PROMISE AND PERIL: NAVIGATING MACHINE LEARNING IN FINANCIAL RISK AND REGULATION

PALAHEPITIYA GAMAGE, MIHINI THULANGA
Economics, College of Social Sciences

ABSTRACT

In a rapidly evolving financial industry, the integration of AI and machine learning has brought about significant advancements, such as establishing new standards for efficiency, precision, and innovation. This transformation has revolutionised decision-making and operational processes within markets and institutions. However, it has also presented challenges, including speculative risk, bias, and security concerns. This article examines their impact on fraud detection, credit scoring, and algorithmic trading allowing for a better understanding of their potential benefits and inherent risks. Additionally, these insights are crucial for addressing the social and ethical implications to ensure a balanced and responsible adoption of AI and machine learning within the financial industry.

INTRODUCTION

The financial industry has experienced vast changes through the continual acceleration of technological advancements and the infusion of Machine Learning (ML) and Artificial Intelligence (AI). This has impacted key financial risk and regulation management branches, including fraud detection, algorithmic trading, and credit scoring. ML and AI enable financial institutions to stay competitive by optimising decision-making and navigating complex markets. Insufficient human oversight raises ethical concerns, such as overgeneralisation, data bias, and privacy risks. These challenges reveal an inherent tension in the integration of these technologies without effective regulatory practices. By considering a wide range of uses of ML and AI, this research will foster a balanced discussion between the promise of innovation and the essential need for transparency and responsibility within the financial industry. This paper critically examines how ML and AI are reshaping financial risk management and regulation, highlighting their transformative potential while emphasising the ethical and regulatory frameworks necessary for their responsible integration.

FRAUD DETECTION AND PREVENTION: COST REDUCTIONS AND SECURITY CONCERNS

The use of Machine Learning (ML) in financial institutions is ever-growing, driven by the increasing sophistication of financial fraud. Fraud detection refers to finding unusual events across financial branches, including account applications, insurance claims, and screening credit card transactions (Wei et al., 2020; Aggarwal, 2021; Mahalakshmi et al., 2022). This section aims to investigate how ML enhances fraud detection by detecting subtle changes in large datasets and to consider key and significant challenges that require careful management.

ML can analyse large volumes of data efficiently. By combining new sources of information, it can detect anomalies or patterns that human analysis may overlook (van Liebergen, 2017; Lui and Lamb, 2018; Donepudi, 2019; Fernandez, 2019; Huber, 2020; Buchanan and Wright, 2021; Bin Sulaiman, Schetinin and Sant, 2022). By using advanced technology, credit card fraud can be detected. The technology provides specific information including the locations and behaviour of clients, which enables more effective combatting of financial fraud (Jain and Pandey, 2017; Bin Sulaiman, Schetinin and Sant, 2022; Mahalakshmi et al., 2022). MasterCard uses this technology to create a 'default transaction' that contrasts and scores new clients' transactions with their generic transactions to prevent identity fraud (Ahmed and Siddique, 2013; Donepudi, 2019). The integration of AI has ensured further comprehensive searches compared to manual fraud detection. With automated processes and enforced security, the workload and operational costs of fraud investigations significantly decrease due to their ability to detect fraud at record speeds in real time (Davenport and Ronanki, 2018; Chan et al., 2019; Xie, 2019; Mahalakshmi et al., 2022). For example, J.P. Morgan reports that the use of AI in fraud detection results in savings of $150 million per year. Additionally, AI has the potential to bring an additional £630 billion into the UK financial sector by 2035, proving its value in cost-effective fraud detection and within the wider financial services (Hall and Pesenti, 2017; Huber, 2020; Buchanan and Wright, 2021). While such benefits highlight the transformative potential of ML, it is equally important to address its challenges to ensure ethical and effective fraud detection.

While AI improves detection accuracy, it simultaneously introduces challenges regarding safeguarding consumer data and privacy (Fernandez, 2019; Mehrotra, 2019; Aggarwal, 2021; Bin Sulaiman, Schetinin and Sant, 2022; Gautam, 2023). As AI systems advance, they may expose vulnerabilities that cybercriminals can exploit, necessitating robust cybersecurity measures. Digital challenger banks, like Atom and Monzo, rely heavily on predictive technology and AI, leveraging customer data to drive their business models and compete (Lui and Lamb, 2018). This access to large sets of customer data places them as targets for cybercriminals. Digital challenger banks are also susceptible to issues involving false negatives, caused by insufficient reasoning in algorithms and failure to decline fraudulent transactions. This exposes banks to financial losses and damages their reputations by allowing fraudulent activities to persist. Conversely, over-generalised algorithm guidelines lead to false positives which can be detrimental to customer loyalty, leading to higher attrition rates (Huber, 2020; Buchanan and Wright, 2021; Bin Sulaiman, Schetinin and Sant, 2022; Gautam, 2023). Operationally, these inaccuracies require banks to invest resources in customer support while refining algorithms to reduce errors. Moving forward, cross-collaborative research should study effective ways to integrate human expertise and judgment with automated fraud detection systems. Combined with training and educational programs on the responsible use of AI and ML, this approach could help promote awareness of the ethical implications of these technologies. These considerations emphasise the need for robust regulatory frameworks and guidelines to ensure the benefits of ML are gained within fraud detection without compromising customer trust across the industry. The implementation of the General Data Protection Regulation (GDPR) within the European Union in 2018 has been a step towards better regulatory compliance (Buchanan and Wright, 2021). The field of Regulatory Technology (RegTech) leverages big data and ML to streamline regulatory and compliance activities while continually innovating to establish ways to automate the implementation of rules (Citi, 2018; Buchanan and Wright, 2021).

ALGORITHMIC TRADING AND HIGH-FREQUENCY TRADING (HFT): EFFICIENT GAINS AND MARKET RISKS

Algorithmic trading refers to leveraging advanced computing and decision-making models through the use of complex algorithms to automate and optimise trading processes (Treleaven, Galas and Lalchand, 2013; Dakalbab et al., 2024). High-frequency trading (HFT), a branch of algorithmic trading, refers to automated trading occurring in extremely short bursts of time through sophisticated algorithms and increased computing power (Treleaven, Galas and Lalchand, 2013; Addy et al., 2024). Algorithmic trading employs pre-tested strategies and predetermined methodologies applied across various markets (Dakalbab et al., 2024). Back-testing refers to simulating real market conditions to evaluate and refine trading strategies before applying them in real markets (Treleaven, Galas and Lalchand, 2013; Mehrotra, 2019; Xucheng and Zhihao, 2019; Dakalbab et al., 2024; Pattnaik, Ray and Raman, 2024).

The use of algorithms in trading allows for non-biased trades to happen without the intervention of human emotions or a basis of intuition or experience (Mogaji, Soetan and Kieu, 2021; Mahalakshmi et al., 2022; Addy et al., 2024). With an ability to adapt to real-time changes, this provides financial institutions with a competitive advantage (Donepudi, 2019; Mogaji, Soetan and Kieu, 2021; Mahalakshmi et al., 2022; Kothandapani, 2023; Addy et al., 2024). This automation, in comparison to human trading, has allowed data-driven trades to be completed with high speeds and efficiency, in addition to the increased levels of precision and feasibility (Treleaven, Galas and Lalchand, 2013; Xie, 2019; Addy et al., 2024). By leveraging ML algorithms to extract patterns and trends in data, trading decisions become more reliable and accurate. This enables swift action to capitalise on market opportunities (Das et al., 2015; Chan et al., 2019; Buchanan and Wright, 2021; Addy et al., 2024). HTF's unparalleled precision and speed have significantly increased trade volumes, further justifying the effectiveness of algorithmic trading. While traditional algorithmic trading often relies on rule-based strategies, HFT increasingly leverages ML to enhance performance and adaptability (Chan et al., 2019; Xucheng and Zhihao, 2019; Dakalbab et al., 2024).

Despite the range of advantages algorithmic trading provides, careful management is necessary to deal with unprecedented challenges for the industry. While HFT algorithms enable trades at unparalleled speeds, they also risk amplifying volatility during market stress, as seen during the 2010 'flash crash', where automated trades caused a sudden $1 trillion drop in market value before rebounding. To overcome risks of market instability, overfitted models, and systemic challenges (including liquidity disruptions and cascading failures during market shocks), further technological advancements are required to find a balance between effective and responsible trading practices (Bin Sulaiman, Schetinin and Sant, 2022; Addy et al., 2024). Due to the nature of Machine Learning, there is uncertainty about the interpretation of complex models which have the potential to lead to incorrect conclusions thus affecting both algorithms and approaches to trades (Bazarbash, 2019; Gautam, 2023; Addy et al., 2024). This issue is referred to as overfitting, when algorithms rely too heavily on historical data, leading to inaccurate predictions in current market conditions. To navigate this, consistent validation of models and cross-validation are essential. Likewise, despite the elimination of human emotional biases, systemic biases can be inherited through historical data which can lead to skewed trading decisions impacting market fairness (Donepudi, 2019; Aggarwal, 2021; Addy et al., 2024). Although high-frequency trading enhances efficiency and precision, it raises concerns regarding market stability and liquidity due to the speed of their functions (Samad, Dennaoui and Nemar, 2023; Addy et al., 2024). To prevent market disruptions, regulatory measures and continuous monitoring of algorithmic trading are essential to ensure stability and safeguarding of the market. In the United States, this is seen with annual stress tests carried out by the Federal Reserves on major banks which assess the minimum levels of capital they must hold against operational, market, and credit risk (van Liebergen, 2017; Kothandapani, 2023). The rise in regulations and supervisory measures following the 2008 financial crisis included numerous initiatives to improve the quality of supervisory data and enhance financial institutions' ability to provide it (van Liebergen, 2017). Despite profits being at the forefront of the model, ethical considerations are necessary to prevent the compromise of market fairness or the exploitation of information and data. This would ensure an effective maintenance of trust within the financial markets (van Liebergen, 2017; Mehrotra, 2019; Addy et al., 2024). For a responsible integration of AI into algorithmic trading, calls for prioritising transparent and interpretable trading models through investment and research can ensure the avoidance of discriminatory practices and encourage the use of alternative data (Xucheng and Zhihao, 2019; Addy et al., 2024; Dakalbab et al., 2024). To maintain market integrity, regulatory bodies must standardise frameworks, strengthen oversight of all services, emphasise privacy protection, and cross-collaborate across global regulatory bodies to balance innovation and trust. Standardising reporting requirements, mandating periodic audits of trading algorithms, and implementing circuit breakers during rapid price swings can play a role in mitigating the risks associated with HFT. As the reliance on AI-driven trading grows, the critical nature of integrating transparent, interpretable models and fostering a culture of accountability becomes more prominent to maintain trust in financial markets.

CREDIT SCORING AND RISK ASSESSMENT: COMPREHENSIVE CHECKS AND REGULATORY CONCERNS

Credit scoring and risk assessment refers to the statistical assessment of customers based on patterns of past credit performance and comparisons against similar customers' historical financial transaction data (Aggarwal, 2021; Hentzen et al., 2021; Addy et al., 2024). The involvement of AI and ML in credit scoring is referred to as "algorithmic credit scoring" and builds upon traditional credit scoring. In comparison to traditional credit scoring, which relies on a set of limited factors such as credit history, algorithmic credit scoring processes more diverse data utilising advanced ML techniques for analysis (Bazarbash, 2019; Xie, 2019; Aggarwal, 2021; Hentzen et al., 2021).

The use of AI has allowed credit scores to be based on more complex and sophisticated regulations instead of conventional scoring systems. This ensures a wider spread of data is considered and more accurate scores are calculated (Khandani, Kim and Lo, 2010; Mehrotra, 2019; Schmitt, 2020; Mahalakshmi et al., 2022). With the integration of AI, alternative data such as utility payments, rent, and educational data are considered, enabling a more comprehensive and precise credit assessment (Chan et al., 2019; Pothumsetty, 2020; Mogaji, O. Soetan and Kieu, 2021; Gautam, 2023). While this broadens access to individuals with limited traditional credit histories, concerns may arise regarding fairness, particularly when certain data points disproportionately disadvantage those in lower socioeconomic groups. However, sophisticated AI algorithms adapt to changing credit cycles and default rates, reducing prediction errors and improving decision-making accuracy (Khandani, Kim and Lo, 2010; Aggarwal, 2021; Buchanan and Wright, 2021). By automating the credit scoring process, there is greater efficiency within financial institutions through reduced time and cost (Stiglitz and Weiss, 1981; Aggarwal, 2021; Mogaji, O. Soetan and Kieu, 2021). Since AI's ability to predict the likelihood of loan repayment no longer requires applicants to have an adequate amount of credit information to be considered 'scorable', credit scoring becomes more accessible (Agarwal, 2019; Bazarbash, 2019; Fernandez, 2019; Pothumsetty, 2020). While this benefits those with little or no credit history, the reliance on historical data risks perpetuating systemic biases. Marginalised groups, often with limited access to credit systems, may be disproportionately disadvantaged due to their underrepresentation in training datasets, exacerbating disparities in credit access.

While the integration of AI and ML is significant for the financial industry, it is paramount to incorporate ethical and social considerations into discussions, alongside calls for clear and adaptive regulatory frameworks (Lui and Lamb, 2018; Hentzen et al., 2021; Addy et al., 2024). Banks and financial institutions have regulations requiring transparency and accountability for all actions and decisions especially when dealing with client-related services, such as credit risk assessments and loan approvals (Donepudi, 2019; Buchanan and Wright, 2021; Hentzen et al., 2021; Gautam, 2023). The 'black-box' nature of AI's decision-making process makes it difficult for institutions to meet regulatory requirements that demand transparency (Lui and Lamb, 2018; Donepudi, 2019; Fernandez, 2019; Gautam, 2023). As a result, customers with a right to know the rationale behind credit decisions may lose trust in institutions if this information remains inaccessible. The lack of transparency may lead to an erosion of customer loyalty, undermining the cost cuts and efficiency gained through automation. Banks must ensure a strong compliance team can navigate a dynamic regulatory environment to address these unique challenges (Lui and Lamb, 2018; Chan et al., 2019; Mehrotra, 2019; Gautam, 2023). Furthermore, following access to substantial amounts of data, ethical concerns regarding consent, privacy, and the potential for unintended bias arise. The recognition of these systemic biases is essential to prevent unintended discrimination against marginalised communities (Lui and Lamb, 2018; 2019; Mehrotra, 2019; Gautam, 2023; Addy et al., 2024). If left unchecked, these biases could exacerbate existing inequalities, disproportionately disadvantaging marginalised groups while creating new forms of digital exclusion. Addressing these challenges requires a balanced approach combining innovative practices with regulatory oversight and ethical responsibility (Mogaji, O. Soetan and Kieu, 2021; Addy et al., 2024). By prioritising transparency, fairness, and trust, financial institutions can ensure fair credit assessments that promote equity across demographics, creating a more inclusive financial environment.

CONCLUSION

Despite the ongoing journey of navigating the full effects of Machine Learning and Artificial Intelligence within the financial industry, this critical review has demonstrated the power of both to usher in a new era of transformation in reshaping the industry. This review of fraud detection, algorithmic trading, and credit scoring highlights the predictive accuracy and efficiency of AI and ML while presenting ethical and operational challenges. In fraud detection, ML has improved detection accuracy and efficiency while introducing challenges regarding transparency and biases. In algorithmic trading, the incorporation of AI has brought on conflicts regarding speed and precision against market stability concerns. While AI's predictive power can be harnessed to enhance predictions, social inequities are at risk of being perpetuated if not managed effectively within credit scoring. These examples highlight technology's ability to automate specific tasks. Conversely, this potential must be approached critically, considering the broader implications for the financial industry.

Risk management must prioritise ethical and social implications, fairness and accountability, and emphasise transparency at every stage of AI deployment. ML and AI hold immense potential to revolutionise financial markets. However, their integration demands responsible use, particularly when applied to global markets and sensitive consumer data, in order to mitigate the risk of unintended consequences. Ongoing human oversight, such as regular audits, is essential to identify risks of automation, ensuring ethical considerations are upheld and unintended consequences are mitigated. Globally, consistent fairness and transparency standards must be set to address moral and regulatory concerns effectively. International collaboration among stakeholders, regulators, and the public is vital to form a unified framework customised for diverse market needs and global ethical standards. The integration of ML and AI must be guided by robust regulatory oversight and a commitment to ethical practice to ensure their benefits are equitably realised while minimising potential harm.

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