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Integrating Financial and Textual Indicators for Enhanced Financial Risk Prediction: A Deep Learning Approach

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ABSTRACT

The study evaluates the effectiveness of financial indicators in financial risk prediction and develops a framework using financial and textual data. It emphasises the importance of both data types in risk assessment and prioritises liquidity and industry specific metrics. The analysis of the existing literature affirmed the significance of both data types in risk assessment. The findings of the study revealed a strong correlation between financial and textual indicators. The selection of deep learning was based on its adeptness in handling diverse unstructured data, justifying its application. This innovative methodology enhances financial risk prediction and supports strategic decision-making.

INTRODUCTION

Predicting financial risk is a crucial problem in finance since it enables companies, investors, and governments to make wise choices and avert possible financial disasters. According to the study by Mashrur *et al.* (2022), the process of accurately predicting financial risk is complex. It depends on a number of variables, including textual data and conventional financial indicators (Mashrur *et al.*, 2020). Al-Eitan *et al.* (2019) have highlighted that financial analysts have traditionally based their assessments of a company's financial health and risk on traditional financial indicators, including liquidity ratios, leverage ratios, and return on assets (ROA). However, Fridson & Alvarez, (2022), has noted that financial indicators sometimes give inconsistent signals in real-world situations, making risk prediction a challenging endeavor (Al-Eitan & Bani-Khalid, 2019). Another issue highlighted by Arnold *et al.* (2022), that threatens the stability of prediction models is the multicollinearity of financial indicators and worries about missing data. Indicators for cross-border risk assessment are gradually being standardized through the adoption of international accounting standards like IFRS (Arnold *et al.*, 2022; Phan *et al.*, 2018).

Textual information, such as sentiment analysis and language from financial news articles, is increasingly important for predicting financial risk (Bawa, 2023). Textual data changes in regulatory stance and management tenor might be crucial in anticipating financial risk (Feyen, 2023). However, Humphreys & Wang, (2018), has stressed that issues like bias in sentiment analysis and mistakes in reporting must be resolved. Additionally, there is still little research on how textual indicators interact with certain financial metrics like ROA or solvency ratios (Feyen *et al.*, 2023; Humphreys & Wang, 2018; Karas & Režňáková, 2020). Malekloo *et al.* (2022), has stated that these components' intricate interrelationships call for in-depth examination. The study further highlights that with the introduction of big data and advancements in artificial intelligence, the existing financial environment is changing quickly (Malekloo *et al.*, 2022). Therefore, it is crucial to investigate cutting-edge methods for estimating financial risk that may make use of both financial and textual data (Xing *et al.*, 2018).

According to Mai *et al.* (2019), comparing the effects of both types of indicators on predicted financial performance, can close the gap between established textual data analysis and traditional financial analysis. Furthermore, it also stresses that the goal is to construct more reliable risk prediction models by using the synergy between these components as well as their separate contributions (Mai *et al.*, 2019). The study Neale, B. (2021). The craft of qualitative longitudinal research: the craft of researching lives through time. Neale *et al.* (2021), has explored the dynamic nature of financial markets and the demand for cutting-edge instruments to negotiate their complexities serve as the driving forces behind this inquiry. The study has also provided insights at how deep learning can integrate financial and textual indicators, to provide insightful information for enhanced financial risk prediction techniques (Neale, 2021).

Financial Risk Indicators

The process of predicting financial risk is complex and involves a number of different indicators and variables (Henrique *et al.*, 2019). Peng & Huang (2020) state the financial risk prediction procedure includes a number of processes that evaluate the possible risks a firm can encounter on its financial path (Peng & Huang, 2020). It

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is crucial to comprehend how this approach will affect a company's stability and operations (Lee *et al*., 2022). In this process, & Riyanto (2020), emphasizes that liquidity ratios, such as the quick ratio and current ratio, measure a company's short-term solvency while Nukala& Prasada (2021), emphasizes that leverage ratios, such as debt-to-equity ratios, evaluate its long-term financial structure and have significant importance in the financial risk prediction process. The importance of striking a balance between these ratios has also been emphasized by Dianova & Nahumury, (2019), as high leverage can increase the risk of financial distress and low liquidity can make it difficult for a firm to meet immediate obligations. However, there may also be some shortcomings that financial risk experts need to investigate (Dianova & Nahumury, 2019; Maisharoh & Riyanto, 2020; Nukala & Prasada Rao, 2021).

As Stephany et val. (2023) noted, financial indicators can give conflicting signals when assessing risks, hence it is important to carefully examine these signals when predicting financial risk (Stephany *et al*., 2020). Such as Mohamed, (2022), underlined the necessity for a nuanced interpretation and an investigation of deeper underlying concerns if a business displays a high Return on Assets (ROA) despite bearing a significant debt load (Mohamed, 2022). Multicollinearity among financial indicators, which show strong correlations, is one such significant issue. Lasso regression is one of the statistical methods that Urdes *et al*. (2022) devised to deal with multicollinearity and increase the resilience of prediction models. These techniques aid in separating the web of connected indications (Urdes *et al*., 2022). However, regularity in the data is necessary for the implementation of such procedures, which is frequently disrupted by missing values. Winsemius *et al*. (2018), illustrates how assessing financial risk may be hampered by missing or inadequate data. Data imputation and amputation are two techniques that Washburn *et al*. (2018) cover in their discussion of viable approaches to this problem. These techniques simplify dataset reconstruction and enable more thorough risk assessments (Washburne *et al*., 2018; Winsemius *et al*., 2018).

The selection of accounting standards is yet another important issue that needs to be carefully taken into account (Weygandt *et al*., 2018). The decision between international accounting standards like IFRS and nation-specific elements has relevance in the globalized financial landscape for standardizing indicators in cross-border risk assessment. Swanepoel (2018), has looked at how these decisions may affect how reliable and comparable risk assessments are in different international contexts. Zio (2018), has stated that construction of reliable risk models requires a thorough understanding of various financial risk prediction components and how they interact. The study has further explored the collective knowledge of the field and increase our understanding of financial risk prediction by combining ideas from various academic studies (Chen *et al*., 2021; Swanepoel, 2018).

Implication of Textual Indicators in Financial Risk Prediction

Textual indicators, such as managerial tone and tone indexes, are becoming more and more important parts of the process of predicting financial risk (Zhang *et al*., 2022). They have been cited as playing crucial roles in improving risk assessment by several academics. According to. Iqbal & Riaz (2021), the management's tone of a company's communications, including annual reports or press releases, might offer insightful information (Iqbal & Riaz, 2021). Investor confidence and subsequent financial performance can be impacted by positive or negative management attitude (Platonova *et al*., 2018). Additionally, biases in textual data may be inherent and result from biased reporting or inaccurate sentiment analysis. It is important to note that financial experts are aware that manual evaluation of textual data might be more effective at eliminating these biases (Metaxa *et al*., 2021) . This practical method enables a more precise analysis of subtle textual clues. Textual indicators also interact with financial measurements like Return on Assets (ROA) and Return on Equity (ROE), therefore they do not exist in a vacuum (Alduais, 2022). These interactions, as explained by Zio (2018), influence the results of risk assessments and give a comprehensive picture of a company's financial health. The study highlights that professionals may collect nuanced information, improve decision-making, and lessen data biases by including textual indicators into the financial risk prediction process (Zio, 2018). This integration acknowledges the importance of textual data in the modern financial sector while reflecting the changing environment of risk assessment.

LITERATURE REVIEW

Financial risk prediction is a crucial field of research in finance and economics, having important consequences for organizations, investors, and decision-makers (Win *et al*. 2018). Arnold *et al*. (2018), explains that financial risk forecasting heavily relies on historical financial data. Risk assessment is based on historical financial performance, which includes income statements, balance sheets, and cash flow statements (Goh *et al*. 2022). To analyze historical data and spot patterns, time series analysis and statistical models like autoregressive integrated moving average (ARIMA) and GARCH have been used (Alghamdi *et al*. 2019).

Financial risk is significantly influenced by market volatility and macroeconomic variables (Fang *et al*. 2018). Gu *et al*. (2020), credit risk and asset values are influenced by changes in the stock market, changes in interest rates, and macroeconomic indicators like the GDP growth rate. According Morad *et al*. (2019) a crucial component of financial risk assessment is credit risk prediction. In assessing loan defaults, variables including credit ratings, debt ratios, and default probability are crucial.

Support vector machines and neural networks are two examples of machine learning techniques that are increasingly being used in credit risk analysis (Teles *et* *al.* 2021). Chang & Wang (2018), highlights that he use of sentiment analysis and news sentiment data as fresh indicators of financial risk has also grown in popularity. News and social media attitude can influence the state of the market and the value of assets (Masuda *et al.* 2022). In essence, components that can anticipate financial risk include sentiment analysis, credit risk indicators, market and macroeconomic conditions, and historical financial data. By combining these elements with cutting-edge analytical methods, risk assessments can be improved, assisting decision-makers (Terzi *et al.* 2019).

Integrating Financial and Textual Indicators for Financial Risk Prediction

The effects of combining financial and textual data in financial risk prediction are extensive. For a thorough risk assessment, certain businesses need specialised financial criteria (Nyman *et al.* 2021). Risk prediction is greatly influenced by historical financial performance, including debt ratios and earnings stability (Sathyamoorthi, 2022). When projecting financial risk, objective financial health metrics like liquidity and solvency ratios frequently outperform market sentiment, especially during economic downturns (Nazareth & Reddy, 2023). When assessing financial stability, short-term financial measures like liquidity ratios take center stage (Zorn *et al.* 2018). Sector-wide statistics, however, may outperform firm-specific indicators in high-risk circumstances (FLACHENECKER l *et al.*, 2020).

The accuracy and reliability of risk prediction are improved by text indicators, such as sentiment analysis and tone indices (Zhang *et al.*, 2022). According to Mushtaq *et al.* (2022), risk evaluations are influenced by how management tone and language sentiment interact with financial measures like ROA and ROE. The study further highlights that the efficiency of textual indicators is impacted by legislative changes and current affairs. Furthermore, Manual data review can be used to address possible biases in textual data, such as sentiment analysis errors and reporting biases (Díaz *et al.* 2018). With consequences that vary among industries, historical settings, and market dynamics, the combination of financial and textual indicators enhances the forecast of financial risk (Cavalcante *et al.* 2016). Additionally, there is a huge area of study that will improve this integration, increasing the accuracy of risk assessment models.

Analyzing Financial and Textual Indicators Relationship Through Deep Learning Approach

Understanding financial risk has been transformed by the convergence of deep learning, big data, and analysis of financial and textual indicators (FI and TI) (Kim *et al.* 2022). The prediction of risk has now expanded in new directions with the introduction of Deep leaning methods including python and big data technologies (Abkenar *et al.* 2021). According to Zhou *et al.* (2021), Python's machine learning packages make it easier to build deep learning models for integrating FI and TI. Massive datasets, such as real-time financial reports and textual data from news and social media sources, may be collected and stored using big data systems (Hariri *et al.* 2019).

Recurrent neural networks (RNNs) and transformers are examples of deep learning approaches that improve FI-TI synergy by automatically discovering complex correlations (Lienhard *et al.* 2022). For the purpose of capturing complex market emotions and financial health indicators, Taleb *et al.* ((2018). highlights that a process both unstructured textual data and structured financial data is required. The above approach takes into account the dynamic relationships between FI and TI to assist fast risk assessment. Integration of these technologies offers more precise and responsive financial risk models as Python and big data continue to develop (Fu *et al.* 2021).

Literature Gap and Hypothesis Development

The observed gap in the literature and the theoretical groundwork extracted to the literary analysis serve as a strong foundation for the hypotheses developed in this study. The analysis of the literature found a paucity of thorough studies integrating both financial and textual indicators for improved financial risk prediction using deep learning techniques. The work uses well-established financial risk prediction theories and models to close this gap while also recognizing the growing importance of textual indicators. The foundation for the assumptions comes from theoretical frameworks including Altman's Z-score model, Beaver's financial ratios, and contemporary deep learning methods. To fill the current research gap, these hypotheses reflect an original strategy that blends conventional financial analysis by employing the financial and textual indicators through state-of-the-art deep learning techniques. Based on these observations the following hypothesis are formed:

Hypothesis 01: Financial risk prediction factors like financial and textual indicators has significant positive trends over the years.

H2: Financial indicators has significant positive impact on financial risk prediction

H3: Textual indicators has significant positive impact on financial risk prediction

H4: Both Financial and Textual indicators has significant positive correlation and have significant positive impact on financial risk assessment or organizations.

The presented study used a quantitative research methodology to look at the elements that financial risk experts find most useful in predicting financial risk. The cross-sectional approach was used to examine and comprehend interrelationships. The choice of quantitative research depends on its capacity for efficient and objective data collecting and processing. The positivist viewpoint places a strong emphasis on employing unbiased, verifiable data to support the progression of the process. According to Lombardo *et al.* (2019), more generalizable results are associated with bigger sample sizes. Quantitative research thrives when using standardized and methodical data gathering approaches, as Creswell and Hirose (2019) explained.

METHODOLOGY

Research Design

The current study leveraged a deep learning approach implemented using Python through Jupyter Notebook for the analysis of financial and textual data (Tatsat *et al.* 2020). The data collection involved the extraction of financial indicators and textual information from diverse sources, including financial reports, news articles, and publicly available data (Pejić *et al.* 2019). The existing research has then helped in formulating a structured open-ended survey on the integration of different financial and textual indicators in financial risk passement processed as highlighted by Azizi *et al.* (2021). Furthermore, The survey responses were gathered qualified financial risk experts of China. The official qualified financial reliable sources to collect accurate and effective insights (Wu *et al.* 2020). Furthermore, Data preprocessing was a crucial step, encompassing the cleansing and standardization of financial data and natural language processing (NLP) techniques applied to textual data (Aldunate *et al.* 2022). Based on this the NLP facilitated the extraction of meaningful textual indicators, ensuring the integration of unstructured textual information with structured financial data.

Analysis and Modeling

To examine the association between study sections and the mean scores given to particular factors, this study used linear regression analysis. Three crucial columns made up the dataset: "Section," "Variable," and "Mean." 'Section' stood for several sections, 'Variable' stood for research variables, and 'Mean' included the mean scores for each variable inside each section.

Preparation of Data

The dataset was put into a Panda DataFrame called "df_means," and the "Section" variable underwent label encoding to convert its values into numbers appropriate for regression analysis.

Model for Linear Regression

For the linear regression analysis, Scikit-learn's 'LinearRegression' class was used. Section_encoded served as the independent variable, reflecting encoded section values, while 'Mean' served as the dependent variable, including mean scores related to each variable (Galioulline, *et al.* 2023).

Model Fitting

Using the 'fit' procedure, the linear regression model was adjusted to the data. The goal of this fitting procedure was to find the regression line that suited the data the best and minimized the gap between anticipated values and actual mean scores.

RESULTS AND DISCUSSIONS

Results of Regression

The following important factors were shown to assess model performance:

Intercept

Depicting the y-intercept of the regression line.

Coefficient (Slope)

Identifies the slope of the regression line, indicating how the mean scores vary when the units in the encoded section change.

R-squared

A measure of the coefficient of determination that expresses the amount of variance in mean scores that the model is able to account for.

Data Visualization

The findings were shown as a scatter plot, with blue data points representing the actual mean scores, supported by McDermaid *et al.* (2019). The regression line was shown by a red line to show how well it suited the data. In order to accomplish the goals of the study, this linear regression analysis provided insights into the link between study sections and mean scores for particular variables (Grotzinger *et al.* 2019).

Analysis and Conclusions

The results of the deep learning models were analyzed in the study to acquire understanding of how the combination of textual and financial variables improves financial risk prediction. To improve understanding and encourage practical decision-making, qualitative analysis and visualization methods were used (Martins, *et al.* 2022). This method is an innovative approach for predicting financial risk since, as Kang *et al.* highlights that it combines deep learning and NLP to glean insightful information from both organized and unstructured data sources. The results of this ground-breaking study will be presented and discussed in the following parts, with an emphasis on their consequences and potential applications in the field of financial risk assessment (Babich *et al.* 2018).

Participants Information

The frequency analysis demonstrated in Fig. 1 shows that majority of truth financial risk experts participated in the study are familiar with financial risk prediction through deep learning approaches, whereas an equal amount of participants has opted for less familiarity to slightly familiar in the study.

The fig 2 illustrates that majority of the participants had 2-4 years of experience whereas considerable number of participants have 4-5 years of experience, but also a good amount of participants were observed to does not have much familiarity with financial risk prediction integrating the textual and financial indicators.

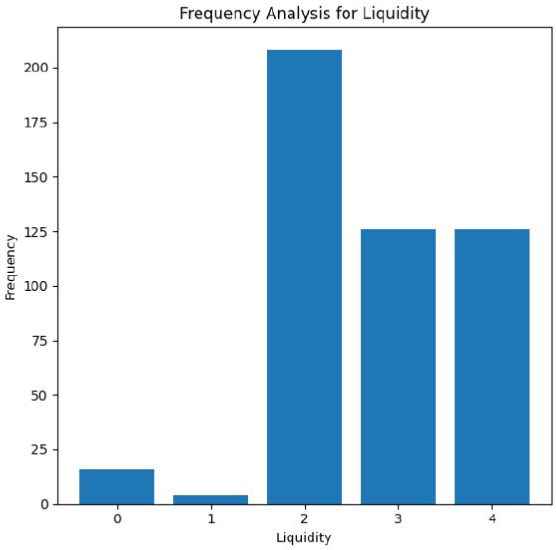

Figure 1: Participants familiarity with financial risk prediction

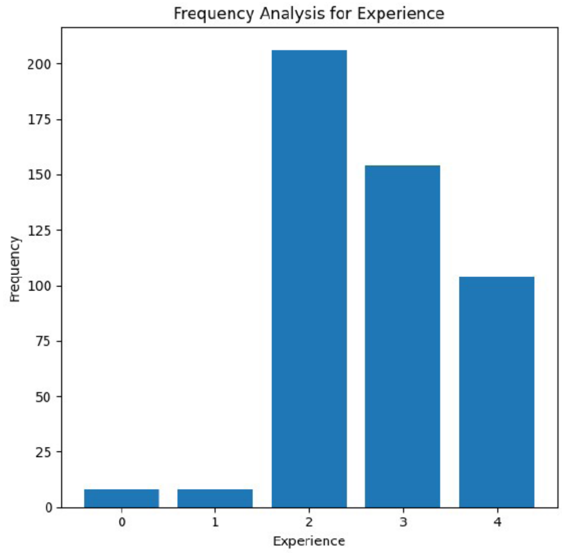

Figure 2: Experience of participants

Section 02: Financial Risk Predictors

The mean values derived from financial risk experts' responses, collected on a 5-point Likert scale, provide insights into their views on identified financial risk prediction factors:

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Mean Preferences of Liquidity: 1.9958333333333333
Mean Financial Indicators and Conflict Signals: 2.029166666666667
Mean Multicollinear Issues: 1.9333333333333333
Mean Missing Data: 1.75
Mean Standardizing Indicators: 1.6666666666666667
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Figure 3: Financial Risk Predictors

Preferences of Liquidity

The observed mean on the preferences of liquidity ratios over leverage ratios as a financial risk predictor is 1.996. It reflects that experts generally agree that liquidity plays a crucial role in financial risk prediction as compared to leverage ratios.

Financial Indicators and Conflict Signals

The observed mean for the creation of conflicting signals such as high ROA but high debt was 2.029. This illustrates that experts tend to agree that managing financial risk effectively involves dealing with conflicting signals from financial indicators.

Multicollinear Issues

The observed mean for on the multicollinear issues in the financial risk prediction can be resolved by stepwise regresses ion and leads model instability as compared to Lasso regression Mean is 1.933. This shows that there is an agreement that multicollinearity among financial indicators can lead to model instability.

Missing Data

The observed mean on the employment on amputation techniques to resolve missing values is: 1.750. It reflects that Experts agree that missing data problems can be resolved using amputation techniques.

Standardizing Indicators

The mean of the collected responses on the preference of IFRS while dealing with financial indicators in international contexts as compared to country-specific factors for standardizing indicators for cross-border risk assessment was observed in the analysis is 1.667. This illustrates that the lowest mean value indicates strong agreement that international accounting standards are more efficient for standardizing indicators in cross-border risk assessment.

Section 03: Integrating Financial Indicators in the Financial Risk Prediction

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Mean Critical for Specific Industries: 1.65
Mean Historical Performance: 1.4833333333333334
Mean Financial Health and Risk Indicators: 1.4458333333333333
Mean Short-term Financial Indicators: 1.425
Mean Historical Sector Wide: 1.6666666666666667
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Figure 4: Financial indicators and Their Implication

Critical for Specific Industries

The observed mean on the preference of financial indicators over textual indicators is 1.65. Experts generally agree that certain financial indicators hold industry-specific significance in financial risk assessment. This underscores the recognition of tailored risk evaluation approaches.

Historical Performance

The observed mean on the influence of historical performance in te financial risk prediction process is 1.48). The mean indicates a strong agreement that historical financial indicator performance influences financial risk predictions. This reflects the experts' belief in the predictive power of past financial data.

Financial Health and Risk Indicators

The observed mean on the preference of financial health indicates for the risk assessment over market and investors perception indicators is 1.45. This reflects that financial risk experts strongly agree that financial health and risk indicators outweigh market and investor perception indicators in financial risk predictions. This highlights the priority placed on fundamental financial metrics.

Short-term Financial Indicators

The observed mean on the preference of short-term financial indicators over long term indicators is 1.43. The mean suggests a consensus that short-term financial indicators, like liquidity ratios, hold higher importance when assessing financial stability compared to long-term indicators.

Historical Sector

The observed mean on the preference of historical sector wide is preferred over firm specific data in high-risk scenario is 1.67. it illustrated that there is strong agreement that, in cases of high-risk indications, historical sector-wide data is preferred over firm-specific data. This emphasizes the importance of broader industry context in risk assessment.

In the context of the study, these means signify a shared belief among experts regarding the significance of industry-specific considerations, historical data, and fundamental financial health metrics in the financial risk prediction process. It underscores the value of these factors in developing comprehensive risk assessment models.

Section 4: Implication of Textual Indicators in Financial Risk Prediction

The mean values for Textual Indicators and Their Implication variables, gathered on a 5-point Likert scale, provide valuable insights:

Textual Indicators Reliability

The observed mean of the reliability of textual indicators in the financial risk prediction process is 1.95. This reflects that experts tend to agree that textual indicators, such as sentiment analysis, are accurate and reliable for financial risk prediction. This suggests their confidence in the utility of textual data in risk assessment.

Management Tone and Tone Indexes

The observed mean on the importance of. textual indicators, such as management tone and tone indexes in financial risk prediction is 1.6. The mean indicates agreement that management tone and tone indexes play a significant role in financial risk prediction, underlining the relevance of management communication in risk assessment.

Regulatory Changes or News Events

The observe mean on the employment of manual review of textual data more efficiently in the financial risk assessment is 1.59. This illustrates that experts generally agree that regulatory changes and news events influence the use of textual indicators in financial risk prediction. This highlights the timeliness of textual data.

Potential Biases

The observe mean on interaction of with specific financial indicators (e.g., ROA, ROE) in shaping risk assessment outcomes is 1.95. This reflects that there is a consensus that potential biases in textual data, like sentiment analysis inaccuracies or reporting biases, can be more efficiently resolved through manual review. This reflects a practical approach to mitigating biases.

Language Sentiment

The observed mean on the language sentiment analysis in the financial risk prediction is 2.05): The highest mean suggests that textual indicators, like management tone and language sentiment, interact significantly with specific financial indicators, impacting risk assessment outcomes.

In the study context, these means underscore the experts' acknowledgment of the reliability of textual indicators, the influence of management tone and external events, and the importance of addressing potential biases. They emphasize the intricate relationship between textual and financial data in enhancing financial risk prediction models.

Section 5: Relationship between Financial Predictors and Indicators (Regression Analysis)

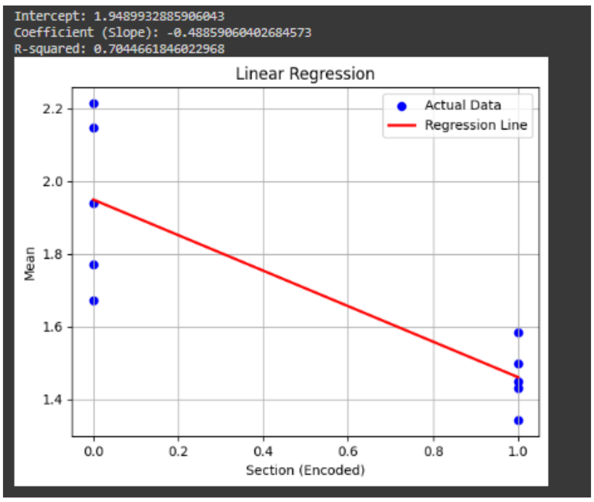

Figure 5: Regression Between Financial Predictors and Indicators

The linear regression analysis between financial prediction factors and financial indicators presented in section 2 & 3 by using their mean values yields the following insights:

Intercept (Intercept)

When the prediction factors reach zero, this represents the estimated mean value of financial indicators, which is (1.949). Within this context, the figure is approximately 1.949.

Coefficient (Slope, Coefficient)

When financial prediction factors vary by one unit, this indicates a significant impact on financial indicators (-0.489). Financial indicators decrease by around 0.489 units for every one-unit boost in financial prediction factors.

R-squared (R-squared)

As indicated by (0.704), the specific proportion of variance in financial indicators that can be attributed to the predicting factors is quite substantial. Around 70.4%, or approximately 0.704, of financial variability can be attributed to the factors examined in the analysis.

The results of the regression analysis indicate a notable connection between financial prediction factors and financial indicators. Increased financial prediction factors lead to a drop in financial indicators, pointing towards an inverse connection. A sizeable portion of the variation in financial indicators is accounted for by the financial prediction factors, as evidenced by the impressive R-squared value, signaling their criticalness.

Section 6: Relationship between Financial Predictors and TextualIndicators (Regression Analysis)

In the linear regression analysis between financial prediction factors and textual indicators presented in section 2 & 4 by computing their means has led to the following results:

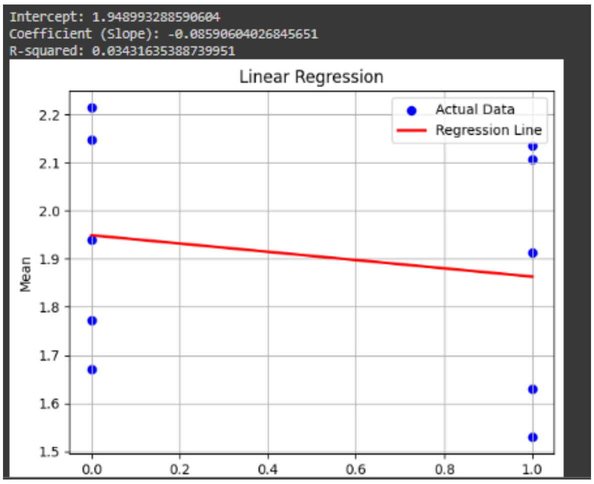

Figure 6: Relationship between Financial Predictors and TextualIndicators

Intercept

About 1.949 is the estimated mean value when predictor factors are zero.

Coefficient (Slope)

With each one-unit increase, there is a corresponding decrease of approximately 0.086 units in textual indicators due to the influence of prediction factors.

R-squared

The predictive power of textual indicators can be attributed to approximately 3.4% of their variability.

A weak bond exists between textual indicators and financial prediction factors, the analysis reveals. A negative coefficient suggests that slight decreases occur when textual indicators are influenced by increased prediction factors. A minor contribution to textual indicators is made by these factors, indicating limited effect on financial risk prediction.

Section 7: Pearson Correlation Matrix

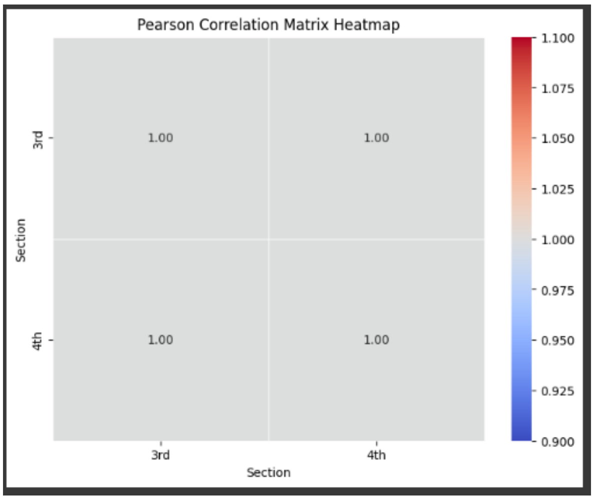

Figure 7: Pearson Correlation Matrix

A complete positive linear link between both variables is shown by the positive correlation coefficient of 1 in all four quartiles of the correlation matrix between textual indicators and financial indicators. This suggests a significant positive correlation between textual and financial characteristics in the context of predicting financial risk, such that when one set of indicators rises, the other set rises in lockstep.

DISCUSSION

Using a deep learning approach, the study sought to examine the fusion of financial and textual indicators in financial risk forecasting. Through analysis, we gained insight into how various factors relate to one another and their potential influence on risk assessment. Constructing the foundation on West *et al.* (2022) work, analyzing the dataset consisting of "Section," "Variable," and "Mean," allowed us to investigate the association between study sections and mean scores through linear regression. By leveraging Scikit-learn's 'LinearRegression' class, 'Section_encoded' represented the independent variable, while 'Mean' played the role of the dependent variable. The study findings suggest that Liquidity is expected to play a critical role in predicting financial risk, as highlighted by Nguyen *et al.* (2022), that it outranks leverage ratios' importance. Additionally, the study also contended that it is vital to handle conflicting signals from financial in dictators when managing financial risk. Supporting findings of the current study have also illustrated that there is consensus among experts that collinearity issues can compromise financial model accuracy which can also be seen in Wang *et al.* (2020) work. The findings have also illustrated that to solve missing data challenges, consensus is required among specialists regarding the use of amputation strategies (Kolossvary *et al.* 2019). Lastly, the IFRS has been observed to travels across borders without receiving preferred risk assessment indicator standard treatment. Highlighting...risk assessment's key elements has been emphasized (Subramanian *et al.* 2022). In risk assessment, specific financial indicators have industry-related importance. The performance of historical financial indicators heavily influences financial risk projections. Financial stability assessments prioritize short-term liquidity ratios which are ahead of market and investor perception indicators. For high-risk situations, historical sector-wide data takes precedence over firm-specific data. Historical data, industry-specific considerations, and financial health metrics are crucial for accurate risk assessment. Experts concur that textual indicator, such as sentiment analysis, are useful for predicting financial risk. Financial risk prediction relies heavily on textual indicators such as tone indexes and management tone. Risk assessment outcomes are influenced by both financial indicators and textual indicators, with their interaction being essential. By shedding light on the reliability of textual indicators, these discoveries underscore the significance of management communication and the need to uncover biases within textual databases. Financial prediction factors and financial indicators exhibit a significant relationship, as shown in a linear regression analysis. Financial prediction factors impact the decrease in financial indicators. In order to make informed decisions regarding investments, a clear understanding of the market is crucial.

When comparing textual indicators and financial prediction factors, a fragile connection emerges (Tang *et al.* 2020). Minor variation in textual indicators occurs alongside enhanced prediction factors, denoting restricted contribution to financial risk prediction (Liang *et al.* 2020). The presence of correlation coefficients of 1 in every quartile of the matrices in the analysis implies a robust connection between textual and financial measures. Bellay *et al.* (2021), stresses that this insight illuminates the synchronization of financial and textual indicators in predicting financial risk. Risk assessment requires careful consideration of liquidity, conflict resolution, historical data, and fundamental financial metrics (Waswa, *et al.* 2018). Furthermore, the findings also stress the need to address biases, as well as the reliability of textual indicators. Correlation between textual and financial markers illustrates their dependence in evaluating risk. Expanding this the study by Lin *et al.* (2018) highlights that by advancing deep learning techniques, future research can further unlock the potential of integrated approaches for more accurate financial risk prediction. By improving predictive abilities, this study creates a pathway towards more educated choices in financial risk analysis (Grover *et al.* 2018).

CONCLUSION

Employing quantitative techniques, this research investigates the fusion of financial and textual indicators for predicting financial risk. Tackling multicollinearity problems and handling liquidity are significant risk prediction findings. Focusing on industry-specific metrics, experts prioritize short-term data when evaluating high-risk sectors, while historical trends hold less weight. According to textual indicators, sentiment analysis is just one of the reliable predictors, with the need to address biases included. While textual indicators exhibit a weaker bond, linear regression reveals a substantial relationship between financial prediction factors and indicators. Enhanced methodologies are achieved through the correlation between their interdependence in risk prediction, resulting in improved decision-making.

RECOMMENDATIONS

Based on the findings of the current study that, financial risk assessment professionals emphasize the significance of liquidity indicators in risk evaluation, address the management of conflicting signals from financial data, adopt strategies for mitigating multicollinearity problems, consider the use of amputation techniques for missing data challenges, and investigate the application of International Financial Reporting Standards (IFRS) for standardizing cross-border reporting. The should also employ past sector-wide data for high-risk scenarios while giving previous financial performance data and short-term financial indicators priority. Continue to place your faith in textual indications like sentiment analysis and managerial tone, but aggressively address any biases through manual inspection and look into deep learning approaches to improve the integration of financial and textual data even more. These initiatives will support more thorough and accurate financial risk assessments, eventually enhancing risk analysis decision-making procedures.

Novelty

The study uses advanced deep learning techniques to integrate financial and textual indicators for financial risk prediction. It uses recurrent neural networks and transformers to analyze the synergy between these sources, improving the precision of financial risk models. The study uses a quantitative and qualitative approach, incorporating real-world insights from financial risk experts in China. The research identifies a research gap in the literature and contributes to the field of financial risk prediction by combining financial and textual indicators.

Contribution to Knowledge

The study enhances financial risk prediction by integrating financial and textual indicators and exploring deep learning techniques like recurrent neural networks and transformers. It provides insights into risk assessment dynamics and bridges the gap between quantitative and qualitative research. The study identifies a research gap in existing literature and offers practical recommendations for financial risk professionals, emphasizing liquidity indicators and considering IFRS for cross-border reporting. It lays the groundwork for future research in deep learning techniques and financial risk prediction.

Research Gap

The study identifies a gap in literature regarding the integration of financial and textual indicators for improved financial risk prediction using deep learning techniques. It emphasizes the need for a holistic approach, focusing on each type of data individually. The study also highlights the lack of deep learning applications in financial risk prediction and the potential benefits of advanced methods. It also calls for more in-depth investigation into the reliability of textual indicators and the integration of quantitative and qualitative research methodologies.

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