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Research Article

ARTIFICIAL INTELLIGENCE'S (AI): IMPLICATIONS IN MANAGING FINANCIAL RISKS (FRM)

[1]Abhijeet Kumar, [2,*]Avinash Kumar, [3]Swati Kumari, [4]Neha Kumari, [5]Sneha Kumari, [6]Puja Mishra and [7]Ajit Kumar Behura

[1,6]Faculty of Commerce and Management, Sarala Birla University, Ranchi, India
[2,7]Department of Humanities and Social Sciences, Indian Institute of Technology (Indian School of Mines) Dhanbad, India
[3]Department of Electrical Engineering and Computer Science, Indian Institute of Technology, Bhilai, India
[4]School of Education, Rani Durgavati Vishwavidyalaya, Jabalpur, Madhya Pradesh, India
[1,5]Bank of India, Government of India (U/T), [1]Goa Zone/ [5]Dhanbad Zone, India

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Abstract

This paper looks at how various forms of AI can manage financial risk management. The impetus for this change is the revolutionary impact that financial technology has had on business operations, necessitating a complete overhaul of the financial sector. Financial risk management must reorganise because conventional approaches have become inefficient. Artificial intelligence methods are primarily practical and have aided in the quick, cheap, and effective management of financial risks in businesses and financial institutions. This paper aims to provide an overview of the current state of artificial intelligence (AI) techniques applied to the field of financial risk management and to indicate potential future directions for research and development in this area. The data for the study was gathered by reading an assortment of articles, books, and reports regarding the implementation of AI in financial risk management. Methods: The question is whether artificial intelligence (AI) techniques (particularly machine learning) might help manage financial risks by systematically reviewing the relevant literature. Conclusions: Model validation, risk modelling, stress testing, and data preparation are all areas where AI has significantly benefited market risk and credit risk management. Data quality control, fraud detection, and text mining for data augmentation are all areas in which (AI) artificial intelligence techniques have proven useful. The financial sector will continue to be influenced by financial technology as incumbents are compelled to adopt new operational methods and strategies. Consequently, it is realistic to anticipate that AI will become a mainstream component of financial risk management systems. The paper's contribution is a survey of AI's uses in three fields: financial (market and credit), risk management and operational (business continuity and disaster recovery). The paper went over the most promising AI methods that should impede better managing risks in the changing financial sector.

Keywords: Credit Risk, Market Risk, Operational Risk, Machine Learning, Artificial Intelligence.

INTRODUCTION

Without artificial intelligence (AI) techniques, managing financial risks is impossible today. There are numerous reasons for this. However, one of the most significant is that conventional approaches, methods, and strategies for financial risk management have grown to be expensive, time-consuming, and insufficient. Specifically, a good blend of conventional (FRM) financial risk management and (AI) artificial intelligence techniques be the foundation for practical enterprise applications. That will increase each participant's productivity, self-assurance, and potential for expansion in today's turbulent business environment, regardless of industry. We can categorise the issues that have arisen over the past decade and have yet to address as follows: Market Risk Modelling (Day, 2017), Validation of market risk management models (Regan, 2017); reduction of costs by determining which assets it would be advantageous to take a position in; assessment referred to as "market impact" (i.e., the firm's trading impact on market pricing); (Heaton, 2017). In the last five years, advancements in financial technology (Fintech) have facilitated the rapid growth of artificial intelligence (AI) techniques that have revolutionised the financial services sector. Introducing new technologies such as blockchain, AI, and big data analytics has revolutionised the financial sector, making it possible for more people to gain quick and easy availability of (FS) financial services. Despite this, Fintech has brought about several threats that could compromise the safety of the involved parties (e.g., market risk in compliance, credit-rating underestimation). That caused a commotion in the financial sector, necessitating new and better methods of managing financial risks. Financial risk management will rely on cutting-edge technologies to improve productivity and decision-making accuracy. For this reason, it is no longer optional for businesses and financial institutions to employ AI.

Here is how the rest of the paper is sequenced:

- The potential of AI in managing Credit Risks Management (CRM) is in section second.
- The third section discusses the role of AI in controlling Market Risk Management (MRM).
- In the fourth section, we discuss how artificial intelligence can help Operational Risk Management (ORM).
- In the fifth section, we examine the difficulty posed by AI in Financial Risk Management (FRM).
- In the sixth part, we discuss how AI can help with Financial Risk Management (FRM).

At last, in section seven, we offer some final thoughts and outline potential avenues for future study.

Corresponding Author:** ***Avinash Kumar,
Department of Humanities and Social Sciences, Indian Institute of Technology (Indian School of Mines) Dhanbad, India.

Integration of Artificial Intelligence (AI) into Credit Risk Analysis/ Management (CRM)

Inability of a counter party to fulfil their contractual obligations is the source of credit risk. The danger of financial loss due to credit default or a deterioration in creditworthiness is known as credit risk (Bogojevic Arsic, 2009, p. 439). Credit risk analysis/ management (CRM) identifies and analyses risk factors, measures risk levels and selects appropriate credit activity management measures to reduce or eliminate credit risks. Credit risk management has used various statistical methods for decades. Fintech made these methods insufficient for managing credit risk management (CRM). As a result of the as a result of the inadequacy of conventional credit risk modelling approaches, financial institutions began using AI.

AI techniques outperform traditional statistical techniques in credit risk modelling, However, only their union improves accuracy (Altman, 1994). AI credit risk assessment is the most difficult (for instance machine learning {ML}). AI can assist in determining credit risk events and estimate defaulting costs (Bogojevic Arsic, 2020). Machine learning makes better lending decisions for consumers as well as small and medium businesses. Support vector machines and decision trees can save money and improve credit risk modelling (Khandani, 2010). (Yao, 2015). Small and medium-sized businesses can better estimate their credit risk using machine learning techniques to find outliers (Figini, 2017). Also, the deep reinforcement learning method, a new way to choose features, can be applied in order to improve credit risk management and analysis (Ha and Nguyen, 2016). Also, machine learning (ML) methods improved the growth of fundraising on the basis of lending by improving credit scoring and creating credit rating profiles. That made it simpler for borrowers to obtain loans (particularly for start-ups and small businesses) and for lenders to believe the information and be prepared to give loans (Ha, 2019), (Byanjankar, 2015). Last but not least, deep learning has proven its worth over conventional methods in the areas of predictions of credit risk and default risk forecast. As well as this is true across the board, from conventional lending through banks to alternative lending through online marketplace lenders (Hou, 2020; Son, 2016; Thang, 2019; Van-Sang, 2019).

Artificial Intelligence (AI) Application in Market Risk Management (MRM)

The phrase is market risk term used to describe shifts in the value of financial instruments or contracts brought on by unforeseen changes in asset prices, such as those of commodities, rates of interest, rates of foreign currency exchange, and other market indexes. The possibility that the value of a portfolio would vary due to shifts in price level or market price volatility is known as market risk (Bogojevic Arsic, 2009). That implies that all financial market party is directly or indirectly open to market risk. Participants must manage this risk based on their financial stability and the size of their exposed positions. Financial institutions actively manage this threat by selecting, according to their preferences, the kind of market risk they wish to be exposed to an understanding of the volatility of market prices. On the other hand, non-financial businesses work to minimise or, if feasible, eliminate this threat in addition to different risk categories (to reduce or eliminate market risk, as well as other types of trouble). The use of AI methods in market risk management has the potential to improve performance significantly. The primary AI technique, machine learning, has enormous potential to improve market risk analysis/ management (MRM).

According to the basis of (Financial Stability Board, 2017), artificial intelligence has helped market risk management at each phase of the procedure, including data preparation, model validation, modelling, and stress testing. Machine learning techniques contributed significantly to data preparation by demonstrating their capacity to handle raw data from financial institutions, markets, or businesses. While machine learning (ML) methods (includingneural networks, decision trees, and deep learning) help clean data, research published by (Wang 2019), (Ghrobani and Zou, 2018),(Ding and Simonoff, 2010),(Twala, 2009), (Garcia-Laencina, 2008), and (Garcia-Laencina, 2007). Various machine learning methods are also used in classification, allowing for better precise data as model inputs. This model includes the risk of using a model that is insufficient, incomplete, incorrect, or, in some cases, no longer valid. In this regard, market model stress testing for the determination of unintentional risk can be accessed using AI techniques (for example, various machine learning techniques). Model stress testing can also impede the identification of risks that affect trading behaviour and serve as a benchmark or feedback mechanism for decisions to reduce or reduce market risk. Many Institutions of finance have attempted to implement machine learning for trading books, which have become a significant source of risk since the 2009 financial crisis, as well as for estimating Value-at-Risk and expected shortfall (Wilkens, 2019) such as (PNP Paribas). The potential application of AI varies, trusting on the model risk, the origin of the risk, and the risk measurement (Klein, 2015). For market risk managers to identify acceptable market risk levels and more effectively minimise market risk, (Abramov, 2017) provided an outline of how to evaluate market risk designs and how machine learning approaches should be employed. AI applications are inevitable because they can lower operational expenses and provide more precise information to support strategic risk management decisions, allowing financial companies and institutions to survive, compete, and grow.

Artificial intelligence (AI) application in operational risk management (ORM)

The operational risk is the possibility of suffering losses because of physical deterioration, technological failure, and human mistakes during an enterprise's or institution's business operations, including fraud, poor management, and operation mistakes (Bogojevic Arsic, 2009).Due to their unique characteristics (such as risk preferences, business portfolio structure, Etc.) that influence operational risk exposures, this type of risk has a different meaning for each enterprise or institution.AI can assist businesses and enterprises at every phase of the operational risk management (ORM) strategy (Sanford and Moosa, 2015). The ORX Association researched this, the most significant in the financial sector, operational risk is associated; financing in AI implements could make the operating corporation more competitive, efficient, affordable, predictive, and low-risk (Carrivick and Westphal, 2019). Artificial intelligence can help develop a suitable operational risk mitigation strategy and determine the best way to shift or trade this risk? The preparation of data, analysis, and classification of extensive data, as well as the performance to stem outward failures, must come first when applying AI to operational risk management.

According to (Carrivick and Westphal, 2019), operational risk management can benefit from AI, particularly machine learning.

- A reduction or eradication of labour-intensive as well as repetitive processes and tasks (For example, some financial companies were able to reduce the number of processes that required review),
- Greater data insight (to acquire useful data),
- A more straightforward method for making decisions based on the provision of both more comprehensive and concise information,
- Creation of competent workers and leaders. Who can interact with customers and regulators quickly and accurately across the organisation,

Machine learning can help with the operational risk management (ORM) in three primary ways: improving data quality, using text mining to enhance data, and detecting fraudulent activity (Carrivick and Westphal, 2019). By more accurately detecting duplicated data entries and extreme data values, machine learning can aid in collecting high-quality data (e.g., identifying risks in an unstructured or unlikely manner). Machine learning implies analysing the vast quantities of data required for risk management (such as Information on internal and external losses, measures of risk, macroeconomic trends, etc.) as well as maintaining and storing data. That allows various machine learning techniques to categorise specific entries and enrich the data. The final application utilises machine learning to identify money laundering and fraud. The classification of financial transactions into suspicious and harmless is a standard method of detecting fraud because it is difficult to spot. Machine learning can assist by accurately categorising these transactions, and declining faulty alarms when defrauding trades are unidentified.The standard machine learning enactment helps prevent credit card fraud and detect securities scams (foreign exchange fraud, commodity pool fraud, stock fraud, Etc.).

The Artificial Intelligence (AI) Challenge in Financial Risk Management (FRM)

The development of artificial intelligence in financial risk management (FRM) is multifacet and influenced by various factors (specific business lines, nature of business, organizational structure, regulations, geography, etc.). According to (Chartis Research, 2019), capital market financial risk management, retail banking, and commercial banking are the primary industries where AI techniques consider. Retail banking has used AI to improve models and conduct stress tests (such as support vector machines and decision trees) through classification methods and supervised machine-learning techniques. Using behavioural and segmentation integration and behavioural models, scenario generation in asset pricing and portfolio optimization will precede AI implementation developments in these areas. Due to their large and complex documentation, poor data management, and lack of well-structured benchmark and credit curve data, commercial banks pose a significant challenge to AI applications. Some tasks, like passive strategies, must be partially automated to guarantee profitable operation. In addition, AI applications in strategy development and evaluation, credit portfolio management (CPM) and credit risk analytics (CRA) are possible. The creation of databases, the detection of anomalies in the volatility surface and yield curve, and portfolio construction are all examples of applications of AI (i.e., various machine learning techniques). More complex and powerful AI applications can predict scenario design, portfolio optimization, model validation, and equity and credit risk modelling.

Artificial Intelligence (AI) Can Help with Financial Risk Management (FRM)

The disruption in the financial sector brought about by Fintech has had a profound effect on financial risk management. Financial risk management focuses on optimizing how financial institutions or corporations take financial risks. Artificial intelligence (AI) is a subset of financial technology (Fintech) that has revolutionized how financial risk is being “taken care of”. Additionally, AI has aided financial risk management through improved decision-making. Artificial intelligence (AI) is a broad field focused on applying various techniques based on human-like intelligence, as has already been mentioned. These methods make intelligent and efficient use of prior knowledge (such as multiple data sets) (mimic human behaviour). Machine learning is the most important form of artificial intelligence when making decisions about financial risks because it enables data collection, cleaning, and prediction. Supervised learning and unsupervised learning are the two primary subfields of machine learning. Methods like artificial neural networks, decision trees, deep learning, principal component analysis, partial least squares, selection operator and most minor absolute shrinkage, ridge, least angle regression and support vector machine are used in supervised learning to make predictions based on the available data (van Liebergen, 2017).

In managing financial risks, we can use any of the above mentioned methods. Credit risk management thus makes more frequent use of specific methods. Principal component analysis (PCA), is commonly used, for example, to determine credit repayment risk, to evaluate credit, and as an input for artificial neural networks to anticipate asset price and stock index (Wangand Wang, 2015), as well as for equity portfolio management (Hamdy and Hussein, 2016). The support vector machine learning also predicts the risk of a loan default (Nazemi, 2018). Credit default prediction (Abedin, 2018), credit scoring (Harris, 2015), estimation of value-at-risk (Radovic and Stankovic, 2015), credit risk assessment (Lean, 2014), and other terms are examples of credit-related terminology. Combining support vector machines with different machine learning methods, like neural networks, revealed that they were better than traditional methods. Unsupervised techniques are essential to perform grouping the data into clusters and classification. Their advantage is that these techniques do not require users to have a priori assumptions about data structures. A clustering technique requires no resources for initialization. Finally, deep learning and neural networks should be seen as supervised and unsupervised machine learning components since they may use them to learn from data and offer more precise indicators for financial risk management. They can apply to output forecast (such as the market level or credit risk). Credit risk evaluation, asset price forecasting, and credit risk prediction are all common uses of artificial neural networks (Pacelli and Azzollini, 2011). Deep learning integrates neural networks with methods that allow representative data to be automatically discovered for variation detection and classification. Deep understanding follows a hierarchical structure of artificial neural networks to facilitate nonlinear data processing. This cutting-edge method augments input data with so-called masked layers (variables), allowing for modelling their interactions. In this manner, deep learning aids in the solution of the “black box” problem. The “black box” is inherent in financial risk decision-making (FRDM), which is of utmost importance for financial risk management. The estimation of asset pricing models for specific stock returns can be done by combining deep learning approaches (Chen, 2019). Deep learning can also use in other fields, such as market risk management (MRM), bank trading book: trading risk prediction, risk management, Etc. (Kim, 2019).

Conclusion

Financial risk management will continue to be significantly impacted by Fintech’s continued development. Further transformation and change in financial risk management will be necessary due to this influence. In this regard, financial institutions and other market participants may incorporate AI into their framework for managing financial risk. That indicates that AI would enable data management automation and simplification, enhanced scenario generation and stress testing, new approaches for tackling complex, non-linear optimization, and multivariable problems (Chartis research, 2019). Additionally, a broader application in lending-based and equity-based crowd funding may anticipate by facilitating and accelerating the process of raising capital through the issuance of equity or the approval of loans to prospective borrowers. Additionally, AI can help create credit ratings for possible borrowers and improve their credit scores, which are necessary for venues to function as an intermediate in crowd funding. Applying AI techniques in financial risk management is not hindered by the abovementioned facts. These methods will provide real-time information on the different financial risk categories to which organisations and businesses are revealed and which call for sophisticated risk management. In other words, adequate and enhanced financial risk management will incorporate conventional statistical and AI methods like cutting-edge classification techniques, artificial neural networks and deep learning.

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