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Chapter 2: How artificial intelligence is reshaping portfolio strategy, wealth allocation, and investment advisory

2.1. Introduction

To the best of our knowledge, this is the first paper that highlights the impact of artificial intelligence (AI) on three main areas of wealth management: portfolio strategy, portfolio construction, and advisory, and how it is changing the landscape and tradition of one of the oldest professions in history. Therefore, we aim to shed some light on the influence of AI on portfolio strategy, wealth allocation, and investment advisory and raise several important questions and considerations while pointing to the opportunities and challenges that AI poses on this field which has not received much attention yet. As with other sectors of the economy, wealth management is also undergoing a significant transformation caused by digitalization and disruptive technological innovation (Lunkkadd & Bhandari, 2023; Martin et al., 2023). People move from offline to online in every aspect of collecting and exchanging information, as well as in executing transactions related to banking, wealth, and insurance management. Today, many traditional banks and wealth managers compete with so-called fin-techs that offer new technological driven solutions. In order to adapt, survive, and prosper in this fast changing environment, traditional banks and wealth managers are required to revamp and rethink their strategies related to portfolio management and advisory. Technology is seen as a key driver for differentiating offerings, enhancing efficiency of operations, and improving customer experience. Improving customer experience is important, because customers revenue generation is shrinking driven by a decline in profits interests and high levels of competitiveness. New sources of revenues and value creation must be pursued, which could lead to a more profitable business model. Recently, the rise of artificial intelligence has radically shifted the components and characteristics of the technological landscape and its importance in the business decision making. AI promises to enhance decision making in several ways, supporting financial analysts and advisors in their recommendations and allowing investment solutions to be achieved faster, at lower costs, with higher margins, as well as be more informed and controlled (Generative AI Team, 2025; Harper, 2025; WealthBriefing, 2025).

2.2. The Evolution of Artificial Intelligence in Finance

To comprehend where we are going with AI-enhanced investment advisory, we must first explore where we have been. In finance, there have been at least three distinct epochs of financial AI, most of which are coupled with the evolution of computing hardware, availability of large data sets, development of algorithms, and capacity for testing in a reasonable time frame. Each of these epochs has been associated with the use of algorithms for high-frequency decision making on trades, in order to supplant institutional traders and exploit information asymmetries to achieve excess trading profits. The first epoch, which we term 'narrow AI', began with the rise of computerization of information flows in the 1980s and 1990s, and use of financial databases to develop quantitative strategy for various investment styles that were fed into institutional trading desks and management companies.

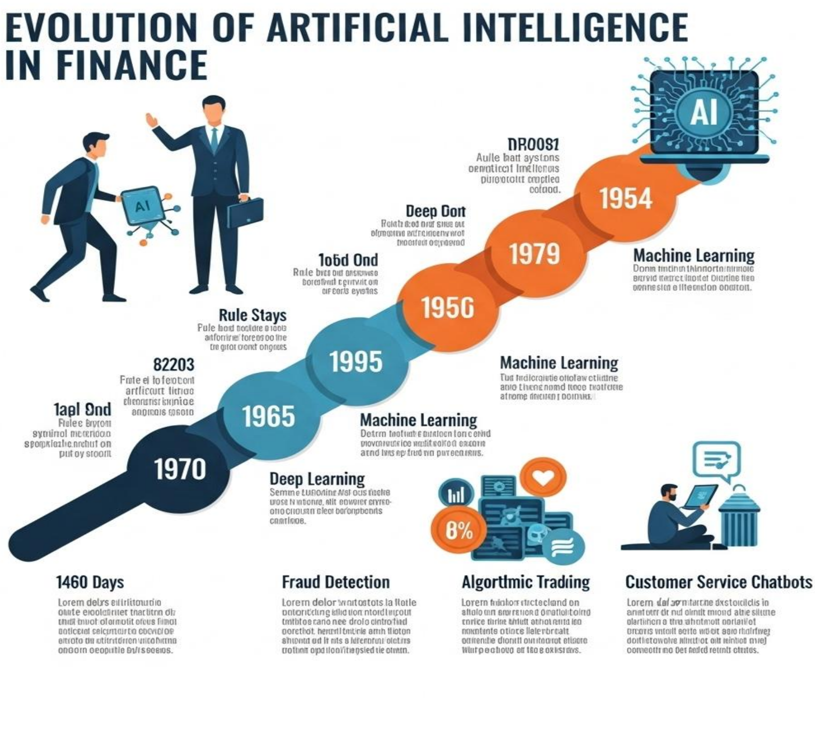

Fig 1 : The Evolution of Artificial Intelligence in Finance

The second epoch is characterized by multi-variant statistical approaches, usually based on factor classification schemes that are used to predict the historical relative performance of asset classes, factors, or instruments, and their smoothing over time and space. With more substantial, classified, and cleaned financial data being made available, especially for alternate investments, the third epoch began to explore the use of novel algorithms based on neural nets and related technologies, notably deep learning, that became practical from 2010 onwards, especially for image detection and analysis, and then migrated to other time-series and sequential data pattern detection problems like sentiment analysis. This third epoch has shown promise for classification of systematic relative-market-risk-and-return strategies over time series, and can be innovatively implemented for risk management in loss control during adverse volatility.

2.3. Understanding Portfolio Management

Portfolio Management is the idea of developing an optimal investment portfolio from different investments. An investment decision is an at once un-hedged gambit on the uncertain outcome of the future. Investment portfolios seek to optimize outcomes against investment uncertainty faced by investors. Portfolio decisions are therefore of utmost importance. No investment motive or reason-based return concept can do without a consideration of investment risk and vice versa. Investment risk and return mean a lot more than just volatility about the mean of observed financial asset returns. The captain of the ship is not bothered or even cares about the small waves generated by a passing jet ski if the ocean is in calm waters. But when the ocean is dark, stony, angry, and towering, the on-looker watches in stunned silence from the safety of the shore and quivers with fear at the approach of a hurricane and hopes for divine intervention. It is this occurrence of rare albeit disastrous multi-periodly high and positive or negative extreme returns and their nearby high correlation that makes portfolio management critically different from primitive investment decision-making.

One of the earliest pioneering theoretical studies of Portfolio Management is the famous Mean-Variance Portfolio Theory. The social planner risk-return theorem tries to optimize the allocation of capital towards different assets. This theory has been embellished with many embellishments like considering different distributions, a distribution pruning optimization mathematical model, and risk premiums taking into account density estimates or time-varying investors' risk preferences. All these embellishments aim to minimize the objective function defined to mean variance utility. The theory is very elegant in its precision and the tools and logic it uses. It has actually set in motion the immense growth of modern derivatives with it facilitating a large number of relative price models used in the market at any point in time for trading in derivatives and other securities.

2.4. AI Technologies in Portfolio Strategy

Outreach has been either relatively sparse or relatively undeveloped when it comes to exploring the impacts of AI technologies on portfolio strategies. There have been a growing number of research papers that explore microstructure, volatility, or informational asymmetry questions using deep learning, but only a small handful of papers have suggested methods, proof of concept implementations, or outlined specific implications and effects of portfolio decision analysis and portfolio construction strategies using deep learning or other machine learning methods. Specifically, the work that has utilized these methods is often exploratory and describe success as the result of an optimization approach, suggesting a simulated AI portfolio system. Aside from the strong reinforcement learning portfolio construction work, which proposes a theory of asset pricing in which reinforcement learning plays a significant role, much of the published work has looked backwards at synthetic results over a limited timeframe with limited real-world specification using deep learning techniques.

Overall, AI technologies are still at an early phase of affecting portfolio strategy and wealth allocation architecture in the wealth management industry, and our guess is that the first effects will probably involve NLP systems that face the advisor and client in the task of understanding the needs and desires of the client. Optimization and prediction from big data is likely to follow, as is client management and onboarding from improved NLP capability. As demonstrated in the previous section on NLP, there are quite a few papers that have implemented or designed sentiment, mood or emotional informed models already; it is a good guess that NLP methods indeed will be among the first AI technologies to affect wealth management portfolio approaches, probably supporting advisors instead of replacing.

2.4.1. Machine Learning Algorithms

Machine learning algorithms seek to estimate the parameters of a function that is in itself unknown, given an input dataset in order to output the corresponding observations. The classic statistical simplest way to approach this task is through regression models like ordinary least squares. Here, one specifies a type of relationship between the input variables and the output variable in terms of a parametric function. Then, the parameters of this function are estimated from the training sample through minimizing the chosen loss function. However, this approach is often not feasible since the functional form defining the relationship between inputs and outputs is frequently not known. In this case, a parametrization of the relationship between the two with respect to the chosen input variables is not attempted. Instead, one specifies a particular parametric machine such as a neural net or a boosted tree ensemble but no prior functional relation, between the two. Then, one fits in the training sample a particular machine from this space of machine alternatives, given the observations, which minimizes the chosen loss function. The decision of which inputs to allow into this "machine" is again a trial-and-error process and the researcher relies upon experience as well as accommodating or overfitting fitted errors. More recent advances such as dropout or slack in the case of neural nets specifically address this overfitting issue, by randomly slackening the emphasis on certain specifically chosen weights.

Recently, machine learning algorithms from supervised to semi-supervised to unsupervised to reinforcement learning have become more commonly used. Along the supervised learning paradigm, models become more common when the input and output datasets are from the same training distribution. They adapt easily from similar tasks and are used in applications like parameterized predictive modeling, error-detecting coding, neural machine translation, and speech analytic applications such as speech recognition and speech synthesis. They perform explicitly worse than semi-supervised algorithms in applications like sentence classification and statistical machine translation on labeled datasets. The broad class of generative algorithms includes contrastive divergence, discriminative algorithms include structured perceptrons, and adversarial algorithms include generative adversarial networks. These approaches are often using difficult-to-create unannotated datasets.

2.4.2. Natural Language Processing

Natural language processing is also a practical field within the broader Artificial Intelligence paradigm and focuses on applications involving interaction between computers and human languages. NLP has allowed developers to build systems that understand any text-based query and then immediately executing such tasks. It offers a unique learning experience using unstructured, contextually complex data.

NLP applications have greatly improved in recent years, especially with developing Large Language Models – NLP models that are based on Transformer Neural Network Architectures and leverage vast training datasets combined with Reinforcement Learning from Human Feedback. LLMs have increasingly become the go-to Pet Project Technology and can now successfully solve over 60% of the tasks in known NLP benchmarks. These tasks, such as sentiment prediction or dubbed 'next word prediction,' are less than perfect but are sufficient enablers for industry applications.

The Token and ChatGPT LLMs have been the hot topics recently. However, the task automation and sentiment analysis offerings based on simpler, either rules-based or less powerful, in-house taxed LLMs, had already been integrated into many corporate strategies across industries such as e-mail auto classification triggered, proposal pricing, financial reporting digitization, sales prediction and customer service. Familiar financial services examples include Fraud Alerts and Credit Scoring at the loan origination accuracy improvement stage, Regulatory Compliance and Risk Reports generation forecasting bots, and Investor Relations analyzing firms' actual versus forecasted results queried. The banking needs have always existed – only the people capacity required to address them has increased.

2.5. Risk Assessment and Management

AI opens the door to a comprehensive, multi-dimensional view of risk, spanning diverse types of risks, asset classes, time horizons, and investment objectives. This promises to transform risk from the Achilles' heel of the portfolio approach to its cornerstone. When investing in a portfolio, investors expose themselves to a multitude of risks, including asset price risk, trapping investors on the wrong side of an asset price bubble or collapse; dimension risk, incorrectly estimating the cost of capital, which can trigger drastic misallocation toward high- or low-risk dimensions, such as equity versus fixed income, domestic versus international markets, or growth versus value companies; correlation risk, designating very correlated assets or non-correlated assets for behavioral reasons to a portfolio, especially during times of market stress or turmoil; financing risk, estimating the wrong cost of capital or leverage while investing; and trading risk, totally overlooking liquidity in equity or debt positions, triggering the inability to exit the position when needed.

Investors who follow the modern portfolio theory are aware of their exposure to the above risks but are unable to view them holistically in a manner that shows how they ultimately impact portfolio performance simultaneously. Some investors have traditionally relied on consultants or risk modeling solutions to provide some of this value-added, but in very serious conversations with many wealthy clients, it has been found that they have undergone this process without any formal thinking. AI has given the high-net-worth investor and family office decision-maker the opportunity to efficiently do this in-house, using AI-driven predictive analytics tools that are now easily accessible and whose cost is coming down rapidly. They are able to embed their personal investment philosophy, behavioral biases, moral values, and investment beliefs just as seamlessly as they used to get this service from their advisor.

2.5.1. AI in Risk Modeling

The efficient market hypothesis asserts that financial markets are efficient with respect to information, precluding retrospective predictive ability of extraordinary accuracy for price portfolios. This, however, does not apply to risk modeling, which estimates probable changes in the values of securities and portfolios that may occur due to identifiable factors. While the efficient market hypothesis would make it implausible to use pure data analytic methods to forecast security values with unusual accuracy, it does not negate the potential of these methods to provide valuable insight into predicting changes in risk, and in risk exposure, particularly at the extremes. Like house prices on average, highly priced assets are unlikely to face dollar declines in value that will not be reflected in similarly poor performance by a multitude of assets that form the risk factors. Security prices form no barrier against portfolio-based analyses of risk modeling, whether these are factor-based models or data-based models that identify risk factors through principal components or machine learning clustering algorithms. Given that risk modeling is not subject to the efficient market hypothesis, for the past unconstrained portfolio, AI analysis is highly predictive.

It has been successfully employed to capture the dynamics of changes in the factor sensitivities of stocks for risk monitoring and risk attribution over shorter intervals of time. While enhanced predictive ability is possible only if sufficient historical data on the characteristics of risk exposure across assets and/or portfolios have been stored, state-of-the-art neural network architecture is also available for transfer learning. Further, extensive research to date has established that while traditional methods may have their own challenges and drawbacks, they can still yield informative and reliable results on the dynamics of risk factors available.

2.5.2. Predictive Analytics for Risk Mitigation

Various risk assessment reports have highlighted forecast increases in geopolitical, economic, environmental, and technological risks. Therefore, the need to factor downside risks during the investment decision phase is paramount. This consequently increases the demand from clients for risk-conscious return-motivated wealth allocation strategies. Here, predictive analytics, including machine learning techniques, can be extremely useful in mitigating and delineating investor portfolio risks in the wealth allocation process.

AI tools, through their reinforcement learning algorithms, can help assess whether an event would have a significant effect, even if that event is not an immediate concern. This is significant given that the data used for our forecast does not include several of the events currently being discussed, which could lead to political unrest, and a subsequent downturn in GDP growth. Whilst we are yet to achieve a cognitive machine, in general, AI currently struggles to process vague concepts. However, through Big Data sets that capture vague concepts, researchers are trying to automate the consideration of uncertainty surrounding complex predictive statements used in risk assessments. Opportunity identification is an essential part of the wealth allocation process for as long as it offsets the potential risk associated with holdings. Investment in AI in the near future is clearly essential for more efficient portfolio-wide asset selection and trimming efficiency.

AI tools have also made advancements in effort optimization of asset risk management. Such tools can be integrated to help determine maximum risk tolerances. They can also be efficient in portfolio optimization through effective asset and sector allocation. Many global fund houses have recalibrated their risk management divisions to seek further efficiencies through digitalization with such predictive analytic tools as partners. Such capabilities would ensure that portfolios remain inherently risk adequate across market cycles and exploit active asset selection opportunities.

2.6. Wealth Allocation Strategies

Within the accepted Investment Policy Statement (IPS) each client specific investment strategy is articulated and approved. The process to develop the IPS and the wealth strategies it contains utilize factors like historical performance for the specific investor's risk profile, how these asset classes are expected to behave in the future, the time horizon necessary for compliance with the investment objective, and the specific tax considerations for that investor. It may also include questions about liquidity needs and preferences in the event of substantial portfolio gains or losses, cost tolerance during maintenance of the portfolio, desire for diversification, etc. These elements taken together dictate appropriate strategy and mix, but strategy-conflicted advisors and management teams may influence the optimal weighting within the asset classes – particularly equities. Non-optimized weighting within the asset classes can be responsible for unexcused underperformance. Asset managers that focus on a particular stylized or regional execution strategy may dictate portfolio weights that vary significantly from the asset class level.

The IPS is a guiding framework that must be updated as the client's life cycle evolves, changing their risk-return proclivities as they age or as their businesses progress through their growth stage into the harvest and maturity stages. Dynamic asset allocation (DAA) manages asset class weights at levels and speed parameters consistent with the investment objective using the Life Cycle Asset Allocation (LCAA) as a baseline. Weighting band deviation from LCAA defined baseline weights can further protect against asset managers pushing equities larger than the client risk profile can manage. Factor-based investing strategies may be employed to determine the operational equity weights to justify the active-manager weights used to populate the relevant asset classes. Factors can further refine beta tiny allocation within the equities asset classes. Both DAA and factor-based investing can enhance alpha within the equities asset class.

2.6.1. Dynamic Asset Allocation

Dynamic asset allocation is a rule-based investment strategy where long-horizon investors such as pension funds temporarily deviate from their strategic asset allocation mandate by gradually increasing (decreasing) their investment in risky assets as their levels of funding deficits (surpluses) grow (shrink). For instance, if a pension fund underfunds its growing liabilities due to falling bond prices, it would increase the duration of its characteristic investment in long-term bonds. If this does not bring the fund back on track, the fund ought to gradually increase (decrease) the share of low (high) expected excess return assets such as equities (bonds) in its asset mix, which simultaneously reduces (increases) the hedging role of bonds that is crucial for regulating funding risk.

Most long-term institutional investors use proxies in their networks of treasury managers and asset allocation committees to decide when to deviate from traditional models-based strategic asset allocation in which they optimize terminal wealth while maintaining solvency and liquidity throughout the investment horizon by holding a fixed portfolio of stocks and bonds with weights based on expected returns and model estimates of risk. They respond reactively to significant changes in their funding position such as after market drops at steep declines in the price of risky assets or periods of poor performance. Instead, they should regularly use data models to proactively decide when and how to adjust their risk exposure on a much more systematic and frequent basis driven by market valuation and the funding position. The regularly generate from historical back-testing one-step-at-a-time optimal risk budgets based on expected returns would be much more useful than implicit long-duration assumptions about the current investment horizon, expected excess return, risk, or risk aversion.

2.6.2. Factor-Based Investing

The Insights From Factor-Based Investing will be a promising blueprint of the Strategies in a New Era of Web 3.0. In this part, we shed light on the insights from factor-based investment strategies for the following reasons. The building blocks of financial markets indicate investment opportunities in explorers of new paradigms of unexplored innovations in early stages of developing tiles of new Blocks are becoming appealing. Factors, considered as pricing errors over the long run, are the potential exploitable factors that can be generated by the Agents in financial markets. Therefore, the ground works of Long Short Strategies will also be favorable for investors to build up Long Short Strategies over the Pricing Errors in the financial markets, which serve as pricing errors over the long horizon of exposures to hexagonal blocks designed by ubiquitous factors. Given that Algorithms have played and will continue to play a big role in efficient price discovery across the markets of Finance and Economics, it is also likely that Factor Based Investing can work with Allocation Strategies to be developed by Imitative Agents to reshape the Exploring and Exploiting Strategies.

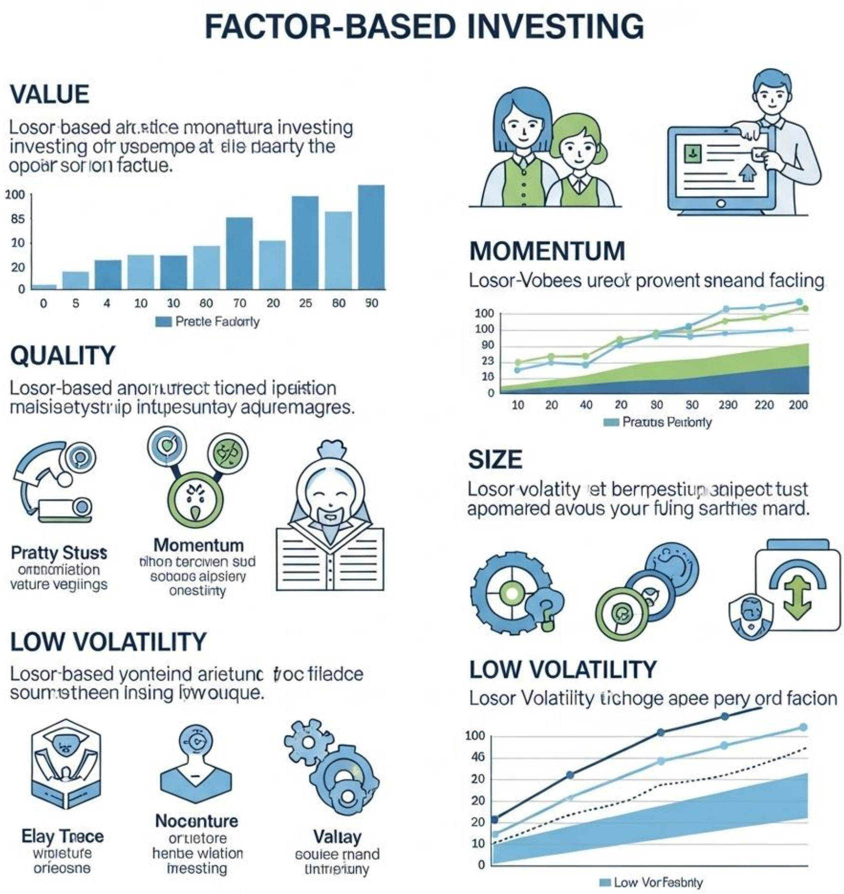

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Fig 2 : Factor-Based Investing

Factor modeling is based on the assumption that the returns on a security and portfolio can be explained by exposures to a number of exogenously specified factors. Mathematically, we express the excess security and portfolio returns as a linear function of factor surprises. These factors can also be grouped by their bases -style, behavioral, exploration, growth, energy and crisis. Style factors, notably size, book to market, momentum, stock prices, earnings estimates, and stock price volatility, are considered to be the pioneering inducements of process-oriented investing who seek mispricing opportunities in the pricing process. On top of the established factors, sentiment based behavioral factors are newly gaining prompts from sentiment indicators which aim at discovering non-fundamentally informed agents who influence mispricing dynamics.

2.7. Personalization in Investment Advisory

2.7. Personalization in Investment Advisory Investment advisory, including recommendations pertaining to investing on the equities and fixed income markets, commodities and synthetic products, encompasses an array of strategies with differing risk-return profiles. They can perform opportunistic but tactical allocations into investing styles based on liquidity adjustments, such as value, growth, credit risk and momentum. Structural investment strategies are often classified according to major cyclical growth regimes, which include inflation, recovery, mature growth and recession. There are arbitrage strategies, which seek to profit from temporary price discrepancies. Investment advisors base their recommendations on asset price modeling processes and on major economic inputs likely to govern future price dynamics. Predicting business cycles is thus crucial. Since the Global Financial Crisis, many questions have arisen on the existing investment models, including the asset allocation mechanism which interpolates mean-variance efficient portfolio allocation, with a priori views exerted on the risk premia for equities, fixed income, foreign exchange and currencies markets.

2.7.1. Robo-Advisors Robo-advisors have entered the investment advisory services landscape, offering scalably cheap portfolio management services for young investors. Based on the modern portfolio theory, they create and manage multi-asset and diversified strategies focusing on total return from long-term capital appreciation and income based on inferred investors risk-return affinities. Tuning portfolio track record data to optimized liquidity and risk appetites, robo-advisors have integrated behavioral finance into their algorithms and have added various thematic advisor options, such as environmental, social and governance (ESG), factor based approaches, cryptocurrency allocations, security selection and strategy performance comparisons into their platforms.

2.7.1. Robo-Advisors

Robo-advisors are online investment platforms that provide automated financial advisory services. Driven by algorithms and artificial intelligence, these services are changing the landscape of wealth management—that is, the investment advisory space traditionally occupied by commercial banks, brokerage firms, or private banks and wealth management asset managers. Robo-advisors employ advanced algorithms for various tasks associated with the portfolio creation process. From client onboarding and risk check, through asset allocation and rules-based rebalancing, to reporting and tax-loss harvesting, most of the major tasks are fulfilled by algorithms with the minimum human interaction. Fees charged by traditional wealth managers and private banks are high due to the complexity and personalized nature of their investment services. Robo-advisors are betting on a 'one-size-fits-all' tunnel vision and promise to provide investment advisory services for minimum fees. The trade-off is minimal face-to-face interaction with clients and a more generic nature of portfolio solutions.

While the advantages of low fees and focus on young, tech-savvy, and lower-wealth customers add a level of empathy and beauty to the robo-advisory model, it fails in many cases to provide the depth of personalized service and portfolio solutions typically offered by a human investment advisor. There are various areas along the wealth management investment advisory process flow where human capabilities, judgment, and experience deliver superior value and returns. Wealth planning, estate management, philanthropic planning, and family dynamics require a behavioral perspective and judgment reflection. Most certainly, the robo-advisory model has modified and catalyzed the wealth management industry business model.

2.7.2. Client Profiling Using AI

Real estate and art have been important parts of investment portfolios for thousands of years. They are a legacy of vast empires and considerable wealth. At first, because of their illiquidity, they were not part of most asset allocation problems. Then came product innovation. During the past fifty years, real estate investment trusts have made real estate more liquid. And art funds were created about twenty years ago. Tokenization and blockchain are now bringing art and real estate to the general market. From a portfolio wealth allocation perspective, they are asset classes together with stocks, bonds, commodities, and currencies.

Effective portfolio management requires two sets of expertise. First is the know-how on different markets. Such knowledge accumulates with experience—either from making the trades, or, in the case of wealth managers, from overseeing or helping clients make the trades, and feeling the consequences. Second is an understanding of the particular client's profile, needs, and objectives. A wealth manager needs to decipher the financial situation and wealth objectives of the client in order to manage the portfolio satisfactorily. Before the digital age, the process involved was entirely manual. The client would meet the manager, answer a number of questions, and further information would be gathered from the client's financial advisors, tax advisors, banks, and other players. The entire exercise was tedious, time-consuming, and often inefficient. The advent of digital solutions has made it much quicker and easier to gather large pools of data from varying sources, such as online accounts linked to banking, payments, transactions, and other services. AI can organize different types of data to find hidden, insightful, useful patterns.

2.8. Ethical Considerations in AI-Driven Investing

In modern portfolio allocation and investment advisory, artificial intelligence (AI) offers many advantages, but it also presents new challenges, especially ethical risks that have so far received little attention. We will elaborate on AI ethics through two specific and important dimensions: algorithmic bias and transparency and accountability. Explaining the ethical challenges that accompany AI is needed as an introduction to the optimizing portfolio maximization problem itself in that richness enhancement and risk hedging with AI. Richness enhancement and risk hedging entail incorporating investors' idiosyncratic preferences to the portfolio and designing a wealth allocation for investors that takes the wishes of investors into account while at the same time representing financial stability for society. AI can help the advisor serve customers better and support the customer-advisor relationship. In doing so, it takes the secret out of the art of investing.

Technology cannot remain a black box if investors are to benefit from investments services supported by AI technologies. The technology has to be explainable so that the customer understands to a sufficient degree in what way the AI solution supports the advisor and the decisions. Also, the advisor needs to understand to a sufficient degree what the AI is doing; otherwise, the advisor cannot provide value-added services to his or her customers that are not covered by the AI. Although wrapping the AI in a more conventional structure or model might decrease the performance, it can make economic sense for the underlying service provided by the advisor custodian of a portfolio, especially if the AI-based solution has become a commodity solution.

2.8.1. Bias in Algorithms

Outsourcing decisions to algorithms has raised the concerns of large swathes of civil society about the biases we expose into the decisions we offload such that contemporary companies are not outfitting decision-making processes free of bias. Should we permit the rationale behind our saving and investing decisions to be determined by forces external to trusted entities? Bias is defined as a necessarily defined deviation from a true measure. The development of algorithms to assist in decision making involves the association of influences to be filtered through heuristic decision rules. Datasets are identified to actually offset-develop algorithms in predictive analytics. What influences investor decisions? The application of predicted investor behavior to portfolios and products may enable differentiation and customization. However want of care taken with judgement, design, and testing of algorithms on the road to digitalization in finance creates digital bias.

The data that drive algorithms are biased through the variables selected for inclusion and exclusion from the predictive equation. Portfolios are made from instruments often weighted on risk/reward criteria. It is a short distance from these decisions to the weighting of predictive analytics associated with customer characteristics to motivation, need, and sentiment. Portfolio bias may thus reflect algorithm bias. Algorithmic bias enters the customer decision-making and the investor data analytics used to represent sentiment at the various portfolio levels. Such bias may be cumulative along the value chain through the varying algorithmic portfolio actions of the various players. All are competing for the same client resource, the affordable and investable dollar. Bias associated with lack of care in decision making all along the pathway to digitalization may have its most serious future impact on custom client wealth creation, the business of both portfolio managers and financial advisors.

2.8.2. Transparency and Accountability

There is a growing demand for transparency and accountability in investment processes. Whether it's the need for statement coverage in investment strategies and trade generation, the explainability of a model that suggests buying a certain amount of an asset from a basket of possible transactions, or the documentation of every activity involving sensitive data, it is important to ensure that investors have the ability to trust both the data on which decisions are based and the algorithms driving business workflows.

Under the Investment Advisors Act of 1940, regulated investment companies like mutual funds must disclose their strategy and seek to adhere to their guidelines. When a firm registers as an RIAs, they offer a full set of investment descriptions and portfolio restrictions. This investment company has a fiduciary responsibility to shareholders, and any deviations from an investment objective or strategy must be disclosed. These stringent requirements obviously do not extend to all financial market players. For instance, systematic hedge funds are not required to disclose their models or even report their results. Regulatory considerations, depending on the jurisdiction and the entities involved or available means of recourse, differ for the institutional and retail clients of algorithmic decision-making systems handling sensitive personal data and using algorithmic techniques that reduce the potential for disclosure. However, the lessons in cybersecurity breaches at companies that handle consumer data exemplify how no one is immune from the consequences of abuses of sensitive data when it becomes public.

2.9. Challenges of Implementing AI in Finance

The implementation of AI in finance is not without its challenges. The first major hurdle is the availability of robust data. If we assume that finance is properly built upon reasonable assumptions such as market efficiency, the asset price at time T just reflects the information available at T. There is thus a tendency to reject the relevance of past information in terms of trading strategy, which creates a skepticism towards the relevance of the more sophisticated AI machine learning techniques. Regulators impose additional constraints, along the concept of fair and non-discriminatory behavior of financial institutions. It is fair to say that the amount of potentially available data offered by the different regulators is poor relative to the amount of data publicly available compared to what is the competitors' prerogative.

Data privacy has become a major concern today. It is of utmost importance for consumers to feel protected from predatory tactics that could stem from the wealth of data available in company databases, which makes the necessity of regulation imperious. This may be a special concern for financial markets which have been subject to numerous scandals over the years, which negatively impacted the reputation of the banks in the eyes of the public. The potential use of the various modeling AI techniques that would allow financial institutions to deliver personalized predictive models for clients transgressing the ethical boundary of client data confidentiality is enormous, and needs to be framed within the boundaries offered by the new legislation imposed by regulators. Building on this danger of loss of trust by customers, the second challenge for institutions is the trustability of the information processed. Financial institutions have built their reputation over hundreds of years around their competence and expertise that allow them to be confident prescribers.

2.9.1. Data Quality and Availability

Data quality is often overlooked as an important component of finance data. Strategic use of the 5Vs of big data analysis: Volume, Velocity, Variety, Veracity, and Value can help counteract quality issues. Financial databases typically consist of error-prone data repositories populated with company information either from official company reports or machines scraping data from company websites. Financial data has also been estimated to contain a significant portion of missing, incomplete, inconsistent, and inaccurate data entries. Important factors such as human involvement in available data processes, difficulty in verification of the available data, speed of data gathering processes, scale of data accrual, and management practices of how data is collected can determine quality of such databases. Wall Street’s interest in using sentiment analysis of corporate earnings calls has led to several resources deploying different versions of this technique; however, had serious data issues. The main issue raised though was at the time in terms of completeness of the database for companies and their respective calls.

Additionally, many sentiment analysis techniques ignore fully the voice of the corporate executives. Other AI approaches have relied upon previous human-generated assessment of the content of the calls - for example transcript markers on a five-point scale from "none" to "very strong"; however, most private firms working with new technologies prioritize algorithm sophistication over pulled data quality concerns. Current investors prefer substitutive intelligence rather than synthetic intelligence when dealing with big data analytics.

2.9.2. Regulatory Compliance

Compliance with regulatory requirements represents another area of concern among finance professionals. Incurring penalties for failure could be costly, in some cases, even a shutdown of the business. Thus prudent managers are cautious about adopting Bayesian deep learning which generates opaque predictions without understanding why and how these predictions are affected by varying model inputs, weights, and prior distributions. Recent high-profile cases of unethical use of AI have led to calls for the creation of stronger rules and regulations by stakeholders, especially as the technology proliferates and democratizes. But of course this is not unique to AI, other complex technologies like blockchain and cryptocurrency have exacerbated regulatory compliance concerns.

Financial regulators have unique concerns about the influence of AI on finance. These include fairness, accountability and transparency (or interpretability) of AI algorithms, accountability of AI algorithm creators, algorithmic risk management principles, and resistance to adverse shocks, among other issues. Given these unique concerns, financial regulators may decide on regulatory compliance rules that are more stringent than those of the general market regulators. The first step toward greater regulatory clarity is a fuller understanding of AI deployments, new AI-specific risk categories, and models used by these companies. Regulators are unlikely to shun risk, but they will want to prepare for new categories with novel characteristics and on new scales, as well as atypical response and contagion mechanisms which could also be influenced by proprietary AI decision systems.

2.10. Case Studies of AI in Investment Firms

We present real cases of AI applications in investment firms focusing on systematic and quasi-systematic portfolios. For some firms, successful AI investment solutions were structured exclusively by AI systems, while for others, a human plus AI hybrid system benefited from both algorithms and human insights. The examples are unequivocal in terms of investment success and profits for those firms, which is surprising given how conservative the investment industry is in terms of budget allocation and risk-taking.

A well-known hedge fund has built a dominant position in the algorithmic trading sector, specializing in very short-term trading of deep liquid market instruments, including foreign exchange, equities, and derivatives. This hedge fund has repeatedly registered stunning profits and ROI for many years. The fund is known to utilize quantitative strategies based on AI and machine learning advantages in data processing capabilities. Its success through algorithmic trading during the last three decades warrants specific mention here. Although algorithmic and quantitative trading seems to be de facto offered services by the majority of hedge funds today, this story is much more than that.

Other hedge funds also utilize machine learning as part of their multi-strategy, multi-instrument, and mostly multi-time horizons portfolios. One is known as a pioneer in the use of machine learning for equities and has made a number of pioneering contributions to machine learning's use in investing. Another is also known for its intellectual achievements, bringing associates mainly from the high-tech industry, and there is a culture of innovation at the core of the firm's foundation.

2.10.1. Successful Implementations

Some investment firms are already productively embracing AI technology for investment alpha discovery, wealth portfolio strategies, and client relations. In the realm of investment alpha discovery, one firm boasts an AI-driven fund known for its dedicated efforts, along with strategists who are now heading towards AI investment use-cases. Another firm has assembled a team of quant researchers to develop new AI-driven portfolios. In the time-series forecasting and pattern recognition sphere, a firm is using fulfillment and logistic technology to predict commodity returns. A trend-following firm suspects that machine learning will boost CTAs to a 3% CAGR excess return.

One of the most ambitious projects focused on augmenting insights from predictive Big Data with a deep learning ML algorithm to mine signals in time-series for daily asset returns is another firm. This firm commercializes a fund and offers consulting in predictive Big Data methods for asset classes and portfolios. Another firm analyzes financial statements and news to integrate qualitative insights into its analytics product for active managers. In the Generalization domain, alternatives to classical portfolio hedging techniques, such as minimum variance portfolio or max-drawdown portfolio, are offered by another firm. A UK-based investment firm automates millennial wealth management choices for tax-efficient, diversified global asset allocation based on client category, risk/reward profile, and investment horizon in a fully regulated manner.

2.10.2. Lessons Learned from Failures

Various such firms have attempted to implement AI over the past decade. Unfortunately, several have either struggled in going down this route, or have had disappointing results. In the interests of building a picture that also contains negative case experiences, a handful of these are described here. The early implementation of AI at Acadian Asset Management and the introduction of machine learning techniques at a major financial institution to sift through the lessons to be learned are discussed. Struggles by two of Europe's largest financial institutions to fully harness the potential of machine learning are also noted. Several firms described the struggles that many have had to embrace or fully harness AI potential.

The AI hype creating expectations that proper data-based predictions would be possible very quickly and without much effort is the underlying reason for such failures. It is argued that AI cannot solve every problem related to investments, and that studies had uncovered only a very small number of such investment problems for which their use had been able to enhance returns over existing data-based approaches. The number of high-return cases is so small that AI would always need to be applied in conjunction with the common-sense approaches which already have proven their capabilities of solving the overwhelming majority of investment problems, requiring very little change versus existing, simpler quantitative approaches and models in many cases.

2.11. Future Trends in AI and Investment Strategies

The future of AI and investment strategies will likely emphasize two key areas: ESG frameworks and advancements in predictive modeling. An increasing number of investors, even in the institutional sphere, is preferring funds and strategies combining financial performance with investments that improve the outcome of environmental, social and governance issues. ESG investing is often seen as a way to reduce inequality gaps and the current investment community has also a stronger sense of purpose than the previous generations. AI is also reshaping research on the predictive power of factors and alternative data. Data has applied to many of the drivers of asset price behavior. AI, increasingly referred to as the fourth industrial revolution, is also there to optimize business processes, including investments. The current machine learning algorithms used in finance are too simplistic in their data treatment given the complexity of business processes affected by economic, social, including behavioral biases, and political dynamics.

Prediction, and especially prediction about the future, is a domain where AI is going to have significant improvements in the coming years. This is necessary. The financial sector suffers from falling forecast performance of traditional econometric models, both in terms of explanatory power and of forecast accuracy. In their analysis of the equity risk premium, it was shown that the power of traditional predictor variables, some of them recently extended via alternative data, declines as the time horizon increases. It was concluded that the predictability of equity returns is low or nonexistent at forecast horizons beyond one year. It was proposed that investors should ignore asset class forecasts because of the small economic magnitudes, the small number of applicable predictors, the declining predictive power for longer horizons, the poor value in market timing, the lack of periodic updates, and the long record of forecasters' dismal accuracy at long horizons.

2.11.1. AI and ESG Investing

The intersection of Artificial Intelligence (AI) and Environmental, Social, Governance (ESG) Investing provides a clear roadmap to navigate the increasingly complex frontier of impact investing and climate change. AI has emerged as a powerful partner in the onslaught of challenges we face in our rapidly changing, uncertain world. As more investors focus on the wider business impacts of companies, from climate change and sustainability to consumer perceptions of corporate virtue and community effects of corporate activity, the role of AI in helping to shape and assess the possible and probable consequences of these factors in investment decisions will only grow. Currently, ESG investing looks for positive impact through screens, relying on official corporate disclosures of governance and CSR actions. Despite the benefit of shareholder review, corporate disclosure of social impact information often lags corporate decision-making and may be either incomplete or unduly filtered through corporate public relations apparatuses. AI offers a powerful way to deepen investor understanding of and engagement with company and corporate community dynamics through new data sources and appreciation of ESG risk and investment opportunity.

Investing and the capital markets are not divorced from the impetus to consider stakeholders rather than shareholders. More and more investors believe that companies should take into account the public and private interests of all of their stakeholders, not just shareholders, who are often not even the long-term owners of companies. We have long understood the econometric correlation between corporate social responsibility expenditures and improved corporate performance through lowered operating, recruiting, retention, and turnover costs. AI offers a powerful way to take that understanding deeper through predictive models developed through data science initiatives coupled to corporate financial data, analyst assessments, and corporate stakeholder interviews.

Fig : AI and ESG Investing

2.11.2. Advancements in Predictive Modeling

By generating specific probability distributions around expected returns, AI allows investors to effectively combine forecasts of returns and risk premia to determine optimal portfolio compositions. However, research has shown that traditional mean-variance optimization is sensitive to errors in expected returns and thus investors would be treated better if expected returns are replaced with their longer-term average levels. AI may be able to provide such longer-term estimates based upon the probability distributions it creates; these more accurate estimates may reduce the overall sensitivity of the portfolio optimizer's eventual asset weight estimates, although in many cases requiring a premium to be compensated for taking a bet on an excess view. In fact, advances in predictive accuracy around expected returns through long-horizon estimators could create new and viable long-horizon means of portfolio management. The focus in most AI research has been on a relatively short-term horizon; both for returns, volatility, and covariances, because these have been most amenable to the sort of estimation approaches commonly utilized in supervised learning. This opens the gate to consider what additional insight AI methodologies could contribute to multiple-asset probability distribution estimation, particularly on terms of interest to practitioners looking for longer-horizon accuracy via monthly-frequency returns which are the natural domain of investment.

2.12. Conclusion

In conclusion of this study, Artificial Intelligence (AI) is flattening the world by making proprietary investment strategies available to households and individuals. Wealth management and investment advisors perform value-added work for clients on the shoulders of this technology. The more complex a family's circumstances or the greater its net worth or assets under management, the higher the value this family can derive from outsourced wealth allocation and investment decisions. In the near future, we should expect to see AI continue to fine-tune and calibrate the risk and opportunity set in portfolio construction, allowing for strategy diversification and overlays that can enhance returns and performance at extremely low or no cost. AI will also continue to facilitate advisory processes for transaction planning, asset movements, gifting, and even the design of trust and foundation structures. AI has the potential to improve the probability of appealing family outcomes better than anything available in the market to date. On the other hand, the fiduciary risk posed by an advisor's stewardship role in flexibility throughout this entire process is extreme. It makes sense for every advisor to organize and categorize family contexts in the same way that portfolio and investment processes have segmented their private banker and investment manager partners. In this regard, AI will never replace creative clients and the advisors who work closely with them to conceptualize unique solutions. In the future, we will all get better at using machines to generate ideas more efficiently. But the most beautiful designs will be born from trust, time, and a vision–financial art rather than algorithmic science, the marriage of epochs that defines the luxury of the twenty-first-century human experience.

current problem or opportunity. With a targeted approach, companies increase their chances for success by addressing problems with a track record for predetermined AI techniques.

References

Generative AI Team, "Generative AI in Investment and Portfolio Management," SSRN, 2025.

D. Martin et al., "Enhancing Portfolio Management Using Artificial Intelligence," Frontiers in AI, 2023.

L. Lunkkadd and S. Bhandari, "Evaluating how advancements in technology are reshaping investment," JETIR, 2023.

WealthBriefing, "How AI Reshapes Wealth, Asset Management – A French Perspective," Feb. 2025.

S. Harper, "7 Unexpected Ways AI Can Transform Your Investment Strategy," Investopedia, 2025.