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Artificial Intelligence: The Strategy of Financial Risk Management

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ABSTRACT

This research examines the use of artificial intelligence (AI) as a financial risk management tool. The concept is motivated by the revolutionary effects that financial technology has on business operations. Traditional methods of financial risk management are no longer effective and require revision. The **purpose** of the study is to assess the role of artificial intelligence in the management of financial risks and offer recommendations for its further use in the financial sector of the economy. Methodological analysis of relevant scientific literature showed that AI, in particular machine learning, can help in managing financial risks. It has been **concluded** that AI improves the management of market and credit risks in model verification, risk modelling, stress testing and data preparation. AI helps to monitor the quality of information received, detect fraud and search for the right information on the Internet. In the future, financial technology will continue to influence the financial sector as operating companies modify their operations. Thus, financial risk management tools will include AI. The study examines the possibilities of AI use in financial (market and credit), risk management and operational sectors (business continuity and emergency recovery). The paper presents the most promising AI technologies and techniques such as RPA, Data Management, Blockchain, MRL, MRC, CRU, Deep Learning, OML, Modelling and Stress Testing, Machine Learning and Algorithms, Neural Networks, Decision Trees, CPM, CRA, Black Box, etc. to improve "Financial Risk Management (FRM)".

Keywords: artificial intelligence (AI); credit risk (CR); operational risk (OR); market risk (MR); machine learning (ML)

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INTRODUCTION

Managing financial risks requires employing solutions based on artificial intelligence (AI). There are many different explanations for this. However, one of the most crucial is that standard approaches, methods, and strategies for financial risk management have grown to be expensive, time-consuming, and insufficient. That is one of the reasons why. Specifically, the framework for actual enterprise applications should consist of an effective combination of traditional (FRM) financial risk management and (AI) artificial intelligence methodologies. The current tumultuous business environment will boost the participants' individual productivity, sense of self-assurance, and possibility for advancement in any sector.

The following is a list of the problems that have cropped up throughout the past ten years and have not yet been resolved: validation of market risk management models [1]; market risk modelling [2]; 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); market impact modelling [3, 4].

In the past five years, developments in financial technology (Fintech) have permitted the rapid expansion of artificial intelligence (AI) techniques, revolutionizing the financial services sector. This growth has been made possible by advances in blockchain technology. Innovative technologies in the financial industry, such as blockchain, artificial intelligence, and big data analytics, have revolutionized the industry and made it possible for more individuals to obtain access to financial services (FS) rapidly and efficiently. Despite this, Fintech has given rise to several risks that could jeopardize the safety of those involved (e.g., market risk in compliance, credit-rating underestimation). That produced an uproar in the financial industry, which necessitated the development of new and improved strategies for managing financial risks. Technology on the cutting edge will be essential to financial risk management to boost productivity and ensure more accurate decision-making. Because of this, using AI in commercial enterprises and financial institutions is no longer a choice but a must.

Here is how the rest of the paper is sequenced:

• The second portion discusses using artificial intelligence to manage credit risks, often known as CRM.

• The third section covers the role of AI in regulating Market Risk Management (MRM).

• In the fourth segment, we will discuss how artificial intelligence might assist with operational risk management (ORM).

• In the fifth session, we look at artificial intelligence's challenge for financial risk management (FRM).

• In this sixth and final instalment, we will cover how AI may assist with managing financial risks (FRM).

In the seventh and final section, we will present some concluding remarks and discuss possible research directions for the future.

ARTIFICIAL INTELLIGENCE TO MANAGE CREDIT RISKS ANALYSIS/ MANAGEMENT (CRM)

The origin of credit risk is when a counterparty cannot meet the commitments outlined in a contract they are "subject to". Credit risk refers to the possibility of suffering a monetary loss due to a credit default or a decrease in creditworthiness [5]. The process of identifying and analysing risk variables, measuring risk levels, and selecting appropriate credit activity management strategies is what credit risk analysis and management (CRM) is all about. The end goal is to decrease or eliminate credit risks. For decades, many statistical approaches have been utilized to control credit risk. These approaches to credit risk management became obsolete due to the rise of fintech (CRM). Artificial intelligence was first introduced in the financial industry once it became clear that traditional approaches to modelling credit risk were inadequate.

AI algorithms perform better than traditional statistical techniques when it comes to modelling credit risk. However, only combining the two can increase accuracy [6]. The most challenging aspect of artificial intelligence credit risk assessment is machine learning (ML). The events associated with credit risk can be determined using AI, and defaulting costs can be estimated [7].

Through machine learning technology, consumers and small and medium-sized businesses benefit from improved financing decisions. Support vector machines and decision trees can potentially reduce costs while improving credit risk modelling [8, 9]. Using machine learning algorithms to identify outliers enables small and medium-sized firms to more accurately estimate the credit risk they face [10]. In addition, the deep reinforcement learning method, a novel approach to selecting features, can be utilized to facilitate improvements in credit risk management and analysis [11].

Additionally, machine learning (ML) methods increased credit scoring and created credit rating profiles, both of which contributed to the expansion of fundraising activities based on lending. That made it easier for borrowers to secure loans (especially for start-ups and small enterprises) and made it easier for lenders to believe the information and be prepared to make loans [12, 13].

In forecasting credit risk and default risk, deep learning has demonstrated its superiority over more traditional methods, which is not the least of its accomplishments. In addition, this is the case regardless of whether one talks about traditional lending through banks or alternative financing through online marketplace lenders [12, 14, 15].

AI IN REGULATING MARKET RISK MANAGEMENT (MRM)

This market risk term is used to describe shifts in the value of financial instruments or contracts brought on by unexpected changes in the prices of assets. These unexpected changes can include changes in the prices of commodities, interest rates, rates of exchange for foreign currencies, and other market indexes. Market risk is the potential for a portfolio's value to change due to shifts in the price level or fluctuations in the market price. This possibility is known as market risk [5]. That suggests that every financial market participant is directly or indirectly exposed to market risk. Participants are responsible for mitigating this risk based on the strength of their financial circumstances and the extent of their exposure. Financial institutions actively manage this risk by selecting, according to their preferences, the type of market risk they wish to be exposed to and gaining awareness of the volatility of market prices. That allows the institutions to manage this hazard actively.

On the other hand, non-financial organizations aim to minimize or, if possible, eliminate this risk category in addition to the many other risk categories they face (to reduce or eliminate market risk and other types of trouble). The application of AI-based techniques to the management of market risk has the potential to result in considerable performance enhancements. Machine learning, the fundamental AI method, offers tremendous untapped potential to advance market risk research and management (MRM) significantly.

According to the findings presented in (Financial Stability Board, 2017), the application of artificial intelligence has proven beneficial to market risk management throughout the process, from data preparation and model validation to modeling and stress testing. Machine learning algorithms have significantly contributed to the data preparation process by demonstrating their ability to deal with raw data originating from financial institutions, markets, or enterprises.

Research that was published by [16–20] and others found that although machine learning (ML) methods (such as neural networks, decision trees, and deep learning) help clean data, there are still issues that need to be addressed [21].

The categorization process also makes use of a variety of machine learning approaches, which enable the use of more accurate data as model inputs. Utilizing this model may result in the use of a model that is either inadequate, incomplete, wrong, or, in some instances, no longer viable. In this sense, artificial intelligence approaches can be used to gain access to market model stress testing to determine inadvertent risk (for example, various machine learning techniques). Testing models under stress can also impede the identification of risks that affect trading behaviour and serve as a benchmark or feedback mechanism for decisions to reduce market risk. That can be a problem because these risks can guide decisions to reduce the market.

Since the global financial crisis of 2009, many financial institutions have attempted to implement machine learning for their trading books, which has become a significant source of risk in the industry and estimating Value-at-Risk and expected shortfall [22]. Such as the number of defaults that are expected to occur in the future (PNP Paribas). The possible applications of artificial intelligence vary widely depending on the model risk, the risk source, and the risk measurement [23].

An outline of how to analyse market risk designs and how machine learning strategies should be utilized was offered by Abramov (2017) to assist market risk managers in determining what levels of market risk are acceptable and, more effectively, mitigating market risk [24].

Applications of artificial intelligence are unavoidable because they have the potential to reduce operational expenses and provide more accurate information to support strategic risk management decisions. That will allow financial companies and institutions to continue to exist, compete, and grow.

ARTIFICIAL INTELLIGENCE ASSIST WITH OPERATIONAL RISK MANAGEMENT (ORM)

The possibility of incurring losses due to physical deterioration, technological failure, or human error during an organization's or institution's business operations is known as operational risk. Examples of operational risk include fraud, ineffective management, and operation mistakes [5]. The meaning of this type of risk is different for each enterprise or institution because of the unique characteristics (such as risk preferences, business portfolio structure, Etc.) that influence operational risk exposures. These characteristics include risk preferences, business portfolio structure, and so on. Artificial intelligence has the potential to aid companies and businesses at every stage of the operational risk management (ORM) plan [25].

The ORX Association conducted a study on this topic, which is the most significant in the financial sector and is related to operational risk; funding in AI implementations has the potential to make operating corporations more competitive, efficient, affordable, predictive, and low-risk [26].

Can artificial intelligence assist in formulating an appropriate operational risk mitigation strategy and identifying the most effective means by which to transfer or exchange this risk? When using AI for operational risk management, the first step must be the production of data, followed by the analysis and classification of enormous amounts of data, as well as the performance to prevent failures from occurring on the outside.

The use of AI, and more specifically, machine learning, can be beneficial to operational risk management, according to Carrivick and Westphal (2019).

- The reduction or elimination of labour-intensive processes and activities, as well as those that are repetitive (for example, some financial companies were able to reduce the number of processes that required review).
- A more precise way of making decisions based on the availability of both more extensive and succinct information.
- The creation of skilled workers and leaders who can interact with customers and regulators quickly and accurately across the organization [26]. Machine learning can help with operational risk management (ORM) in three primary ways: improving data quality, using text mining to enhance data, and detecting fraudulent activity.

Machine learning can assist in gathering high-quality data since it can detect duplicated data entries and extreme data values with more accuracy (e.g., identifying risks in an unstructured or unlikely manner). Machine learning entails the maintenance and storage of data and the analysis of the enormous quantities of data required for risk management. That includes information on internal and external losses, measurements of risk, and macroeconomic patterns, among other things. That enables a variety of machine learning approaches, which may then be used to categorize individual entries and improve the data. The finished product is an application that uses machine learning to detect fraudulent activity and money laundering. Because fraud is notoriously difficult to recognize, one common strategy for uncovering instances of it is to divide money dealings into two categories: suspicious and safe. Machine learning can assist by correctly classifying these transactions and reducing the number of false alerts generated when fraudulent trades are not recognized. Implementing essential machine learning helps prevent the fraudulent use of credit cards and uncovers fraudulent activity in the securities market (foreign exchange fraud, commodity pool fraud, stock fraud, etc.).

ARTIFICIAL INTELLIGENCE'S CHALLENGE FOR FINANCIAL RISK MANAGEMENT (FRM)

Artificial intelligence's evolution in financial risk management (also known as FRM) is complex and subject to a wide range of factors (specific business lines, nature of business, organizational structure, regulations, geography, etc.).

According to Chartis Research (2019), the key businesses that artificial intelligence approaches take into consideration are commercial banking, retail banking, and financial risk management in the capital market. The retail banking industry has utilized classification strategies and various forms of supervised machine learning to enhance existing models and carry out stress testing. Examples of these models include support vector machines and decision trees. Scenario generation in asset pricing and portfolio optimization will come before improvements in AI's application in these areas. That will be accomplished by the integration of behavioural and segmentation data as well as behavioural models. Commercial banks present a substantial obstacle to the development of AI applications due to their extensive and complicated documentation, inadequate data management, and the absence of well-structured benchmark and credit curve data. In order to ensure a profitable operation, certain operations, such as passive strategy implementation, need to be largely automated. There is also the potential for AI to be applied in areas such as formulating and evaluating strategies, credit portfolio management (CPM), and credit risk analytics (CRA).

Examples of uses of artificial intelligence include:

- Developing databases;
- Identifying anomalies in the yield curve and the volatility surface;
- Building investment portfolios (i.e., various machine learning techniques).

Applications of artificial intelligence that are more sophisticated and powerful can anticipate scenario design, portfolio optimization, model validation, and equity and credit risk modelling.

THE APPLICATION OF ARTIFICIAL INTELLIGENCE (AI) IN THE MANAGEMENT OF FINANCIAL RISK CAN BE BENEFICIAL (FRM)

The transformation that Fintech has brought about in the financial industry has significantly impacted how financial risk is managed. Financial risk management aims to maximize the return on investment obtained from financial risks by financial institutions or enterprises. How financial risk is "taken care of" has been fundamentally altered by the application of artificial intelligence (AI), which is a subset of financial technology (Fintech). In addition, artificial intelligence has helped improve decision-making, which in turn has improved financial risk management.

As was previously noted, artificial intelligence (AI) refers to a vast discipline that focuses on applying various methodologies based on human-like intelligence. This field is known as "deep learning." These strategies use prior information intelligently and efficiently (by utilizing numerous data sets, for example) (mimic human behaviour). Because it facilitates data collection, cleansing, and prediction, machine learning is the most effective form of artificial intelligence to consider when making decisions concerning the potential consequences of taking financial risks.

Machine learning may be broken down into two basic categories: supervised learning and unsupervised learning. In supervised learning, predictions are made based on previously collected data using techniques such as artificial neural networks, decision trees, deep learning, principal component analysis, partial least squares, selection operators, most minor absolute shrinkage, ridges, least angle regression, and support vector machines [27].

Any of the approaches mentioned earlier can be utilized by us when managing financial risks. Because of this, specific strategies are utilized significantly more frequently in credit risk management. Typical applications of principal component analysis (PCA) include calculating credit payback risk, evaluating credit, serving as an input for artificial neural networks used to predict asset prices and stock indexes [28], and equity portfolio management [29].

In addition, support vector machine learning can forecast the probability of a loan going unpaid [30]. Some examples of vocabulary connected to credit include credit default prediction [31], credit scoring [32], evaluation of value-at-risk [33], credit risk assessment [34], and other phrases. It was shown that when Support Vector Machines (SVMs) were combined with other machine learning approaches, such as neural networks, they performed significantly better than conventional methods.

Unsupervised procedures are essential when combining the data into clusters and doing classification. These methods have the advantage that users are not required to have any a priori assumptions about the data structures they are working with; a clustering technique requires no resources for initialization.

Finally, deep learning and neural networks should be regarded as supervised and unsupervised machine learning components, respectively. That is because they can utilize them to learn from data and provide more precise indicators for controlling financial risk. They apply to production prediction (such as the market level or credit risk). The appraisal of credit risk, the forecasting of asset prices, and the prediction of credit risk are all typical applications for artificial neural networks [35].

Deep learning is the process of integrating neural networks with other types of learning methods that enable the automatic discovery of representative data for variation detection and classification. The topology of deep understanding is similar to that of artificial neural networks and hierarchy to assist nonlinear data processing. This cutting-edge technology enhances the input data by adding what is known as masked layers (variables), enabling the modelling of the relationships between the variables. In this way, deep learning contributes to resolving the "black box" problem. The so-called "black box" is essential to making decisions on financial risk, which is of the utmost significance for financial risk management. Combining several deep learning strategies allows for estimating asset pricing models for specific stock returns [36]. Deep learning has applications in a variety of other domains as well, including market risk management (MRM), bank trading books (trade risk prediction), risk management, and so on [37].

CONCLUSION

The continuous growth of fintech is expected to impact financial risk management substantially. Because of the influence of this factor, additional transformation and changes in financial risk management will be required. Within this context, financial institutions and other market participants may choose to include AI in their framework for managing financial risk. That suggests that AI would make it possible to automate and simplify data administration, improve scenario generation and stress testing, and develop new strategies for addressing complicated, non-linear optimization and multivariable problems.*

* The state of AI in risk management: Developing an AI road map for risk and compliance in the finance industry. Mumbai: Digital Services Limited & Tata Consultancy Services; 2019. 56 p. URL: https://www.tcs.com/content/dam/global-tcs/en/pdfs/insights/whitepapers/State-of-AI-in-Risk-Management.pdf

Additionally, a broader application of lending-based and equity-based crowdfunding may be anticipated, with the potential to facilitate and expedite the process of raising capital through the issuance of equity or the approval of loans to prospective borrowers. That is accomplished by anticipating a broader application of lending-based and equity-based crowdfunding. In addition, AI may assist in creating credit ratings for potential borrowers and improving their credit scores, both of which are required for venues to operate as an intermediary in the crowdfunding process.

The use of AI strategies to control financial risk is not impeded in any way by the facts presented. These technologies will provide information in real-time on the various kinds of financial risk to which organizations and corporations are exposed and require sophisticated risk management strategies. In other words, adequate and improved financial risk management will incorporate traditional statistical and AI methods such as cutting-edge classification techniques, artificial neural networks, and deep learning. These are examples of strategies that fall under the umbrella of artificial intelligence.

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Authors' declared contribution:
Abhijeet Kumar — problem statement, paper concept development, financial and banking approach, risk analysis, financial risk management, issues and challenges.
Avinash Kumar — literature review, content analysis, developed the research framework, financial risk management.
Swati Kumari — technology AI and ML, literature review, results description, conclusions, Machine Learning and Algorithms, Neural Networks, Decision Trees.
Sneha Kumari — financial and banking approach, problem statement, results description, conclusions, risk analysis, financial risk management, issues and challenges.
Neha Kumari — results description, conclusions, language, interpretation etc.
Ajit Kumar Behura — administrative support and guidance.

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