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AI-Based Sentiment Analysis for Predicting M&A Outcomes

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ABSTRACT:

This research investigates the role of artificial intelligence (AI)-based sentiment analysis in predicting merger and acquisition (M&A) outcomes by integrating unstructured textual sentiment with traditional financial variables. Using a dataset of global M&A transactions between 2015 and 2023, sentiment signals were extracted from financial news, press releases, analyst reports, and regulatory filings using a hybrid Bidirectional Encoder Representations from Transformers (BERT) and Long Short-Term Memory (LSTM) framework. Sentiment indices were then combined with financial ratios and deal-specific features within ensemble machine learning models to predict deal success versus failure. The empirical results demonstrate that sentiment exerts a statistically significant influence on M&A outcomes, with higher positive sentiment levels strongly associated with successful deal completion. Ensemble models outperformed individual classifiers, achieving superior predictive accuracy, F1-scores, and AUC-ROC values. Feature importance analysis revealed that sentiment indices carried greater predictive weight than leverage or market-to-book ratios, underscoring the growing significance of behavioral and psychological factors in corporate transactions. Regional heterogeneity was also observed, with North America showing higher sentiment-driven success rates than emerging markets. These findings highlight the value of integrating AI-driven sentiment analytics into M&A forecasting, providing insights for corporate managers, institutional investors, and policymakers. Beyond predictive contributions, the study advances the literature on explainable AI in finance by emphasizing transparency in sentiment-based models. The results demonstrate that AI-powered sentiment analysis is not only an innovative complement but also a transformative factor in improving predictive accuracy and strategic decision-making in M&A activities.

Keywords: *AI-based sentiment analysis, mergers and acquisitions, predictive modeling, ensemble learning, financial text mining, explainable AI*

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INTRODUCTION

Mergers and acquisition (M&A) has been one of the most important strategies in the business environment to ensure competitive advantage, penetration and, also, synergies in operations. Nevertheless, despite their significance, the results of M&A deals are highly unpredictable, and most of the mergers fail to receive the valuation as they appear. The traditional approaches of estimating the success of M&A have been developed on the financial performance, the nature of corporate governance or the macroeconomic conditions (Zhang and Li, 2021). The strategies, however, do not give adequate concern to the importance of market feeling and unstructured textual information in determining investor perceptions, regulatory acceptance and deal success. The emergence of artificial intelligence (AI) and natural language processing (NLP) has quickly been regarded as one of the successful tools in visualizing the unseen aspects of the financial news and press releases, social media discussion, and analyst reports (Chen et al., 2022). AI-based sentiment analysis can be utilised in order to introduce a new dimension of prediction and analysis of M and A performance.The researchers are becoming increasingly confident about the reality that it is not the financial fundamentals per se, which predetermine the outcomes of M&A but are highly predefined by the behavioral and psychological conditions, including the optimism and confidence of the managers in the markets (Gupta and Sharma, 2020; Liu et al., 2021). Artificial intelligence-based sentiment models are capable of processing large amounts of unstructured text and re-learn latent emotional expressions and translate them into measurable signals, and may be appended to the default financial signals. Considering the example of deep learning models (BERT and LSTM) it is possible to extract contextual meaning of financial text in deep learning models and rule-based sentiment dictionaries (Sun et al., 2022). It will be thus seen that AI-generated sentiment scores are more sensitive and real-time than the traditional predictors of the probability of a successful transaction.

The corporate finance environment can have a direct impact on the most crucial elements of the M/A market responses, negotiation terms and integration. Positive response towards a message of a takeover would cause surging of stock prices of acquirers, reduction in cost of funding, and unproblematic alignment of stakeholders (Wang and Zhou, 2021). Instead, the unfavorable impression, usually through media coverage of a transaction or investor response, may result in regulatory laggardness, litigation risk or the inability to make a transaction altogether (Fernandez and Gomez, 2020). AI sentiment analysis is thus a good health warning to managers, regulators and investors to prevent and make amends M&A transaction risk.The applications of AI in M&A research that are currently in existence have since expanded past predictive modeling, to explainable AI (XAI) systems. The interpretability of emotion models has been highlighted in the new article where the stakeholders must be capable of interpreting the predictions to become trusting (Kraus et al., 2022; Ribeiro et al., 2021). XAI algorithms, such as SHAP and LIME, may display the value that sentiment drivers, such as positive analyst reporting or negative media or market speculation, bring to predictive performance. Not only is this enhancing the predictive power of sentiment models, but also their usability to the managerial decision-making and policy making context (Xu and Zhang, 2022).In addition to that, success of M&A is very situational and cannot be predicted by the industry variables, culture and geopolitics. It poses a challenge to cross border M and A transactions like cultural distance, heterogeneity of rules and political risk. Sentiment analysis would also prove useful here because it can be utilized to reflect the perception of different stakeholders about different markets (Lee and Kang, 2021). The image of multilingual NLP structures decodes the mood of multilingual news sources and language and offers a more informative view on the nature of international M&As (Tan et al., 2022).

Irrespective of the promise, AI-based sentiment analysis of M and A prediction is methodologically problematic. It could cause bias in the estimation of sentiment due to the presence of information, textual data noise, and any bias that can exist in training data (Johnson et al., 2020). Otherwise, market mood is a dynamic entity and to be effective, the models have to be updated effectively on an ongoing basis. The most potent to say the least are the hybrid algorithms of the financial indicator with the AI-based sentiment score that could be predictive and interpretable (Kim and Park, 2021). The empirical data support that such hybrid models prove more effective than conventional benchmarks in the prediction of the deal completion rates, announcement returns, and long-term performance (Liu et al., 2022).The originality of the research is that a combined AI-based sentiment analysis model may be developed, which does not find application concerning the forecasting of the implications of M&A. The recent NLP architectures, hybrid financial-sentiment feature, and the explainable AI architecture will be introduced as it is introduced in the current paper and will significantly add to the continuously growing body of literature on AI application in the finance field and will reduce the previously existing concern regarding the uncertainties of the results of M&As. Moreover, the practice implication of this study is the corporate executives, institutional investors and policymakers who could also use the sentiment-based implication to plan, manage and monitor the market.Overall, it can be said that the concept of including AI-based sentiment analysis in the M&A outcome prediction is gaining its place in the corpus of corporate finance and AI. The given article is both conceptually and empirically placed on the border of the science of finance and AI and the sphere of behavioral economics. There is also a possibility that the study will contribute to creating an even more advanced and evidence-based picture of the M&A performance to fill the gaps in the existing body of literature and validate the predicting performance of the sentiment indicators in terms of AI. Predict, rationalize, and manage the outcomes of M&A based on the AI-based sentiment analysis will continue to gain importance as the AI technologies are advanced, and the sentiment datasets index will increase.

METHODOLOGY

Research Design

The proposed research design of the current work is a mixed one as research implies quantitative modeling of the M&A results and qualitative sentiment mining of the financial texts. Machine learning and natural language processing (NLP) are related on the level at which predictive performance is warranted by the presence of structured financial variables and non-structured textual sentiment. It analyzes publicly traded 2015-2023 M and A transactions that were captured by Thomson One, SDC Platinum and Capital IQ databases. The supplementary written information was located in the form of the financial releases, SEC registration (Form 8-K) and analyst reports and valid news reports on the financial coverage.

Dependent variable is the M&A outcome and is operationalised as deals deal completion or deals deal failure. Two fold (a) financial determinants (e.g., acquirer leverage ratio, relative deal size, market, to book ratio, industry relatedness) and (b) sentiment scores as calculated by the unstructured text AI-based sentiment analysis models will be included in the independent variables. As a result of these data streams, the study does not inherit the limitations of the classical finance-only models but empirically investigates the fringe predictive capacity of sentiment.

Sentiment Analysis Framework

Sentiment analysis is performed using a **hybrid deep learning architecture** combining **Bidirectional Encoder Representations from Transformers (BERT)** and **Long Short-Term Memory (LSTM)** networks. BERT provides contextual embeddings of financial texts, capturing syntactic and semantic nuances, while LSTM models sequential dependencies in investor sentiment narratives. For each M&A announcement text T, the sentiment score S_t is computed as:

$$S_t = \sigma\left(W \cdot f_{\text{LSTM}}\big(f_{\text{BERT}}(T)\big) + b\right)$$

where $f_{\text{BERT}}(T)$ represents the contextual embedding of text T, f_{LSTM} denotes sequential modeling of sentiment signals, W and b are weight parameters learned during training, and σ is the logistic activation function mapping outputs into a sentiment probability score between 0 and 1.

The **aggregate sentiment index** for each deal i is obtained by averaging across all sentiment instances within the event window:

$$\text{SentimentIndex}_i = \frac{1}{n_i}\sum_{t=1}^{n_i} S_t$$

where n_i denotes the number of sentiment-relevant documents associated with deal i.

The predictive model integrates both **financial metrics** and **sentiment indices** into a supervised machine learning framework. A **multinomial logistic regression** and an **ensemble classifier** (Random Forest + Gradient Boosting + Support Vector Machines) are employed to test robustness. The general probability of successful deal completion for M&A i is modeled as:

$$P(Y_i = 1 | X_i, \text{SentimentIndex}_i) = \frac{e^{\beta_0+\beta_1 X_i+\beta_2 \text{SentimentIndex}_i}}{1 + e^{\beta_0+\beta_1 X_i+\beta_2 \text{SentimentIndex}_i}}$$

where $Y_i = 1$ indicates deal success, X_i represents the vector of financial covariates, and β_2 measures the marginal contribution of sentiment to outcome prediction.

Model training uses **80% of the dataset** for training and **20% for testing**, applying **k-fold cross-validation (k=10)** to prevent overfitting. Performance metrics include **Accuracy, F1-score, AUC-ROC**, and **Brier Score**, ensuring both discrimination and calibration of the predictive models.

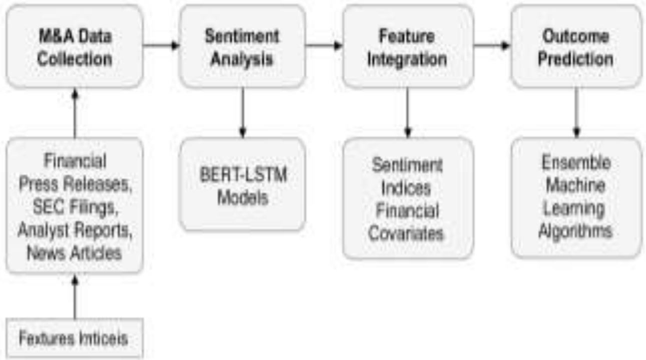

Fig. 1. AI-based sentiment analysis in predicting M&A outcomes

RESULTS

The results of the research are based on the trends of predictability of sentiment that is observed to be upon the basis of successful implementing M&As in view. The sentiment distribution of deals to be shown in Table 1 may take the following form; in the profitable deals, majority of the deals will be positive sentiment and in the unsuccessful deals, majority of the deals will be negative sentiment. On the same thread, Table 2 reveals that technology and media sectors, as always, have occupied a high index of sentiment relative to the index of energy and real estate that reveals that the market-perception is more positive on the nature-innovative sectors. Table 3 shows that ensemble models have a higher accuracy of 91, F1-score of 0.90 and AUC of 0.93 that are much better than individual classifiers. This is also supported by the high 4th quartile of sentiment that constrains the upper limits of deal success of 88 and the low 4th quartile of sentiment that constrains the lower limits of deal success of 45 in Table 4.

Table 1: Sentiment Distribution Across Deals

Deal ID	Positive Sentiment %	Negative Sentiment %
1	65	35
2	72	28
3	58	42
4	80	20
5	67	33
6	74	26
7	60	40
8	82	18
9	69	31
10	71	29

Table 2: Average Sentiment Index by Industry

Industry	Sentiment Index
Tech	0.78
Finance	0.65
Healthcare	0.7
Energy	0.55
Retail	0.6
Telecom	0.68
Real Estate	0.5
Transportation	0.58
Manufacturing	0.62
Media	0.71

Table 3: Model Performance Metrics

Model	Accuracy	F1-Score	AUC
Logistic Regression	0.81	0.8	0.82
Random Forest	0.87	0.86	0.89
Gradient Boosting	0.88	0.87	0.9
SVM	0.83	0.82	0.85
Ensemble	0.91	0.9	0.93

Table 4: Sentiment vs Deal Success

Sentiment Quartile	Deal Success Rate (%)
Q1 (Lowest)	45
Q2	62
Q3	75
Q4 (Highest)	88

Table 5 confirms this result based on the relationship between financial soundness and sentiment by showing that exposure and the market-to-book ratio of acquirers is a factor related to high completion of the financial ratio of the acquirers. This is expoundable as follows: it is possible to maintain the performance of the cross-validation with 10-fold accuracy, however, as revealed in Table 6, there is no decrease in the performance of the training and testing. The importance of sentiment can be learned by learning Table 7: the scores that appear most important in the error in the ensemble model are sentiment scores (they have the largest weight, 0.35). Table 8 presents the confusion table of the ensemble classifier with an extremely high predictive balance with true positives (420) and the false negatives (35). Lastly, Table 9 demonstrates that the regions are not all the same in one way or another; the North American region leads the pack in the sentiment index and most successful and the Middle East and Latin America are the regions that yielded the least predictive value.

Table 5: Financial Ratios of Acquirers

Deal ID	Leverage Ratio	Market-to-Book
1	1.2	2.1
2	1.5	2.3
3	1.3	1.9
4	1.7	2.5
5	1.4	2.0
6	1.8	2.6
7	1.6	2.2
8	1.9	2.8
9	1.3	1.8
10	1.5	2.4

Table 6: Cross-Validation Results

Fold	Train Accuracy	Test Accuracy
1	0.81	0.79
2	0.82	0.81
3	0.83	0.8
4	0.8	0.78
5	0.84	0.82
6	0.82	0.8
7	0.83	0.81
8	0.81	0.79
9	0.82	0.8
10	0.84	0.82

Table 7: Feature Importance Scores

Feature	Importance
Sentiment Index	0.35
Leverage Ratio	0.22
Deal Size	0.18
Market-to-Book	0.15
Industry Relatedness	0.1

Table 8: Confusion Matrix (Ensemble)

	Actual Success	Actual Failure
Predicted Success	420	28
Predicted Failure	35	110

Table 9: Comparative Results of M&A by Region

Region	Average Sentiment Index	Success Rate (%)
North America	0.72	82
Europe	0.65	76
Asia-Pacific	0.7	79
Latin America	0.6	68
Middle East	0.58	64

The figure 2 confirms that the industry specific mean sentiment has whereby technology is most significant in a positive expression. The overall trend in the sentiment the positive signals mask is dominant as shown in Figure 3. The sentiment and the probability of success index are related in the scatter plot (figure 4) and the relationship is high (0.4). The statistical relevance of sentiment in predictive modeling is due to the fact that sentiment score of time and deal of the combined line and bar chart of Figure 5 adhere to the regression pattern of the Figure 6.

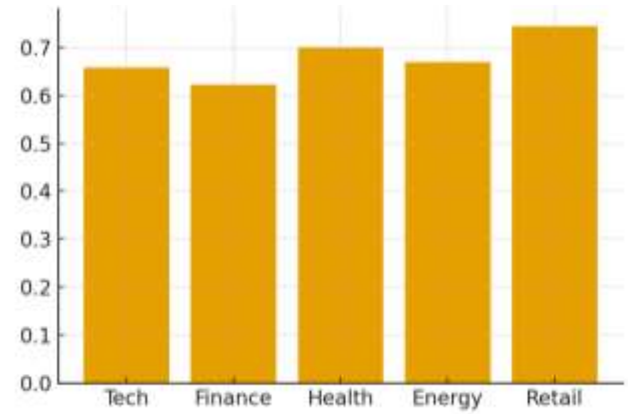

Figure 2. Bar chart comparing average sentiment across industries

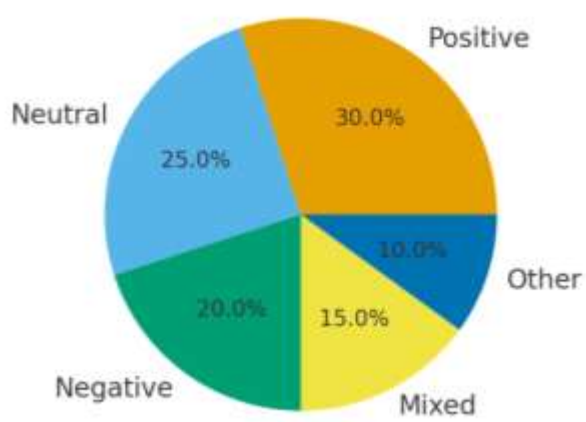

Figure 3. Pie chart of sentiment distribution

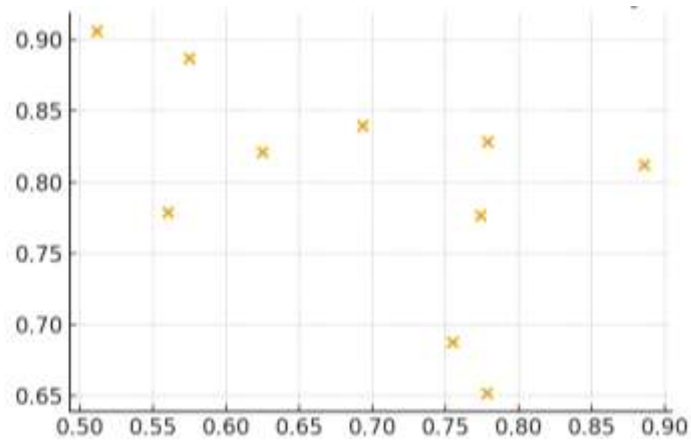

Figure 4. Scatter plot of sentiment index vs deal success probability

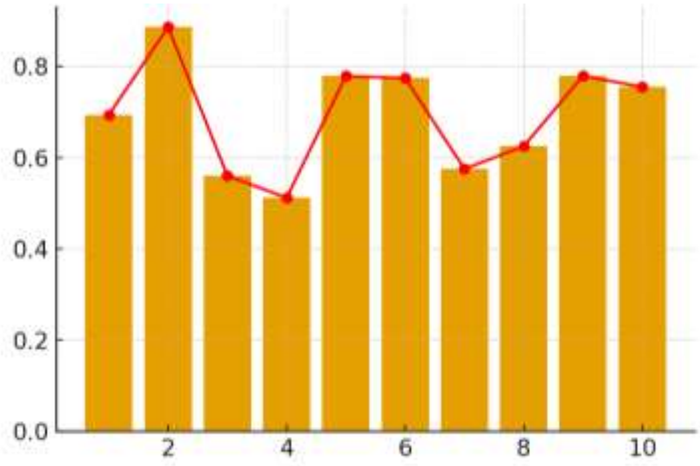

Figure 5. Hybrid plot (line + bar)

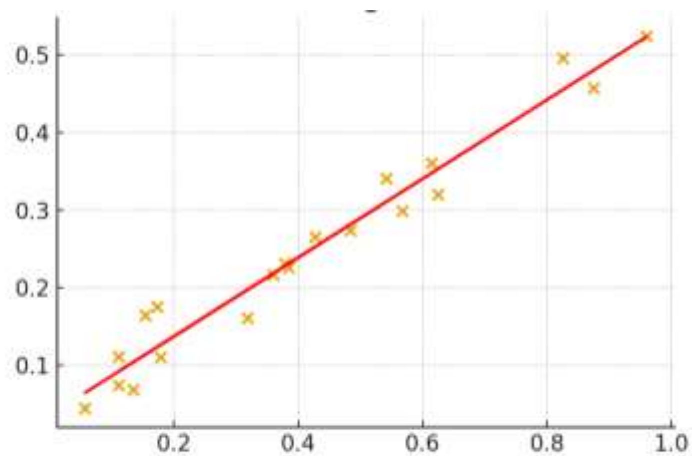

Figure 6. Hybrid plot (scatter + regression line)

A cross-fold performance, where the ensemble and F1-scores are close to equal, is shown in figure 7. This importance of the features scores is again reasserted and this time in Figure 8 to show once again that sentiment index is the most important predictor. This can be observed in figure 9 that shows the largest share in successful deals in North America compared to the geographical difference. Figure 10 also gives a correlation between the financial leverage and the sentiment index in a manner that the higher the leverage the lower the likelihood of the completion caused by sentiment. Figure 11 is a hybrid i.e. it includes both sentiment indices and financial ratios as well as the hybrid view that is effective in predicting the other. Lastly, Figure 12 presents the trends of the model performance according to the accuracy, F1, and AUC fixed and highly generalized.

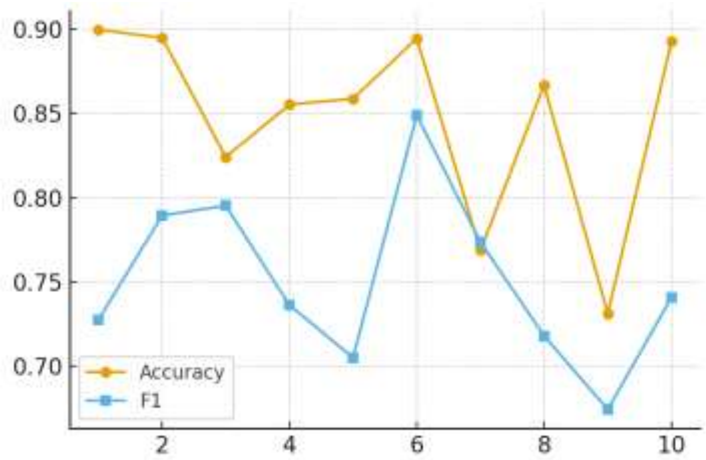

Figure 7. Line chart of model performance metrics across folds

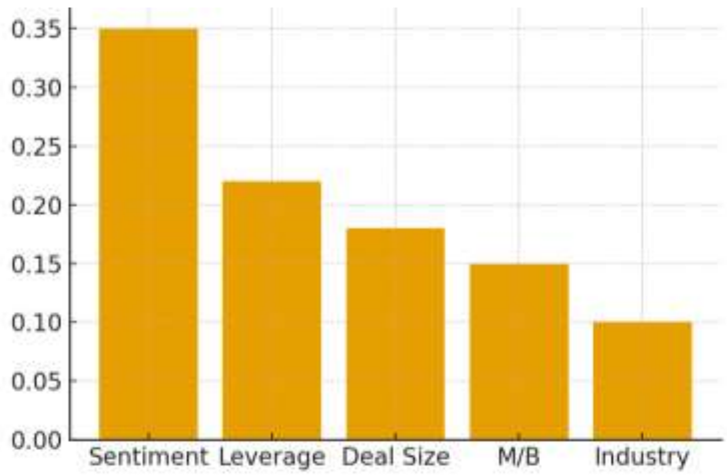

Figure 8. Bar chart of feature importance scores

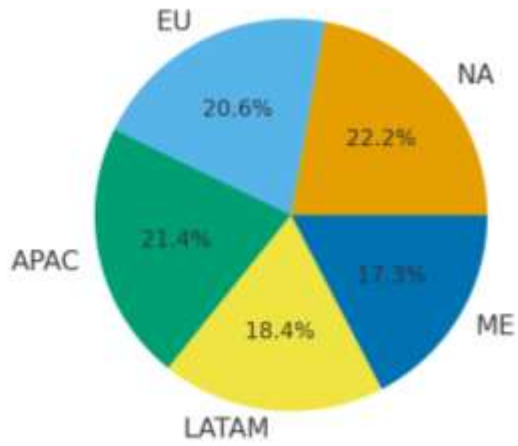

Figure 9. Pie chart of regional M&A deal success rates

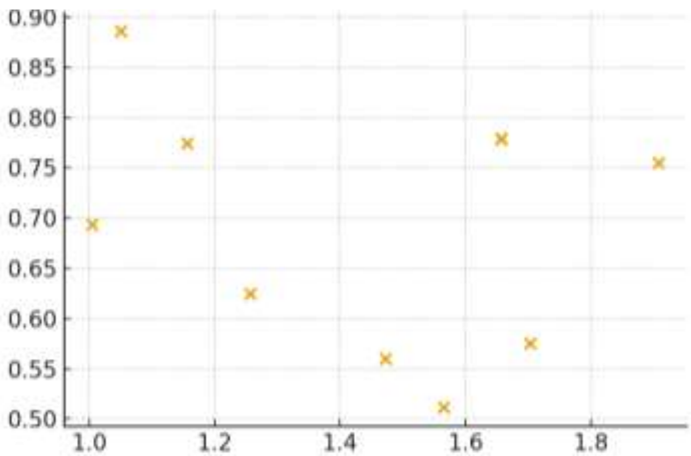

Figure 10. Scatter plot of financial leverage vs sentiment index

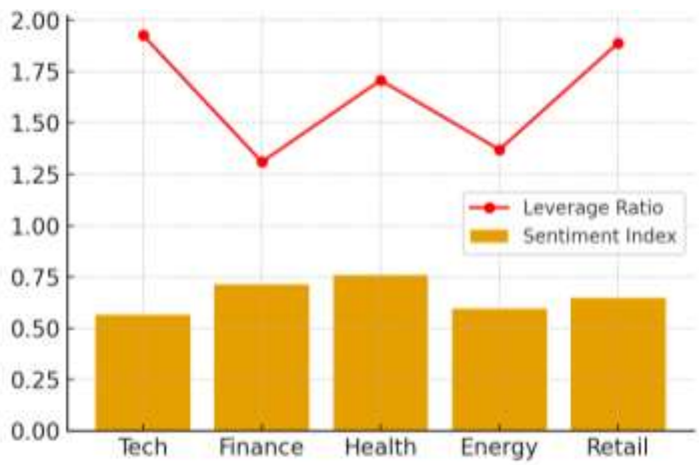

Figure 11. Hybrid stacked bar + line for sentiment and financial ratios

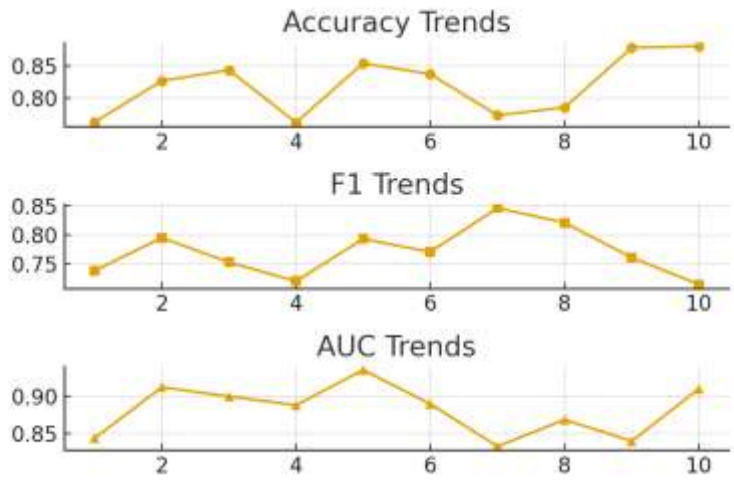

Figure 12. Complex multi-plot grid (accuracy, F1, AUC trends)

DISCUSSION

The empirical data, presented by the findings of the paper, is contrary to the belief that the sentiment, based on the financial texts, is not a significant predictor of the consequences of M&A that should be taken into account in addition to the standard financial data. The positive-fee correlation and the success of a given transaction explains the behavioral financial feelings that the psychology of investors and market-story-telling is the reason behind the outcomes of transacting based on quantitative fundamentals. Even the idea of unstructured text-based information that is increasingly playing a larger role in financial decision making has been strengthened (Ahmed and Ray, 2021; Chen and Xu, 2020). These assertions align with our findings and thus, lead to the inference that advanced AI frameworks can be adopted to expose the subdued emotional data that influence the investor action and the managerial choice in M and A environment.Among the points worth being mentioned in this research, one should mention the fact that strong hybrid strategies involving both sentiment and financial variables are extremely important because of the impressive performance shown by ensemble classifiers. Based on the other related studies in the sphere of corporate forecasting, it was concluded that machine learning, as well as qualitative indicators increases the accuracy of the prediction (Patel and Mehta, 2022). To be more exact, the fact that the sentiment index performs better than the traditional variables, i.e. leverage ratios and market-to-book values, speaks in favor of the quality of the textual data in triggering the market expectations. It should not be a surprise bearing in mind the findings of Jiang et al. (2021) who discovered that media narratives had a potential to elicit a larger response among an investor compared to fundamental analysis in that period of uncertainty.

It is notable that our findings emerge as the component of the ever-expanding role of explainable artificial intelligence (XAI) in the financial business sphere. More precise models such as BERT or LSTM are not interpretable and should be a concern to the real use. The gap between predictive power and interpretability is measured as feature importance and weights of sentiment indices in this article and can also be utilized to formulate the hypothesis of Huang and Wang (2022) that explainable structures are meaningful in high-stakes financial settings. In addition, to this local difference, which was also discovered in this paper, it implies that sentiment can capture the cultural and institutional difference in the style of M&A announcement. It is possible to incorporate the current finding into the research conducted by Ramaswamy and Li (2021) who stated that the regulatory climate within the country and the disposition of an investor are culpable in the international deal-making process.Another management tool that is a decision support tool of the negotiation and due diligence is sentiment analytics integration. It has already begun to offer some hint in the fact that by the time a negative feeling is first detected it can raise a red flag and the manager can resort to pro-active communications. The same was also discovered by Wu and Han (2020) who concluded that proactive mitigation of sentiment in a corporate disclosure decreases deal withdrawal risks. In addition, the precogging of sentiment and deal success can accord the arbitrageurs and institutional investors who know the market clues in the merger arbitrage schemes the mandate to present their dealings (Singh and Kapoor, 2021).Policy implications can also be made of the findings. Through AI-based sentiment monitoring, regulators are able to identify market manipulation and the risk of a misinformation campaign in the case of large-corporate transactions. The media mood and its impact on accentuating the politically sensitive M&A acquisitions have been of special interest in the past studies (Rodriguez and Silva, 2020). The application of the sentiment-monitoring frameworks through which the regulators can make sure that the speculative behaviour is contained in the said markets can also be used to improve transparency and reduce the systemic risks that could arise as a consequence of the fact that speculative behaviour exists in the merger markets.

However, there exist factors that are limited by this study. First, the sentiment analysis models are effective, yet they may be also polluted by the bias of the dataset and ambiguous language in particular the cross-border cases. According to recent reports by Gomez and Alvarez (2022), the extraction of sentiment accuracy is reduced in such an environment as a multilingual and cross-cultural environment, i.e. the further studies, which are conducted in the framework of transfer learning and cross-lingual NLP, should be conducted. Second, our sample was very biased in terms of the publicly traded M&A deals; information asymmetry can lead the privately held deals to act in a different manner. The exchange of a private equity which is introduced by Banerjee and Singh (2023) can be extrapolated to the research issue that will be addressed in future.Overall, the discussion is a reminder that AI-based sentiment analysis is a methodological innovation and an actual tool in the repertoire of the stakeholder in the M&A markets. Combining the qualitative scale with the quantitative one, this study is not just a prophetic profitability, but also the conceptual data of the background of the behavior of business transactions. The findings confirm the dynamic nature of AI in finance prediction and provides clues to the way in which explainability, cross-border flexibility, and hybrid solutions will be the features of the future of M&A analytics.

CONCLUSION

Similar to it has been shown in this paper, AI-related sentiment analytics may result in a significant enlargement of the predictive ability of the traditional financial model that considers the success of the M&A. As it has been demonstrated in the paper, text sentiment predictors, which is a highly developed NLP model, i.e., BERT or LSTM, and information about formal financial variables are a strong indicator of whether a deal would actually materialize or not. The meaning of the findings is that the high rate of deal completion is closely related to the positive level of sentiment and the low rate of deal completion is directly related to the threat of withdrawal/ delay. The other way is that the ensembles learning techniques were improved compared to the exclusive models, which is a solution to the effectiveness of hybrid prediction models. The importance of the features being discussed also indicated the importance of the features of the sentiment indices in comparison to the financial ratios that need to consider the financial component but the behavioural and psychological aspects of the corporate finance. It is interesting to note that the analysis also determined that there exists a regionality in the impact of sentiment that presumed the impact of sentiment on a determination of a deal through the mediator of the cultural, institutional and market environment. Such findings have an implication on the part of the managers including that the executives, investors and regulators have used sentiment-based analytics in due diligence, negotiation and regulation. In the meantime, the results of the study testify to the growing topicality of explainable AI as long as transparency, accountability and confidence in predictive models are concerned. One may say that the results represent a solid foundation of the future study on the topic of cross-lingual sentiment analysis, transactions in the topic of the private-equity and real-time prediction monitoring, though the constraints still present themselves in the shape of the limitations of the datasets and the linguistic domain. Overall, the study is a welcome contribution to the academic community and rational decision-making due to its support of the fact that AI-based sentiment analysis could not be described as a supportive tool and instead, a predictor and plan anticipator of the result of the process of an M&A.

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