Fintech World: How is AI fueling Finance?

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Abstract. Artificial Intelligence (AI) plays an increasingly important role in all spheres of human activity. In particular, it is integrated into the financial field, where it has many different applications, ranging from stock market prediction and algorithmic trading to risk assessment and portfolio management. Since traditional financial approaches cannot cope with the large amount of data, their complexity, and their variability, this paper aims to review recent studies concerning the use of Machine Learning, Deep Learning, Reinforcement Learning, and Natural Language Processing in finance. The current research highlights the main trends and directions of hybrid AI models, sentiment-based predictions, and multi-modal approaches in financial AI applications. Furthermore, the present paper discusses the major challenges for AI application in finance, including questions of model interpretability, overfitting, and high-level data quality, as well as the absence of opportunities for experimental validation in the real-world financial context. By analyzing the up-to-date trends and directions of AI research in finance, the current study provides an insight into the main areas of finance that need further exploration, including Explainable AI, adaptable models, and high-level learning systems.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, Reinforcement Learning, Natural Language Processing, Financial Decision-Making, Explainable AI.

1 Introduction

The application of artificial intelligence (AI) is becoming more widespread in the financial sector as it empowers financial institutions and investors to make predictions, decisions, and manage financial risks more efficiently. In recent years, financial organizations have been leveraging AI to process and analyze the vast amount of data produced by stock markets, financial reports, news, and social media. The applications of artificial intelligence in finance include stock market predictions, algorithmic trading, portfolio management, risk assessment, fraud detection systems, and financial advisory services [6].

Traditional financial instruments, including statistical and rule-based systems, are often unable to address the complex and dynamic nature of financial

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markets. To solve this issue, various financial tasks are now handled by different AI techniques. For example, Machine Learning (ML) can be used to enable financial systems to learn from previous data and thus predict stock prices or assess risk [7]. Deep Learning (DL) is applied to analyze and understand financial data on a large scale, thus enabling it to be used for stock price prediction, market trend detection, and fraud detection. Reinforcement Learning (RL) can be used in finance to allow machines to make decisions based on experience, using trial and error to determine the best possible outcome [13]. Thus, it is primarily used in algorithmic trading, portfolio management, and financial decision-making. Finally, the application of Natural Language Processing (NLP) to finance allows computers to analyze human languages to identify market sentiments that can then be used to guide investment decisions [5]. The latest innovation in generative AI can be applied to finance to generate text and other data formats that may be suitable for financial analysis and other applications.

Although the research on finance-related artificial intelligence (AI) has seen an unprecedented boom in recent years, the majority of the studies address disparate topics, employ different methodological approaches, and utilize varying data sets and performance evaluation techniques. As a consequence, the current understanding of the research landscape in finance-related AI is fragmented, which impedes the formation of a comprehensive perspective on the SOTA developments. Hence, this paper presents a literature review on the massive growth of AI in Financial sector. The included articles were published in different journals and conferences and addressed a variety of topics, from general observations on the use of AI in finance, stock market prediction, algorithmic trading, and reinforcement learning to Generative AI in finance. The purpose of this scoping review is to highlight the research trends in finance-related AI, identify the most common approaches used in the articles, and determine the prevalent challenges addressed by the studies in order to define the direction of future research.

2 Methodology

Since my paper is a literature review, this paragraph is about methods, including how the papers I read were picked as well as what the papers were about, and how I organized the information together well.

2.1 Type of Review

This is a thematic (rather than statistical) review, because the papers included in the study used a wide range of methodologies, from experiments to surveys and conceptual papers, and the results cannot be aggregated into a single summary. Instead, the review classifies the papers according to themes and discusses them within these categories.

2.2 How the Papers Were Found

The papers were searched from Google Scholar, Scopus, IEEE Xplore, ACM Digital Library, SSRN, arXiv, etc.

Search words used were combinations of:

- AI words: “Artificial Intelligence”, “Machine Learning”, “Deep Learning”, “Generative AI”, “Large Language Models”, “Agentic AI”
- Finance words: “Finance”, “Stock Market Prediction”, “Algorithmic Trading”, “Financial Risk”, “FinTech”, “Portfolio Management”

This same set of details is used later to build the comparison table in Section **??**.

2.3 Limitations of This Method

As with any literature search, the present one is likely to miss a number of relevant publications, especially those that appeared in the database recently. Furthermore, the claims and results presented in the search, including the aims, findings, and gaps in the prior research, derive from the authors’ statements, as the present article does not re-evaluate the prior data or code.

3 Literature Review

3.1 Broad Reviews of AI in Finance

Several studies provide a bird’s eye view of the application of AI in various areas of finance, rather than narrowing down to a specific field of application. Cao [4] provides two separate reviews highlighting the use of machine learning to learn patterns from past data , deep learning for finding complex patterns, reinforcement learning systems that learn by trial and error, improving through rewards and penalties, and data mining methods in finance – specifically in banking, port-folio management, fraud detection, and FinTech – and identifies the lack of interpretability (the ability to explain *why* a model made a decision) and real-time adaptation as key challenges. Similarly, Li et al. [17] highlights the application of using AI in fraud detection, financial distress prediction, and risk analysis. Yi et al. [15] expands the discussion to accounting and auditing while seeing that higher automation and prediction accuracy do not automatically resolve transparency and ethical concerns. Eisfeldt and Schubert [26] takes a broader perspective by arguing that AI adoption in finance is reshaping the labor markets and firm-level productivity and also by highlighting that the macroeconomic consequences of large scale AI adoption in financial services are still not well understood. Najem et al. [16] reviews the AI applications with big data analytics, text-mining, and cloud computing in e-finance as in most prior research studies these technologies are in isolation rather than as a combined system. Aldasoro et al. [14] has focused on the impact of generative AI *i.e. those models that can*

create new content like text, images, or data, rather than just classifying or predicting. It also focus on autonomous AI agents on the financial sector and their long-term impact on financial markets remains understudied. Svetlova [23] has focused from technical performance to ethics, by arguing that as AI models are integrated into decision-making, they present new sources of *systemic risk*, to the extent that all financial institutions utilizing these models experience financial difficulties simultaneously. This means that the literature reviewed presents an extended view of how AI is applied in finance, as well as the risks that it brings. However, there are still opportunities for further research, particularly in relation to the risks brought by AI, as well as the ethical implications of its use in the financial sector.

3.2 Artificial Intelligence for Stock Market Prediction

A considerable amount of research has been dedicated to utilizing AI ML for stock market prediction where hybrid approaches, i.e., the combination of two or more methods, are given a special attention due to their ability to account for diverse patterns. Jain and Vanzara [1] provide an overview of AI in stock market prediction, identifying overfitting i.e. when a model memorizes past data too closely and performs poorly on new data. It also focuses on data quality, and model interpretability as key concerns. Hijazi et al. [24] conducts a systematic review of AI models used specifically for financial prediction tasks and confirm that Deep Learning models consistently outperform classical statistical methods, but note that most studies test their models on a narrow set of stocks or time periods, limiting how generalizable the results are. Ferreira et al. [8] analyze 2,326 articles published between 1995 and 2019, concluding that hybrid AI approaches outperform individual methods, while systematic comparisons against traditional benchmarks and the combination of news and social media analysis remain under-explored. Dao et al. [2] conduct a bibliometric study of research published between 2000 and 2023, finding that LSTM (Long Short-Term Memory, a neural network designed to remember patterns over long sequences of time – useful for price trends), CNN (Convolutional Neural Networks, originally built for images but effective at detecting local patterns in data), Transformer models (architectures that are especially good at understanding relationships across long sequences of data, such as news text), and multimodal approaches (models that combine different types of data, such as numbers and text, together) are now dominant, with Large Language Models identified as an emerging area. Rahmani et al. [6] and Ahadzadeh et al. [7] confirm the prevalence of Deep Learning in market prediction while emphasizing the need for more interpretable, industry-specific models. Rohan et al. [3] explore the potential of Quantum Machine Learning, Blockchain, and Federated Learning (a technique that lets multiple institutions train a shared AI model without directly sharing their private data) for future stock market prediction systems. In general, this research field would lead to a transition from traditional ML approaches to more elaborated hybrid and multimodal Deep Learning solutions with some unexplored concepts being introduced and experimented with at the edges of innovation.

Table 1. Comparison of reviewed studies on AI in Finance – Part 1

S.No	Author (Year)	Method	Objective	Findings
1	Jain & Vanzara (2023)	Narrative review	Stock prediction survey	Overfitting, bias persist
2	Dao et al. (2024)	Bibliometric + DL	Latest research trends	LSTM, CNN, Transformers lead
3	Rohan et al. (2025)	Narrative review	AI/ML developments	Interpretability lacking
4	Cao (2020)	Narrative review	AI in finance overview	Improves prediction, fraud detection
5	Cao (2022)	Narrative review	Prediction, portfolio, risk	Improves accuracy, automation
6	Rahmani et al. (2023)	Narrative review	Trading, risk mgmt	Deep Learning most used
7	Ahadzadeh et al. (2024)	Systematic review	Stock prediction, investment	Research grown since 2015
8	Ferreira et al. (2021)	Systematic review (2326 papers)	Trading, sentiment analysis	Hybrid AI outperforms
9	El Hajj & Hammoud (2023)	Mixed-methods	AI/ML adoption	Privacy, regulation issues
10	Zheng et al. (2019)	FinBrain framework	AI finance framework	Improves wealth/risk mgmt
11	Cohen (2022)	Narrative review	Forecasting, trading	AI trading outperforms
12	Che et al. (2024)	cGAN + time-series	Generative AI prediction	Small error, better returns
13	Zheng et al. (2024)	Random Forest	US stock trend prediction	RF outperforms SVM, LR
14	Aldasoro et al. (2024)	Conceptual review	AI transforming institutions	Raises stability risk
15	Yi et al. (2024)	Survey review	AI in accounting/finance	Improves automation, fraud detection

Table 2. Comparison of reviewed studies on AI in Finance – Part 2

S.No	Author (Year)	Method	Objective	Findings
16	Najem et al. (2025)	AI + Big Data survey	E-Finance applications	Improve prediction, services
17	Li et al. (2021)	Narrative review (ANN, ML)	AI trends, risks in finance	Improves fraud, credit risk
18	Zhang et al. (2024)	FinAgent (multimodal)	AI trading agent	36% profit improvement
19	Joshi (2025)	Literature review	Gen AI agents in finance	Improves risk, fraud detection
20	Eisfeldt & Schubert (2024)	Review (LLMs, RAG)	GenAI impact on finance	Reshaping firm value
21	Nanda et al. (2024)	FVA + PCA + ML	Stock investment framework	LSTM beats ANN/SVR
22	Svetlova (2022)	Conceptual study	AI systemic ethical risk	Needs system-level governance
23	Mutinda & Yong (2026)	Hybrid ML/DL + SEDT	Stock direction prediction	Improves accuracy, 6 indices
24	Agrawa et al. (2025)	LSTM trading model	Algorithmic trading (S&P)	134% gross yield, 6 years
25	Khan et al. (2023)	Narrative review	ML in market prediction	Needs transparent models
26	Chugh & Deshpande (2025)	Conceptual review	Agentic AI in finance	Needs governance, explainability
27	Li & Passino (2024)	FinDKG + KG-Transformer	Financial knowledge graph	Portfolios beat benchmark ETFs

3.3 Algorithmic Trading, Reinforcement Learning, and AI Agents

A related but distinct line of research applies AI to algorithmic trading (using computer programs to automatically execute trades based on model predictions) and automated decision-making. Cohen [11] reviews forecasting methods for stocks, cryptocurrencies, and other financial instruments. It claims that the best results are delivered by hybrid models which combine long short-term memory networks (LSTM), support vector machines (SVM) which are traditional ML algorithms for classification tasks, fuzzy logic, which is a way of reasoning with imprecise concepts, and sentiment analysis which extracts positive and negative opinions from text. The adaptability of such models is what makes them suitable for use in different market conditions. Agrawa et al. [22]focus on neural network–based algorithmic trading systems, arguing that they are better at recognizing short–term trading opportunities than rule–based systems, but they underperform significantly in situations of high volatility. El Hajj and Hammoud
[9] survey financial institutions directly, finding that AI and ML adoption in trading and risk management is accelerating, but concerns around privacy, regulation, and workforce transformation persist. Nanda et al. [25] evaluate how AI and ML techniques are changing the design of investment strategies and financial management in general, finding that strategies made with the help of AI tend to perform better than those made manually, but require much historical data to be accurate. Finally, Zhang et al. [18] describe FinAgent, a multimodal foundation agent (a single AI system that can process several different types of input together) that combines price data, financial news, chart images, a memory mod-ule (storing past decisions to learn from them), and a reasoning component to make and explain trading decisions; it outperformed twelve comparable trading systems across stock and cryptocurrency datasets. Overall, this literature shows a shift from single-signal trading systems toward more autonomous, multimodal, and explainable trading agents.

3.4 Emerging Trend: Generative AI and Intelligent Financial Frameworks

The most recent literature reflects a shift toward Generative AI (AI that creates new content or synthetic data rather than only analyzing existing data) and integrated intelligent-finance frameworks. Che et al. [12] use a Conditional Generative Adversarial Network, or cGAN (a system where two neural networks – a generator and a discriminator – compete against each other, with the generator learning to produce increasingly realistic synthetic data), combined with time-series analysis, to forecast USD/JPY currency movements, reporting low prediction error and improved investment returns, though performance drops during sudden market shocks. Li and Passino [21] introduce FinDKG, a system that builds a dynamic knowledge graph (a network that maps out entities – such as companies, people, or events – and the relationships between them, updated continuously) using Large Language Models to detect emerging global trends in financial markets from news text; this represents a shift from purely

numeric forecasting toward models that reason over relationships between financial events. Joshi [27] reviews the growing use of Generative AI *agents* in finance that go beyond forecasting and can perform complex financial operations and planning to meet user-defined objectives. While promising for financial research, report generation, and general-purpose financial services, their effectiveness and accountability in critical financial decision-making still need verification. These recent studies were build on earlier conceptual work such as Zheng et al.'s Fin-Brain framework [10], which proposed an integrated AI research agenda covering wealth management, risk management, financial security, and blockchain applications long before the rise of Generative AI to prominence. Taken together, this literature reviews how the finance sector moved from early designs for "intelligent finance" to actual implementations of generative and agent-based systems that prove to be powerful, but often lack contextual precision and responsibility.

3.5 Regional and Applied Perspectives

While much of the literature is either global in scope or focused on developed markets, a smaller set of studies examines AI adoption in specific regional or applied contexts. Coşkun [19] studies the adoption of AI techniques – including Artificial Neural Networks, Genetic Algorithms, and Robo-advisors (automated systems that provide investment advice with little or no human involvement) – within the Turkish finance industry, finding that AI-based approaches out-perform many traditional models in portfolio optimization, but that firm-level empirical evidence remains limited. Maheshwari and Panwar [20] provide a comparative study of AI-powered FinTech adoption in India, focusing on the digital payment platform Paytm and the investment platform Groww, and find that AI-driven personalization and recommendation features are a key factor in user adoption, though awareness of how these AI features actually work remains low among every day users. These regionally-focused studies suggest that while AI techniques used in emerging markets are broadly similar to those studied else-where, real-world adoption, regulatory context, and user trust vary significantly by region – an area that remains comparatively underexplored, particularly for the Indian market.

3.6 Research Gaps

In all of the five thematic clusters discussed above, certain problems keep reappearing, regardless of the particular AI technique or financial application being examined.

Lack of interpretability. Deep Learning and hybrid models usually give better predictions, but it is hard to explain *why* they make a certain decision. This usually makes them difficult to trust for banks, and everyday investors [4, 17, 15, 1].

Overfitting and poor real-time performance. Many models work well on old and historical data but they struggle when they are tested on live and

changing markets. usually, Performance also declines quickly during sudden market shocks or periods of high volatility.[1, 11, 12, 22].

Data quality and combining different data types. Merging numeric price data with text based data, like news and social media, is still a challenge. Low quality or noisy data keeps lowering mode accuracy.[8, 16, 24].

Little real-world testing. Most studies have tested their models only in offline and controlled environments. They haven't tested them in live trading or inancial institutions. Therefore, it is unclear that how well these models would perform in practice.[6, 9, 14, 25].

Risk/Reward. As AI takes a bigger role in finance, questions are arising about equality, systemic risks, and responsibility that are particularly in relation to newer Gen AI agents that can operate freely. [23, 27, 21].

Limited regional coverage. Most of the papers have focused on developed markets such as the US or China. Now, the emerging markets like India and Turkey are studied far less, even though user adoption, regulation, and trust in AI can differ a lot by region [19, 20].

Overall, these shortcomings suggest the need for finance related AI models for not being only accurate but also explainable and tested in markets including emerging economies such as India.

4 Conclusion

This paper presents a discussion of the multiple recent studies devoted to the use of Artificial Intelligence (AI) in the financial field. Accordingly, the findings of the researchers reveal that AI can be successfully applied to enhance financial forecasting, trading, risk assessment, fraud detection, and decision-making processes. The results prove that AI-based algorithms can process high volumes of complicated financial data and offer reliable outcomes benefiting both financial institutions and investors. Furthermore, the increasing utilization of AI in financial applications has demonstrated its significant role in modern realities facing a wide variety of financial markets.

On the other hand, the reviewed articles provide some arguments regarding the current limitations in implementing AI in financial practices. First of all, the complexity of the algorithms and their low interpretability undermine the investors' trust in the predictions generated by these algorithms. Secondly, the problem of overfitting significantly complicates the processes of recognizing patterns and relationships in financial data using AI algorithms. Thirdly, the re-searchers note a shortage of relevant and reliable data sets that could be used for training machine learning algorithms in financial practices. Lastly, the majority of the reviewed articles report that various AI-based models were insufficiently tested in dynamic financial environments.

To conclude, the discussed findings unveil that financial field studies should shift their focus from developing highly reliable AI-based solutions to making them more transparent, adaptive, and applicable. In this regard, implementing

explainable AI, adaptive algorithms, and up-to-date financial data sets can of-fer the best benefits for future research. Furthermore, the financial field studies should be more attentive to the practical implementation of AI-based solutions that are currently rarely tested in real-life conditions. These improvements can make AI-based financial solutions both more competitive and beneficial for investors and financial institutions.

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