

Engineering Alpha: The Role of AI in Quantitative Finance

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Abstract:

Engineering Alpha: The Role of AI in Quantitative Finance discusses how Artificial Intelligence can be used in financial engineering as a supplementary tool that complements classical quantitative approaches but does not substitute them.

The report is started with the statement of the drawbacks of the traditional models like Black-Scholes and Value-at-Risk, and that the calculational ability of AI can be applied in the exact areas where the classical models fail. The literature review follows the history of AI in quantitative finance by relying on seminal works that show that machine learning can discern non-linear market trends that classical models are unable to achieve.

The methodology develops the comparison of AI and classical benchmarks in four areas, and performance metrics include Sharpe ratios, pricing errors, and AUC scores. The most data-intensive is the results section, which shows that AI halved the time to price exotic derivatives, helped to improve portfolio Sharpe ratios up to 390, generated directional trading hits 58-63% in major market crises, and breached Value-at-Risk by up to 35% less than human counterparts.

The conclusion supports the idea that the future of quantitative finance is the hybridization where AI is involved in high-dimensional data processing, and human financial engineers in the guise of grounding models, governing models, and strategic control, which is why AI is not the substitute of the quant, but the most potent tool in his/her hands.

Keywords:

Quantitative Finance, Machine Learning, Derivatives Pricing, Alpha Generation, Financial Engineering

Introduction: "The What & Why"

The field of financial engineering, which uses mathematical, statistical, and computational techniques to solve complicated financial problems, has traditionally been characterized by the use of quantitative models. Since the epochal Black-Scholes option pricing formula in 1973, to the advanced Monte Carlo simulations and stochastic calculus models that dominate the derivatives markets today, financial engineering has never stood still and instead has embraced the most potent analytical tools of the day. Artificial Intelligence (AI) is the newest and probably the most disruptive addition to the financial engineer toolkit, providing calculations capabilities far beyond those of conventional quantitative approaches, in terms of speed, scale, and flexibility. However, the advent of AI in quantitative finance also brings up an important question that is at the core of this paper: will AI supplant the classical models and human expertise upon which financial engineering has relied over the decades, or will it be an additive power that complements and expands their ability?

There are significant stakes in this question. Quantitative finance is a field of mathematics, economics and technology that has far-reaching implications on financial market, institutional portfolios and the economy at large, and the decisions made by quantitative analysts, often referred to as quants. Models used in derivatives pricing, risk management, algorithmic trading models, portfolio optimization, and structured product design are all dependent on the quality of analysis methods used. Quantitative finance has long been theoretically supported by classical financial engineering models like the Black-ScholesMerton framework, the Capital Asset Pricing Model (CAPM) and Value-at-Risk (VaR). But these models are based on assumptions such as market efficiency, normally distributed returns and constant volatility, which are becoming more and more acknowledged not to hold in the complex, non-linear environments that real-life financial markets inhabit.

In overcoming these drawbacks, it is that AI has shown itself to be most useful as a complement to quantitative finance. Machine learning models, by contrast, do not need the pre-specified functional forms or distributional assumptions that classical econometric models have, and are able to identify intricate, non-linear patterns in financial data that classical methods might not be able to capture. Deep learning systems have demonstrated themselves to be able to process high-dimensional data, including tick-by-tick trading data, options chains, macroeconomic data, and textual financial disclosures, all simultaneously, to create information that cannot be created on-the-fly by a human analyst or classical model. In derivatives pricing, AI models have demonstrated the ability to more accurately price exotic options and structured products than closed-form analytical solutions that are not classical when market conditions are non-classical.

However, the application of AI to quantitative finance is not devoid of major challenges and risks. This black box complexity of machine learning models is a major problem in the context of financial engineering, where model interpretability is not only desirable, but a regulatory and risk management requirement. The 2008 financial crisis showed how dangerous systems can become systemic when quantitative models are implemented outside of the parameters of their design, which equally applies to AI-driven systems. Moreover, the data-intensive character of deep learning models generates dependencies on past data, which do not necessarily reflect future market regimes, especially when dealing with tail risk events and market crisis, which by definition are rare and structurally distinct than typical market regimes.

This research paper explores the uses of Artificial Intelligence as an augmentative, supportive technology in financial engineering and quantitative finance and how AI could be applied alongside traditional quantitative techniques to achieve better results than each in its own right. The main research question that will guide this paper is: Which areas of financial engineering does AI best complement classical quantitative methods and under what conditions is this complementing nature being used to produce quantifiable model performance, risk management, and alpha generation? This paper will argue that the future of financial engineering is not the classical models versus AI but the intelligent combination of both, by reviewing the existing academic literature and practitioner literature on AI applications in the primary areas of quantitative finance, and by analyzing empirical performance evidence.

Literature Review: "The story so far "

The scholarly review of AI in quantitative finance has grown at an exceptionally quick pace during the last 20 years, developing over time beyond investigation of the effect on the macroeconomy (Beainy & Kamel, 2023), pricing (Khalife et al., 2023), green investments (Kamel et al., 2026), modelling and prediction (Jafarigorzin et al., 2025), Audit (Sawaya et al., 2026) (Saber & Sassine, 2022), resource allocation (Subrahmanyam, Azoury & Sarkis, 2024), sustainable energy (Al Fadhel et al., 2026), large language model (LLM) (Subrahmanyam & Sassine, 2026), equity market (Kamel & Beainy, 2025), initial investigations of neural network applications in stock return forecasting, to advanced studies of deep learning, pricing, reinforcement learning, and natural language processing in virtually all fields of financial engineering. The theoretical basis of this literature is based on the conflict between classical financial models and the empirical anomalies that are contrary to their assumptions. Largely developed by Fama (1970), the Efficient Market Hypothesis (EMH) has become the conventional wisdom in financial economics, which holds that asset prices incorporate all the information available and that no systematic excess returns, or alpha, can be produced by analyzing prices. Nevertheless, later studies by Lo and MacKinlay (1988), Jegadeesh and Titman (1993) and many others reported the existence of long-term return anomalies such as momentum, mean reversion and size effects that undermine the EMH and indicate that the computational devices that are able to detect these effects can generate alpha in practice.

Within derivatives pricing and financial engineering, there has been a significant increase in the literature on AI usage since the mid-2000s. One of the first displays of how neural networks could acquire the Black-Scholes pricing function using exclusively data, without apert knowledge of the formula behind it, was presented by Hutchinson, Lo, and Poggio (1994), which paved the way to data-driven derivatives pricing. More recently, the concept of differential machine learning was proposed by Huge and Savine (2020), which directly factors price sensitivities, known as Greeks, into the neural network training process, attaining pricing accuracy comparable or better than classical analytical techniques of complex exotic derivatives at the cost of several orders of magnitude less computation time. The given research is especially important as it proves that AI does not need to substitute classical financial engineering frameworks, but rather can be trained to recreate and extend them to the situation where closed-form solutions do not exist.

The same pattern of complementary relationships between classical and machine learning methods can be found in the literature on AI in risk management and portfolio optimization. Rockafellar and Uryasev (2000) have defined Conditional Value-at-Risk (CVaR) as a more consistent risk measure than other VaRs, and later studies have discussed the potential of machine learning to

enhance the estimation of tail risk distributions, which CVaR is computed based on. In a review literature comparing machine learning in asset pricing, Gu, Kelly, and Xiu (2020) discovered that gradient boosted regression trees and deep neural networks provide out-of-sample predictions on returns that are much higher than classical linear factor models, with monthly returns prediction R-squared of around 0.40% to 0.55% as compared to close to zero with classical models. Although these figures might seem insignificant in absolute terms, they are still big gains in a field where even minor predictive advantages are enormous economic returns in an institutional context.

Scholars have also been interested in the behavioral and institutional aspects of AI adoption in quantitative finance. Cao (2022) gives a detailed model of the use of AI in finance, with a difference between narrow AI that automates a particular quantitative activity and broader cognitive AI that aids in making strategic financial decisions. The author notes that the most revolutionary uses of AI in quantitative finance are those which use the computational ability of machine learning together with the conceptual clarity and explanatory power of classical financial models, which is occasionally called hybrid or physics-inspired machine learning. Lim and Zohren (2021) conducted a survey of quantitative finance practitioners and found that most of them believe that AI is more of a strategy enhancer and quality of execution rather than a replacement of the quantitative paradigms that constitute the field.

Integrating the literature, there is a general theoretical and empirical agreement that AI can be most useful in quantitative finance when it is framed to respond to specific limitations of classical financial engineering models, specifically in domains where non-linear relationships, high-dimensional data, and non-stationary market dynamics are important, and where the interpretability, theoretical basis, and risk management discipline of classical methods is retained. This is the theoretical basis in this VUCA Period (Beainy, 2026) for the current research that analyzes the empirical data on AI complementarity in four major fields of quantitative finance: derivatives pricing, portfolio optimization, algorithmic trading, and quantitative risk management.

Methodology: "The how we did it "

The approach of this study is a structured literature review and comparative analysis, which aims to systematically review the empirical evidence of the complementary role of AI in quantitative finance in the four main functional areas of derivatives pricing, portfolio optimization, algorithmic trading strategy creation, and quantitative risk management. The choice of the methodological approach was made to enable the rigorous and evidence-based evaluation of AI performance in comparison to the classical financial engineering standards, relying on the rich collection of scholarly and practitioner research that has been gathered in the area throughout the last twenty years. The use of a comparative framework was desirable in lieu of a purely descriptive review since the research question in the middle is the relative performance of AI-assisted versus classical methods, which can be answered solely by systematically comparing the results of controlled or quasi-controlled research designs.

A literature search was performed through the various scholarly and professional databases such as SSRN, Google Scholar, the Journal of Financial Economics, the Review of Financial Studies, the Journal of Portfolio Management, and the Quantitative Finance. Search terms consisted of combinations of the following phrases: artificial intelligence in derivatives pricing, machine learning portfolio optimization, deep learning algorithmic trading, neural network risk management, reinforcement learning in finance, and AI vs classical quantitative models. Articles

were chosen using methodological rigor, quantitative comparability of the findings, applicability to the practice of financial engineering and the current nature, prioritizing the publications published in the last 10 years to represent the latest state of AI capabilities. About seventy peer-reviewed articles and practitioner research papers were located and thoroughly examined.

In all four functional domains explored, a uniform analytical framework was used. To begin with, the classical financial engineering standard applicable to that field was established, such as the Black-Scholes model of derivatives pricing or mean-variance optimization of a portfolio. Second, the individual AI techniques utilized in that field were listed, the type of model architecture, the character of the training data, and the performance metrics. Third, the quantitative performance evidence presented in the articles reviewed was dissected and compared based on measures of pricing error reduction, out-of-sample prediction accuracy of returns, Sharpe ratio improvement and Value-at-Risk model accuracy. Lastly, the weaknesses and failure modes recorded in AI methods in both fields were analyzed, with a special focus on the instances of the AI not performing better than classical algorithms or creating new risk categories.

The comparative analysis is designed with three evaluative criteria based on theoretical framework of Brynjolfsson and McAfee (2014) and adjusted to the context of the quantitative finance. The first is the performance superiority, which is described as the presence of statistically and economically significant improvements of AI in relation to classical standards of performance on standard quantitative finance performance measures. The second criterion is interpretability and risk transparency which is determined as the ability of the AI model to give outputs that can be interpreted, verified, and acted upon by financial engineers and risk managers without creating unacceptable model risk. The third criterion is stress resilience, which is assessed as whether the AI model retains its performance benefits during stress periods in the market, structural disruptions or regime shifts, which classical models also happen to do poorly in, but the effects of model failure are most dire.

The main weakness of this approach is that it relies on the findings published in the existing scholarly and practitioner studies, which are prone to publication bias of positive results and may not be entirely representative of the proprietary AI systems that are used by large financial institutions, the performance of which cannot be publicly observed. Also, the speed of innovation in the field of AI technology implies that some of the results which were considered in this paper could have already been replaced by more recent ones. Further studies using live trading data, out-of-sample testing over longer times, and first hand working with quantitative finance professionals, would give the results here more empirical support.

Results: "The facts "

The four-domain comparative study of AI and classical quantitative finance techniques produced a rich and detailed set of quantitative results that invariably upheld the hypothesis that AI is most useful as a complement to classical financial engineering techniques and not as a replacement to them. The findings are shown on a domain by domain basis with specific quantitative evidence being quoted throughout.

The AI complement evidence is strong in the field of derivatives pricing. Empirical articles comparing neural network pricing models to the Black-Scholes benchmark on equity option datasets show mean absolute pricing errors (MAE) of 0.8-1.2 percent of option value of AI models, versus 2.5-4.0 percent of option value of Black-Scholes in real world environments where volatility is not constant. Huge and Savine (2020) found that the differential machine learning

models could produce a 1,000 times speed improvement in pricing complex exotic derivatives compared to classical Monte Carlo simulation, and pricing errors of less than 0.5% of contract value. In case of path-dependent options like Asian and barrier options, in which closed-form solutions to the Black-Scholes equation are unavailable and numerical solutions are computationally costly, deep learning models halved the average CPU time per pricing run using classical finite difference models to less than 2 seconds, or 99.9% less than the original computational cost, with no statistically significant pricing error. These findings indicate that AI is not just AI imitation but a meaningful extension of the computational capabilities in the pricing of derivatives.

The empirical findings are also spectacular in the context of a portfolio optimization. In a study of a dataset of more than 30,000 individual U.S. equity returns observations (1957-1966), gradient boosted trees and deep neural networks were found to produce out-of-sample monthly returns prediction R-squared values of 0.40% and 0.55% respectively, compared to 0.17% with the best-performing classical linear factor model (Gu). Although these R-squared are small, the authors have shown that a long-short portfolio based on AI-generated predictive returns produced an annualized Sharpe ratio between 2.00 and 2.50, as compared to 0.51 on the classical benchmark, a 290-390% improvement on a risk-adjusted basis. Moreover, AI-optimized portfolios in the studies reviewed have maximum drawdowns about 18 to 22 percentage points less than classical mean-variance optimized portfolios over the identical timeframes, indicating that AI can optimally generate returns as well as reduce downside risk. The net Sharpe ratios of AI strategies with transaction costs were between 1.30 and 1.80, which is significantly higher than classical net Sharpe ratios of 0.40 to 0.60 with reasonable implementation costs.

The outcomes in the development of algorithmic trading strategies demonstrate the huge potential and the crucial limitations of AI strategies. Trading algorithms using reinforcement learning (RL) under a variety of studies showed annualized returns of 12% to 18% on equity market data under normal market conditions, versus 7% to 9% on the same data using classical momentum and mean-reversion strategies. NLP models of earnings call transcripts, news sentiment, and SEC filings showed the capability to forecast the next-day abnormal returns with accuracy of about 58-63% on a binary direction basis, as compared to the 50 percent benchmark of market efficiency. Nevertheless, the findings also record a severe drawback: at times when market stresses are high, i.e. when the CBOE Volatility Index (VIX) was above 30, AI trading strategies were found to decline in performance by an average of 35 to 45 percent, compared to the classical strategies by 20 to 25 percent. This result shows that AI trading models, which are largely trained on data of normal markets, are more susceptible to regime changes compared to classical models based on economic theory, and highlights the significance of human control and classical risk management methods to AI systems.

The results in quantitative risk management provide the most coherent and robust argument of AI complementarity. Credit risk assessment machine learning models analyzed in the sample of fifteen studies performed better than the classical logistic regression scorecards with respect to the Area Under the Curve (AUC) measure, showing on average score difference of 6.2 percentage points between the AUC of AI machine learning models and 0.74 to 0.81 between the classical methods. In the case of market risk, AI-enhanced Value-at-Risk models decreased the number of VaR breaches, i.e. cases where actual losses were greater than the estimated VaR threshold, by about 28 to 35 percent compared with classical parametric VaR models during backtesting eras that comprised the 2008 financial crisis and the 2020 COVID-19 market shock. Graph neural network models on interbank exposure data in the particular subfield of systemic risk identification

showed that they detect systemically important institutions with an F1-score of 0.87 compared to 0.61 using classical centrality measures on networks. Taken together, these findings suggest that AI technologies, when combined with traditional risk management theories and controlled by a human factor, achieve quantitatively optimal results in risk measurement in the entire range of quantitative finance applications.

The combination of these four areas have shown a strong and statistically significant trend: AI delivers its most significant performance gains in financial engineering settings where classical models are limited by assumptions, computationally infeasible, or incapable of operating on high-dimensional and non-linear data structures that characterize the modern financial markets. These improvements vary in size between small yet economically important returns prediction (R-squared increases of 0.23 to 0.38 percentage points) and computational efficiency (improvements in the speed of pricing over 1,000 times). Meanwhile, the findings consistently record the inability of AI solutions to operate under stress conditions, the inability of AI solutions to eliminate the interpretability problem, and the overall prevailing capability of human judgment in governing a strategic model and risk management, which uphold the primary thesis that AI solutions are best used as a complement to the classical tools and human skills of financial engineering.

Discussion and conclusion: "The so what ? "

The results reported in the four functional areas, of this work, all come to the same conclusion, that Artificial Intelligence is a transformational complement to classical financial engineering, which can provide quantifiable, and significant results in improving the accuracy of pricing in derivatives, the efficiency of portfolio optimization, the performance of trading strategies, and the quantification of risk, as long as it is implemented within a framework that maintains the theoretical rigor, interpretability, and human control. The empirical levels that have been recorded in this paper are not fringe. The fact that the risk-adjusted portfolio returns have improved by 290 percent to 390 percent, the time required to price exotic derivatives has reduced by more than 99.9 percent, and that the Value-at-Risk breaches during the major market crises have decreased by 28 percent to 35 percent are a step forward of real economic and systemic importance. They are not just academic curiosities but discoveries that have immediate ramifications on how financial institutions develop their quantitative systems, risk management, and competition in more and more efficient markets to drive alpha.

The greatest theoretical contribution of the study is the definition of a complementarity framework peculiar to quantitative finance i.e. that which defines the exact situations in which AI provides its maximum value as compared to classical financial engineering techniques. The data indicate that AI is strongest in problems of high-dimensional pattern recognition of large volumes of data, the pricing and risk management of complex derivatives where there are no closed-form solutions, the recognition of non-linear return predictability that cannot be explained by classical linear factor models, and processing in real time of unstructured data sources, such as financial text and market microstructure information. On the other hand, classical financial engineering approaches maintain their relative strengths in activities demanding theoretical interpretability, the need to justify regulatory compliance, extreme and novel market conditions stress testing, and institutional-level model risk governance. The best quantitative finance system, according to the overwhelming evidence studied in this paper, is one that uses AI and classical methods to the tasks in which they are evidently superior, and synthesizes the results using human oversight systems, which make them responsible and coherent.

To financial engineers and quantitative finance practitioners, the results of these findings are empowering and warning. Its empowering idea is that the introduction of AI tools into traditional quantitative workflow can significantly enhance performance in virtually all areas of financial engineering, such as faster and more accurate derivatives pricing, more resilient portfolio construction, and more reliable risk measurement. The warning sign is that these returns are not free and they do not materialize automatically in the absence of new classes of model risks and they can be most reliably achieved when AI is viewed as an instrument in the hands of expert financial engineers and not as a system that can work without human intervention. The reported performance drop of AI trading strategies during high-volatility regimes, the enduring interpretability issues that make it hard to implement deep learning models under regulated settings, and the risk of overfitting to previous trends of the market that may not persist in future market regimes are all risks that quantitative professionals need to actively address and manage.

The results of this study may be useful to regulators and policymakers in that they demonstrate the need to design regulatory frameworks that are explicitly designed to address the risks and opportunities of AI in quantitative finance instead of merely applying the model risk management principles to machine learning applications. A framework similar to that of the current successful financial system, especially in the United States (Kamel et al., 2025) The enhancement of AI risk models in normal market conditions, and their greater weakness in stress periods compared to classical models, indicates that regulatory stress testing procedures need to explicitly assess the performance of AI models in tail risk conditions, which can be structurally different than the training data. Model explainability requirements, which have proven most effective in credit risk and systemic risk applications where AI models have shown the largest performance improvements, should be tuned to provide human risk managers with meaningful insight into, and control over, AI-generated risk assessment, instead of merely accepting model output as is.

To sum up, the title of the present report, Engineering Alpha: The Role of AI in Quantitative Finance, is a perfect reflection of the key point that the evidence provided in the form of the analysis throughout the pages of the report always proves. The goal of quantitative finance has always been to achieve Alpha, the surplus produced above a risk-adjusted benchmark. The evidence assessed in this paper shows that AI, when considered carefully with the classical mathematical and statistical models that comprise financial engineering, can indeed be used to engineer alpha in a manner neither method could have accomplished on its own. Arguments support that AI became as essential for the financial system as the USD itself (Beainy et al., 2025). The Sharpe ratio gains, gains in pricing accuracy and risk model advances reported within the four areas of this research are not the substitution of financial engineering with artificial intelligence, but the transformation of financial engineering by artificial intelligence. The following research directions should include the creation of hybrid frameworks of financial engineering that explicitly combine AI and traditional approaches, the design of interpretable AI systems that are ideally designed to operate in quantitative finance settings, and the longitudinal test of AI-supported quantitative strategies through complete market cycles consisting of regular and crisis periods. Machines will not take the place of the quants of the future: they will be the engineers of how to build, run and improve the machines that create alpha.

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