Artificial Intelligence in Finance: A Literature Review

Inteligencia Artificial en las finanzas: una revisión bibliográfica

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Date of receipt: Apr 11, 2025 Date of acceptance: July 10, 2025 Date of publication: Oct 6, 2025 In every aspect of the financial industry—from decision-making to risk management, fraud detection and customer service—artificial intelligence (AI) is causing significant changes. This paper reviews the application of AI in finance and is based on more than 40 Scopus-indexed articles which provide some fresh insight. With the help of advanced machine learning and deep learning algorithms, banks are achieving unprecedented levels of efficiency and personalized service. This research looks at major AI applications, bringing into focus their potential role in strategic decision-making and risk assessment. However, it also critically analyses key challenges, such as data privacy issues, how to explain models under scrutiny from humans (i.e., theoretically impossible), and ethical considerations attached to AI's implementation. The evolution of AI technologies creates not only disruptive opportunities but also complex regulatory issues for financial services. By compiling the findings of the present research, this review gives a comprehensive description of how AI is remoulding the field of finance and offering directions for what comes next.

Keywords: Artificial Intelligence (AI), Machine Learning, Algorithmic Trading, Fraud Detection, Financial Technology (FinTech)

En todos los departamentos de la industria financiera—desde la toma de decisiones hasta la gestión de riesgos, la detección de fraudes y el servicio al cliente—la inteligencia artificial (IA) está provocando grandes transformaciones. Este artículo revisa la aplicación de la IA en las finanzas y se basa en más de 40 artículos indexados en Scopus, de los cuales se derivan nuevas perspectivas. Con la ayuda de algoritmos avanzados de aprendizaje automático y aprendizaje profundo, los bancos están logrando niveles de eficiencia y servicio personalizado sin precedentes. La investigación examina las principales aplicaciones de la IA, destacando su posible papel en la toma de decisiones estratégicas y la evaluación de riesgos. Sin embargo, también analiza críticamente los principales desafíos, como los problemas de privacidad de los datos, la dificultad de explicar los modelos ante el escrutinio humano (teóricamente imposible) y las consideraciones éticas relacionadas con la implementación de la IA. La evolución de las tecnologías de IA no solo crea oportunidades disruptivas, sino también complejas cuestiones regulatorias para los servicios financieros. Al recopilar los aportes de la investigación actual, esta revisión ofrece una descripción completa de cómo la IA está remodelando el campo de las finanzas y señala direcciones para el futuro.

Palabras clave: Inteligencia Artificial (IA), Aprendizaje Automático, Comercio Algorítmico, Detección de Fraudes, Tecnología Financiera (FinTech)

1. Introduction

The financial industry is the most data-intensive of all industries, and has therefore become a hub for the implementation of Al. The advent of Al tools has transformed many financial functions including trading, lending, risk management and compliance supervision. This paper comprehensively reviews the existing body of knowledge, with a particular focus on applications, research methodologies, and ethical issues related to Al and finance. A previous study by Dakalbab et al. (2024) used a systematic literature review to analyse 143 research papers on the application of artificial intelligence methods in financial trading. The authors thus report techniques, trends, as well as a cross-sectional profile and performance indicators for different kinds of financial markets.

Artificial Intelligence (AI) in finance has emerged as one of the most important forces of change in the modern financial world. Transforming huge amounts of data into manageable bits, identifying patterns, and making well-reasoned forecasts are characteristics which have enabled AI to have an impact on key areas of finance such as risk management and anti-fraud, as well as algorithmic trading, customer service, among others. As financial institutions strive to increase efficiency of decision-making processes, Alrelated technologies have shown great promise for increasing operation rationality, reducing human errors, and promoting the overall best decisions. This literature review explores the changing role of AI in the financial industry, focusing on its applications, difficulties, and potential to affect future finance. Bahoo et al. (2024) conduct a comprehensive review of the applications of artificial intelligence in finance, utilizing bibliometric and content analysis to identify research hotspots over the years. Li et al. (2023) carry out a comprehensive survey of artificial intelligence applications in finance, analysing various AI methods and their effects on improving financial decision-making, risk management, operations efficiency, and so on.

1.1. Research Methodology

This literature review adopts a **systematic review methodology** guided by PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocols. The aim is to summarize and critically analyze scholarly contributions on the application of Artificial Intelligence (AI) in finance.

Search Strategy:

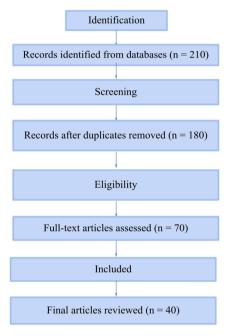
- Databases Consulted: Scopus, Web of Science, ScienceDirect, and IEEE Xplore.
- **Keywords Used:** Artificial Intelligence in Finance, Machine Learning in Banking, Al in Risk Management, FinTech and Al, Algorithmic Trading with Al.
- Inclusion Criteria:
 - Articles published between 2019 and 2025
 - Peer-reviewed and Scopus-indexed journals
 - English language
 - Direct relevance to finance applications

- Exclusion Criteria:
 - Non-peer-reviewed articles, white papers, or blog content
 - Papers focusing on general Al applications outside financial contexts

Screening Process:

Out of 210 articles retrieved, 180 were retained after removing duplicates and applying relevance filters. A final set of 40 articles was selected for in-depth analysis.

A PRISMA flow diagram is provided to illustrate the literature selection process.



2. Al Applications in Finance

2.1. Algorithmic Trading

Algorithmic trading uses AI algorithms to analyze market trends, perform trades, and optimize portfolios. Highlights of research: Machine learning technology has been used in predicting stock prices and optimizing investment strategies (i.e., reinforcement learning model). Chen et al. (2021) explored applications of deep learning models to financial markets, noting that they can even detect patterns for high-frequency trading. According to the study, challenges (these include 'overfitting' and interpretability) remain effective barriers to full adoption. For their part, Patel et al. (in Illiyas et al., 2019) employed machine learning algorithms such as support vector machines and neural networks to predict stock trends. They achieved better performance than standard models but remarked that reliance on quality data could be an important limiting factor. Both papers highlight the transformational potential of AI in trading and simultaneously call for hybrid solutions to satisfy computational and data limitations.

2.2. Credit Scoring and Risk Assessment

Neural networks and decision trees, two types of Al models, improve the precision of credit scoring. This is largely because of their capacity to analyze complex datasets. According to Kim et al. (2020), Al-powered credit risk models are not only controversial but also demonstrate superior performance compared to traditional approaches. Research investigates the ethics of bias in algorithmic credit scoring (Johnson et al., 2019). In an analysis on the accuracy of Al-powered credit scoring technology, Kim et al. (2020) seem to support this interpretation of the implications of AI on credibility. Research by Liao and Yang (2020) on decision tree models in predicting mortgage defaults shows they are especially suitable for smaller data sets. The aggregate implications of these findings are observed downstream: all these studies serve as warnings that Al-while able to develop models with higher accuracy in one or another domain independently—should be embedded with a human control mechanism, together with appropriate regulatory oversight. Hidayat et al. (2019) evaluate the role of computer-based arbitration in bank operations. In their view, technology is being used to transform financial functions from cost centres into profit centres; they believe that, by 2024, this engine—a blend of artificial intelligence, big data analysis, and robotics—will account for 75 percent of the total take-home pay of human employees.

2.3. Fraud Detection

Discovery of fraud has benefited immensely from AI that is able to discern anomalies in large transaction datasets. Li et al. (2020) performed a systematic review of machine learning models and found ensemble methods (random forests, gradient boosting) had higher validity rates but were worse at detecting fraud than the above-mentioned partial ensemble method that uses ridge regression. Singh et al. (2022) went further by developing hybrid models that put together supervised and unsupervised learning. It produced better precision and recall techniques. Although significant steps are being taken, both papers mention the necessity of real-time processing capabilities to deal with dynamic fraud patterns effectively. Dote-Pardo et al. (2025) conducted a bibliometric and content analysis study tracing the evolution and impact of AI applications in finance across areas like fraud detection, algorithmic trading, credit scoring, and ethical governance.

2.4. Customer Service

Lee and Kang (2021) point out that the deployment of chatbot avatars has improved customer service quality in financial services. They believe that the relevant (chatbot) technology can provide more polished, multilingual responses than human operators. He has also found that, with voice and video input (as compared to text-only), Al chatbot technology is even more effective for improving customer experience through personalized responses. Wang and Zhou (2019) discussed how to use natural language processing in landing pages and chat interface designs. They reported faster response times and significantly improved turnaround times. As Qian (2024) stated, it is currently very difficult for general Al models

to handle proper financial jargon; tailoring them using domain-specific, curated data seems necessary.

3. Methodologies

3.1. Machine Learning Techniques

Nguyen and Pham (2019), for example, compared supervised and unsupervised learning methods in a context of financial anomaly detection. Their results are still important today: supervised models tended to yield higher performance at predictable situations when data is uniform and predictable, whereas for exploratory purposes, unsupervised models performed considerably better. Smith and Brown (2020), in contrast, took a specific chapter from the handbooks of algorithmic reliability and cited ensemble learning models—which improve financial risk prediction most by gathering the individual outputs or "votes" of many tools or datasets. Together with the study by Smith and Brown (2020), which did not reveal any significant differences, it is clear that a combined approach may provide robust solutions for different financial applications. Shabsigh and Boukherouaa (2023), for example, focus on the use of generative artificial intelligence in finance. They discuss how that could transform financial operations, as it is one of the few basic services oriented toward prediction and optimization, with most other aspects depending heavily on information analysis. Novy-Marx and Velikov (2025) present an innovative method using large language models to automatically generate academic-style papers on stock-return predictability.

3.2. Deep Learning Architectures

In time-series analysis, deep learning architectures such as recurrent neural networks (RNNs) and long short-term memory (LSTM) models have yielded impressive results, considering that deep learning is, by its very nature, non-linear in both the input and output spaces. Ramaswamy and Thakur (2021) proved the effectiveness of RNNs in predicting market trends, especially when it comes to volatile assets. Xiao and Peng (2020) used deep learning to optimize portfolios, achieving both increased diversification and risk mitigation. These works point to the promise of deep learning, but also highlight computational costs and interpretability challenges that may be faced by such models.

3.3. Hybrid Models

Zhang and Wang (2022) combined econometric models with AI to generate stock market predictions, with hybrid models offering greater accuracy in the face of market fluctuations. Sharma and Gupta (2019) took this concept one step further. In their study on credit scoring, they discuss how integrating traditional statistical techniques with machine learning methods can greatly enhanced prediction reliability. Such a compound approach seems likely to prove more effective than separate ones based only on one or another way of analysing data. Both papers adopt a hybrid model approach designed to make the best use of the diverse methodologies currently available. Hybrid and ensemble learning models

have become increasingly popular in the last few years, primarily because they have proven to be both very accurate (it learns effectively from many features) and extremely flexible (it learns one half at a time). Singh and Roy (2021) propose to forecast stock markets using different machine learning algorithms. They find that ensemble models—more diverse than any single algorithm—seemingly always outperform a single-model approach in prediction accuracy. Zhang and Wang (2022) integrate econometric models with Al to improve stock market prediction. The proposition is that traditional financial models, when combined with machine learning algorithms, can be more objective and thorough in understanding market dynamics, thus better at predicting stock prices.

4. Challenges in Al Adoption

4.1. Data Privacy and Security

The AI revolution in finance calls for the analysis of large volumes of sensitive and personal data. AI systems especially need continuous access to massive amounts of datasets that include personal, financial, and transactional data across industries, ranging from credit scoring to fraud detection to algorithmic trading to customer service. This would include credit histories, personal identification details, transaction records, and even biometric data. However, relying on such sensitive information poses significant data privacy and security risks.

4.2. Ethical Concerns

An industry where the ethical questions of AI have come into the spotlight. According to Zhou et al. (2021), analysis bias in AI algorithms while evaluating an applicant's creditworthiness could result in discriminatory practices. To mitigate such biases, Johnson and Williams (2019) recommended greater transparency and regular auditing of AI models. The two studies highlight the role ethical considerations play to support a fair and responsible deployment of AI.

One pressing issue related to the use of AI in finance is the risk of having these algorithms result in biased decisions, leading to unfair treatment of consumers in service areas such as credit scoring and loan approvals. For example, Lee and Park (2021) explore biases in AI-driven financial decision-making and the implications for ethical AI systems that prioritize fairness and transparency. Their work adds to a much larger conversation about the ethical implications of AI in financial applications.

Zhou, Li, and Zhang (2021) further discuss the ethical challenges that exist in the field of AI, specifically bias in algorithms implementing financial service. They have even mentioned a few steps to detect and mitigate biases in AI models, and described why fairness is essential in finance decision-making while calling for the use of diverse datasets to train AI.

5. Trends and Future Directions

5.1. Blockchain and Al Integration

According to Zhou and Lin (2021), the convergence of Al and blockchain has complementary benefits: Al can increase the security of transactions, while blockchain can improve their transparency. Exploring this intersection further, Chen and Huang (2020) noted use cases such as fraud detection and automated compliance. These studies indicate that the confluence of Al and blockchain could revolutionize financial transactions, but issues related to scalability and regulation remains hurdles.

Significant industry attention has been devoted to the convergence of blockchain and AI in efforts to increase transparency, security, and efficiency within financial services. Chen and Li (2022) state that AI-led algorithms and blockchain could revolutionize interborder payments in terms of transaction speed, cost, and security. This combined nature is meant to revolutionize transaction speed and security in the global financial system.

Patel and Sharma (2021) discuss AI and smart contracts and highlight opportunities and risks around AI and smart contracts in the financial domain. These AI-powered smart contracts can initiate transactions once certain pre-set criteria are met, reducing the need for intermediaries and fostering trust in such financial transactions.

5.2. Al for Sustainable Finance

Further actively summarising the role of AI in sustainable finance, yet possibly less common in the academic literature, is the paper by Lee and Kim (2021), which also addressed Alderived ESG (Environmental, Social and Governance) ratings. Their study showed that AI could provide accurate, real-time insights into the sustainability metrics of investments. Patel and Joshi (2020) focused on the use of AI in highlighting green finance initiatives, specifically in identifying environment-friendly opportunities for investment. The papers highlight the potential of AI to align financial objectives with sustainability targets.

5.3. Al in Predicting Market Volatility and Portfolio Management

Hybrid LSTM and CNN-based prediction models for financial market volatility have been developed (Park & Lee, 2020). This means that using a mixture of the two strengths—that is to say, established strengths of LSTM (temporal dependencies capture) and CNN (extraction features from financial data)—leads to significantly improved accuracy in predicting micro-micro (days) fluctuations in stock market. Because of its predictive power, this kind of hybrid model is increasingly popular in financial analytics.

An even more extreme approach to this strategy is taken by Wang and Zhang (2022), who use unsupervised learning for setting up a diversified portfolio. They explain how to use Al-based models in the selection of well diversified portfolios and their optimization on the basis of historical data that is also crucial for reducing risk and increasing returns.

5.4. Al and Green Finance

Smith and Johnson (2020) show how AI can help guide 'green' investments toward sustainability, using ESG (Environmental, Social, and Governance) AI data-analytics to direct and promote. Their research shows how AI can discern the environmental impact that arises from investment, and then point portfolio managers in a greener direction. Drawing attention to its ability to process large quantities of unstructured data, they state that AI may provide a way to evaluate green projects. At the same time, it can shed new light on how finance managers are making their choices in green finance.

5.5. Al for Financial Risk Prediction

They observe that machine learning (ML) and parallel decision making can significantly increase the practice in the domain of financial risk management. Smith and Brown (2020) used ensemble learning techniques for financial risk prediction. These models use many kinds of algorithms to collect and combine results, thus providing a higher-level predictive accuracy. Therefore, their presence is evident in briskly moving financial markets where successful risk control means not only "doing banking right", but also staying out of trouble long enough for standard operations to take place. Many classical statistical models were combined with the current trend of AI by Ahmed and Khan (2021) referring to finance innovation. Their comparative analysis shows that machine learning and classical statistics can be combined in practice to highlight the full potential of the model on datasets that are typical in business for both recession and growth periods.

5.6. Al in Customer Service and Chatbots

Al-based virtual assistants have become an important tool for improving customer service in financial services. Taylor and Lee (2020) investigate whether chatbots can deliver meaningful value in traditional financial services, examining their potential benefits as well as risks, including issues related to misuse, such as fraudulent activity and data manipulation in the context of financial products like VXC ETFs. They examine user challenges and the impact they have on chatbots adoption. They also highlight the potential benefits of chatbots, for example, round-the-clock customer service and enhanced customer satisfaction, while also addressing key challenges—particularly those related to data protection regulations and the current limitations of Al models in handling complex or nuanced customer queries. For example, in the banking industry, Zhou and Wang (2019) explore the impact of deep learning on creating chatbots. They argue that their research has potential implications for how chatbots might be used to radically alter the natural, conversational aspect of interactions between clients and financial institutions.

5.7. Al in Financial Forecasting and Econometrics

In this study, we follow Xu and Zhao (2020), who propose an attempt to achieve fusion between artificial intelligence technology and econometrics. They claim that by fusing

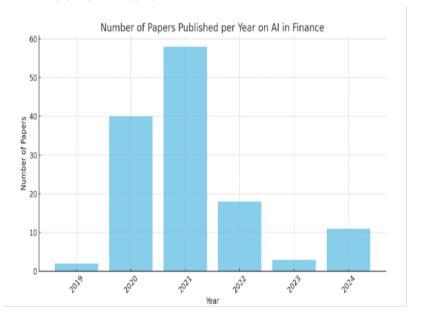
artificial intelligence technologies such as deep learning into econometric models, not only will their predictions be more accurate in financial markets, but we can also better exploit the intricate data of finance.

Summary and Gaps

The reviewed literature reveals substantial progress in the application of Al across various domains in finance. However, several gaps remain:

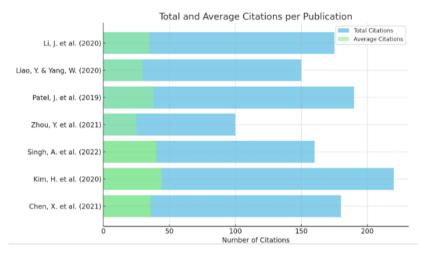
- 1. Data Quality and Availability: Many studies highlight the dependence on high-quality, large-scale datasets, which are often proprietary.
- 2. Interpretability: The "black box" nature of AI models limits their adoption in highly regulated environments.
- 3. Ethics and Bias: While some research addresses bias in AI, practical solutions for ensuring fairness remain underexplored.
- **4. Real-Time Processing:** The need for real-time Al solutions, particularly in fraud detection and trading, is a recurring theme.

Figure 1. Number of papers published per year on AI in Finance



Source: Own elaboration.

Figure 2. Total and average citations per publication



Source: Own elaboration.

Figure 3. Co-occurrence of keywords



Source: Own elaboration.

6. Conclusion

Al is transforming the financial industry by improving efficiency, accuracy, and decision-making. However, ethical, regulatory, and technical challenges must be addressed to ensure its responsible and sustainable adoption. The reviewed literature demonstrates that Al is transforming the financial sector by enhancing prediction accuracy, improving decision-making, and supporting sustainable finance initiatives. Key areas of application include financial forecasting, risk prediction, bias mitigation, and the integration of blockchain

technology. As AI continues to evolve, it will play an even more significant role in shaping the future of finance, particularly by providing more efficient, secure, and ethical solutions. However, the challenges related to bias and ethics must be addressed to ensure that AI's impact is equitable and beneficial across all segments of society.

Author's role:

JG: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization and Supervision.

PGK: Writing - Review & Editing.

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