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An Empirical Investigation of Artificial Intelligence Instruments for Forecasting Credit Risk in the Digital Age

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Abstract: Credit risk is the danger that a bank's debtors will not fulfil their obligations by skipping payments on their credit cards or loans. Credit risk is the most important and difficult issue confronting bank management. The objective of this study is to examine the potential of artificial intelligence (AI) instruments for forecasting credit risk in the digital age. This research will use an empirical approach to answer the research questions through the collection of data, analysis, and interpretation of the results. This research will be conducted using an empirical investigation to understand the use of artificial intelligence instruments for forecasting credit risk in the digital age. The research process will involve three main steps, including data collection, data analysis, and results interpretation. AI-based instruments can quickly process large amounts of data from multiple sources and accurately identify potential credit risk. Furthermore, these instruments can also be used to identify customer behaviour patterns and inform more accurate decision-making.

Keywords: *Credit risk, Artificial intelligence, decision-making, forecasting*

1. Introduction

Machine learning (ML) advancements have recently had a tremendous influence on academics and industry, ultimately altering people's daily lives. The use of artificial intelligence (AI) has helped almost every facet of human activity, notably pattern identification, image classification, business, farming, and finance. The primary focus of this work is the use of ML in finance and credit risk evaluation. The foundations of modern financial organisations are credit and trust. Credit risk is an important determinant of how likely a debtor is to default. Appropriate credit risk calculation is essential for the entire system. Systemic errors, like the subprime crisis of 2008, can occur when credit risk is not appropriately estimated. Lenders devote a lot of resources to this endeavour in order to foresee a customer's and the business's creditworthiness and develop appropriate lending strategies to lower their risks (Beque and Lessmann, 2017). Credit risk techniques have traditionally used statistical techniques like Linear Discriminant Analysis and Logistic Regression. Large datasets, meanwhile, are difficult for these approaches to manage.

According to Apostolik et al. (2009), credit risk is the probability that debtors to a bank may stop making payments on their debts or will not satisfy loan repayment dates. Credit risk is the most important and difficult issue confronting bank management.

Dermirgue-Kunt & Detragiache (1998) stated in several studies on bank failures that the condition of resources was a numerically relevant leading indicator of liquidation and that financial companies worldwide continue to have a high proportion of non-performing loans.

The financial system and overall economic activities are severely harmed when creditors are unable to appropriately evaluate the credit risk of prospective borrowers. Decision-makers in financial institutions all around the world have paid close attention to credit risk assessments in the past ten years. This was partially a result of the current developments in financial legal systems and the world economic crisis. Additionally, as a result of the rising competition in the banking industry, numerous organisations have developed creative approaches to risk prevention guidelines to preserve their diligence. In 2013, Harris. As a result, financial institutions in today's business and economic climate run a greater risk of suffering damages as a result of bad credit authorization choices. More effective credit assessment methods are continually being devised in order to control the rising default risk that financial companies face. In this regard, the creation of novel risk analysis techniques attempts to enhance banks' capacity to identify the risk category of businesses making loan requests.

A crucial tool in credit risk analysis, credit scoring helps businesses determine whether to extend credit to customers (Thomas, 2000).

A popular method of credit scoring involves classifying data from past clients (both those with strong credit and

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those who have fallen behind on their payments) in order to determine whether there is a correlation between the client's traits and their likely inability to pay back their debt. To assess whether applicants will be able to pay their debts back, institutions utilise credit scoring algorithms that consider the consumer's prior credit history and present economic situations.

Financial organisations use credit scoring as a significant tool to evaluate credit risk and make management choices (Yu et al., 2008). A new credit application must be categorised into one of the predetermined classifications, which is what credit scoring is in practise. Most traditional methods for credit scoring are relied on statistical parametric approaches including logistic regression (LR), discriminant analysis, and linear regression. Yet, non-parametric approaches and AI tools like decision trees, ANN, and SVM have become increasingly prevalent in current credit scoring. These different approaches do not necessitate any prior information, in contrast to parametric statistical techniques. From learning observations, they are utilised to automatically extract knowledge.

Large credit datasets and improvements in computer power paved the path for AI-Driven credit risk estimate techniques like conventional ML and deep learning (DL). Compared to statistical approaches, traditional ML techniques like k-Nearest Neighbour, Random Forest, and SVM are more efficient and adaptable. When applied to a huge credit risk data lake, DL algorithms in specific performs better than their predecessors in terms of reliability and productivity.

1.1 RESEARCH GAP

The application and accuracy of artificial Intelligence instruments for predicting credit risk in different sectors is well known. However, the effectiveness of predictive models and AI tools for predicting credit risk in the banking sector, retail sector and other financial sectors need to be studied. Moreover, the research gap can be extended to analyse if the use of AI instruments can lead to a reduction of false-positive and false-negative results in forecasting credit risk. This can help financial institutions to make more informed decisions.

1.2 RESEARCH OBJECTIVES

The objective of this study is to describe what extent AI is implemented in the financial services industry and to what degree it is in accordance with the existing research in the area.

2. Literature Review

Previous research suggests that classifiers' predictions of financial risk may function differently depending on the performance measures and the conditions. The paper by Peng et al. (2011) created a two-step evaluation process for classification algorithms used in financial risk prediction. It creates a performance score to gauge the effectiveness of classification algorithms and introduced TOPSIS, PROMETHEE, and VIKOR as three techniques to offer a final ranking of classifiers. Seven real-world credit risk and fraud risk datasets from six different nations was compared in terms of different classification algorithms used. The findings demonstrated that TOPSIS, PROMETHEE, and VIKOR rank linear logistic, Bayesian Network, and ensemble approaches as the top three classifiers.

Pacelli & Azzollini, (2011) investigated about how well an artificial neural network model can predict a panel of Italian industrial companies' credit risk. This research offers a literature assessment on the use of AI systems for credit risk management from a theoretical perspective. In order to demonstrate the variances between the two ANN models, this study examined the framework of the model created to the other one created for research carried out in 2004 with a comparable panel of organisations.

The evaluation of financial credit risk is a crucial and challenging academic issue in the domains of accounting and finance. There have been multiple attempts in this area since the first one last century. The study of financial credit risk evaluation is presently getting more and more attention considering one of the biggest financial crises ever documented in the recorded history of the world. Both society and the economy depend on accurate financial credit risk assessment and company failure prediction. This is the reason why in recent years, a growing number of approaches and algorithms have been suggested. From this point on, it is vitally important to understand the modern techniques used to evaluate financial credit risk. With an emphasis on the current developments as the encouraging trend in this field. Chen et al, (2016) summarised conventional statistical models and cutting-edge intelligent approaches for financial crisis predicting in this study.

In peer-to-peer lending, where issues with class imbalance are common, credit risk prediction is a useful technique for determining if a prospective borrower would repay a loan (Namvar et al, 2018; Ramesh et al., 2018; Shahmir and Muhammad 2020). Few credit risk prediction methods for social lending account for the fact that the best resampling method to use with unbalanced data is still up for debate. This work offered an empirical comparison of several combinations of classifiers and resampling methods inside an original risk assessment methodology that considers imbalanced data in order to tackle these issues. The credit estimates from each combination are assessed with a G-mean measure to remove bias against the majority class, which has not been considered in analogous research. The outcomes suggest that an approach for assessing the credit risk of loan applications in social lending marketplaces may be a combination of random forest and random under-sampling.

Because of the credit industry's rapid growth and increased competition, predicting corporate credit risk is becoming more significant for organisations that extend credit. In a study a study by Wang & Ma (2011), a combined ensemble method for predicting corporate credit risk dubbed RS-Boosting, which is based on two well-known ensemble techniques, boosting and random subspace was presented. According to experimental findings, RS-Boosting outperforms the other six methods—logistic regression analysis (LRA), decision tree (DT), ANN, bagging, boosting, and random subspace.

In the study by Angelini et al, (2008), the use of neural networks is to credit risk assessment presented by applying two, one with a conventional feedforward network and the other with a particular structure. The programmes were evaluated using actual data from Italian small enterprises. They suggested that with proper data analysis, data pre-processing, and training, neural networks may be quite effective at learning and predicting the in bonis /default inclination of a borrower.

Sousa et al, (2016) suggest a brand-new dynamic modelling approach for assessing credit risk that goes beyond the current credit scoring models relying on static settings based on historical data. The central concept imitates the structure of films by building the model out of a series of photographs rather than a single image. As a result, the dynamic modelling process involves incremental learning from fresh incoming data. The understanding that various amounts of memory can be studied simultaneously makes a significant contribution. The quantity of historical data needed for estimating is referred to as memory. This is crucial in the credit risk sector, which frequently experiences shocks. Limiting memory during a shock is crucial. Sometimes having a bigger memory makes sense. The application of our approach to a credit card dataset from a Brazilian financial institution provides an example of how it can regularly outperform the static modelling schema.

3. Research Methodology

This research will be conducted using an empirical investigation to understand the use of artificial intelligence instruments for forecasting credit risk in the digital age. The research process will involve three main steps, including data collection, data analysis, and results interpretation.

Data Collection: The data is collected from primary and secondary sources. The primary sources of data involve surveys and interviews conducted with experts in the field of artificial intelligence and credit risk analysis, as well as interviews with financial institutions that are already utilizing artificial intelligence instruments for credit risk analysis. In total, 140 professionals in the financial services industry received the survey. The secondary sources of data will include published reports, studies, and literature on the use of AI instruments for credit risk analysis and forecasting.

Data Analysis. Both qualitative and quantitative methodologies were used to analyse the data. Using content analysis, which entails classifying the data into themes for additional research, the qualitative data was examined. The quantitative data were analyzed using descriptive and inferential statistics.

This research was managed using a mixed-methods that combines quantitative and qualitative approaches. On the quantitative side, a survey of financial institutions operating in the digital age was conducted to assess their adoption of AI instruments for forecasting credit risk. This survey included questions regarding the type of AI instrument used, their perceived effectiveness, and other relevant factors. A summary of the distribution of financial categories across different designations is given in Table 1

Table 1: Distribution of financial categories across different designations.

Designation	Micro	Small	Medium	Large
Business owner	30%	45%	20%	5%
Manager	15%	30%	40%	15%
Executive	10%	20%	50%	20%

On the qualitative side, interviews with financial professionals were handled to gain an in-depth knowledge of the reasons behind the adoption of AI instruments. This will include questions about the challenges that financial institutions face in terms of forecasting credit risk, the benefits, and disadvantages of using AI instruments, and the potential areas of improvement.

4. Result

The survey consisted of 10 close-ended questions regarding the usage of artificial intelligence instruments in predicting credit risk. The results are based on unique responses from professionals working with credit risk management in the financial services industry.

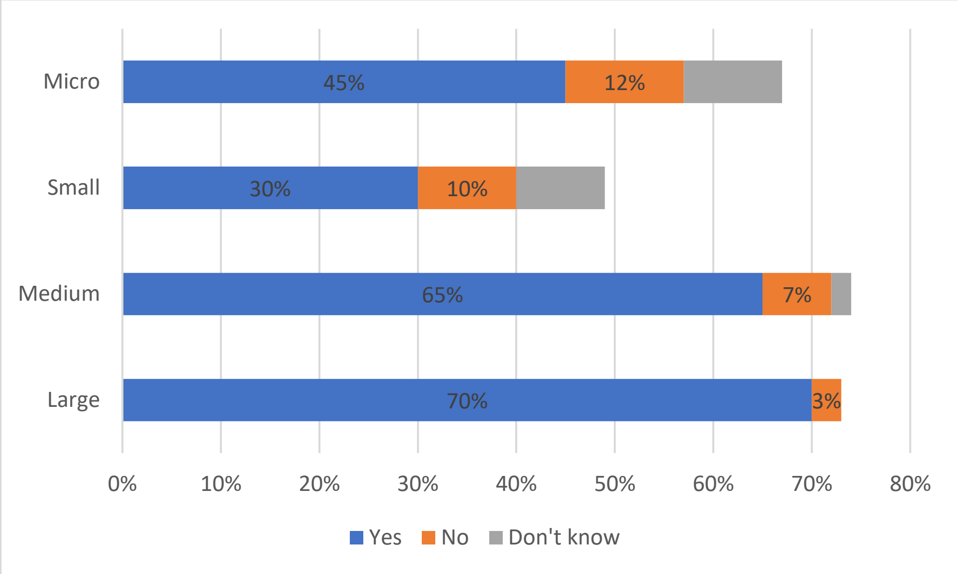

Fig.4.1. Responses to the question 'Is credit risk forecasting possible using AI instruments?'

The above chart in Fig.4.1 shows the percentage of credit risk forecasting that can be achieved using AI instruments, based on the size of the organization. For large organizations, 70% of credit risk forecasting can be achieved using AI instruments, while for medium organizations, 65% of credit risk forecasting can be achieved. For small and micro-organizations, 30% and 45% of credit risk forecasting can be achieved, respectively. Additionally, for all sizes of organizations, there is a small percentage of uncertainty regarding the accuracy of credit risk forecasting.

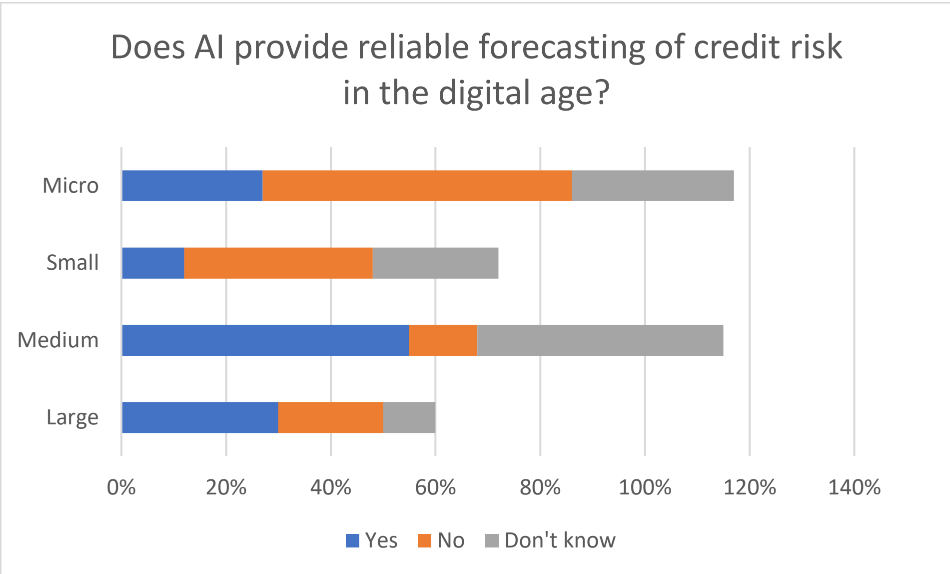

Fig.4.2. Responses to the question 'Does AI provide reliable forecasting of credit risk in the digital age?'

The survey in Fig.4.2 results indicate that most people agree that AI can provide reliable forecasting of credit risk in the digital age. However, there is still some skepticism among people, with 30% of large organizations, 55% of medium-sized organizations, 12% of small organizations, and 27% of micro-organizations saying that AI does provide reliable forecasting of credit risk. On the other hand, 20% of large organizations, 13% of medium-sized organizations, 36% of small organizations, and 59% of micro-organizations say that AI does not provide reliable forecasting of credit risk. Finally, 10% of large organizations, 47% of medium-sized organizations, 24% of small organizations, and

31% of micro-organizations answered that they do not know if AI provides reliable forecasting of credit risk.

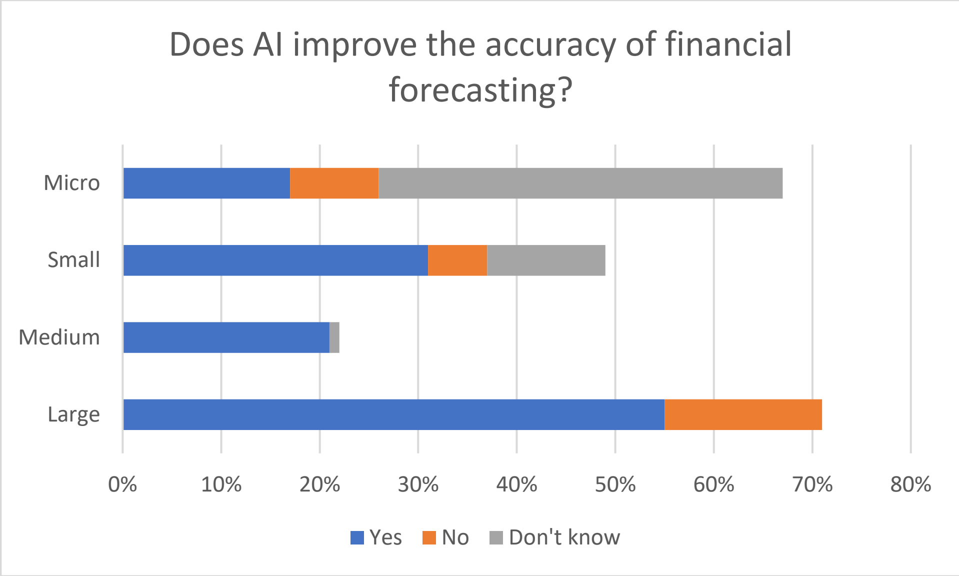

Fig.4.3. Responses to the question 'Does AI improve the accuracy of financial forecasting?'

The data in Fig 4.3 shows that of those surveyed, the majority of those who responded with a large company (55%) said yes, AI does improve the accuracy of financial forecasting. 21% of those surveyed from medium-sized companies and 31% of those from small companies also said yes. The majority of those from micro-sized companies (41%) said they did not know if AI improves the accuracy of financial forecasting, while 17% said yes and 9% said no.

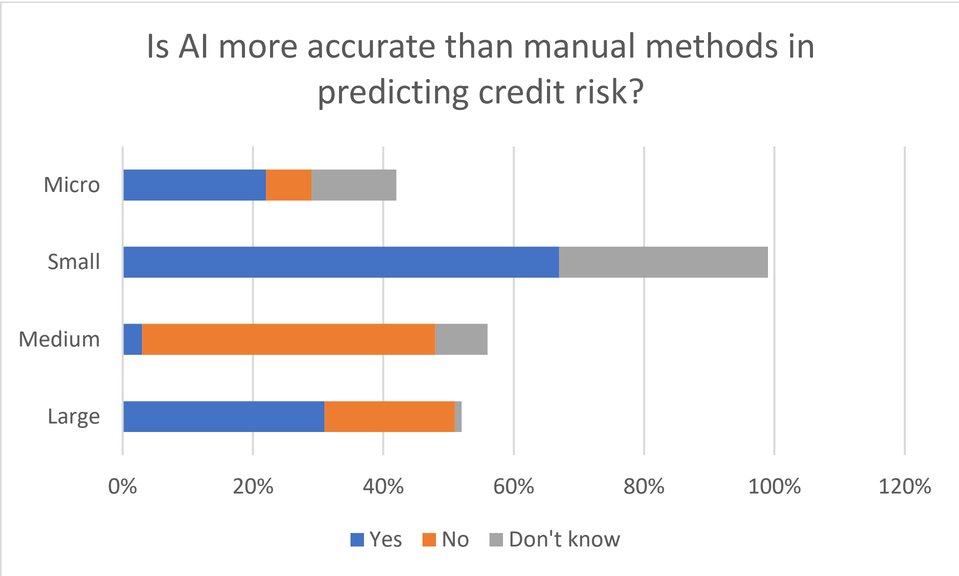

Fig.4.4. Responses to the question 'Is AI more accurate than manual methods in predicting credit risk?'

The results of a survey in Fig. 4.4 suggest that most respondents believe that Artificial Intelligence (AI) is more accurate than manual methods in predicting credit risk. Large respondents had the most confidence in AI with 31% indicating that they believe AI is more accurate and only 20% indicating that they do not. Medium respondents were more divided with 45% indicating that AI is more accurate and only 8% indicating that they do not. Small respondents were the most confident in AI with 67% indicating that they believe AI is more accurate compared to only 32% who do not. Micro respondents were also slightly more confident in AI with 22% indicating that they believe AI is more accurate compared to only 7% who do not. Overall, most respondents believe AI is more accurate than manual methods in predicting credit risk.

5. Discussion

In conclusion, Artificial Intelligence (AI) has many applications in the financial industry, including credit risk forecasting. The ability to predict and mitigate prospective credit losses is made possible by credit risk forecasting, which is a crucial duty for financial organisations. AI can be used to generate forecasts of credit risk with greater accuracy than traditional methods, as well as to identify patterns and trends that may otherwise be difficult to detect. AI can be used to automate the process of credit risk analysis, reducing the amount of manual labour involved and improving accuracy. Additionally, AI can be used to monitor and analyse customer data in order to identify possible issues and risks before they become serious.

Additionally, AI can be used to create prediction systems that can be utilised to find high-risk clients and offer specialised services. Overall, AI has the potential to revolutionize the way credit risk is managed and forecasted. AI can provide a more accurate and efficient way of forecasting credit risk, while also providing a more comprehensive view of customer data. With the right investments in technology and resources, AI can become a powerful tool for financial institutions that can help them better manage their credit risk.

AI-enabled instruments are being used more and more by financial institutions to improve their customer service, reduce costs, and improve risk management. They are also being used to enhance the accuracy of credit scoring models, which can have a direct impact on the cost of credit, the likelihood of loan defaults, and the overall customer experience. Overall, the use of AI-enabled instruments for credit risk forecasting in the digital age has tremendous potential. Their ability to quickly and accurately process large amounts of data, identify customer behaviour patterns, and improve decision-making have enabled them to revolutionize the way we approach credit risk forecasting. With the continued development of AI-based instruments, it is likely that they will become even more popular in the digital age, and continue to improve the accuracy of credit risk forecasting.

6. Conclusion

In conclusion, Artificial Intelligence (AI) has revolutionized the way we approach credit risk forecasting in the digital age. AI-enabled instruments such as ML algorithms, Natural Language Processing (NLP), and Predictive Analytics (PA) are just a few of the powerful tools that have been developed to accurately predict credit risk in the digital age. AI-based instruments can quickly process large amounts of data from multiple sources and accurately identify potential credit risk. Furthermore, these instruments can also be used to identify customer behaviour patterns and inform more accurate decision-making.

7. Challenges

One of the major challenges in the application of artificial intelligence for forecasting credit risk in the digital age is the lack of sufficient data. The data available usually consists of information from past transactions, which is insufficient to determine the credit risk of a future potential borrower. Another challenge is the precision and reliability of the results. AI models are only as good as the data used to train them, and this data is often incomplete or out-of-date. Finally, there is a risk of the models having bias due to the nature of the data and the algorithm used to generate the predictions. As such, it is important to ensure that the models are tested thoroughly before they are used in any production environment.

8. Limitations

The use of AI in forecasting credit risk in the digital age has several limitations. Firstly, AI models require large amounts of data to be trained and this data can be difficult to obtain, especially for smaller businesses. Moreover, AI models may not be able to capture all relevant variables, such as human emotions and complex financial patterns, leading to inaccurate predictions. Additionally, AI models can be vulnerable to manipulation and errors due to mislabelled data. Finally, AI models could not be able to adapt to shifting market conditions or correctly identify future credit risks.

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