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Explainable and Sustainable Artificial Intelligence in Finance: Opportunities, Risks, and Future Innovation

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Abstract— Artificial Intelligence is revolutionizing the banking and financial services sector through improved efficiency, data analytics, and innovative customer experience. AI is being used in several applications within the financial services sector such as algorithmic trading, credit scoring, compliance, and fraud detection. The current study emphasizes the opportunities offered by artificial intelligence to the financial sector while simultaneously discussing the associated challenges such as data security, ethics, algorithmic bias, and legal uncertainty. It also pertains to future topics, which include XAI, AI for sustainable finance, RegTech improvements, and hybrid human-AI collaboration. This research proposes to provide a complete evaluation of the prospects and challenges of AI in finance, along with providing recommendations for future studies.

Keywords— Artificial Intelligence, Financial Services, Machine Learning, Explainable AI, Sustainable Finance

1. Introduction

Artificial intelligence (AI) can be understood as an ensemble of computer sciences that take their inspiration from how humans utilize their neural systems and, just like human bodies, can observe, perceive, and get affected by their environments (Raj & Kos, 2023). It encompasses technologies like machine learning, deep learning, natural language processing (NLP) platforms, predictive application programming interfaces (APIs), image recognition, and speech recognition (Bahoo et al., 2024). Artificial intelligence has emerged as one of the technologies that could be utilized for anything, as seen in its extensive use across multiple sectors and its transformative impact across industries like manufacturing, health, and agriculture (Rashid & Kausik, 2024). The development of artificial intelligence technology has enabled its application in diverse fields because many companies apply this technology and use it to transform their processes. The impact of artificial intelligence technology is experienced in fields such as manufacturing, healthcare, and agriculture, among others (Rashid & Kausik, 2024). Artificial intelligence (AI) has grown over time and becomes one of the important technological advancements. Companies have applied AI technology in order to improve their operations and have been successful with this move. Some of the multinational corporations that have applied AI are Facebook, Google, IBM, and Microsoft, among others (Ahmed et al., 2022). Indeed, many organizations within the financial sector are allocating substantial resources into acquiring skilled individuals in the domain of data science and machine learning. This includes traditional hedge fund managers and investment/banking institutions, as well as those offering services related to FinTech (Goodell et al., 2021).

The use of artificial intelligence has been widely integrated into the finance sector over the last decade owing to automation issues, sophisticated analysis, and prompt decision-making. Several firms involved in the finance sector have started using various AI technologies in order to increase their efficiency levels, prevent any fraud cases, enhance client satisfaction rates, and make policies related to risk management (Bahoo et al., 2024). Some of the significant developments witnessed in the global AI in finance market include digital banking, finance technology ecosystems, and financial data products (Misheva et al., 2021).Various applications, including machine learning algorithms, natural language processing, and generative AI, have been employed by many banks in activities like customer relations, credit scoring, regulatory requirements, and financial portfolio management (Misheva et al., 2021). Also, adoption of intelligent automation and cloud financial solutions has revolutionized banking into modern-day financial organizations. One point that can be made is that AI is not just an innovation in the financial industry but a necessity (Quinn, 2023).

However, the increasing prevalence of sophisticated AI models in the finance industry has led to significant challenges in terms of transparency. The excessive emphasis on the effectiveness of predictive models or systems often results in a lack of interpretation or explanation, which causes decision-makers to be cautious of or even reject AI systems (Chang et al., 2024). To address these issues, more and more legal frameworks require algorithmic decision-making to be open and honest. Companies are required to give relevant information about the logic involved in algorithmic decision-making, as well as the relevance and the anticipated repercussions of such processing for the data subject. This is a requirement that is becoming increasingly prevalent in regulatory frameworks (Blacklaws, 2018). In order to achieve this goal, the idea of explainable artificial intelligence (XAI) came into existence. This concept introduced a set of machine learning (ML) techniques that produce models that provide an acceptable balance between explainability and predictive utility. These models also enable humans to comprehend, trust, and manage the generation of AI models that are currently being developed (Misheva et al., 2021). Consequently, post-hoc strategies for human-interpretable black-box models have increased. Experts utilize similar arguments to identify discriminating biases in black-box models. LIME and SHAP are well-used, local, model-agnostic techniques for explaining a black box classifier's specific prediction (Slack et al., 2020). Banking AI will generate innovation and risk, and therefore research on both its advantages and disadvantages will be required. AI has the promise of better risk assessment, real-time detection of fraud, individualized financial products and services, and operational efficiency. Privacy of information, ethical regulation, model bias, and compliance are still a challenge. The future finance AI structures need to drive responsible innovation, ensure interpretability, maintain public trust, and maximize the benefits of this disruptive technology.

2. Literature Review

The foundation of artificial intelligence lies in machine learning, which, as Jordan & Mitchell (2015) expound, focuses on the development of computer systems that can automatically enhance their performance and ability over a period through the learning of data and amassed experience. Their study provided a theoretical basis for the application of AI in finance with respect to predictive modeling and risk assessment. Along the same lines, Heaton et al. (2016), in their research paper, pointed out the superiority of deep learning as a powerful approach towards prediction and classification in finance through greater levels of accuracy by capturing complex nonlinear patterns. The new approach has successfully debunked many of the existing theories, such as market efficiency, and created new definitions and perspectives for financial economics, expanding predictions within different financial domains. Expanding on this idea further, Kraus and Feuerriegel advanced the application of deep learning to finance studies by examining how multi-hidden layer neural networks can be used to extract hierarchies in financial disclosures. Empirical results showed that deep learning approaches have significantly outperformed traditional approaches with respect to directionality and economic performance in order to establish benchmarks for text-based prediction (Kraus & Feuerriegel, 2017).

Giudici (2018) addresses the integration of FinTech and AI risk management with reference to the demand for upcoming regulatory technologies (RegTech) and supervisory technologies (SupTech). The article throws light on applying AI for addressing creditworthiness determination challenges, fraud, and market risk regulatory challenges and highlights the need for collaborative frameworks in balancing supervision and innovation. Buchanan (2019) chronicles a detailed survey of AI in finance, from fraud detection and robo-advisory platforms to algorithmic trading and regulatory compliance. The introduction sets the context from econometric models to machine learning and raises the ethical and regulatory implications of AI-driven decision-making in finance. Mhlanga (2020) discusses the application of artificial intelligence to foster digital financial inclusion of weaker segments such as low-income people, women, and micro-enterprises. The study highlights applications of AI for anti-fraud efforts, risk assessment, and customer service through chatbots. The study adds that AI mitigates information asymmetry and advises its adoption to supplement institutional access to financial services. Goodell et al. (2021) elaborated that various financial institutions such as hedge funds, banks, and FinTech companies are seriously considering hiring data science and machine learning experts. With the increased access to alternative data and computer power, it is a strategic response to proprietary modeling in market forecasting, credit risk assessment, and customer understanding. This is being done with the consideration of the presence of alternative data.

In the work of Al-Sartawi et al. (2022), they speak of what they call the "green finance revolution" pertaining to the use of artificial intelligence (AI). The authors mention in particular the use of AI in improving ESG investment and CSR disclosure, as well as in the long-term decisions of the firm. They are in agreement that artificial intelligence can be an agent in reducing social ills such as poverty, pollution, and environmental degradation. More than just considered as a technical tool, artificial intelligence should be understood as an ethical and sustainable finance enabler strategically, the authors strongly stress. In 2023, there is an article by Barry

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Quinn on a future and historical perspective of AI in finance, following its path from early statistical methods to advanced machine learning and describing how explainable AI is increasingly being embedded in fundamental financial instruments. Quinn also points out that the future EU regulation demands broader XAI studies in order to enable transparency and trust for financial AI systems (Quinn, 2023).

Bahoo et al. (2024) provide a comprehensive discussion on applications of finance artificial intelligence and highlight ten major research areas ranging from trading models, portfolio management, credit risk, and investor sentiment analysis. Using bibliometric and content analysis, the authors highlight the path of development of AI based studies in finance for the last two decades. They also emphasize the need for further research in new and emerging AI technologies, ethics, and AI as part of global financial system infrastructure. Likewise, Ridzuan et al. (2024) discuss about adoption of artificial intelligence in finance and give examples of credit risk management, fraud detection, investment portfolio management, and customer services. The main issues mentioned by the authors include data privacy, algorithm bias, and governance transparency. Moreover, the authors provide a summary of current AI regulations across geographies including US, EU, China, and Singapore among others, along with the need for ethical regulation of AI. In another paper, Sai et al. (2025) have explained the application of generative AI in finance, fraud detection, stock prediction, risk analysis, and document processing.

The paper proceeds to discuss domain models such as BloombergGPT and FinanceGPT and their contribution to decision making as well as to automate the finance job. The paper also discusses issues of bias, interpretability, and resource requirements and as a result gives way to change the order of priority of AI applications in finance. There is already some research under way that looks at how artificial intelligence can embed Environmental, Social and Governance (ESG) factors in financial instruments, in particular credit rating. Giudici and Wu (2025) argue that while machine learning techniques like random forests and gradient boosting are great at producing accurate forecasts, they are low in explainability and sustainability. They attain this by suggesting aggregating machine learning approaches, which not only ascertain the nonlinear impact of the ESG factors but also provide the models explainable and fair. There is proof that accessible ESG information can be used to improve predictability, and as a result, credibility and therefore support sustainable finance in the long term if applied within AI-driven credit scoring models.

3. Application and Opportunities of AI in Finance

Financial services are being revolutionized by Artificial Intelligence (AI) through a wide range of applications—each with strong potential for efficiency, precision, personalization, and new opportunities.

3.1 Fraud Detection and Early Warning Systems

The capacity of AI to detect typical behavior and out-of-the-ordinary trends enables real-time anti-fraud activity. A thorough review in SN Business & Economics says "AI and financial fraud detection/early warning system" as one of the leading clusters of research, with the comment that conventional methods are outrun by ML-based models (Bahoo et al., 2024). After. A systematic review in the Journal of Big Data notes that AI, machine learning, and deep learning methods "could be alert to the latest fraudulent activities," thus implying the necessity for always-adapting systems in fraud detection (Hafez et al., 2025). In addition, specialized studies highlight the technical benefits of ensemble and deep learning approaches. For instance, in a recent paper about multi-banks, it was revealed that using graph techniques enabled fraud and money laundering attempts to be detected in 93% accuracy by determining coordination among perpetrators (Olowu et al. 2024). Furthermore, according to another study by Abi (2025), unsupervised machine learning algorithms like autoencoders and clustering models can detect zero-day frauds and hidden coordination strategies with high accuracy, even without utilizing training datasets. Within hybrid AI systems, these algorithms provide better adaptability and precision, making them appropriate for dynamic fintech settings.

3.2 Credit Risk, Underwriting and Scoring

AI is the current top financial tool because of its great ability to predict market events while reducing market asymmetries and fluctuations. Risk management is achieved by means of the accurate prediction of bankruptcy and credit risks due to fraud detection and early warning systems, which facilitate financial stability and performance assessment (Bahoo et al., 2024). The effectiveness of supervised models like Support Vector Machine, Random Forests, and deep neural networks has been shown regarding their better performance in predicting credit risk than classical statistical models. Besides, for those borrowers whose credit histories are incomplete, ensemble learning and gradient boosting models work much better. SHAP offers greater transparency with regard to automated underwriting, which means that companies can be regulated and still have their systems understandable (Adewuyi et al., 2023). Such advancements make it possible to automate the decision-making process,

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improve borrower inclusion, and perform dynamic risk assessment. The underwriting process undergoes a major transformation because of all the above mentioned innovations. Table 1 demonstrates traditional and AI credit scoring.

Traditional Models	AI Models
Static data	Real-time data
Manual processing	Automated decisions
Limited flexibility	Dynamic profiling
Lower inclusion	Better inclusion

Table 1. Traditional vs AI Credit Scoring

3.3 Algorithmic Trading and Investment Strategy

Artificial intelligence has revolutionized algorithmic trading from a rule-based automated process to an adaptive, self-evolving model. Algorithmic trading has gained speed, with complex systems using artificial intelligence to adapt to the changing market environment depicted in fig. 1. Sentiment analysis and deep learning algorithms enhance prediction accuracy. Although platforms such as MetaTrader have made it easy for everyone, there are some regulatory challenges. Ethical artificial intelligence models and explainable artificial intelligence are essential for transparency and fairness (Jukl & Lansky, 2025). Models that employ transformers have begun utilizing unstructured data such as news articles and transcripts of earnings calls to forecast asset prices and headline news to generate price predictions. Addy et al. (2024) highlight how AI integrated into algorithmic trading influences the constantly evolving What their research indicates is an unprecedented phenomenon in the financial world that goes beyond the erstwhile, largely rule-based system. Such technologies, innovative and positive as they are, raise ethical, regulatory, and trust issues. The authors emphasize the need for responsible development of AI and extending the guidelines to all actors of the regulatory space to maintain and support the integrity of the market.

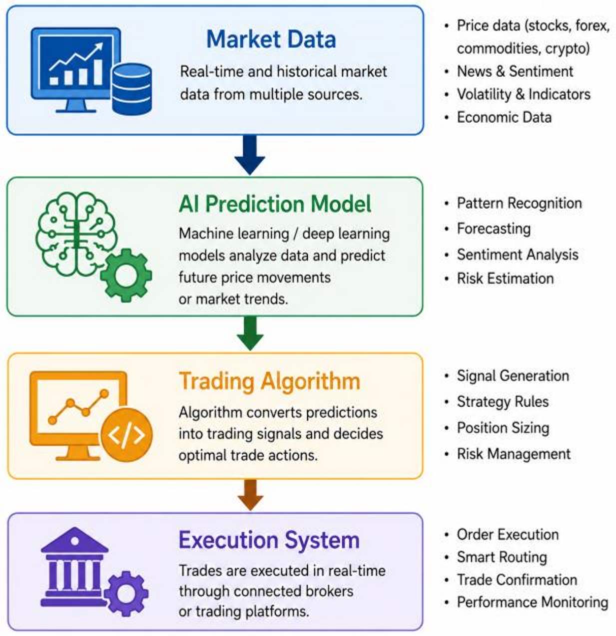

Fig. 2 AI Trading Architecture

3.4 Customer Experience and Personalisation

Artificial intelligence is transforming customer engagement in finance into hyper-personalization and smart automation. Artificial intelligence-powered recommendation systems are gaining momentum in online banking to understand behavior and deliver customized financial products shown in Fig. 2. Customer experience: traditional banking and AI-enabled banking. Sengupta and Sharma (2023) found that AI plays an important role in finance marketing in the form of improved lead conversion, retention of customers, and tailored engagement. Based on trends of 2018–2021, their research focuses on AI ethical usage, cybersecurity, and predictive analytics as the future primary drivers. Conversational finance is also being revolutionized by generative AI. Financially corporately trained transformer chatbots can now effectively handle complex queries with near-perfect accuracy. Raghavan (2025) had introduced a framework of reliable financial chatbots based on explainability, accessibility, and adaptive learning. The research highlighted that contemporary AI-powered chatbots could satisfy high expectations of transparency and compliance with regulatory standards while enhancing customer satisfaction through savvy, context-aware interactions.

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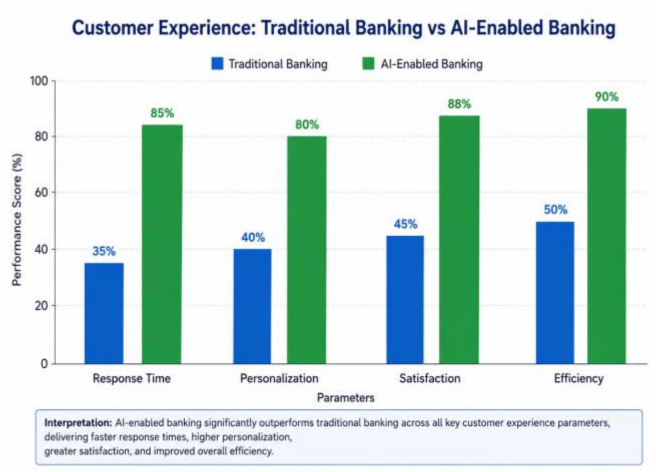

Fig 2 . Customer experience Traditional Banking and AI enabled Banking

3.5 AML, KYC, and Regulatory Compliance

Artificial intelligence is also enhancing the effectiveness of compliance functions better, especially in anti-money laundering (AML) and Know Your Customer (KYC) functions. Artificial intelligence-based transaction monitoring systems have shown significant improvement in effectiveness. Artificial intelligence is transforming financial compliance with better fraud detection, reduced AML system false positives, and automated regulatory work. Machine learning and NLP also enhance efficiencies, agility, and precision, and compliance turns into a data-driven, efficient exercise (Kothandapani, 2024). The technologies enable institutions to respond in real time to evolving threats and regulatory changes with less cost and manual working of processes shown in Fig. 3, AI Compliance Ecosystem. AI platforms are able to adapt to advanced compliance environments, identify relevance-based anomalies in real time, and provide scalable surveillance. The innovation helps financial institutions maintain integrity while accelerating decision-making and auditing readiness optimization.

4.Industry Applications and Case examples

Artificial intelligence is no longer just a prototype concept but rather a crucial component of the current financial system. Top global financial organizations have adopted AI technology in their work to become more efficient, automate their decision-making procedures, strengthen their fraud detection mechanisms, and improve their clients' experience. Machine learning, natural language processing, generative AI, and predictive analytics technologies have enabled financial organizations to develop sophisticated financial ecosystems. According to the findings of the most recent study concerning the issue, the AI market in the field of finance will exceed $190 billion globally by 2030 owing to rapid growth in digital banking, financial automation, and intelligent analytics software. Many significant financial enterprises have started using AI technology to perform document processing, transaction analysis, security monitoring, customer service, and regulatory compliance management. TABLE 2 shows the real-world AI applications in finance.

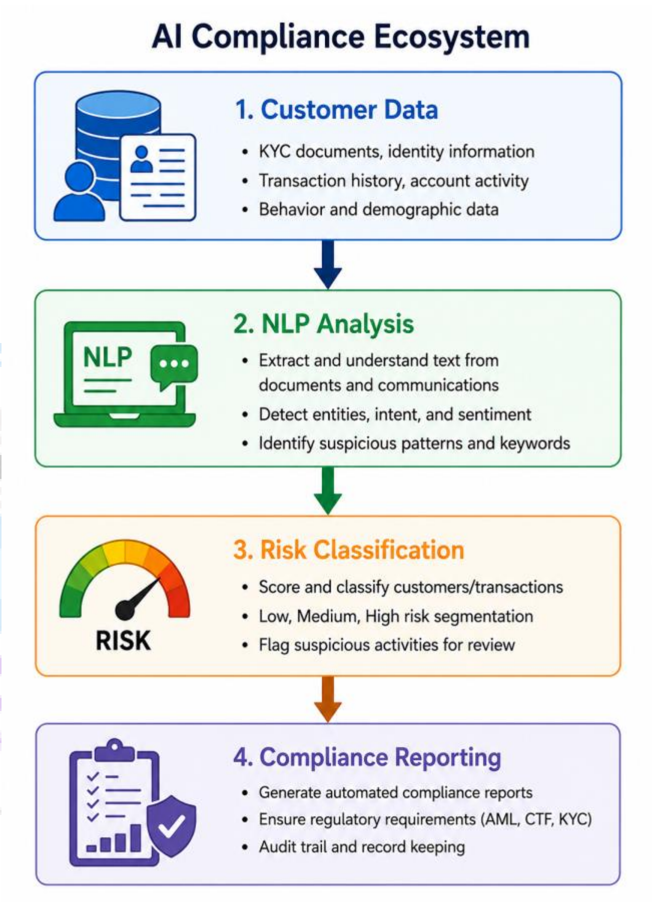

Fig. 3 AI Compliance Ecosystem

4.1.JPMorgan Chase — COIN Platform and AI Automation

In regard to applying artificial intelligence technologies for the benefit of banks, one of the pioneers in this area is JPMorgan Chase Company. In particular, the company has launched a unique solution – Contract Intelligence (COIN). The COIN software aids in reviewing legal and financial documents. Before the introduction of this solution, the banks had to spend more than 360,000 hours annually on examining commercial loans. With this innovation, however, all the necessary information can be extracted from documents within several seconds using machine learning and NLP algorithms. The company is known for using AI technologies for fraud detection, financial payment protection, data mining, and other processes. As reported, JPMorgan Chase spends billions of dollars annually on implementing innovations, including various applications of artificial intelligence. Today, JPMorgan Chase applies the AI solution for potential fraud detections and financial analyses (https://www.jpmorganchase.com).

4.2.BloombergGPT and Financial Language Models

Bloomberg also introduced the BloombergGPT, a huge language model tailored to suit financial applications. The BloombergGPT language model has undergone training using about 50 billion parameters based on financial data and public language data. The language model is expected to carry out various natural language processing tasks related to the financial field, including sentiment analysis, market intelligence extraction, question answering, financial report summarization, and news classification. Differently from AI language models that use any kind of language, BloombergGPT was designed to process the language used in the financial market. As revealed by the research results, BloombergGPT proved far much superior to other language models in the execution of financial NLP tasks. The introduction of BloombergGPT reflects the importance of generative AI and language models in the current financial sector. Several organizations have started examining the possibility of employing similar technology in their financial operations (https://www.bloomberg.com/asia).

4.3.PayPal and AI-Based Fraud Detection

PayPal utilizes artificial intelligence-based systems for detecting fraud in millions of payments that are made daily using its payment system. Every year, PayPal processes billions of payments and therefore having an artificial intelligence-based security system is quite helpful in identifying frauds that happen on a real-time basis. PayPal utilizes machine learning algorithms to scrutinize the transaction history, customer behaviors, transaction devices, geographic information, and purchasing trends to identify any fraudulent activities. By implementing artificial intelligence technology for fraud detection, PayPal has been successful in boosting the security of its transactions and reducing the number of fraudsters who carry out fraudulent activities. Through the implementation of predictive analytics tools, PayPal has been able to predict and identify any emerging fraudulent practices. PayPal has been successful in gaining customer trust through implementing artificial intelligence technologies (https://www.paypal.com/us/home).

4.4.Mastercard and AI Security Systems

The AI technology of Mastercard has been significantly advanced by implementing high-end platforms of fraud detection and cybersecurity. For instance, the company has launched the Decision Intelligence Pro, which is an artificial intelligence platform that leverages generative artificial intelligence and neural networks for detecting fraud cases in real time. The company makes millions of transactions annually in over 210 countries and territories worldwide, thus requiring advanced and highly scalable infrastructures for AI security purposes. According to the reports provided by Mastercard, the implementation of the Decision Intelligence Pro platform allows the organization to detect fraud cases based on transaction behaviors, merchant activities, geographical locations, and spending behaviors within milliseconds. Additionally, the tool provides high-end detection of fraudulent activities without declining transactions. Besides, the firm collaborates with various organizations that provide cyber solutions, including Feedzai, in order to create better solutions for cryptocurrency frauds, anti-money laundering, and financial crimes (https://www.mastercard.com).

4.5.Goldman Sachs and AI-Driven Trading Systems

Artificial intelligence technologies have been integrated into the operations of Goldman Sachs, including the processes of trading surveillance, investment analysis, and financial advisory services. The company employs AI-based technologies to conduct an in-depth analysis of large volumes of financial markets data and trading processes. Artificial intelligence models can be used to estimate market trends, investment decisions, and price prediction through the use of predictive analytics and machine learning. The company utilizes artificial intelligence technologies to optimize the research process, provide financial information summaries, and improve the efficiency of investment banking. On the other hand, Goldman Sachs and other corporations have voiced their concerns regarding AI hallucination and cybersecurity issues. In addition, the widespread application of artificial intelligence raises serious data privacy and ethical governance risks (https://www.goldmansachs.com).

Company	AI Application	Key Technology	Major Purpose	Impact
JPMorgan Chase	COIN Platform	ML + NLP	Contract analysis	Reduced 360,000 manual work hours annually
Bloomberg	BloombergGPT	Generative AI	Financial NLP	Improved financial analytics and summarization
PayPal	Fraud Detection System	Machine Learning	Transaction security	Real-time fraud monitoring
Mastercard	Decision Intelligence Pro	Generative AI + Neural Networks	Fraud prevention	Reduced false positives and improved security

Goldman Sachs	AI Trading Systems	Predictive Analytics	Trading and investment analysis	Enhanced market forecasting and automation

TABLE 2. Real-World AI Applications in Finance

5. Challenges and Risks of Using AI

5.1 Data Quality, Bias, and Privacy

Availability of good quality, representative data is still one of the largest problems with the implementation of AI in financial systems. In the real world, the financial data are imbalanced, unstructured, and historic, which generally results in potentially biased predictions and discriminatory outcomes. For example, credit scoring models learned from biased data may systematically exclude various marginalized groups from access to finance. Additionally, using sensitive personal information is a severe threat to privacy, especially in environments that are regulated by laws like GDPR. In the absence of ethical data stewardship, transparency, and corporate digital accountability, AI-driven fintech systems can lead to a reduction in the public trust and can also perpetuate social disparities, as Aldboush and Ferdous (2023) observe.

5.2 Model Opacity and Explainability

Another major challenge of using financial AI is the transparency of deep learning models that have a tendency to behave as "black boxes" with low interpretability. This obstructs institutions from auditing decisions, validating regulatory compliance, and maintaining stakeholder trust. Explainable AI (XAI) has the potential, but its application in finance is limited due to trade-offs between predictive precision and interpretability. Černevičienė and Kabašinskas (2024) state that it is worth mentioning that even though XAI can contribute to increased transparency within the model, most financial systems are mainly performance-oriented with underdeveloped explainability. This leads to issues of accountability in situations where high-risk financial choices are encountered.

5.3 Uncertainty of Law and Regulation

The pace of AI adoption in finance has comfortably overtaken efforts at legal and regulatory standards. Most jurisdictions in the world today lack adequate quality, substantive regulatory standards for autonomous decision systems, algorithmic credit allocation, and end-to-end data management. This absence of regulation increases the compliance risk, creates uncertainty for financial institutions, and can even deter good innovation. Yadava (2023) highlights that, in the absence of good governance, AI systems will tend to reinforce bias, erode public confidence, and remove accountability. He supports the creation of multidisciplinary frameworks that will merge the ethical norms and regulatory structures to render financial systems transparent, equitable, and accountable in the utilization of AI.

5.4 Social and Ethical Implications

Financial AI systems can perpetuate social injustice unknowingly with biased data and black-box decisions. Individuals may be sactioned by economic surrogates like zip code or degree level. Svetlova (2022) claims that ethics for AI must develop to address structural risks with attention to relational processes and serendipitous algorithmic interaction effects rather than individual events. This view emphasizes ethics for coordinated action by autonomous systems. Within financial high-frequency markets these effects can be devastating, and system-level accountability is key to the provision of equity and trust in financial decision-making through AI.

5.5 Cybersecurity and Systemic Risk

AI finance systems are more vulnerable to cyber attacks, including data poisoning, adversarial manipulation, and model evasion. The network interdependence of algorithmic trading platforms amplifies the systemic risk, as a coordinated response to market shocks may trigger cascading failures. Joshi (2025) emphasizes that generative AI is both a defense capability and a potential threat vector that needs "strong risk management frameworks and regulatory direction to deal with changing vulnerabilities and protect institutional resilience." Modular architectures, anomaly detection models, and adaptive decision engines need to be adopted by financial institutions to counteract these risks and ensure operational integrity in more autonomous, high-frequency environments. Table 2 highlights the risks and mitigation strategies of using AI in finance.

Risk	Impact	Solution
Bias	Discrimination	Fair AI auditing
Cyber attacks	Financial loss	AI security
Privacy	Trust issues	GDPR compliance
Black-box AI	Low transparency	Explainable AI

Table.3 Risks and Mitigation Strategies

6. Future Innovations and Future research directions

6.1 Explainable and Reliable AI

Explainability is important when banks implement AI models to provide clarity, fairness, and regulatory adherence. Post-hoc interpretability methods such as SHAP and LIME provide some sort of explanation, but they lack context sensitivity in financial decision-making. Yeo et al. (2025) state that there does indeed exist a real lack of taxonomies of specific, concrete domains and context-sensitive, domain-specific models. They also proposed the creation of FinXAI systems according to stakeholders' requirements and regulation logic and future research needs for addressing FinXAI problem-solving challenges, i.e., developing appropriate measures for explanation quality assessment, protection against excessive dependence on misleading output, and NLP integration in explanation-building processes. Greater model transparency by default is also needed for establishing trust, equity, and accountability in the financial decision platforms.

6.2 RegTech and SupTech Innovation

AI is playing a growing central role in regulatory and supervisory technology development in finance. Its incorporation into RegTech and SupTech platforms allows for real-time monitoring of compliance, predictive risk forecasting, and automated reporting. As Lawrence et al. (2025) note, the use of AI instruments for supervisory purposes and regulatory compliance has become imperative, with AI being key to enabling financial institutions to fulfill regulatory requirements, reinforce compliance, reduce risk, and drive operational efficiency. The move toward smart oversight highlights the importance of having scalable, ethically based AI models supporting transparent, traceable, and internationally interoperable financial regulation.

6.3 AI for Sustainable and Green Finance

AI is being touted as the bedrock of sustainable finance, providing sophisticated tools for measuring ESG factors, identifying greenwashing, and feeding into responsible investment decision-making. Banks are incorporating more unstructured data more and more regularly—news feeds and satellite images, to name just two—but the problem of data quality and bias in algorithms still afflicts them. Application of the ESG-AI Maturity Index to institutional AI readiness is also what Elhady and Shohieb (2025) suggest. They further opine that ESG information continues to be heterogeneous, methodologically unclear, and fragmented, particularly for climate investments. Standardized ESG data sets, interpretability of models, and developing ethically sound AI systems for global sustainability reporting need to be addressed in the future.

Conclusion

Artificial intelligence is transforming the financial system by enhancing business effectiveness, allowing data-driven decision-making, and leading to better customer experiences. It has multiple uses ranging from fraud detection, credit risk scoring, and algorithmic trading to regulatory compliance, with game-changing possibilities in every aspect or area of the industry. But even with the potential comes the imposition, and with the imposition come severe challenges—from data bias and model explainability to regulatory uncertainty and system risk. Solving these problems needs to have a balanced response that focuses on technological innovation with ethical governance, transparency, and strong control. Prominent fields like Explainable AI, RegTech, and AI for sustainable finance emphasize the need and requirement of multidisciplinary research along with the policy frameworks guaranteeing responsible deployment. As financial institutions are becoming more and more dependent on AI, attention should be given to building honest, inclusive, and resilient systems that enhance performance as well as fairness and accountability. The future of AI in finance is in reconciling innovation with integrity.

References

1. Abi, R. (2025). AI-Driven fraud detection systems in fintech using hybrid supervised and unsupervised learning architectures. *International Journal of Research Publication and Reviews*, *6*(6), 4375–4394. https://doi.org/10.55248/gengpi.6.0625.2161.
2. Addy, N. W. A., Ajayi-Nifise, N. a. O., Bello, N. B. G., Tula, N. S. T., Odeyemi, N. O., & Falaiye, N. T. (2024). Algorithmic Trading and AI: A Review of Strategies and Market impact. *World Journal of Advanced Engineering Technology and Sciences*, *11*(1), 258–267. https://doi.org/10.30574/wjaets.2024.11.1.0054.
3. Adewuyi, A., Nwangele, C. R., Oladuji, T. J., & Akintobi, A. O. (2023). Advances in Machine Learning for Credit Risk and Underwriting Automation: Emerging Trends in Financial Services. *International Journal of Advanced Multidisciplinary Research and Studies*, *3*(6), 1860-1877.
4. Ahmed, S., Alshater, M. M., Ammari, A. E., & Hammami, H. (2022). Artificial intelligence and machine learning in finance: A bibliometric review. *Research in International Business and Finance*, *61*, 101646. https://doi.org/10.1016/j.ribaf.2022.101646.
5. Aldboush, H. H. H., & Ferdous, M. (2023). Building Trust in Fintech: An analysis of ethical and privacy considerations in the intersection of big data, AI, and customer trust. *International Journal of Financial Studies*, *11*(3), 90. https://doi.org/10.3390/ijfs11030090.
6. Al-Sartawi, A. M. a. M., Hussainey, K., & Razzaque, A. (2022). The role of artificial intelligence in sustainable finance. *Journal of Sustainable Finance & Investment*, 1–6. https://doi.org/10.1080/20430795.2022.2057405
7. Bahoo, S., Cucculelli, M., Goga, X., & Mondolo, J. (2024). Artificial intelligence in Finance: a comprehensive review through bibliometric and content analysis. *SN Business & Economics*, *4*(2). https://doi.org/10.1007/s43546-023-00618-x
8. Bahoo, S., Cucculelli, M., Goga, X., & Mondolo, J. (2024). Artificial intelligence in Finance: a comprehensive review through bibliometric and content analysis. *SN Business & Economics*, *4*(2). https://doi.org/10.1007/s43546-023-00618-x.
9. Blacklaws, C. (2018). Algorithms: transparency and accountability. Philosophical Transactions of the Royal Society a Mathematical Physical and Engineering Sciences, 376(2128), 20170351. https://doi.org/10.1098/rsta.2017.0351

10. *Bloomberg*. Bloomberg. https://www.bloomberg.com/asia
11. Buchanan, B. G. (2019). Artificial intelligence in finance. In *Zenodo (CERN European Organization for Nuclear Research)*. https://doi.org/10.5281/zenodo.2612537
12. Černevičienė, J., & Kabašinskas, A. (2024). Explainable artificial intelligence (XAI) in finance: a systematic literature review. *Artificial Intelligence Review*, *57*(8). https://doi.org/10.1007/s10462-024-10854-8.
13. Chang, V., Xu, Q. A., Akinloye, S. H., Benson, V., & Hall, K. (2024). Prediction of bank credit worthiness through credit risk analysis: an explainable machine learning study. *Annals of Operations Research*. https://doi.org/10.1007/s10479-024-06134-x
14. Elhady, A. M., & Shohieb, S. (2025). AI-driven sustainable finance: computational tools, ESG metrics, and global implementation. *Future Business Journal*, *11*(1). https://doi.org/10.1186/s43093-025-00610-x
15. Giudici, P. (2018). Fintech Risk Management: A research challenge for artificial intelligence in finance. *Frontiers in Artificial Intelligence*, *1*. https://doi.org/10.3389/frai.2018.00001
16. Giudici, P., & Wu, L. (2025). Sustainable artificial intelligence in finance: impact of ESG factors. *Frontiers in Artificial Intelligence*, *8*. https://doi.org/10.3389/frai.2025.1566197.
17. Goldman Sachs. https://www.goldmansachs.com/
18. Goodell, J. W., Kumar, S., Lim, W. M., & Pattnaik, D. (2021). Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. *Journal of Behavioral and Experimental Finance*, *32*, 100577. https://doi.org/10.1016/j.jbef.2021.100577.
19. Goodell, J. W., Kumar, S., Lim, W. M., & Pattnaik, D. (2021). Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. *Journal of Behavioral and Experimental Finance*, *32*, 100577. https://doi.org/10.1016/j.jbef.2021.100577.
20. Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *Review of Financial Studies*, *33*(5), 2223–2273. https://doi.org/10.1093/rfs/hhaa009
21. Hafez, I. Y., Hafez, A. Y., Saleh, A., El-Mageed, A. a. A., & Abohany, A. A. (2025). A systematic review of AI-enhanced techniques in credit card fraud detection. *Journal of Big Data*, *12*(1). https://doi.org/10.1186/s40537-024-01048-8.
22. Heaton, J. B., Polson, N. G., & Witte, J. H. (2016). Deep learning for finance: deep portfolios. *Applied Stochastic Models in Business and Industry*, *33*(1), 3–12. https://doi.org/10.1002/asmb.2209
23. Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255–260. https://doi.org/10.1126/science.aaa8415.
24. Joshi, S. (2025). Gen AI in Financial Cybersecurity: A Comprehensive review of architectures, algorithms, and regulatory challenges. *International Journal of Innovations in Science Engineering and Management.*, 73–88. https://doi.org/10.69968/ijisem.2025v4i373-88.
25. JPMorganChase. Retrieved May 15, 2026, from https://www.jpmorganchase.com/
26. Jukl, D., & Lansky, J. (2025). Systematic Review on Algorithmic Trading. *Acta Informatica Pragensia*. https://doi.org/10.18267/j.aip.276.
27. Kothandapani, N. H. P. (2024). Automating financial compliance with AI: A New Era in regulatory technology (RegTech). *International Journal of Science and Research Archive*, *11*(1), 2646–2659. https://doi.org/10.30574/ijsra.2024.11.1.0040.
28. Kraus, M., & Feuerriegel, S. (2017). Decision support from financial disclosures with deep neural networks and transfer learning. *Decision Support Systems*, *104*, 38–48. https://doi.org/10.1016/j.dss.2017.10.001
29. Lawrence, T. S., Oyirinnaya, P., Adesola, A. A., & Iguodala, O. D. (2025). THE CRUCIAL ROLE OF ARTIFICIAL INTELLIGENCE IN FINTECH FOR SUPTECH AND REGTECH SUPERVISION IN BANKING AND FINANCIAL ORGANIZATIONS. *International Journal of Artificial Intelligence Research and Development*, *3*(1), 38–50. https://doi.org/10.34218/ijaird_03_01_003.
30. *Mastercard - Una empresa tecnológica global en la industria de pagos*. (n.d.). Mastercard. https://www.mastercard.com/
31. Mhlanga, D. (2020). Industry 4.0 in Finance: The impact of Artificial intelligence (AI) on digital financial inclusion. *International Journal of Financial Studies*, *8*(3), 45. https://doi.org/10.3390/ijfs8030045
32. Misheva, B. H., Osterrieder, J., Hirsa, A., Kulkarni, O., & Lin, S. F. (2021). Explainable AI in credit risk management. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2103.00949.
33. Olowu, N. O., Adeleye, N. a. O., Omokanye, N. a. O., Ajayi, N. a. M., Adepoju, N. a. O., Omole, N. O. M., & Chianumba, N. E. C. (2024). AI-driven fraud detection in banking: A systematic review of data science approaches to enhancing cybersecurity. *GSC Advanced Research and Reviews*, *21*(2), 227–237. https://doi.org/10.30574/gscarr.2024.21.2.0418
34. Pay, send and save money with PayPal. *PayPal*. https://www.paypal.com/us/home
35. Quinn, B. (2023). Explaining AI in Finance: past, present, prospects. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2306.02773.
36. Raghavan, N. S. R. (2025). Trustworthy Chatbots in Finance: A framework for explain ability, accessibility, and AI governance. *International Journal of Scientific Research in Computer Science Engineering and Information Technology*, *11*(3), 314–323. https://doi.org/10.32628/cseit2511420.
37. Raj, R., & Kos, A. (2023). Artificial intelligence: evolution, developments, applications, and future scope. *PRZEGLĄD ELEKTROTECHNICZNY*, *1*(2), 3–15. https://doi.org/10.15199/48.2023.02.01
38. Rashid, A. B., & Kausik, M. a. K. (2024). AI Revolutionizing Industries Worldwide: A comprehensive overview of its diverse applications. *Hybrid Advances*, *7*, 100277. https://doi.org/10.1016/j.hybadv.2024.100277
39. Ridzuan, N. N., Masri, M., Anshari, M., Fitriyani, N. L., & Syafrudin, M. (2024). AI in the Financial Sector: The Line between Innovation, Regulation and Ethical Responsibility. *Information*, *15*(8), 432. https://doi.org/10.3390/info15080432.
40. Sengupta, P., & Sharma, P. (2023). A study on the role of ai in marketing financial services: Adoption, tools, and impact on customer engagement. *International Journal of Computing and Artificial Intelligence*, *4*(1), 65–70. https://doi.org/10.33545/27076571.2023.v4.i1a.164.
41. Slack, D., Hilgard, S., Jia, E., Singh, S., & Lakkaraju, H. (2020, February). Fooling lime and shap: Adversarial attacks on post hoc explanation methods. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* (pp. 180-186). https://doi.org/10.1145/3375627.3375830.
42. Svetlova, E. (2022). AI ethics and systemic risks in finance. *AI And Ethics*, *2*(4), 713–725. https://doi.org/10.1007/s43681-021-00129-1.
43. Yadava, N. A. (2023). Ethical and regulatory challenges of AI adoption in the financial services sector: A global perspective. *International Journal of Science and Research Archive*, *10*(1), 1222–1235. https://doi.org/10.30574/ijsra.2023.10.1.0826.