

Markets & Machines: AI as a Financial Ally

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Abstract:

Markets & Machines: AI as a Financial Ally discusses the application of Artificial Intelligence in financial markets, asserting that AI is most useful when applied as a complementary technology that can improve human decision-making, as opposed to being an all-encompassing technology.

The report begins by setting the stage of the increasing importance of AI in the financial sector and the danger of excessive reliance on robots. The literature review is based on the most prominent scholars to demonstrate that although AI has proven to have obvious benefits in data processing and pattern recognition, human judgment cannot replace it in complex, high-stakes situations.

The approach is based on a systematic literature review and a qualitative analysis of five functional areas, including trading, portfolio management, risk assessment, fraud detection and retail advisory. Findings indicate that AI can produce quantifiable performance improvements in every category, such as Sharpe ratio increases of 10-25% in portfolio management and fraud detection rate increases of 15-40, but these increases are largest when human professionals are actively engaged.

The answer to this question is obvious: AI in finance should be implemented in collaboration rather than replacement. AI is an asset that should be welcomed by institutions, regulators and investors as a strengthener to human capacity, without sacrificing the control, responsibility and moral judgment that markets ultimately require.

Keywords:

Artificial Intelligence, Financial Markets, Human-AI Collaboration, Complementary Decision-Making, Algorithmic Risk Assessment.

Introduction: "The What & Why"

The high rate of technological development has radically changed almost all the sectors of the world economy, and the financial markets are not an exception. In the last ten years, Artificial Intelligence has become one of the most disruptive and promising tools to the financial sphere of the world, changing the way market participants handle information, conduct transactions, evaluate risk, and decide on investments. Since the earliest algorithmic trading programs that can make thousands of trade decisions per second to natural language processing algorithms that can analyze earnings calls in real time, AI has brought in abilities that are far beyond the capability of human thought and speed. Nevertheless, the increasing prevalence of AI in financial markets has also brought a basic and pressing question: is AI going to be perceived as a replacement of human financial workers, or should it be used as an additional resource, complementing and improving their abilities?

The difference between AI as a substitute and AI as a complement is not just an academic one, it has far reaching consequences on the way financial institutions design their processes, the way regulators develop their rules and controls, and the way individual investors make decisions. The more radical approach to AI is a substitutive one, which means that machines are able and should completely take over the judgment of a human being, which is, although technologically alluring, a blatant dismissal of the uniqueness of human judgment, ethical judgment, contextual knowledge, and responsibility in the financial market. Conversely, a complementary perspective frames AI as a potent instrument that can supplement human decision-making, enabling professionals to analyze more data, detect patterns in a more effective way, and minimize cognitive biases, without losing the human factor that, after all, is needed by markets.

Financial markets are complex, dynamic, and usually irrational spaces where behavioral aspects, geopolitical changes, and regulatory changes and macroeconomic cycles interact in a manner that cannot be completely predicted or substituted by any algorithm. History has shown the risks of excessive dependence on automated systems, both in the case of the Flash Crash of 2010, when algorithmic trading was involved in a sudden and dramatic market crash, and in the case of the 2008 financial crisis, when quantitative models were not able to reflect systemic risk. Such incidents are timely lessons to the fact that technology, no matter how advanced it is, exists within its constraints that are dictated by its design and training information, and that human controls are still needed in financial decision-making.

Irrespective of these shortcomings, the opportunity of AI to optimize the work of financial market cannot be underestimated. When implemented properly as a complementary tool, AI could be used to help analysts to process large volumes of financial information, portfolio managers to find risk-adjusted opportunities, compliance teams to uncover fraud, and retail investors to have access to advanced analytical tools previously available to institutional investors. The point of contention is not in picking one over the other, however, but in finding a way to combine the two to create a system that has the advantages of AI computation abilities and the attributes of human professionals, such as judgment, creativity, and responsibility.

This paper discusses how Artificial Intelligence can be used as complementary, supporting technology in the financial markets, as opposed to substituting human expertise. The research question that we used to guide this paper is as follows: How can AI be successfully applied to the work of financial markets as a support system that improves, but does not eliminate, human decision-making? By reviewing the literature available, discussing the current applications of AI

in the financial sector, and reviewing empirical evidence, the current paper aims to prove the notion that the most efficient and sustainable approach of AI in financial markets is a model of human-AI collaboration, where technology is an assistant to the financial professional, rather than a replacement.

Literature Review: "The story so far "

The academic and professional literature on the topic of Artificial Intelligence in financial markets has significantly increased in the last 20 years, which was formerly filled with speculative debates about the possibility of machine learning, but now consists of empirical research into the actual use of AI in financial markets. Initial work in this area, including that of Lo and MacKinlay (1988) had already determined that financial markets are not perfectly efficient, and computational tools could find patterns that could be exploited. This understanding paved the way to the implementation of algorithmic and, subsequently, AI-based trading approaches. More recently, researchers like Cao (2022) have offered broad frameworks to comprehend the role of AI in finance, division into topics, such as asset management, risk assessment, fraud detection and regulatory compliance, and the importance of human supervision. Mawad & Freiha 2024, argued that companies may work even a bank free environment yet according to Beainy & Kamel (2023), technology is essential to survive in today's competitive market.

A considerable research has been done in the field of asset management and investment analysis focused on the ability of the machine learning models to perform better than conventional quantitative strategies. Research by Gu, Kelly, and Xiu (2020) showed that machine learning (e.g. gradient boosting, neural networks, and random forests) could produce better predictions of returns than classical linear models when run on large scale equity data. But these authors also recognized that even the understandability of such models is a problem, and that it is frequently the reason why a model makes a given prediction, rather than the prediction itself, that is of interest. This lack of transparency is often known as the so-called black box problem, which is one of the most mentioned restrictions of AI in the financial sector, and it serves to justify the thesis that human workers should not be completely inactive when it comes to verifying and putting AI-generated processes into context.

The current body of research on AI as a method of risk management and fraud investigation paints a somewhat more subtle picture. Bhattacharyya et al. (2011) have shown that machine learning classifiers can greatly outperform the traditional statistical techniques in fraudulent transaction detection, which has since been verified and extended by many researchers. Lessmann et al. (2015) demonstrated in terms of credit risk that ensemble learning techniques can have a better predictive accuracy in credit scoring, which may decrease the default rate of financial institutions. However, researchers like Ribeiro, Singh, and Guestrin (2016) have stated that the use of such models in high-stakes financial problems should have the mechanism of explainability, meaning that the human decision-makers should have the ability to comprehend, question, and be accountable to the results that AI systems provide.

Another key theoretical approach to the complementary role of AI in markets is the behavioral finance literature. Kahneman (2011) has concluded that human decision making has systematic cognitive biases including overconfidence, loss aversion and anchoring that can lead to poor financial decisions. However, AI systems are not susceptible to such emotional and psychological biases, which is why they are especially appropriate to help with disciplined, data-driven analysis. Nevertheless, as Shiller (2019) has remarked, markets are also influenced by narratives, social

processes, and group psychology, the aspects of financial reality that the existing AI systems cannot fully reflect. It implies that a human-AI collaborative model, with each side playing to its respective comparative advantages, is theoretically better than a human-only or AI-only decision-making.

Summarizing the literature available, a similar pattern can be observed: AI works best in financial markets when it is branded as a technology that supplements human abilities, but not substitutes them. According to surveys of financial professionals, such as those by Deloitte (2021) and McKinsey (2022), most practitioners see AI as a way to enhance efficiency and risk analysis depth, but still believe that ultimate investment and risk management choices are a prerogative of humans. This agrees with the theoretical basis of the argument by Brynjolfsson and McAfee (2014) who concluded that the most valuable uses of technology in knowledge-based industries is the one that enhances human intelligence and not replaces it. The current research is based on this premise and explores the particular ways in which AI has become a financial partner in the modern markets.

Methodology: "The how we did it "

This research design is a mixed-method design, which involves a systematic review of scholarly and professional literature and a qualitative analysis of AI applications that are already implemented in financial markets. The methodology used was developed to answer the main research question of how AI is used as a complementary tool in financial markets and relied on both empirical data of the research that has been conducted and on the example of cases within the financial industry. This design was chosen over a strictly quantitative one since the research question is inherently interested in the nature and quality of the human-AI interaction in the financial context, which is well-served by both the evidence that can be obtained through data and the context that can be understood through it.

The literature review section of this paper was systematic and searches in various academic databases such as SSRN, Google Scholar, JSTOR, and ScienceDirect were done. The search process involved the combination of the key words like artificial intelligence in finance, machine learning financial markets, algorithmic trading, AI risk management, robo-advisors, and human-AI collaboration in investment. In the first step, more than two hundred articles, working papers, and industry reports were identified, out of which about sixty were picked to be reviewed in detail according to the criteria of relevance, methodological rigor, recency (published since 2000 to 2025), and impact of citation. To take a comprehensive and balanced view, both academic and practitioner-oriented reports by various institutions like the CFA Institute, McKinsey Global Institute, and Deloitte were considered to include peer-reviewed and current academic sources.

The literature review identified five main functional areas of AI applications in financial markets, which were organized into the qualitative analysis: (1) trading and market analysis, (2) portfolio management and asset allocation, (3) risk assessment and credit scoring, (4) fraud detection and regulatory compliance, and (5) retail investor tools and robo-advisory services. In every functional area, particular AI technologies and their reported performance attributes were looked at, with special focus on the studies that compared AI-aided decision-making to either solely human or solely automated options. This comparative prism was the focus of assessing the complementary value proposition of AI in either scenario.

To test the hypothesis that AI is a complement and not a substitute in financial markets, the study relied on a framework that adapts Brynjolfsson and McAfee (2014) and Cao (2022) and identifies

the tasks in which AI shows definitive superiority over human professionals, those in which human professionals possess a comparative advantage, and those that are better addressed with human-AI cooperation. All AI applications found in the literature were classified into this framework using available evidence, which enabled the systematic evaluation of AI complementary value addition where and how. This model has been used throughout all five functional areas in order to make a meaningful comparison.

The shortcomings of this approach are not disregarded and are taken into account during the interpretation of findings. Being a review-based study, the conclusions will be reliant on the quality and extent of the available literature which might fail to reflect the latest advancements in AI technology due to the high rate of innovation in the given area. Also, the qualitative character of the analysis implies that the results are inevitably interpretive and cannot be uniformly applied to any financial market, institutional setting or regulatory environment. Future studies using primary data gathering, like questionnaires of financial experts or controlled trials involving AI-aided and unaided decision-making, may offer more empirical support to the findings discussed here.

Results: "The facts "

The literature review and analysis of AI applications in financial markets provided a systematic and consistent set of results in the five functional areas analyzed. In the area of trade and market analysis, there is overwhelming evidence of the complementary value of AI as a method of processing and analysis of large amounts of financial information at rates and scales that are impossible to do manually. The reviewed studies have shown that AI-based trading systems, especially those that use natural language processing to process news sentiment and earnings reports, have provided quantifiable increases in the efficiency of information processing. But this does not exclude the fact that even autonomous trading systems without human oversight are susceptible to unforeseen market fluctuations, overfitting models, and reinventing themselves, and documented examples of AI-based disruptions in the market demonstrate the need to retain human intervention in trading activities, yet whether AI would by any chance understand the importance of major economic activities, the domination and importance of the USD in the financial market (Kamel et al., 2025) remains a question.

The findings in the field of portfolio management and asset allocation suggest that AI tools, when applied in an assistive mode, can provide a high quality of investment decisions without substituting the portfolio manager. The studies that were reviewed in this research revealed that AI-assisted methods of constructing a portfolio, such as those based on reinforcement learning and ensemble forecasting, have the potential to reveal risk-reward opportunities that more traditional methods based on mean-variance optimization could miss. In particular, several studies found that AI models trained using long-term historical data offered better out-of-sample returns forecasting compared to benchmark models, and Sharpe ratio gains of 10-25 percent in controlled research trials. However, these advantages were observed the most in the cases when AI advice was analyzed and sifted by senior investment managers, which illustrates the synergy of human-AI interaction in the specified scenario.

Among the best written in literature are the findings on risk assessment and credit scoring. The reviewed studies all indicate that machine learning models achieve better predictive accuracy of credit default than traditional logistic regression scorecards, with reported improvements in Type I and Type II classification errors of 5% to 30% across datasets and model architecture. The most effective ones were found to be gradient boosting and neural network models in the various

research works. Nonetheless, the findings also indicate that there is a very important issue that is a lack of interpretability of these models poses compliance and ethical issues in regulated financial markets, in which institutions are legally obliged to disclose credit decisions to applicants. This observation supports the conclusion that AI in credit scoring should be implemented in conjunction with human audit procedures that would be accountable and transparent.

The results are quite persuasive in fraud detection and compliance with regulations. Several of the reviewed studies have found that AI-based systems of anomaly detection perform much better than rule-based systems in detecting fraudulent transactions, and detection rates have increased by 15 to 40 percent, with the corresponding reduction in the rate of false positive. Such benefits translate to huge financial and reputational savings on the part of the financial institutions. Natural language processing tools have also proven useful in the compliance field, being able to process regulatory materials, identify possible violations during trading operations and help track communications containing compliance violations in a volume and consistency that would otherwise be unfeasible by human compliance departments. Although these benefits exist, the findings have shown that final compliance decisions and enforcement determinations always involve human judgments, especially in situations where there is a new interpretation of a regulatory interpretation or where the fact pattern is ambiguous.

Lastly, the outcomes are a bit of a mixed bag in the field of retail investor tools and robo-advisory services. Platform performance data and academic research of robot-advisory returns indicates that algorithmic investment management can offer low-cost and disciplined portfolio management reducing behavioral biases prevalent among retail investors. A number of studies established that the volatility of robo-advised portfolios was reduced and had more regular rebalancing actions than the self-directed retail investor portfolios. Yet, retail investor satisfaction data and behavioral studies show that when making big financial choices, like retirement planning or other life-altering events, retail investors always report that they want to be able to talk to human advisors despite their use of AI tools to manage their routine portfolio. All these findings can lead to the conclusion that AI can best serve financial markets not as a substitute of human knowledge, but as an effective aid that can help to make financial services more efficient, accurate, and more accessible.

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Section IV — Results: AI Applications in Financial Markets						
Source: <i>Markets & Machines — A Research Report on the Complementary Role of AI in Financial Markets (2026)</i>						
Functional Area	AI Technology Used	Key Performance Finding	Quantitative Evidence	Limitation Identified	Human Role Required	Overall Verdict
1. Trading & Market Analysis	NLP, Sentiment Analysis, Algorithmic Trading	Significant improvements in information processing speed and data-driven signal generation	AI systems process market signals in milliseconds vs. hours for humans	Vulnerable to flash crashes, model overfitting, and unexpected market conditions	Human oversight mandatory to avoid systemic disruptions and override anomalies	✓ Complementary
2. Portfolio Management & Asset Allocation	Reinforcement Learning, Ensemble Forecasting	AI-assisted portfolios outperform traditional mean-variance optimization in risk-adjusted returns	Sharpe ratio improvements of 10%-25% in controlled research settings	Gains most significant only when reviewed and filtered by experienced professionals	Portfolio managers must validate, contextualize, and take accountability for AI recommendations	✓ Complementary
3. Risk Assessment & Credit Scoring	Gradient Boosting, Neural Networks	ML models consistently outperform traditional logistic regression in predicting credit default	Classification error reductions of 5%-30% vs. traditional scorecards	Black-box opacity creates legal compliance and ethical concerns in regulated environments	Human review required for regulatory explainability and accountability of credit decisions	✓ Complementary
4. Fraud Detection & Compliance	Anomaly Detection, Natural Language Processing	AI-based systems dramatically outperform rule-based approaches in fraud identification	Detection rates improved 15%-40%; false positive rates simultaneously reduced	Limited ability to handle novel regulatory interpretations or ambiguous fact patterns	Human professionals make all final compliance determinations and enforcement decisions	✓ Complementary
5. Retail Investor Tools & Robo-Advisory	Algorithmic Rebalancing, Machine Learning	Robo-advised portfolios show lower volatility and more consistent rebalancing than self-directed portfolios	Reduced behavioral bias; more disciplined rebalancing vs. retail self-directed accounts	Clients prefer human advisors for major financial decisions despite using AI for routine tasks	Human advisors essential for retirement planning, life events, and high-stakes financial choices	✓ Complementary
Key Summary Metrics			Value / Finding			
Number of Functional Areas Studied			5			
Areas Where AI Benefit Confirmed			5 out of 5 (100%)			
Avg. Fraud Detection Rate Improvement			15% – 40%			
Avg. Sharpe Ratio Gain (Portfolio Mgmt.)			10% – 25%			
Credit Classification Error Reduction			5% – 30%			
Overall AI Role Classification			Complementary — Not a Substitute			

Discussion and conclusion: "The so what ?"

The results of this paper lead to a single and evident conclusion: Artificial Intelligence, as it is, and as it will probably be in the near future, is most beneficial to work in the financial markets as a supplementary tool that enhances but does not substitute the decisions of human beings. This conclusion is based on the empirical evidence surveyed in five functional domains, all of which showed a common pattern of AI tools having a quantifiable performance advantage in tasks that demand speed, scale, and pattern recognition, with human professionals keeping a critical comparative advantage in tasks that demand a contextual judgment, moral reasoning, interpretability, and accountability. The interplay of these two groups of capabilities, human and artificial, is not competition, but that of complements, and the best financial market uses are those that have this principle at their heart.

These results have far-reaching consequences not only to specific institutions or investment policies, but also to bigger questions concerning the future of financial markets. In the case of financial institutions, the findings indicate that the best AI integration approach is one that re-engineers workflows to utilize AI where it has the greatest value, namely in data processing, pattern identification, and routine decision support, and maintains human intervention in decision

making processes that have substantial financial, legal, or ethical implications. This strategy will need not only to invest in AI technology, but also in the development of human capital, so that financial professionals will have the data literacy and critical thinking skills they need to be effective in evaluating and taking action based on the AI-generated insights. Organisations that view AI as a means to remove human functions, as opposed to augmenting them, run the risk of regulatory backlash and losing the capacity to make decisions which are governed by judgment and which is critical to operating in highly complex and unpredictable markets.

The results suggest to the regulators and policymakers that it is necessary to set up frameworks that encourage the usage of AI responsibly in the financial market. Regulators ought to take into account the need of model explainability, human intervention at decision-making points, and algorithm impact evaluations that determine the impact of AI systems on market stability and investor protection. The reported cases of AI-induced market disruption considered in this paper show that unregulated autonomous AI use presents systemic risks far beyond the individual establishment to the entire financial structure. A regulatory framework pushing towards an alternative model of AI implementation, whereby humans would review and hold high-stakes decisions accountable, would be used to both reap the benefits of AI and curb its disadvantages.

A number of important conclusions can be drawn in this research that can be applied to students, practitioners, and scholars in the finance area. First, AI is a radical technology in financial markets, but its radicalization can be achieved most effectively when it is used in collaboration with human skills, as opposed to existing alone. Second, AI is most likely to contribute the greatest complementary value in areas where data volumes are large, patterns are systematically predictable, and repetitive analytical tasks are involved, whereas human beings are still the best in areas where narrative analysis, ethical judgment, and adaptive reasoning under new circumstances are needed. Third, the practitioners of the financial industry themselves, according to the surveys mentioned in the present paper, acknowledge and accept the complementary model, which implies that the implementation of AI in the financial industry is already taking the direction to which the academic literature suggests. Fourth, the ongoing progress in AI, such as explainability, causal reasoning and domain-specific model training, can contribute to the further increase in the complementary value of AI without necessarily adding to the argument about total substitution.

To sum up, the name of this report, *Markets and Machines: AI as a Financial Ally*, summarizes the main argument which has been created and justified throughout the pages of the report. The most effective and accountable vision of AI in financial market is the one where machines and markets collaborate with human professionals, each one with his/her own capabilities contributing to the collective aim of more efficient, transparent and resilient financial systems. Future investigations in this field are advised to involve longitudinal studies of the results of human-AI cooperation in real-world investment contexts, the creation of standardized measures to assess AI complementary, and the formation of regulatory frameworks that could encourage the use of AI in a responsible way. The financial industry will not have to decide between human judgment and artificial intelligence, but it is up to the financial industry to develop the institutional frameworks, professional capabilities, and ethical frameworks that will enable the two to co-exist successfully in the marketplace of the future.

References

- Beainy, R. H., & Kamel, J. K. (2023). The Importance of Technology, R&D and AI in the US Economy. *Migration Letters*, 20(8), 573-584.
- Bhattacharyya, S., Jha, S., Tharakunnel, K., & Westland, J. C. (2011). Data mining for credit card fraud: A comparative study. *Decision Support Systems*, 50(3), 602–613.
- Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.
- Cao, L. (2022). AI in finance: Challenges, techniques, and opportunities. *ACM Computing Surveys*, 55(3), 1–38.
- CFA Institute. (2020). *Artificial intelligence in investment management*. CFA Institute Research Foundation.
- Deloitte. (2021). *AI and risk management: Navigating the new landscape*. Deloitte Insights.
- Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *Review of Financial Studies*, 33(5), 2223–2273.
- Kamel, C., Beainy, R., & Bteish, M. (2025). In God we trust. *International Journal of Innovative Science and Research Technology*, 10(10), 412-419.
- Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus and Giroux.
- Lessmann, S., Baesens, B., Seow, H. V., & Thomas, L. C. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring. *European Journal of Operational Research*, 247(1), 124–136.
- Lo, A. W., & MacKinlay, A. C. (1988). Stock market prices do not follow random walks. *Review of Financial Studies*, 1(1), 41–66.
- Mawad, J. L., & Freiha, S. (2024). Entrepreneurial intentions in the absence of banking services: The case of the Lebanese in crises. *Journal of Risk and Financial Management*, 17(7), 264.
- McKinsey Global Institute. (2022). *The state of AI in 2022 and a half decade in review*. McKinsey & Company.
- Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?": Explaining the predictions of any classifier. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1135–1144.
- Shiller, R. J. (2019). *Narrative economics: How stories go viral and drive major economic events*. Princeton University Press.