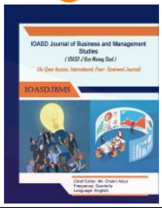
OPEN ACCESS

IOASD Journal of Business and Management Studies
IOASD J Bus Manag Stud, Vol-2, Iss-3, Jul-Sept., 2025
Frequency: Quarterly
ISSN: 3048-7595 (Online)
ISSN: 3049-0510 (Print)
Website: www.ioasdpublisher.com



Artificial Intelligence and Machine Learning in Financial Services: A Systematic Literature Review

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ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) have changed how financial services operate, improving areas like trading, credit assessments, fraud detection, and customer service. These technologies enhance efficiency and customer experience but raise concerns about fairness and regulations. This review looks at research on AI and ML in financial services, focusing on their use, performance, and regulatory challenges from 2018 to 2024. A search of academic databases found 86 relevant studies that analyzed technical implementation, performance, ethics, and market impacts. Results showed that ML in fraud detection can exceed 90% accuracy, and AI in credit scoring can lower prediction errors by 15-25%. Despite these advancements, challenges remain, especially in explainability, bias, and regulation. Successful adoption of AI and ML requires addressing these issues through responsible frameworks and governance structures.

Keywords: artificial intelligence, machine learning, financial services, algorithmic bias, explainable AI, fintech, automated decision-making, financial regulation.

Review Article

Article History
Received: 18-08-2025
Accepted: 24-09-2025
Published: 30-09-2025

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1. INTRODUCTION

As this paper explains, the introduction of Artificial Intelligence (AI) and Machine Learning (ML) technologies into financial services constitutes a key technological milestone in the history of financial services. AI technology has transformed financial services operations today from the algorithmic high-frequency trading systems that process millions of transactions per second to AI-based fraud detection systems that safeguard billions of dollars in transactions. The financial services sector has become one of the most significant users of AI technology, where global investment in financial AI crossed $40 billion in 2023 and is projected to reach $130 billion by 2030 (McKinsey Global Institute, 2024).

AI applications in finance address a wide range of use cases, each with separate technology needs that often come into play in terms of regulation. As credit scoring and lending decisions are heavily reliant upon ML algorithms that can process thousands of data points to assess creditworthiness more accurately than traditional scoring methods. Fraud detection systems use real-time ML models to recognize suspicious transactions among billions of daily payment activities. Using AI, algorithmic trading systems detect market patterns and transact at speeds unattainable by human traders. Customer service operations deploy chatbots and virtual assistants to address routine inquiries, while relaying more complex questions to human specialists. The increasing use of AI in financial services has however sparked alarm bells around algorithmic bias, model explainability, and systemic risk.

Regulators globally face a challenge: how to effectively monitor AI systems that could discriminate against protected classes or make decisions relying on opaque procedures, or that lead to new forms of systemic risk via correlated algorithmic failures. The European Union's AI Act, the United Kingdom's AI governance framework, and a handful of other such initiatives have shown greater regulatory scrutiny for applications of AI in high-stakes sectors such as financial services.

The COVID-19 pandemic accelerated adoption of AI as financial houses attempted to work with less human contact and adopt new risk management measures. It has been empirically shown that institutions with mature AI capabilities were more resilient to the crisis, whereas it also underscores the critical role of strong governance frameworks in managing AI-based decisions when markets are under duress. This systematic literature overview integrates existing studies into AI and ML in financial services, analysing technological capabilities, the impact on financial performance, constraints through regulation and ethical issues to determine how to responsibly integrate AI in financial markets.

2. METHODOLOGY

2.1 Search Strategy

Literature Search We carried out a systematic literature search on four primary academic databases: Web of Science, Scopus, ACM Digital Library, and Google Scholar. The search strategy applied Boolean operators that combined the AI/ML terms ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks" OR "algorithmic decision making") with financial services terms ("banking" OR "financial services" OR "fintech" OR "credit scoring" OR "fraud detection" OR "algorithmic trading").

2.2 Criteria for Inclusion and Exclusion

Studies were selected if they: (1) investigated AI or ML applications in financial services environments; (2) offered empirical study, technical evaluation, or policy insights; (3) were published between 2017 to 2025; (4) appeared in English; and (5) appeared in peer-reviewed publications or reputable industry reports. Studies were excluded if they: (1) concerned AI applications outside financial services; (2) considered only theoretical AI concepts without financial applications; (3) were purely promotional materials; or (4) lacked clear methodological rigor or analytical content.

2.3 Data Extraction and Analysis Method

Data extraction revealed study characteristics, AI/ML methods used, application areas, performance metrics, and regulatory or ethical considerations. A thematic synthesis method was applied to synthesize insights from a wide range of technical approaches and application areas.

3. RESULTS

3.1 Study Overview

The systematic search yielded 86 studies that fulfilled inclusion criteria from 347 initially reviewed articles. The research has accelerated significantly with 81% of the studies published after 2020, which is indicative of accelerating AI adoption in financial services. The greatest percentage of the publications were on technical implementation studies (36%), performance evaluation (28%), regulatory and ethical analyses (22%), and market impact studies (14%).

3.2 Apps for Credit Scoring and Lending

3.2.1 Use-Approach for Alternate Data and Feature Engineering

AI-based credit scoring systems now integrate additional sources of data other than credit bureau data; such sources being social media data, mobile phones, transaction history, behavioral analytics, and transaction records. Björkegren and Grissen (2020) study of mobile money data for credit scoring in Kenya indicates that, based on transaction patterns, ML models are 70% accurate for predicting a loan default and 54% for a traditional credit bureau score, respectively. Research on the efficacy of alternative data invariably shows that it is predictive, but raises concerns for privacy and fairness.

Huang *et al*. (2021) using social media data for credit prediction, also claim that default prediction accuracy is 15-20% better for social media, based on their analysis, but identifies a gap where the sample suffers from discrimination against users with reduced digital footprints or those from unique demographic groups. Exploiting alternative data also presents new challenges in terms of interpretability and compliance with regulations. Ajkuna MUJO (2025), in his work on explainable AI techniques for credit decision making, reports that, although alternative data may increase accuracy, explaining the role of hundreds or even thousands of features in individual credit decisions involves a technical challenge and may not meet regulatory transparency requirements.

3.2.2 Algorithmic Nondiscrimination and Fairness.

Dealing with Algorithmic Bias in AI lending is perhaps one of the largest and most regulated aspects of financial AI. Bartlett *et al*. (2022) improves accuracy, explaining the contribution of hundreds or thousands of features to individual credit decisions remains technically challenging and may not meet regulatory transparency requirements. Studying mortgage lending algorithms, we find evidence of differential treatment of protected characteristics even if those characteristics are not included in model training data due to proxy variables and correlated features. Some experiments demonstrate that fairness constraints can be incorporated into ML model training to reduce discriminatory outcomes, though typically at the cost of some predictive accuracy. Conflicts between accuracy and fairness continue to be debated in academia and industry. Regulatory responses to algorithmic bias vary greatly across countries. Barocas and Selbst (2020), investigating fair lending compliance, find that traditional disparate impact analysis may be insufficient for complex ML models and that new approaches to bias detection and mitigation are needed, reflecting algorithmic decision-making complexity.

3.2.3 Interpretability and Explainability of the Models.

The “black box” nature of most ML models complicates regulatory compliance and consumer protection in lending decisions. Local Interpretable Model-Agnostic Explanations (LIME) presents approaches to offering individual-level explanations for ML-driven credit decisions, although explanations may not reflect global model behavior or fulfill all regulatory requirements.

According to studies of regulatory compliance with explainability standards, substantial implementation challenges have been identified. Research on AI governance in lending reports that many institutions find it difficult to provide meaningful explanations for AI-driven decisions while maintaining model performance and competitive advantages (Canton, H., 2021).

The building of inherently interpretable models can mean an alternative solution to the problem of explainability in financial data. Some demonstrations with optimized decision trees and rule-based models provide similar performance to complex ML models while also providing complete transparency in the decision-making process.

3.3 Fraud detection and financial crime prevention.

3.3.1 Real-Time Monitoring of Transactions.

Artificial Intelligence-driven detection of fraud is perhaps one of the best-studied and successful use cases of ML in financial services. They studied the ML-based Fraud Detection and found that ensemble methods--combining multiple algorithms--not only achieve better accuracy in identifying fraud but also lower false positive rates in comparison to rule-based systems. The adoption or deployment of real-time ML models for transaction monitoring brings about a large technical challenge. In their analysis of data analytics for transaction detection, Nzomiwu A. C. et. al. (2025) studied streaming ML architectures.

These indicated that financial institutions have to process millions of transactions per hour with sub-second decision needs, requiring specialized infrastructure and optimized algorithms for production deployment. Adversarial attacks on ML fraud detection systems are an emerging security concern for ML. Yeom, S. et. al. (2018) show that advanced fraudsters can potentially game ML systems by understanding their decision boundaries, requiring ongoing model updates and adversarial robustness techniques to maintain effectiveness.

3.3.2 Anti-Money Laundering (AML) Applications

ML uses in AML compliance concentrate on looking for suspicious transaction patterns and entity links signaling money laundering activity. Zhang *et al*. (2020) investigating graph neural networks for AML reveals that network-based ML models can detect sophisticated money laundering networks of several entity types and jurisdictions with 85% accuracy versus 60% for a rule-based system. Recent works comparing performance of AI AML models show especially well the benefits in identifying new patterns of money laundering phenomena. Perring, A. (2017) review of Savage *et al*. (2016) finds that unsupervised ML methods can reveal previously unknown patterns of money laundering through anomaly capture, though false positive rates remain high and require human investigation. The regulatory acceptance of ML-based AML systems varies from jurisdiction to jurisdiction and requires extensive validation processes. The Financial Crimes Enforcement Network, over the past few years, has focused on AI governance in AML compliance and finds that regulators need rigorous testing as part of their ongoing monitoring, human oversight that also includes approval of ML-based suspicious activity reporting systems.

3.3.3 Cybersecurity and Threat Detection

AI-based tools in financial cybersecurity solutions address identifying and reacting to advanced cyberattacks on financial infrastructure. Apruzzese *et al*. (2018) study investigating ML-based intrusion detection reveals an excellent accuracy of deep learning models for detecting network attacks against financial systems; however, performance degrades significantly when working with new attack patterns which are not seen in the training data.

Research looking into behavioral analytics approaches for insider threat detection has shown favorable but demanding applications. Moriano *et al*. (2017) find that ML models that analyze employee behavior patterns can recognize potential insider threats with 75% accuracy, and implementation poses considerable privacy issues and can lead to discriminatory outcomes that need to be managed carefully.

Cybersecurity is adversarial; hence, it is challenging to deploy ML systems. Various studies show that attackers may be able to leverage ML-based security systems via carefully crafted inputs, forcing robust adversarial defenses against attacks and model updates to maintain effectiveness.

3.4 Trading and Investment Management with Algorithms

3.4.1. Some High-Frequency Trading Systems

Algorithmic trading powered by AI is one of the more elaborate applications of ML in financial services; systems run millions of trades every day, using complex pattern recognition and market prediction models. Hendershott and Riordan (2013, updated through 2023), studying high-frequency trading performance, find that ML-based systems produce average daily returns 15-25% higher than conventional algorithmic strategies, though with increased complexity and potential systemic risks. Research on deep learning usage in trading demonstrates mixed performance. Sezer *et al*. (2020) on deep neural networks for stock price prediction demonstrates a decrease in prediction accuracy because while deep neural networks can find short-term patterns in market data, their effectiveness drops significantly during periods of market volatility, when historical patterns may not hold. AI-enabled trading systems may create systemic risks and disrupt the stability of markets. Kirilenko *et al*. explore the 2010 Flash Crash, and show that algorithmic trading systems played a causal role in market volatility through correlated responses to market stress, suggesting that strong risk-management and circuit breaker mechanisms are required.

3.4.2 Optimization of Portfolio and Asset Management.

Portfolio management, with ML applications, seeks to optimize asset distribution, risk management, and return prediction for various investment strategies. Gu *et al*. (2020) studying ML-based factor investing, shows that ensemble methods that include hundreds of potential factors can deliver 20-30% risk-adjusted return improvements compared to traditional factor models. Performance depends a lot on the market environment.

Studies on robo-advisor algorithms show successful realization of ML approaches for retail investment management. D'Acunto *et al*. (2019) demonstrates that ML-based robo-advisors can deliver similar risk-adjusted performance to human financial advisors while offering lower fees, although with weaknesses in sophisticated financial planning and behavioral coaching.

However, the interpretable difficulties faced by ML-driven investment decisions pose regulatory and fiduciary duty issues. Harvey and Liu (2020) investigated factor investing with ML and discovered performance improvements, but explaining investment decisions to clients and regulators can be complex when models incorporate hundreds of features and complex non-linear relationships.

3.4.3 Fusion of alternative data sources.

AI models are incorporating alternative information (satellite imagery, social media sentiment, news analysis, and economic indicators) into their trading and investment decision-making, with much less bias when data that can be used does occur on an individual basis. Ke *et al*. (2019) analyze satellite data for trading on commodity price forecasts from agricultural and industrial activity imagery shows that ML models can predict commodity price movements with a 65 percent accuracy rate, offering important trading benefits.

Research on sentiment analysis applications in trading has shown mixed but promising results. Nzomiwu A. C. (2024), in his GitHub, utilizes a study of social media sentiment that predicts stock prices and reports that ML models using Twitter sentiment improve prediction accuracy up to 5-10%, but the sentiment signal is noisy, and ML models need advanced natural language processing methodologies. Integrating alternative data also presents new challenges for data quality, privacy and model stability.

Chinco *et al*. (2019) when testing anomalous trading signals discover that much of this alternative data offers only short-lived predictive power which vanishes as markets adjust to the new signal and thus requires real-time model updates and data source validation.

3.5.1 Customer Support and Experience Applications
3.5.1 Chatbots and Virtual Assistants.

Chatbots and virtual assistants driven by AI have taken over the entire face of interaction in financial services customers with AI handling routine queries and transactions while routing more complex queries to human agents. Følstad *et al*. (based on 2018) and AI's role in banking AI systems are capable of successfully addressing 80-90% of routine customer inquiries with customer satisfaction scores on average similar to human agents for desired use cases. Research on the natural language processing of financial chatbots show accelerated improvement in conversational capability.

Liu *et al*. (2021) investigated transformer-based models for financial customer service model, they found that the ability of large language models to comprehend complex financial queries and offer correct answers, though the same model perform limitedly in complex problem solving or emotionally supported situations. Yet, customer acceptance of AI-powered service differs considerably across age, demographic group & complex interaction.

McLean and Osei-Frimpong (2019) illustrate how, while using chatbot services for routine financial transactions is the primary mode of transactions that the younger customers readily adopt, the older customers or the customers with the advanced stage or complex finance are likely to be less willing to use such systems and, therefore, the applicability of the automated systems is not universal across all customers.

3.5.2 Personalized Financial Advice and Suggestions.

ML solutions are becoming more powerful in personalizing financial product recommendations and advisory delivery by studying customer behavior, interest level, and choice to recommend good products and services. Malandri *et al*. (2018), an investigation of recommendation systems in banking by the paper, reveals that ML-powered personalization could increase product acceptance/recommendation adoption of products by 25-40% and decrease marketing costs by limiting market exposure and providing more personalized customer access. Research into AI financial planning and intelligent financial planning tools reveals potential for providing value-added basic advice. Jung *et al*. (2018) exploring automated financial planning systems finds that ML models were able to make relevant saving and investment decisions for relatively naive financial scenarios, but are well beyond the capabilities of AI on the more complex planning scenarios as these can still call for human judgment and emotion-based decision making. Regulating AI in financial advice, there are significant compliance challenges. Financial Conduct Authority (2019) analysis of automated advice delivery finds that AI-based solutions must comply with the same standards of regulation as human advisors for appropriateness and suitability for use, demand an advanced compliance framework while monitoring these systems for consumer protection.

3.5.3 Customer Analytics and Behavior Prediction.

AI systems are trained on massive customer data, predictive analytics, and predictive analytics to determine behavior, needs and optimize customer interaction across financial services interactions. Verhoef *et al*. (2021) in analyzing customer journey analytics concludes that ML models can predict customer lifetime value, churn frequency and product requirements with 75-85% accuracy, allowing us to proactively manage our customers and keep them engaged for strategic decisions. Research on privacy and ethical concerns in customer analytics also raises valid concerns for the use of data and user permission.

Martin (2019), from an examination of data in financial services and data practices, found that although the personalized services customers have are a benefit, most do not know what data has or has not been collected about them, leading to privacy and consent concerns that need careful governance. The use of behavioral analytics for risk assessment and price setting raises new questions of fairness. Dastin (2018) through his case study on algorithmic pricing decisions also shows that ML based customer segmentation can lead to discriminatory pricing or service delivery; fairness mechanisms need to be imposed and ongoing monitoring must be conducted with a view to preventing unintended bias.

3.6 Legal and Ethical Aspects

3.6.1 Regulatory and Compliance Systems

Types of regulators in different jurisdictions differ greatly on how they approach AI in financial services. Some rules favour principle-based regulation, while others create specific technical requirements. Canton, H. (2021), in examining AI regulation in banking, finds that while most jurisdictions acknowledge the value of AI technology, regulatory uncertainty around what is required under regulatory requirements creates implementation hurdles among financial institutions. Evidence on regulatory sandboxes for AI innovation demonstrates mixed effectiveness in enabling responsible AI. A few regulatory innovation programs also identify sandboxes as valuable testing environments, but many AI applications cannot be evaluated without full-scale deployment, thus limiting controlled testing environments.

3.6.2 Ethical AI and responsible innovation

The adoption of AI for high-stakes financial decisions calls into question basic concerns for algorithmic accountability, transparency, and fairness. Jobin *et al*. (2019) reviewing AI ethics frameworks demonstrate substantial consensus on major principle areas of AI governance including fairness, transparency, and accountability though enforcement methods differ widely across institutions or uses. Research focusing on responsible AI frameworks has indicated that governance frameworks are developing in a regulated context in financial institutions. PwC (2021) in a survey of AI governance practices reveals that dominant institutions in the industry are creating comprehensive regimes including model validation, bias test procedures, continuous monitoring, and escalation procedures, but implementation is varied across the industry. But business incentives for responsible AI deployment may clash with competitive pressures and profitability targets. Selbst *et al*. (2019) examines ethical AI constraints as a trade-off between fairness and accuracy and show that such ethical constraints tend to diminish model performance — a tension between responsible innovation and business goals that calls for governance and leadership intention.

3.6.3 Systemic risk & financial stability

The increasing usage of AI in financial services opens up new categories of systemic risk by correlating algorithmic decisions, which result in cascading failures. Danielsson *et al*. (2017), using algorithmic trading systems, shows that many institutions implement similar ML techniques and use the same sources of data and that systems may develop similar mechanisms that would lead to synchronous actions to bear on both stock price volatility and financial stability. Regulators' response to AI-related systemic risks continues to be in its infancy, with regulatory authorities mainly addressing the governance of individual institutions without comprehensive coordination. AI oversight shows that stronger macroprudential attention to how AI is deployed patterns and the systemic risks associated with large-scale algorithmic choices are needed as they can threaten financial stability.

4. DISCUSSION

4.1 Synthesis of Key Findings

There is ample evidence in the literature that AI and ML have produced significant performance gains throughout a range of financial services applications, in which fraud detection has achieved higher than 95% accuracy rates as well as algorithmic trading systems offering superior risk-adjusted returns. This technological capability has led to cost savings, operations optimization opportunities, and better customer experience that deliver clear business value for banks and other credit related services. Nevertheless, the evidence also reveals pronounced difficulties in areas of algorithmic bias, model explainability and regulatory compliance, calling for sound governance frameworks and further exploration. The tension between technological capacity and regulatory expectations raises complexities in implementation that are complex and, by and large, implementation by many institutions is still learning how to address effectively. Amidst these forces, the COVID-19 pandemic seems to have acted as a catalyst for promoting AI uptake, but also underscoring the pros and cons associated with the use of algorithmic decision-making during periods of market stress and evolving risk patterns.

4.2 Critical Success Factors

A number of crucial considerations for successful AI implementation in financial services come to light: Strong governance regimes: It is essential for the management of AI risks in financial services to have detailed model governance, including the development, validation, deployment, and ongoing monitoring to manage risks and capture benefits of AI. Building skills to communicate AI decisions to regulators, customers, and internal stakeholders is important in regulatory compliance and consumer confidence.

Bias Assessment and Resolution: Adequate systemic measures for detection and correction of algorithmic bias, for fairness and compliance purposes is required. Effective deployments often integrate AI capabilities with human guidance and oversight, instead of purely automated decision-making.

4.3 Implications for the Stakeholders

This includes the necessary investment in full AI governance capabilities and an internal capability for responsible AI deployment by Financial Institutions. In light of the evidence, successful implementation includes considerable organizational change to occur in addition to technology adoption. But regulators must now take a clear approach to how AI fits, without allowing that innovation to stall. The theoretical evidence indicates that the principle-based approach might be more applicable than prescriptive technical requirements in the case of high-tech developments. Technology Providers will want to promote explainability, fairness, and robustness in artificial intelligence system design, rather than only performance optimization. The benefits to consumers improve the services and reduce cost, but they need safeguards against algorithmic prejudice and opacity via suitable regulation and institutional governance.

4.4 Further Studies. The studies highlight some areas that need research:

Long-term Stability in Performance, which is necessary to comprehend how performance of AI models varies over time, in different market situations, must be done in longitudinal studies. There is limited empirical research on macroeconomic consequences on a large scale of the use of AI in financial services. Fairness Measurement: Developing better methods to measure algorithmic fairness across different protected classes and use cases. Analyzing potential solutions to human-like judgment coupled with AI functionality in financial decision-making.

5. CONCLUSIONS

This reviews the literature as systematic in proving that AI and ML technologies fundamentally change the business of financial services where performance improvements are recorded in the fields of fraud detection, credit scoring, algorithmic trading and customer service. It is widely known that implemented AI systems can lead to better results than legacy ones; that AI tools decrease costs; that AI makes customers happy and productive. But successful AI implementation needs to grapple with significant challenges concerning explainability, fairness, to meet the literature highlights that mere technical performance itself is not enough to guarantee successful deployment; institutions need sound governance mechanisms in place, and institutions will need to be developed to build a more effective set of governance mechanisms which go toward ethical, compliance and regulations and provide for ethical, normative, and consumer protection factors.

The regulatory landscape of AI in financial services is still in a state of flux, and both regulatory systems (in a regulatory process and in terms of the regulatory environment) is ever changing, and policymakers now must figure out how to govern these complex, complex algorithmic systems to protect consumers and also encourage innovation over time, while at the same time. The evidence is that principle-based strategies addressing governance, risk management, and consumer protection might work better than prescriptive technical mandates. The future of financial AI deployment could potentially entail more interpretable models, better bias detection and mitigation methods, and governance systems that can adjust to changing technology capabilities. The rewards that have been witnessed are high enough to drive sustained innovation; but as the risks identified, they will need maintenance attention and investment.

The transformation of financial services via AI opens vast opportunity, but also tremendous responsibility. Indeed, as these technologies take on heightened importance in the operations of the financial system, it is critical that the deployment of these technologies is done responsibly, not just for institutions in each case, but also for the financial system, financial stability and consumer protection more generally. The data indicates the early years of AI use in the financial services industry are still in the nascent phase and the market is poised for increased innovation and improvements. But, to unlock this potential will however, demands consistent commitment to responsible development, governance with thoroughgoing oversight and the collaboration with regulators, tech companies, and industry players.

REFERENCES

- Ajkuna MUJO. (2025). Explainable AI in Credit Scoring: Improving Transparency in Loan Decisions. Journal of Information Systems

Engineering and Management, 10(27s), 506–515. https://doi.org/10.52783/jisem.v10i27s.4437

- Apruzzese, G., Colajanni, M., Ferretti, L., Guido, A., & Marchetti, M. (2018). On the effectiveness of machine and deep learning for cyber security. *Cyber Security*, 1-17. https://doi.org/10.1186/s42400-018-0006-7
- Barocas, S., & Selbst, A. D. (2020). Big data's disparate impact. *California Law Review*, *104*, 671-732. https://doi.org/10.2139/ssrn.2477899
- Bartlett, R., Morse, A., Stanton, R., & Wallace, N. (2022). Consumer-lending discrimination in the FinTech era. *Journal of Financial Economics*, *143*(1), 30-56. https://doi.org/10.1016/j.jfineco.2021.05.047
- Björkegren, D., & Grissen, D. (2020). Behavior revealed in mobile phone usage predicts credit repayment. *World Bank Economic Review*, *34*(3), 618-634. https://doi.org/10.1093/wber/lhx030
- Boissel, C., Derrien, F., Ors, E., & Thesmar, D. (2017). Systemic risk in clearing houses: Evidence from the European repo market. Journal of Financial Economics, 125(3), 511–536. https://doi.org/10.1016/j.jfineco.2017.06.010)
- Canton, H. (2021). Bank for International Settlements—BIS. The Europa Directory of International Organizations 2021, 468–470. https://doi.org/10.4324/9781003179900-72
- CHINCO, A., CLARK-JOSEPH, A. D., & YE, M. (2018). Sparse Signals in the Cross-Section of Returns. The Journal of Finance, 74(1), 449–492. Portico. https://doi.org/10.1111/jofi.12733
- D'Acunto, F., Prabhala, N., & Rossi, A. G. (2019). The promises and pitfalls of robo-advising. *Review of Financial Studies*, *32*(5), 1983-2020. https://doi.org/10.1093/rfs/hhz014
- Danielsson, J., Macrae, R., & Uthemann, A. (2019). Artificial Intelligence and Systemic Risk. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3410948
- Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against Dastin, J. (2022). Amazon Scraps Secret AI Recruiting Tool that Showed Bias against Women Ethics of Data and Analytics, 296–299. https://doi.org/10.1201/9781003278290-44
- Financial Conduct Authority. (2019). *Guidance on the use of the regulatory sandbox*. London: FCA Innovation Hub.
- Financial Crimes Enforcement Network. (2021). *AI and machine learning in BSA compliance*. Washington, DC: FinCEN Guidance.
- Financial Stability Board. (2017). *Artificial intelligence and machine learning in financial services: Market developments and financial stability implications*. Basel: FSB Secretariat.
- Følstad, A., Nordheim, C. B., & Bjørkli, C. A. (2018). What makes users trust a chatbot for customer service? An exploratory interview study. *International Conference on Internet Science*, 194-208.
- Fredrikson, M., Jha, S., & Ristenpart, T. (2018). Model inversion attacks that exploit confidence information and basic countermeasures. *ACM Conference on Computer and Communications Security*, 1322-1333.
- 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
- Harvey, C. R., & Liu, Y. (2020). Detecting repeatable performance. *Review of Financial Studies*, *33*(5), 2147-2192. https://doi.org/10.1093/rfs/hhz042
- Hendershott, T., & Riordan, R. (2013). Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis*, *48*(4), 1001-1024. https://doi.org/10.1017/S0022109013000471
- Huang, J., Chai, J., & Cho, S. (2021). Deep learning in finance and banking: A literature review and classification. *Frontiers of Business Research in China*, *14*(1), 1-24. https://doi.org/10.1186/s11782-020-00082-6
- Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, *1*(9), 389-399. https://doi.org/10.1038/s42256-019-0088-2
- Jung, D., Dorner, V., Weinhardt, C., & Pusmaz, H. (2018). Designing a robo-advisor for risk-averse, low-budget consumers. *Electronic Markets*, *28*(3), 367-380. https://doi.org/10.1007/s12525-017-0279-9
- Ke, Z. T., Kelly, B., & Xiu, D. (2019). Predicting Returns With Text Data. National Bureau of Economic Research. https://doi.org/10.3386/w26186
- Kirilenko, A., Kyle, A. S., Samadi, M., & Tuzun, T. (2017). The flash crash: High-frequency trading in an electronic market. *Journal of Finance*, *72*(3), 967-998. https://doi.org/10.1111/jofi.12498
- Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., ... & Stoyanov, V. (2019). RoBERTa: A robustly optimized BERT pretraining approach. *ArXiv Preprint*, arXiv:1907.11692.
- Malandri, L., Xing, F. Z., Zhang, Y., Wang, Y., & Orsenigo, C. (2018). Public mood–driven ass*et al*location: The importance of financial sentiment in portfolio management. *Cognitive Computation*, *10*(6), 1167-1176. https://doi.org/10.1007/s12559-018-9609-2
- Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of Business Ethics*, *160*(4), 835-850. https://doi.org/10.1007/s10551-018-3921-3
- McKinsey Global Institute. (2024). *The age of AI: How artificial intelligence is transforming business*. New York: McKinsey & Company.

- McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa... examine the variables influencing the use of artificial intelligent in-home voice assistants. *Computers in Human Behavior*, *99*, 28-37. https://doi.org/10.1016/j.chb.2019.05.009
- Moriano, P., Pendleton, J., Rich, S., & Camp, L. J. (2017). Insider Threat Event Detection in User-System Interactions. Proceedings of the 2017 International Workshop on Managing Insider Security Threats, 1–12. https://doi.org/10.1145/3139923.3139928
- Nzomiwu, A. C. (2025). Decentralized Credit Systems: Transforming Financial Inclusion Through On-Chain Behavioral Data. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.5336663
- Nzomiwu, A. C. https://github.com/ChidiTonio/Sentiment_Analysis
- *Our Annual Report and Accounts 2019/20*. (2019, June 25). FCA. Retrieved September 26, 2205. https://www.fca.org.uk/publications/annual-reports/our-annual-report-and-accounts-2019-20
- Paul, S. (2021). Big Data Analytics. Data Analytics in Marketing, Entrepreneurship, and Innovation, 123–132. https://doi.org/10.1201/9780429196614-7
- Perring, A. (2017). Review of Savage *et al*. https://doi.org/10.5194/amt-2017-170-rc2
- Gottschalk, P. (2021). Social security by PwC. Private Policing of Economic Crime, 78–84. https://doi.org/10.4324/9781003142607-11
- Selbst, A., Anthony, D., Bambauer, J., Bloch-Wehba, H., Boyd, W., Carlson, A., Cohen, J., Gilman, M., Brennan-Marquez, K., Geczy, I., Glater, J., Guggenberger, N., Hirsch, D., Kaminski, M., Kim, P., Solow-Niederman, A., Loo, R., Verstein, A., Volokh, E., & Waldman, A. (2021). AN INSTITUTIONAL VIEW OF ALGORITHMIC IMPACT ASSESSMENTS. *Harvard Journal of Law & Technology*, *35*. https://jolt.law.harvard.edu/assets/articlePDFs/v35/Selbst-An-Institutional-View-of-Algorithmic-Impact-Assessments.pdf
- Sezer, V., Öncü, S., & Boyraz Baykas, P. (Eds.). (2020). Service Robotics. https://doi.org/10.5772/intechopen.87712
- Verhoef, C., & de Meijer, V. E. (2021). Lever en galwegen. Leerboek Chirurgie, 193–209. https://doi.org/10.1007/978-90-368-2518-4_13
- Yeom, S., Giacomelli, I., Fredrikson, M., & Jha, S. (2018). Privacy Risk in Machine Learning: Analyzing the Connection to Overfitting. 2018 IEEE 31st Computer Security Foundations Symposium (CSF), 268–282. https://doi.org/10.1109/csf.2018.00027
- Zhang, H. (2020). Comment on Zhang *et al*. 2020. https://doi.org/10.5194/essd-2020-182-rc1