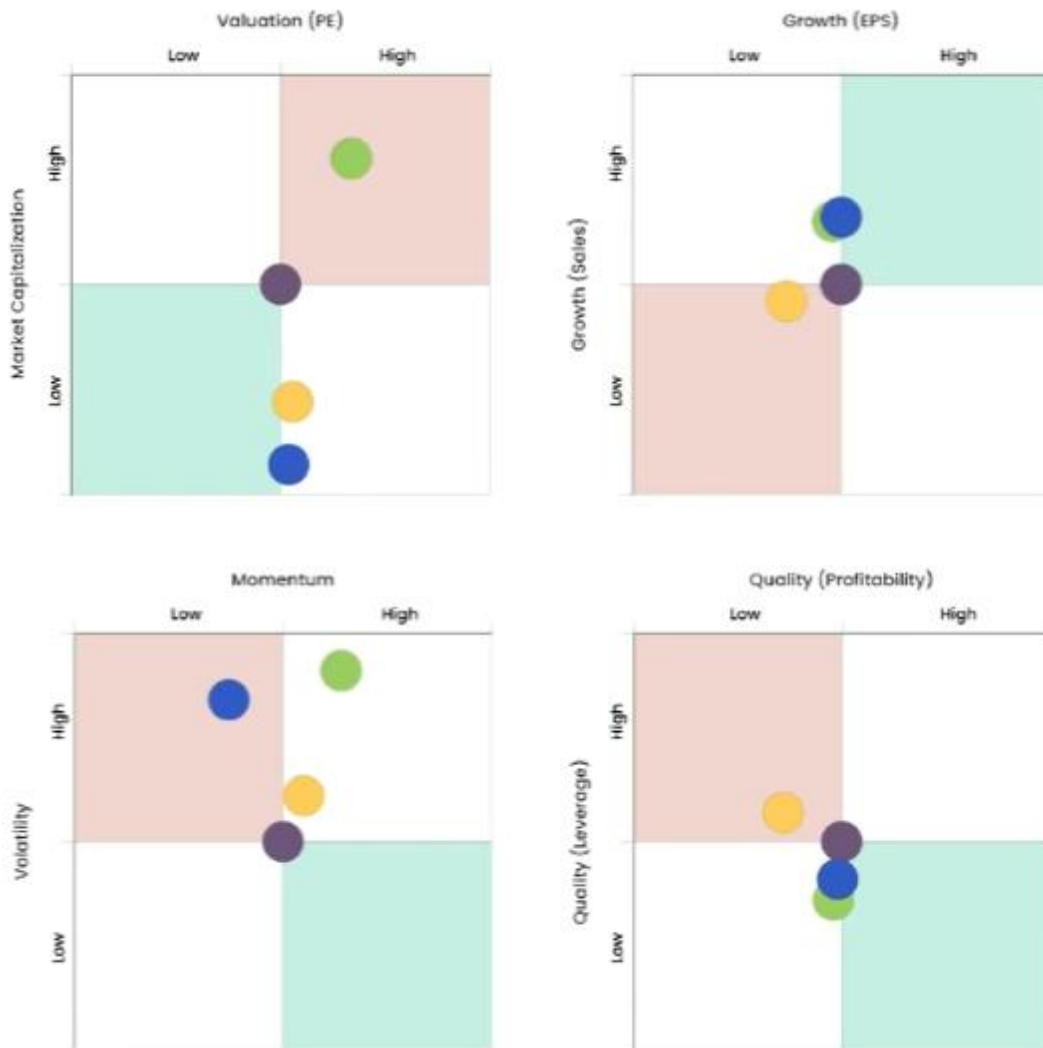


Figure 18. AI-ETFs key factors influencing returns: quality, volatility, growth and momentum

(Data: Finominal)

From a returns-based exposure analysis, these 3 funds are slightly more expensive considering an equity effect, they have a negative exposure value factor, negative momentum exposure and negative low volatility exposure. What is more interesting is the exposure to the stock market. AEIQ and BUZZ have very high betas to the stock market (1.3 and 1.8 respectively) which is a levered bet on the stock market as it indicates the exposure to small caps since these ETFs are more risky than the market.

In general, despite their technological sophistication, AI-powered ETFs have not demonstrated superior risk-adjusted returns and have instead exhibited higher volatility. A central point raised is that AI-driven ETFs have largely missed the large-cap technology rally that dominated U.S. equity markets from 2020 onward. This is particularly relevant for AIEQ, whose algorithmic model tends to diversify across thousands of companies rather than concentrate heavily in the magnificent seven who accounted for a disproportionate share of S&P 500 returns in 2023 and 2024.

<i>Indicator</i>	<i>Fund Name</i>	<i>Type</i>	<i>1-Year Return</i>	<i>Key Features</i>
<i>AIEQ</i>	Amplify AI Powered Equity ETF	AI-managed ETF	17%	Uses IBM Watson to analyse data and make stock picks, trades actively. It was the first true AI-managed ETF in the U.S., launched in 2017. While it underperformed at times, its recent returns are improving.
<i>QRFT</i>	AI-Enhanced U.S. Large Cap ETF	AI ETF	14 -15%	AI selects stocks based on value, quality, momentum, and size factors. It is gaining traction for using deep learning models to select large-cap and value stocks.
<i>NVQ</i>	QRAFT AI-Enhanced U.S. Next Value ETF	AI ETF	18%	Uses AI to identify undervalued U.S. stocks. It has had strong performance post 2020.
<i>BUZZ</i>	VanEck Social Sentiment ETF	AI-driven sentiment ETF	10 -12%	Uses NLP to track social-media sentiment across U.S. equities. Its performance highly dependent on retail-investor trends and online sentiment cycles.
<i>THINK Horizons</i>	AI Powered Equity ETF Canada	AI ETF	12 -14%	Canadian counterpart to AIEQ, managed by Mirae Asset and IBM Watson.

Figure 19. Top AI-Managed Investment Exchange Traded Funds

QRFT and NVQ have delivered more consistent results, largely because they use AI to enhance factor-based strategies rather than to autonomously select individual securities. This hybrid approach appears to mitigate some of the risks associated with fully automated decision-making.

Taking together these results, they highlight that while AIEQ's fully autonomous AI model excels in environments with clear sectoral momentum or rapid recoveries, it is still extremely sensible to periods of high market concentration, macroeconomic shifts or regime changes.

Over the evaluated period, the fund hasn't consistently outperformed the S&P 500 nor its AI-enhanced peers, indicating that currently, portfolio construction solely with IA still faces structural challenges to deliver sustained returns. AI performs better as a complementary tool rather than as the sole portfolio manager.

Current AI models excel at processing large volumes of data but still lack the contextual understanding required to outperform diversified benchmarks such as the S&P 500 over extended periods.

6. CONCLUSIONS

AI-based investment techniques like quantitative and ML approaches have shifted the decision-making process of professionals when examining data and making judgements. AI's rapid data processing and trade execution abilities have been used in quantitative methods such as high-frequency and algorithmic trading. Additional AI adoption and integration in the financial sector is growing fast and opening new investment prospects.

While its 3 core advantages are improved portfolio management, risk management and better operational efficiency, some constraints such as data quality, model interpretation, potential biases or ethical and regulatory issues still need to be considered. Norms and ethical frameworks are being developed to tackle important ethical issues like potential market manipulations or algorithm biases.

Recent improvements in AI model explainability calm regulatory concerns and enhance reliability and trust in AI-driven investment decision-making. Hybrid human-AI approaches

The future competitive advantage of investment funds will likely take a shift from current single investment models to whole integrated AI capable systems. Building these complete AI ecosystems integrating data, algorithms, talent and computing power requires institutions to make long-term investments like accumulating data, developing talent and supporting technology R&D. This proposed framework aims to shed light and help construct these AI system capabilities.

Additional interesting case studies can be Renaissance Technologies and its Medallion Fund, Systematized Intelligence Lab from Bridgewater Associates, Numerai, BlackRock's Aladdin platform or other cases such as roboadvisors.

The future use of AI in fund management is not focused on the complete replacement of humans with machines but the collaboration among both as even top-tier AI technology requires financial expertise. Leveraging the technical advantages of AI like processing massive amounts of information while retaining human creativity, ethical and strategic

judgment as well as value orientation sets the stage for more robust intelligent and sustainable development of investment funds.

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