Artificial Intelligence-Based Sentiment Analysis of Indian Union Budget Speeches Using Finbert: Evidence from Selected Indian Information Technology Companies

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ABSTRACT

Government budget speeches play a vital role in communicating fiscal priorities, economic reforms, and policy directions that shape business expectations across industries. In recent years, advances in Artificial Intelligence (AI) and Natural Language Processing (NLP) have created new opportunities to evaluate such policy documents using data-driven approaches rather than relying solely on qualitative interpretation. Although several studies have explored sentiment analysis in financial news and corporate disclosures, limited attention has been given to analysing Indian Union Budget speeches using finance-specific language models and examining their relationship with corporate financial performance. This study investigates the sentiment expressed in six Indian Union Budget speeches covering the financial years 2021–22 to 2026–27 and evaluates whether policy sentiment is associated with the financial performance of selected Indian Information Technology (IT) companies. The study employs FinBERT as the primary sentiment-analysis model, while VADER and TextBlob are used as complementary techniques for comparison. Financial performance is assessed using secondary data on revenue, operating profit, and net profit for five leading Indian IT companies: Infosys, Tata Consultancy Services (TCS), Wipro, HCL Technologies, and Tech Mahindra. Pearson correlation analysis is applied to examine the relationship between sentiment scores and financial indicators. The findings indicate that Union Budget speeches generally exhibit a positive policy sentiment across the study period, with noticeable variations in sentiment intensity between financial years. However, correlation analysis suggests that the relationship between budget sentiment and company-level financial performance is generally weak and statistically insignificant for most financial indicators. These results imply that while fiscal policy communication contributes to the broader economic environment, the long-term financial performance of large Indian IT firms is influenced more strongly by international demand, digital transformation, technological innovation, exchange-rate movements, and firm-specific strategic decisions than by domestic budget sentiment alone. The study contributes to the growing literature on AI-enabled financial analysis by demonstrating the application of FinBERT to government policy documents and by integrating sentiment analysis with financial performance evaluation. The findings also provide useful insights for policymakers, financial analysts, corporate managers, and researchers interested in applying AI-based text analytics to economic policy assessment.

Keywords: Artificial Intelligence, FinBERT, Natural Language Processing, Sentiment Analysis, Indian Union Budget, Financial Performance

INTRODUCTION

The growing availability of digital financial information has transformed the way governments, businesses, and researchers interpret economic events. Advances in Artificial Intelligence (AI), particularly in Natural Language Processing (NLP), now allow large volumes of textual information to be analysed quickly and systematically. Instead of relying solely on qualitative interpretation, researchers can quantify the tone and sentiment of financial documents and examine how such information relates to business outcomes. This development has expanded the use of AI in finance, enabling more objective evaluation of policy announcements, corporate disclosures, earnings reports, and financial news.

Among the various policy documents released by governments, the Indian Union Budget is one of the most influential. Presented annually by the Ministry of Finance, the Union Budget outlines the Government's fiscal priorities, taxation policies, expenditure plans, and economic reforms for the coming financial year. Beyond presenting financial allocations, the Budget also serves as an important communication tool that influences the expectations of investors, businesses, policymakers, and financial markets. The language used in Budget speeches often reflects the government's confidence, priorities, and economic outlook, making these speeches valuable sources for sentiment analysis.

The Information Technology (IT) sector represents one of the most significant contributors to India's economic growth. Indian IT companies generate substantial export earnings, employ millions of professionals, and maintain business operations across global markets. Because of their international exposure, these firms are influenced by multiple factors, including global economic conditions, exchange-rate fluctuations, technological innovation, digital transformation initiatives, and domestic economic policies. Although Union Budget announcements may shape business sentiment, it remains uncertain whether the sentiment expressed in these speeches has a measurable relationship with the long-term financial performance of major IT companies.

Traditional approaches to analysing policy documents have primarily relied on manual interpretation or dictionary-based sentiment analysis. While these methods provide useful insights, they often struggle to capture the contextual meaning of financial language. Recent advances in transformer-based language models have significantly improved sentiment analysis by enabling algorithms to understand the context in which financial terms are used. FinBERT, a finance-specific adaptation of the Bidirectional Encoder Representations from Transformers (BERT) architecture, has demonstrated superior performance in analysing financial text because it has been trained on financial documents rather than general language datasets. This makes FinBERT particularly suitable for evaluating the sentiment of government budget speeches containing economic and financial terminology.

Despite rapid progress in AI-enabled financial text analysis, existing research has largely focused on corporate earnings reports, annual reports, financial news, and social-media content. Comparatively fewer studies have applied finance-specific language models to government fiscal-policy documents. Even fewer have attempted to relate the sentiment extracted from Union Budget speeches to company-level financial indicators over multiple years. As a result, there remains a gap in understanding whether the tone of government policy communication has any meaningful association with the financial performance of major Indian IT companies.

To address this gap, the present study analyses six Union Budget speeches covering the financial years 2021–22 to 2026–27 using FinBERT as the primary sentiment-analysis model. VADER and TextBlob are also employed to provide comparative sentiment estimates. The resulting sentiment scores are then examined alongside revenue, operating profit, and net profit data of Infosys, Tata Consultancy Services, Wipro, HCL Technologies, and Tech Mahindra using Pearson correlation analysis. By integrating AI-driven sentiment analysis with corporate financial evaluation, the study seeks to provide a broader understanding of the relationship between government policy communication and organisational performance.

The findings contribute to the growing body of research at the intersection of Artificial Intelligence, Natural Language Processing, and financial analysis. In addition to extending the application of FinBERT to Indian fiscal-policy documents, the study offers practical insights for financial analysts, corporate decision-makers, policymakers, and researchers interested in evaluating policy communication using modern AI techniques. It also demonstrates how finance-specific language models can support evidence-based analysis of economic policy while highlighting the limitations of relying solely on sentiment indicators to explain corporate financial performance.

LITERATURE REVIEW

Artificial Intelligence and Financial Sentiment Analysis

Artificial Intelligence (AI) has significantly transformed financial research by enabling the efficient analysis of large volumes of structured and unstructured data. The integration of AI with Natural Language Processing

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(NLP) has expanded the ability of researchers to interpret financial reports, policy documents, earnings announcements, market news, and corporate disclosures. Earlier studies demonstrated that textual information contains valuable insights capable of explaining investor behaviour and financial market movements. Tetlock (2007) established that the tone of financial news influences market returns, while Loughran and McDonald (2011) developed a finance-specific sentiment dictionary that improved the interpretation of accounting and financial documents. These studies laid the foundation for applying textual analysis to financial decision-making.

The rapid development of machine learning further enhanced sentiment-analysis techniques. Reviews conducted by Kearney and Liu (2014) and Nassirtoussi et al. (2014) concluded that sentiment extracted from financial text can improve forecasting accuracy and support investment decisions. Gentzkow, Kelly, and Taddy (2019) further demonstrated that text has become an important quantitative data source in economics and finance, enabling researchers to extract meaningful information from large collections of documents using computational methods.

The introduction of transformer-based language models represented a major advancement in financial text analysis. Devlin et al. (2019) introduced Bidirectional Encoder Representations from Transformers (BERT), which substantially improved contextual language understanding compared with earlier machine-learning approaches. Building on this architecture, Araci (2019) developed FinBERT, a finance-specific language model trained using financial corpora. Subsequent studies by Huang, Wang, and Yang (2023), Shen and Zhang (2024), and Karanikola et al. (2023) consistently reported that FinBERT achieves superior performance in analysing financial documents because it captures contextual financial language more effectively than traditional lexicon-based techniques.

Recent research has also demonstrated the growing importance of AI in broader financial applications beyond sentiment classification. Studies by Bahoo et al. (2024), Cao (2022), Wasserbacher and Spindler (2022), and Sharma (2023) reported that Artificial Intelligence contributes significantly to financial forecasting, budgeting, risk assessment, planning, and strategic decision-making. Similarly, Faheem et al. (2024) and Jain and Kulkarni (2023) found that AI-driven predictive models improve forecasting accuracy and organisational planning compared with conventional statistical methods. These findings indicate that AI has become an essential analytical tool within modern financial management.

Generative Artificial Intelligence has further expanded the scope of financial research. Dowling and Lucey (2023) discussed the opportunities and limitations of generative AI for finance research, while Anica-Popa et al. (2024) highlighted its applications in accounting and auditing. Giudici and Raffinetti (2023) and Rane et al. (2023) emphasized that the adoption of AI should be accompanied by transparency, explainability, and responsible implementation to ensure reliable financial decision-making.

Financial sentiment analysis has increasingly been applied to government policy communications and macroeconomic announcements. Baker, Bloom, and Davis (2016) demonstrated that policy uncertainty significantly affects investment decisions and business performance. More recent studies by Gupta and Sharma (2024), Singh et al. (2025), Mishra et al. (2025), and Kumar et al. (2024) examined the influence of policy communication, budget speeches, and monetary-policy announcements on investor expectations and financial markets. Their findings generally indicate that government communication influences market sentiment and short-term investment behaviour, although evidence relating to long-term corporate financial performance remains comparatively limited.

The growing availability of transformer-based AI models has also improved financial sentiment analysis using multiple textual sources. Research by Brown, Crowley, and Elliott (2020), Zhu et al. (2024), and Bollen, Mao, and Zeng (2011) demonstrated that textual information extracted from financial reports, news articles, and social media can improve forecasting performance and explain variations in market behaviour. Collectively, these studies confirm that AI-driven sentiment analysis provides valuable insights for financial forecasting, investment analysis, and policy evaluation.

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Despite these significant advances, relatively few studies have specifically analysed Indian Union Budget speeches using finance-specific transformer models while simultaneously examining their relationship with accounting-based financial performance measures. Most existing research focuses primarily on stock-price reactions or investor sentiment rather than revenue, operating profit, and net profit. Furthermore, limited research has compared FinBERT with complementary sentiment-analysis techniques such as VADER and TextBlob within a single analytical framework. These limitations provide the basis for the present study, which applies AI-based sentiment analysis to Indian Union Budget speeches and evaluates its relationship with the financial performance of selected Indian Information Technology companies.

RESEARCH METHODOLOGY

Research Design

The present study adopted a quantitative research design to examine the relationship between the sentiment expressed in Indian Union Budget speeches and the financial performance of selected Indian Information Technology (IT) companies. A secondary-data approach was employed, integrating Artificial Intelligence (AI)-based sentiment analysis with statistical correlation techniques. The study analysed six Union Budget speeches covering FY 2021–22 to FY 2026–27 and evaluated their relationship with company-level financial indicators.

Data Sources

The study relied entirely on secondary data collected from authentic and publicly available sources. Union Budget speeches were obtained from the official website of the Government of India, Ministry of Finance. Financial information relating to Infosys, Tata Consultancy Services (TCS), Wipro, HCL Technologies, and Tech Mahindra was collected from published annual reports and cross-verified using Screener. Revenue, operating profit, and net profit were selected as indicators of financial performance because they provide a comprehensive measure of organisational growth and profitability.

Sample Selection

Five leading Indian Information Technology companies were selected using purposive sampling based on their market leadership, consistent financial reporting, and significant contribution to the Indian IT sector. These companies collectively represent a substantial share of India's technology industry and provide a suitable basis for evaluating the possible relationship between government policy sentiment and organisational financial performance.

The analysis covered six financial years corresponding to the Union Budgets from FY 2021–22 to FY 2026–27, enabling comparison across multiple budget cycles.

Sentiment Analysis

Sentiment analysis was performed using three complementary Natural Language Processing techniques: **FinBERT, VADER, and TextBlob**. FinBERT served as the primary analytical model because it is specifically trained on financial language and is capable of accurately interpreting contextual financial terminology. VADER and TextBlob were employed to provide additional sentiment evaluation using lexicon-based approaches, allowing comparison of sentiment patterns across different analytical techniques.

Due to the token limitations associated with transformer-based language models, lengthy budget speeches were divided into smaller text segments before analysis. Sentiment scores generated for individual segments were aggregated to obtain an overall sentiment score for each Union Budget speech.

Financial Performance Variables

Financial performance was evaluated using three accounting-based indicators:

- Revenue
- Operating Profit
- Net Profit

These variables were selected because they represent different dimensions of organisational performance, including business growth, operational efficiency, and overall profitability. Financial data were collected for each selected company over the study period to facilitate comparison with the sentiment scores derived from the corresponding Union Budget speeches.

Statistical Analysis

Pearson correlation analysis was employed to examine the relationship between sentiment scores and financial performance variables. The analysis was performed using Python in the Google Colab environment. Correlation coefficients were interpreted to determine the direction and strength of association between budget sentiment and company performance.

Descriptive statistics were also used to summarise sentiment scores and financial indicators before conducting correlation analysis. The combined use of AI-based sentiment analysis and statistical techniques enabled a systematic evaluation of the research objectives.

Research Framework

The analytical framework of the study consisted of four sequential stages:

1. Collection of Union Budget speeches and company financial data.
2. Preprocessing of textual data and sentiment analysis using FinBERT, VADER, and TextBlob.
3. Compilation of revenue, operating profit, and net profit for the selected IT companies.
4. Pearson correlation analysis to examine the relationship between budget sentiment and financial performance.

Chapter Summary

This chapter described the research methodology adopted for the study, including the research design, data sources, sample selection, sentiment-analysis techniques, financial performance variables, and statistical procedures. The methodology integrates Artificial Intelligence-based text analysis with quantitative financial evaluation to examine whether the sentiment expressed in Indian Union Budget speeches is associated with the financial performance of selected Information Technology companies.

RESULTS

Sentiment Analysis of Indian Union Budget Speeches

The six Indian Union Budget speeches covering the financial years 2021–22 to 2026–27 were analysed using FinBERT to determine their overall financial sentiment. FinBERT was selected as the primary sentiment-analysis model because it has been specifically trained on financial text and is capable of understanding contextual financial language more accurately than general-purpose Natural Language Processing models. VADER and TextBlob were additionally used to compare and validate the sentiment results.

Table 1. FinBERT Sentiment Scores of Indian Union Budget Speeches

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Financial Year	FinBERT Score	Overall Sentiment
FY 2021–22	0.0740	Positive
FY 2022–23	0.1993	Positive
FY 2023–24	0.1539	Positive
FY 2024–25	0.0973	Positive
FY 2025–26	0.0984	Positive
FY 2026–27	0.1305	Positive

The analysis indicated that all six budget speeches exhibited an overall positive sentiment. Although the intensity of positivity differed across the financial years, none of the speeches showed an overall negative sentiment. The positive scores primarily reflected the Government's continued emphasis on economic growth, infrastructure development, digital transformation, manufacturing, innovation, employment generation, and long-term fiscal stability. These findings suggest that the policy direction communicated through recent Union Budgets has remained broadly optimistic despite changing domestic and global economic conditions.

Comparative Performance of FinBERT, VADER and TextBlob

To assess the reliability of the sentiment analysis, the results generated by FinBERT were compared with those obtained using VADER and TextBlob. All three techniques identified the budget speeches as generally positive; however, differences were observed in the magnitude of the sentiment scores.

FinBERT consistently demonstrated greater contextual understanding of financial terminology and policy-related language. In comparison, VADER occasionally overestimated positive sentiment because of its rule-based lexicon, while TextBlob provided broader polarity scores without considering domain-specific financial expressions. These observations support the use of FinBERT as the principal analytical model for evaluating government policy documents.

Correlation between Budget Sentiment and Revenue

Pearson correlation analysis was conducted to examine the relationship between FinBERT sentiment scores and the revenue of the selected Information Technology companies. The analysis revealed weak positive as well as weak negative relationships across the companies, with no consistent trend observed throughout the study period.

These results indicate that revenue growth among the selected organisations cannot be explained solely by the sentiment expressed in Union Budget speeches. Since the companies derive a significant share of their revenue from international markets, factors such as global technology spending, overseas client demand, exchange-rate movements, and business expansion strategies appear to exert a much stronger influence on revenue performance.

Correlation between Budget Sentiment and Operating Profit

The relationship between budget sentiment and operating profit was also examined using Pearson correlation analysis. Similar to the revenue analysis, the calculated correlation coefficients were generally weak across all five companies.

Operating profit reflects the efficiency of an organisation's core business operations and is influenced by operational productivity, pricing decisions, employee costs, project execution, and technological investments.

Consequently, the findings suggest that the sentiment expressed in Union Budget speeches has only a limited association with operating profitability.

Correlation between Budget Sentiment and Net Profit

The final stage of the analysis examined the relationship between budget sentiment and net profit. The results showed that the observed correlations remained weak and inconsistent across the selected companies. While a few organisations displayed moderate positive correlations, others exhibited weak negative relationships.

Overall, the analysis indicates that long-term profitability depends primarily on broader financial and strategic factors rather than the sentiment communicated through annual budget speeches.

Pearson Significance Testing

To determine whether the observed relationships were statistically meaningful, Pearson significance tests were performed for each company and financial indicator.

The p-values obtained from the analysis were greater than the conventional significance level of 0.05 for the majority of cases, indicating that the observed correlations were not statistically significant. Although certain companies displayed moderate correlation coefficients, the statistical evidence suggests that these relationships are insufficient to establish a meaningful association between budget sentiment and corporate financial performance.

DISCUSSION

The findings of this study indicate that although all six Indian Union Budget speeches conveyed an overall positive fiscal outlook, the sentiment expressed in these policy documents exhibited only weak relationships with the financial performance of the selected Information Technology companies. This suggests that positive government communication alone is insufficient to explain long-term organisational performance.

One possible explanation is the highly globalised nature of the Indian IT industry. Companies such as Infosys, Tata Consultancy Services (TCS), Wipro, HCL Technologies, and Tech Mahindra derive a substantial proportion of their revenue from international clients. As a result, financial performance is influenced more by global technology spending, overseas business demand, exchange-rate fluctuations, digital transformation projects, and company-specific strategic decisions than by domestic fiscal announcements.

The findings are broadly consistent with previous studies that reported the influence of policy communication on investor expectations and financial markets rather than on long-term organisational performance. Tetlock (2007) demonstrated that textual sentiment influences investor behaviour, while Baker, Bloom, and Davis (2016) highlighted the importance of economic policy uncertainty in shaping investment decisions. Similarly, Singh et al. (2025) observed that the sentiment expressed in budget speeches can affect stock-market behaviour. However, unlike these studies, the present research focuses on accounting-based financial indicators rather than short-term market reactions, which may explain the weaker relationships observed.

The comparative sentiment analysis also reinforces the effectiveness of FinBERT for analysing financial policy documents. Compared with VADER and TextBlob, FinBERT consistently produced more context-aware classifications because it was specifically developed for financial language processing. This observation supports earlier findings reported by Araci (2019), Huang, Wang, and Yang (2023), and Shen and Zhang (2024), who concluded that finance-specific transformer models achieve higher accuracy than conventional sentiment-analysis approaches.

Overall, the study demonstrates that Artificial Intelligence provides a reliable framework for analysing government policy documents and extracting meaningful financial sentiment. However, the results also indicate that organisational financial performance is determined by multiple internal and external factors, and therefore policy sentiment should be interpreted as one component within a much broader business environment rather than as an independent predictor of corporate success.

CONCLUSION

The present study examined whether the sentiment expressed in the Indian Union Budget speeches has any measurable relationship with the financial performance of selected Indian Information Technology companies. Artificial Intelligence-based sentiment analysis was performed using FinBERT, supported by VADER and TextBlob, on six Union Budget speeches covering FY 2021–22 to FY 2026–27. The sentiment scores obtained were then compared with the revenue, operating profit, and net profit of Infosys, Tata Consultancy Services (TCS), Wipro, HCL Technologies, and Tech Mahindra using Pearson correlation analysis.

The findings indicate that all six Union Budget speeches conveyed an overall positive financial sentiment, with varying degrees of optimism across different financial years. FinBERT successfully identified these variations and proved effective in analysing finance-related policy documents. This supports the growing use of domain-specific Natural Language Processing models for analysing financial communication.

However, the statistical analysis revealed that the relationship between Budget sentiment and the financial performance of the selected companies was generally weak and statistically insignificant. Although a few moderate correlations were observed, the corresponding p-values indicated that these relationships could not be considered statistically reliable. The results suggest that while Union Budget speeches may influence economic expectations and investor confidence, they do not independently determine the long-term financial performance of large Indian IT companies.

The findings also highlight that the financial performance of globally operating IT firms is influenced by several other factors, including international demand for technology services, exchange-rate movements, digital-transformation investments, client spending, global economic conditions, and company-specific strategic decisions. Therefore, government policy communication represents only one component within a much broader business environment.

Overall, the study demonstrates that Artificial Intelligence-based sentiment analysis provides a useful framework for evaluating government policy communication and contributes to the growing application of AI in finance, financial planning, and policy evaluation.

Practical Implications

The findings of this study have practical implications for policymakers, investors, corporate managers, and researchers.

For policymakers, the study demonstrates that Artificial Intelligence techniques can be used to evaluate how government policy documents are communicated and perceived. Such analysis may assist in improving the clarity and effectiveness of future policy announcements.

For investors and financial analysts, the results suggest that Budget sentiment should not be used as the sole indicator for investment decisions. Instead, sentiment analysis should complement traditional financial analysis, macroeconomic indicators, and company-specific fundamentals.

For corporate managers, the study indicates that long-term organisational performance depends on strategic and operational capabilities rather than government communication alone. Managers should therefore consider Budget announcements as one of several external environmental factors affecting business decisions.

Finally, the research illustrates the practical usefulness of finance-specific language models such as FinBERT for analysing economic and financial documents, encouraging wider adoption of Artificial Intelligence tools in financial research and business analytics.

LIMITATIONS OF THE STUDY

Like any empirical investigation, the present study has certain limitations.

The analysis was restricted to six Union Budget speeches covering FY 2021–22 to FY 2026–27. A longer study period may provide additional insights into long-term policy trends.

Only five Indian Information Technology companies were included in the sample. Consequently, the findings cannot be directly generalised to other industries or sectors of the Indian economy.

The study focused exclusively on three financial indicators—revenue, operating profit, and net profit. Other performance measures such as earnings per share, return on equity, stock returns, market capitalisation, or shareholder value were not examined.

Although FinBERT, VADER, and TextBlob provide reliable sentiment estimates, no sentiment-analysis model can perfectly capture every aspect of human language, economic context, or policy interpretation.

Finally, the study used correlation analysis, which measures association but does not establish a cause-and-effect relationship between Budget sentiment and financial performance.

Suggestions for Future Research

Future research can extend the present study in several directions.

Researchers may include additional sectors such as banking, manufacturing, pharmaceuticals, energy, and consumer goods to compare the influence of Budget sentiment across industries.

Future studies may also analyse a longer time period covering multiple decades of Union Budget speeches to identify structural changes in fiscal-policy communication.

Advanced statistical techniques, including regression analysis, panel-data models, vector autoregression, and machine-learning forecasting models, may provide deeper insights into the relationship between policy sentiment and financial performance. Future researchers may also compare FinBERT with recently developed Large Language Models (LLMs) and finance-specific generative AI systems to evaluate improvements in financial sentiment analysis. Finally, incorporating market-based indicators such as stock returns, trading volume, volatility, or investor sentiment may provide a broader understanding of the impact of government policy communication on financial markets.

Ethical Statement

This research used only publicly available secondary data obtained from official Government of India publications and audited corporate financial reports. No human participants, confidential organisational information, or personal data were involved. Therefore, formal ethical approval was not required.

Conflict Of Interest

The author declares that there is no conflict of interest regarding the publication of this research.

Data Availability Statement

The datasets used in this study were obtained from publicly available sources, including the official Union Budget documents published by the Ministry of Finance, Government of India, the annual reports of the selected companies, and publicly accessible financial databases. The processed data supporting the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

1. Anica-Popa, I. F., Vrîncianu, M., Anica-Popa, L. E., Cișmașu, I. D., & Tudor, C. G. (2024). Generative AI in accounting and audit. Electronics, 13(13), 2621.
2. Araci, D. (2019). FinBERT: Financial sentiment analysis with pre-trained language models. arXiv preprint arXiv:1908.10063.
3. Bahoo, S., Cucculelli, M., Goga, X., & Mondolo, J. (2024). Artificial intelligence in finance: A comprehensive review through bibliometric and content analysis. SN Business & Economics, 4(2), 23.
4. Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. Quarterly Journal of Economics, 131(4), 1593–1636.
5. Bayakhmetova, A., Rudenko, L., Krylova, L., Suleimenova, B., Niyazbekova, S., & Nurpeisova, A. (2025). Artificial intelligence in financial behavior: Bibliometric ideas and new opportunities. Journal of Risk and Financial Management, 18(3), 159.
6. Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. Journal of Computational Science, 2(1), 1–8.
7. Brown, N. C., Crowley, R. M., & Elliott, W. B. (2020). Textual analysis in accounting and finance: A survey. The Accounting Review.
8. Cao, L. (2022). AI in finance: Challenges, techniques, and opportunities. ACM Computing Surveys.
9. Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT).
10. Dowling, M., & Lucey, B. (2023). ChatGPT for finance research. Finance Research Letters, 56.
11. Faheem, M., et al. (2024). Enhancing financial forecasting accuracy through AI-driven predictive analytics models.
12. Gentzkow, M., Kelly, B., & Taddy, M. (2019). Text as data. Journal of Economic Literature, 57(3), 535–574.
13. Giudici, P., & Raffinetti, E. (2023). SAFE artificial intelligence in finance. Finance Research Letters, 56, 104088.
14. Gupta, R., & Sharma, V. (2024). AI and NLP applications in financial sentiment analysis for economic policy evaluation. Risks, 12(4), 56.
15. Huang, A., Wang, H., & Yang, Y. (2023). FinBERT: A large language model for extracting information from financial text. Contemporary Accounting Research.
16. Jain, V., & Kulkarni, P. A. (2023). Integrating AI techniques for enhanced financial forecasting and budgeting strategies. International Journal of Economics and Management Studies, 10(9), 9–15.
17. Jegadeesh, N., & Wu, D. (2013). Word power: A new approach for content analysis. Journal of Financial Economics.
18. Karanikola, A., et al. (2023). Financial sentiment analysis: Classic methods vs. deep learning models.
19. Kearney, C., & Liu, S. (2014). Textual sentiment in finance: A survey of methods and models. Journal of Behavioral Finance, 15(2), 171–185.
20. Kumar, A., et al. (2024). Words that move markets.
21. Li, F. (2010). The information content of forward-looking statements in corporate filings. Journal of Accounting Research.
22. Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. Journal of Finance, 66(1), 35–65.
23. Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). The M4 competition: Results, findings, conclusion and way forward. International Journal of Forecasting, 34(4), 802–808.
24. Mishra, A., et al. (2025). Impact of Union Budget announcements on the Indian stock market.
25. Nassirtoussi, A. K., Aghabozorgi, S., Wah, T. Y., & Ngo, D. C. L. (2014). Text mining for market prediction: A systematic review. Expert Systems with Applications, 41(16), 7653–7670.

26. Parghi, V. K., & Zala, D. (2025). Determinants of financial performance in Indian financial services companies.
27. Rane, N., et al. (2023). Leading-edge AI-powered financial forecasting.
28. Sharma, S. (2023). Artificial intelligence in financial forecasting: Evidence from literature. AIP Conference Proceedings.
29. Shen, Y., & Zhang, P. (2024). Financial sentiment analysis on news and reports using large language models and FinBERT. arXiv.
30. Singh, A., et al. (2025). What do sentiments of budget speeches mean for stock returns? Economic Modelling.
31. Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. Journal of Finance, 62(3), 1139–1168.
32. Wasserbacher, M., & Spindler, M. (2022). Machine learning for financial forecasting, planning and analysis. Digital Finance.
33. Zhu, E., et al. (2024). BERTopic-driven stock market predictions: Unraveling sentiment insights.