A Multi-Document NLP Framework for Strict Management Communication Index for Quant Investing

[1]Sonali V. Bharad, [2] Sapana S. Barphe, [3] Iram Rafiq Ahmed Jhetam, [4] Dr. Arun R. Babhulgaonkar

[1]Assistant Professor, [2]Assistant Professor, [3]Assistant Professor, [4]Assistant Professor
[1]Information Technology,
[1]Dr. Babasaheb Ambedkar Technological University, Lonere, India

Abstract: Management communication significantly influences investor perceptions, information asymmetry, and market behavior. Traditional sentiment-based approaches applied to corporate disclosures often overestimate positivity and fail to discriminate across firms due to optimistic language biases and limited sensitivity. This study proposes a Strict Management Communication Index (MCI), an advanced NLP-driven scoring model designed to quantify managerial tone, clarity, uncertainty, and sentiment consistency across multiple corporate documents. The framework extracts text from annual reports, earnings call transcripts, and investor presentations using high accuracy PyMuPDF extraction and evaluates sentiment using the domain specific FinBERT model. Key innovations include (i) a Strict Sentiment Score penalizing neutral-heavy communication, (ii) TF-IDF inspired normalization of optimism, risk, and uncertainty, (iii) a readability penalty based on the Gunning Fog Index, and (iv) uncertainty amplification to penalize evasive communication. We evaluate the model on BSE Sensex 30 companies and show that the Strict MCI produces a significantly wider and more realistic distribution compared to conventional sentiment scores. The MCI can act as a forward-looking soft-information factor in equity selection and portfolio optimization.

Index Terms -Natural Language Processing, Sentiment Analysis, Earnings Calls, Quantitative Finance, Management Communication, Portfolio Optimization.

1. INTRODUCTION

An investor takes an investment decision not only on quantitative financial metrics but also on the qualitative information provided by corporate management. Investors are living today in an environment that is flooded with rapid information flow and extreme uncertainty. In this situation, understanding the intentions, confidence, and risk perception of management is very much important to make a wise decision. Forward looking guidance expressed by management also becomes a vital component for an investor. Three major disclosures like earnings call transcripts, annual reports, and investor presentations communicated by a company play a crucial role in conveying these signals. Each of these disclosures serves a unique purpose that the traditional financial statements may not do.

The earnings call transcript is one of the most informative sources of managerial communication. They capture management's real-time narrative regarding quarterly performance of the company. The present condition of the business, its strategic priorities, and future expectations can also be obtained from earnings call. Earnings calls usually consist of a question-and-answer (Q&A) session in which financial analysts ask management questions related to uncertainty, risky, or sensitive issues of the company. The answers provided by the management during such unscripted conversations mostly reveal how confident management is, what possible risks are being held, and transparency in communication. Various linguistic aspects, such as tone, sentiment, hesitations represent management confidence. It has been highlighted by earlier research that language complexity present during earnings call communications reveals short-term stock returns along with long-term company basics. Therefore, systematic analysis of earnings call transcripts becomes crucial for investors. This will help investor to identify early signals of improvement or potential decline in firm performance.

Annual report published at the end of financial year by every company gives a clear and organized overview of a company's activities, risks, corporate governance, and future plans. The Management Discussion and Analysis (MDA) section explains the reasons behind the company's performance, its position in the market, and the challenges it may face in the future. Although annual reports are usually carefully prepared and well edited, they are still useful for checking whether management communication is consistent over different years. Investors often compare the information in annual reports with earnings call discussions to understand whether the company's messages are reliable and consistent. The investor presentation is treated as forward looking communication tool by the investor that shapes his expectations. The companies usually highlight strategic initiatives, financial targets, product launches, and market opportunities available for them in this disclosure. It is designed for clarity and persuasion about the company. The intent is making their sentiment towards business expansions clear to the investor. Since these presentations may contain critical announcements, analyzing their tone can be used to find the direction in which management wants to steer the market perception. These three documents collectively provide a comprehensive view of management's narrative. The real challenge for an investors is how to systematically synthesize the information embedded in these heterogeneous documents. Manual analysis might be time consuming, subjective, and vulnerable to biases. This calls for automation of this process. A standardized and scientific measure that can distill the real essence of managerial communication will be helpful for the investor to analyze the future of the company.

Research Problem and Gap

Despite extensive use of sentiment analysis in financial disclosures, existing approaches suffer from three critical limitations:

1. sentiment inflation due to optimistic managerial language,
2. lack of penalties for uncertainty, vagueness, and neutral-heavy disclosures, and
3. absence of unified multi-document evaluation across annual reports, earnings calls, and investor presentations.

Current sentiment-based indicators therefore fail to reliably discriminate firms based on the quality of managerial communication and often produce compressed, weakly informative scores.

This study addresses the following research question: Can a strict, multidimensional Natural Language Processing (NLP) based communication index provide stronger discriminative power and economically meaningful signals for equity investors compared to conventional sentiment measures?

To cater to this requirement, we have proposed the Strict Management Communication Index (MCI) measure in this research work. This is a comprehensive scoring system that objectively analyzes the tone, clarity, confidence, and uncertainty conveyed by the management in various disclosure documents. By harnessing the power of sophisticated NLP tools, the Strict MCI system mitigates the positivity bias and lack of sensitivity inherent in traditional sentiment analysis tools. The investors can make use of the MCI as a soft information factor and powerful tool for doing analysis of finance data. The high MCI score can be considered as a sign of clear, confident, consistent, and transparent communication style. It shows good governance and sound business outlook of the company. The lower MCI score shows uncertainty, high risk signals, evasive communication, and strategic ambiguity. This measure can greatly help in improving the stock screening processes for portfolio construction and risk management. The Strict MCI model will convert the qualitative managerial stories into strong quantitative signals. This will help the investors to take informed decisions. It will also serve as a useful input for quantitative investing models like factor models, multi-criteria stock selection models. Thus, the MCI is a diagnostic measure of firm communication. The longitudinal analysis of MCI trajectories may reveal early warning signals of managerial under performance, governance deterioration, and strategic inflection points.

2. LITERATURE SURVEY

The relationship between managerial communication and financial market outcomes has been extensively examined in earlier studies. Early research showed that qualitative disclosures are also important along with quantitative financial statements. In a foundational contribution, [1] demonstrated that generic sentiment dictionaries are not sufficient for financial text analysis. They emphasized that negative language in management disclosures contains predictive information which can be used for predicting returns, volatility, and future firm fundamentals. [2] showed that pessimistic language used in news articles can impact market movements, investor sentiment, and trading patterns. Similarly, [3] found that negative news stories can cause downward move in stock prices. This result is also reinforcing the notion that linguistic information contained in unstructured text is significant in financial markets. The authors in paper [4] demonstrated that the Management Discussion and Analysis (MD&A) portion of the annual report affects investor sentiment, forecasts future earnings, and reflects managerial intent. [5] emphasized the significance of readability in management communication by asserting that overly complex disclosures negatively affect investor comprehension. This could also be an indication of managerial deception. The authors in [6] employed readability scores such as the Gunning Fog Index to identify firm opacity, investor ambiguity, and governance problems. The authors in paper [7] introduced the notion of "soft information". They demonstrated that managerial tone, narrative style, and linguistic emphasis in earnings calls could be employed to forecast stock returns and earnings surprises. The paper [8] illustrated that subtle cues in managerial responses during Q&A portions indicate strategic intent and future performance risks. The authors in [9] analyzed acoustic and vocal characteristics and extended this work by illustrating that vocal tension and stress during conference calls could indicate managerial sentiment. Deep learning and transformer based models revo- lutionized the use of NLP in financial domain. FinBERT, introduced in [10], is an open source, pretrained model specifically designed for financial sentiment analysis. It significantly outperformed the traditional generic sentiment models in financial transcripts. The authors in [11] demonstrated the applications of FinBERT in financial sentiment analysis by using it for return prediction, credit risk modeling, and macroeconomic forecasting. Despite these advancements, still there are some limitations persist in existing sentiment based approaches. Corporate documents use aspirational language that inflates sentiment scores. Many models fail to penalize vague and evasive language and also ignores the importance of cross document consistency. Recent literature provides strong empirical support for the use of sentiment extraction and narrative tone modeling in evaluating corporate disclosures. This gives rise strong foundation to the design of the Management Communication Index (MCI). The authors in [12] used digital disclosure quality and sentiment signals to predict a firms default risk. A. Hasan et al. [13] demonstrated that the narrative tone of financial communication is also impacted by internal governance systems. They employed machine learning to analyze the differences in tone among various firms with different governance systems and proved that the tone of management-driven communication patterns holds significant information for investors. J. Li in [14] employed text-mining methods to identify sentiments in support of the general insight that influence investor views. Similarly, in [15], the annual reports of leading indices like BIST100 indicated that narrative features, tone, clarity, and emphasis on disclosure are important in market interpretation. This once again supports the importance of text metric like MCI. The authors in [16] showed that, aside from corporate disclosures, external media stories also influence investor interpretation through the use of ESG disclosures by banks. The authors in [17] showed that companies with complex annual reports are constrained in terms of financing. This means that readability is not only a linguistic feature but also an important economic variable. A. Faccia et al. [18] applied text-based sentiment analysis to identify accounting transparency and financial irregularities. They showed how linguistic features are indicative of deeper organizational quality. This study inspired us to incorporate the strict sentiment and risk sharpness features into the MCI framework. The authors in [19] argued that textual communication is indicative of internal information environments. They introduced the general theme that companies using data analytics frameworks communicate more coherently and transparently. In addition to these studies, recent research on textual risk disclosure shows that linguistic risk indicators are predictive of actual corporate risk practices, especially in the fintech industry. This further supports the addition of uncertainty amplification and risk sharpness metrics to MCI [20]. Lastly, the creation of explain able sentiment analysis models such as FinXABSA illustrates the increasing application of advanced NLP models in financial prediction and investor decision-making [21]. In sum, these recent studies provide strong academic foundation for the assembly of an integrated communication quality metric like MCI. The shortcomings point to the need for a more robust, nuanced, and multi-faceted sentiment analysis. Although a few studies have attempted multi-document analysis, they have mostly used lexicon-based scoring or naive averaging. Most methods are still lacking in terms of clarity penalties, consistency analysis, and uncertainty amplification. The Strict Management Communication Index (MCI) is an improvement on the existing literature in that it is a comprehensive scoring system that combines:

• FinBERT transformer-based sentiment analysis

• TF-IDF inspired normalization of risk, optimism, and uncertainty

• readability penalties based on the Gunning Fog Index

• uncertainty amplification to penalize ambiguous statements

• cross-document analysis of annual reports, earnings calls, and investor presentations.

The Strict MCI index enhances discriminability, reduces positivity bias, and yields a strong "soft information factor" that is amenable to quantitative investment analysis. By integrating state-of-the-art NLP with financial communication theory, this research represents a substantial methodological leap forward in the field of sentiment-driven investment analysis.

3. METHODOLOGY

3.1 Rationale for the Strict MCI Design

Conventional sentiment scores consider positive, neutral, and negative sentiment symmetrically and may average scores over documents, leading to poor discrimination. By contrast, the quality of managerial communication is necessarily asymmetric, as too much of either neutrality, uncertainty, or complexity is a negative signal. The Strict MCI approach models this asymmetry by discouraging dominance by neutral sentiment, magnifying uncertainty, and mandating competition among the classes of sentiment. This approach is based on established theories of managerial signaling and information asymmetry, converting narrative text into a risk-averse quantitative factor rather than a generic sentiment measure. This section describes the end-to-end methodology for constructing the Strict Management Communication Index (MCI). The pipeline comprises: (i) dataset construction, (ii) text extraction and preprocessing, (iii) transformer-based sentiment scoring using FinBERT, (iv) dictionary- and readability-based auxiliary scores, (v) strict normalization and uncertainty amplification, (vi) MCI formulation, and (vii) integration into portfolio construction. Each step is described formally and accompanied by the mathematical expressions used in the implementation.

3.2 Dataset and Document Types

- The dataset consists of three key disclosure documents for each firm managerial communications:
- Annual Report (AR) — Contains Management Discussion & Analysis (MD&A), CEO/Chairman letter etc.
- Earnings Call Transcript (EC) — Prepared remarks and Q&A.
- Investor Presentation (IP) — Slide decks used for results and strategy.

We extracted financial year 2024-25 annual report and other documents of financial quarter (July 2025 to September 2025) for all listed companies in Indian BSE SENSEX index. Each document is processed using high-precision PyMuPDF-based text extraction and subsequently analyzed using FinBERT. All documents are standardized to searchable PDF or UTF-8 text and stored using a company-identified naming convention, e.g., COMPANY ANNUAL.pdf, COMPANY TRANSCRIPT.pdf, COMPANY PPT.pdf.

3.3 Text Extraction and Preprocessing

Text is extracted from PDFs using PyMuPDF (fitz) for robust layout handling. The preprocessing pipeline for each document includes:
1. Removal of headers, footers, page numbers, and boilerplate disclaimers.
2. Unicode normalization, lowercasing, punctuation cleanup, and whitespace collapse.
3. Splitting into sentence-level chunks compatible with the FinBERT tokenizer.
4. Domain-aware stop word handling (retain sentiment-bearing financial terms).

Let D be a document and $\{ s_1, s_2, \dots, s_N \}$ its sentence chunks after preprocessing.

3.4 Transformer-Based Sentiment (FinBERT)

For each sentence s_i, FinBERT returns class probabilities:

$$P_{\{pos\}}^{\{(i)\}}, P_{\{neg\}}^{\{(i)\}}, P_{\{neu\}}^{\{(i)\}} \qquad with \qquad P_{\{pos\}}^{\{(i)\}} + P_{\{neg\}}^{\{(i)\}} + P_{\{neu\}}^{\{(i)\}} = 1$$

Document-level averaged probabilities are:

$$\boldsymbol{S_{\{pos\}}} = \frac{1}{N}\sum_{\{i=1\}}^{N} \boldsymbol{P_{\{pos\}}^{(i)}} \qquad (1)$$

$$\boldsymbol{S_{\{neg\}}} = \frac{1}{N}\sum_{\{i=1\}}^{N} \boldsymbol{P_{\{neg\}}^{(i)}}$$

(2)

$$\boldsymbol{S_{\{neu\}}} = \frac{1}{N}\sum_{\{i=1\}}^{N} \boldsymbol{P_{\{neu\}}^{(i)}} \qquad (3)$$

These provide the baseline sentiment signals that feed into the strict transformation below.

3.5 TF–IDF Inspired Tone Normalization

To reduce optimism bias when a tone class (e.g. positive) dominates the corpus, we introduce a tone weight:

$$w_{\{t\}} = \frac{1}{1+\log(1+\boldsymbol{ft}\ )}, \quad t \in \{\text{pos, neg, neu}\} \qquad (4)$$

where ft is the frequency (or relative count) of sentences classified as tone t in the document (or in the company-level corpus). The refined (weighted) sentiment probabilities become:

$$\widehat{S_t} = \frac{w_{\{t\}} S_{\{t\}}}{\sum_{t \in \{\text{pos,neg,neu}\}} w_{\{t\}} S_{\{t\}}} \qquad (5)$$

Using this normalization enforces competition among tone classes and attenuates dominance effects.

3.6 Dictionary-Based Auxiliary Scores

We compute three dictionary-based proportions from the cleaned text:
OS = optimism words / total words,
US = uncertainty words / total words,
RS = risk words / total words.
These raw proportions are typically small; later we normalize them to obtain relative contributions. Normalized dictionary scores use a competitive normalization:

$$T = OS+US+RS+ \varepsilon, \qquad (6)$$

$$\boldsymbol{OS_N} = \frac{\boldsymbol{OS}}{\boldsymbol{T}} \qquad (7)$$

$$\boldsymbol{US_N} = \frac{\boldsymbol{US}}{\boldsymbol{T}} \qquad (8)$$

$$\boldsymbol{RS_N} = \frac{\boldsymbol{RS}}{\boldsymbol{T}} \qquad (9)$$

with ε > 0 a small constant to avoid division by zero.

3.7 Uncertainty Amplification

To emphasize the adverse effect of uncertainty-laden language, we amplify the normalized uncertainty score:

$$\text{UA} = \lambda \cdot \text{USn}, \lambda > 1 \qquad (10)$$

Typical choice λ = 1.5 (empirically tuned) increased penalization for ambiguous or evasive management language.

3.8 Strict Sentiment Transformation

We define a strict sentiment metric that reduces the influence of neutral-heavy distributions:

$$\text{SSstrict} = (\hat{\boldsymbol{S}}\,\text{pos} - \hat{\boldsymbol{S}}\,\text{neg}) \cdot (1 - \hat{\boldsymbol{S}}\,\text{neg}) \qquad (11)$$

This form ensures that a high neutral mass suppresses the effective sentiment amplitude.

3.9 Strict MCI: Final Formulation

Combining the components and applying weights yields the document-level Strict MCI:

$$MCI_{DOC} = \sigma(\alpha_1 \,\text{SSstrict} + \alpha_2 OS_N - \alpha_3 \text{UA} - \alpha_4 RS_N + \alpha_5 (1 - \text{RP})) \qquad (12)$$

where α_i are non-negative weights summing to 1 (or scaled appropriately) and σ is an affine normalization that maps the raw score to [0,1], for example:

$$\sigma(\text{x}) = \frac{x - \text{x}_{min}}{\text{x}_{max} - \text{x}_{min}} \qquad (13)$$

In our implementation we used initial calibrated coefficients as: α_1 = 0.25, α_2 = 0.20, α_3 = 0.25, α_4 = 0.20, α_5 = 0.10.

3.10 Aggregation to Firm-Level MCI

For a firm i with documents AR, EC, IP we compute the firm-level MCI as the equally-weighted average (weights can be customized):

$$\text{MCI}_i = \frac{1}{3}(\text{MCI}_{AR} + \text{MCI}_{EC} + \text{MCI}_{IP}) \qquad (14)$$

Alternative weightings (e.g., giving more weight to EC) are possible and should be evaluated in robustness checks.

3.11 Integration into Portfolio Construction

The firm-level MCI is integrated into the stock selection and portfolio optimization pipeline in two principal ways:

1. Screening filter: exclude firms with $\text{MCI}_i < \tau$, where τ is a threshold (median or strategy-specific cutoff).
2. Weight adjustment: use MCI as a multiplicative factor to tilt weights in mean– variance optimization.

3.12 Implementation and Parallelization

The pipeline is implemented in Python using PyMuPDF for extraction, HuggingFace Transformers (FinBERT) for sentiment probabilities, and a multi-threaded executor to parallelize per-document computations. All intermediate scores (positive, negative, neutral probabilities; OS, US, RS; GFI; SSstrict; normalized dictionary scores) are persisted for auditability and further analysis. Parameters such as λ (uncertainty amplification), Gmax (readability normalization), and the αi weight vector are tuned on a development set. Robustness checks include alternative normalizations of dictionary scores (e.g. logscaling) and different document weightings in firm aggregation. The methodology yields a theoretically grounded and empirically tunable index that converts managerial narrative into a quantitative factor suitable for incorporation in quantitative investment workflows. The Figure 1 depicts the entire workflow of the MCI calculation for a company.

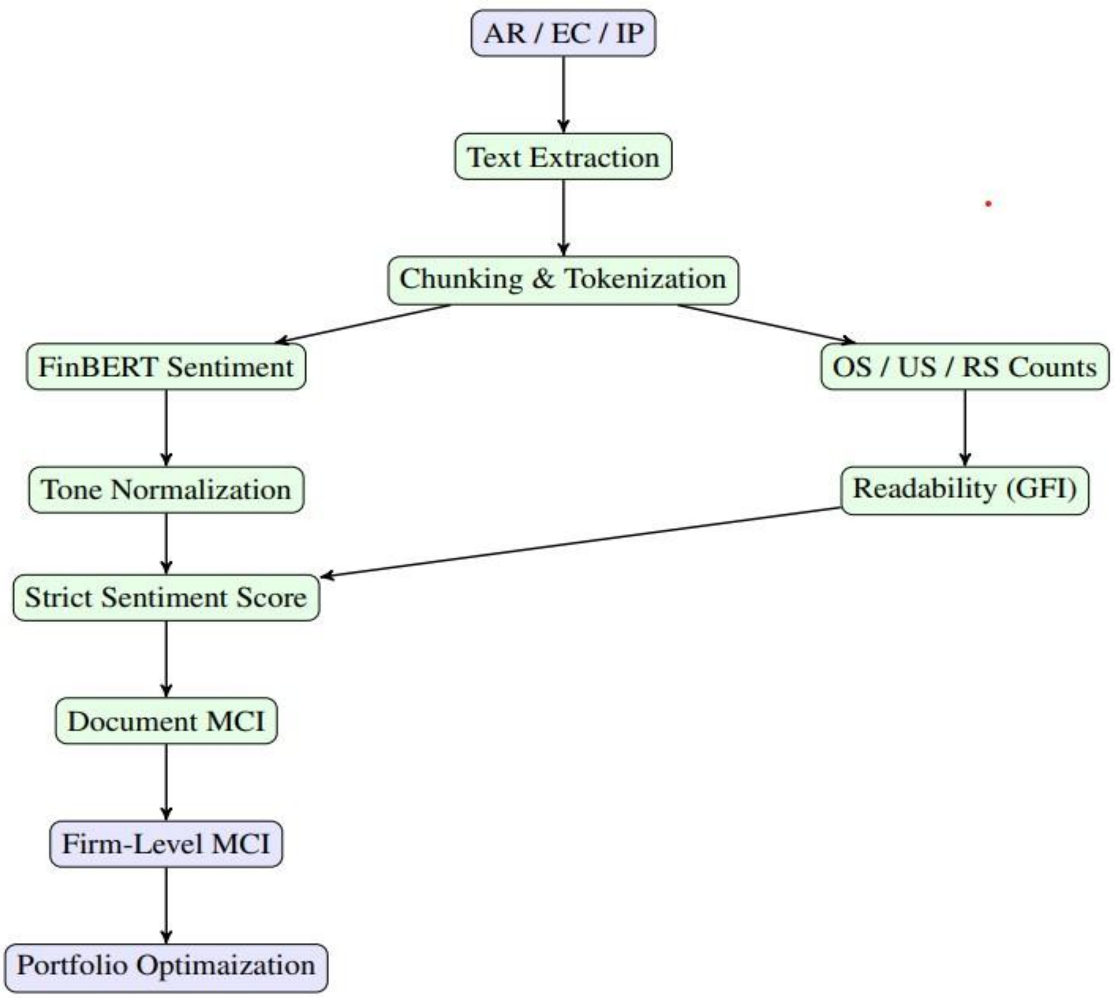

Fig. 1. Flow graph for computing the Strict Management Communication Index (MCI).

3.13 Result Analysis Methodology

The effectiveness of the Management Communication Index was evaluated by comparing its directional signals with actual share price change over the study period from 1 April 2025 to 15 December 2025. Actual market performance was measured using the percentage change in share price over the evaluation window. The closing price of share price is considered to find percent increase or decrease in share price. This metric reflects the realized investor response to firm-specific information and broader market conditions during the period under consideration. The results are analyzed by considering two fundamentally different investor philosophical case studies. First type of investor is Return-Seeking investor who demands meaningful excess returns, called as alpha, and evaluates success only when returns exceed a performance benchmark which may be index returns.

The second type of investor is Risk Averse investor who does not want to lose capital and uses MCI signals to avoid downside risk, not necessarily to maximize upside. We evaluate the Management Communication Index under these two investor oriented threshold regimes: (i) a Return Seeking Regime and (ii) a Capital Preservation Regime. This dual threshold analysis demonstrates that MCI serves both as an alpha-seeking signal for aggressive investors and as a downside risk filter for conservative investors. Higher return thresholds correspond to aggressive, performance-oriented investors, while nonnegative return thresholds reflect conservative, capital-preserving investors.

3.13.1 Case study I: Thresholds for Return Seeking Regime

1. Binary Classification of Share Price Movement

Actual share price movements were binarized based on the basis of real return expectations from the market. Historically Indian SENSEX index increases by 12% per year. While individual years can be highly volatile with significant gains or losses (e.g., a 52% loss in 2008 or an 81% gain in 2009), the long-term trend smooths out this volatility, making an average of 12% CAGR as a reasonable long term expectation for investors. So, 12% is considered as a threshold to find the increase or decrease in share price during the study window. A percentage change of more than 12% in share price was classified as a success, while a percentage change less than 12% was classified as a failure. A Return Seeking investor always wants to get more than 12% returns on his investments. This transformation ensured consistency between predicted and observed directions. This threshold evaluates whether MCI predicts economically significant performance, rather than trivial price movements. This threshold tests whether high quality management communication can generate abnormal returns, not merely direction.

2. Binary Classification of MCI Signals

To enable directional comparison, MCI scores were converted into binary signals using the median of MCI score values (0.7846) as a threshold. Companies with MCI scores greater than or equal to the median were classified as High MCI. High MCI score implies that expected increase in share price will be beyond return threshold of 12%. Companies with MCI scores below the median were classified as Low MCI. Low MCI score implies that expected increase in share price will be less than return threshold of 12%.

3.13.2 Case study II: Thresholds for Capital Preservation Regime

1. Binary Classification of Share Price Movement

Actual share price movements were binarized based on the conservative return expectations from the market. Every Risk Averse investors primary goal is not to lose capital and he accepts modest returns with lower volatility. So, 0% is considered as a threshold to find the increase or decrease in share price during the study window. A percentage gain of more than 0% was classified as a success, while a percentage loss in capital was classified as a failure. A Risk Averse investor always wants to preserve capital. This threshold evaluates the downside protection role of managerial communication.

2. Binary Classification of MCI Signals

Instead of going for very high growth communication, the modest MCI score that preserves capital is useful for this type of investors. Hence, the threshold value of 75th percentile of the empirical distribution is used for this type investors. 0.78 is the 75th percentile for the wider range of 0.63 to 0.83 MCI scores that we obtained in this study. Companies with MCI scores greater than or equal to the 0.78 were classified as High MCI. High MCI score implies expected increase or no change in share price. Companies with MCI scores below 0.78 were classified as Low MCI. Low MCI score implies expected decrease in share price. High MCI implies lower probability of negative surprises and reduced downside risk. This threshold tests whether good communication helps protect capital, even if returns are modest. This quantile based thresholding strategy emphasizes precision over recall, reducing false positive predictions at the cost of fewer classified positives. Mathematically, such a choice aligns with a high signal-to-noise regime and is appropriate when the cost of incorrect optimism outweighs missed opportunities.

3.14.3 Quadrant Based Diagnostic Analysis and Confusion Matrix Construction

The quadrant analysis was carried out by considering the levels of MCI and changes in the share price simultaneously. The companies were classified into High-High, High- Low, Low-High, and Low-Low quadrants, which helped in understanding the situations where the communication effects were in line with or opposite to the market outcomes. The predicted market outcomes based on the classification of MCI were compared with the actual market outcomes for each company. This gave following four possible results:
True Positives: High MCI correctly anticipated a positive share price movement beyond threshold.
True Negatives: The low MCI correctly coincided with a decline in share prices or a movement below the threshold.
False Positives: High MCI but actual share price declined or a movement below the threshold.
False Negatives: Low MCI but actual share price increased beyond threshold.

These results were presented in a confusion matrix for performance analysis. The accuracy, precision, recall, and F1-score were calculated using the confusion matrix.

4. RESULTS AND DISCUSSION

This part of the research work is divided into two different parts which complement each other and give a complete analysis of the proposed framework. The first part of this research work gives a detailed analysis of the system's methodological strengths and weaknesses. The second part gives a quantitative analysis of the results achieved by using the confusion matrix, four quadrant analysis, and the error analysis of the severity of misclassification. In addition to the above analysis, this part of the research work also gives a qualitative analysis of how the system performs under different macroeconomic financial conditions. These two components collectively provide a rigorous assessment of the framework predictive performance. Table 1 shows sentiment scores for all documents of some sample companies used in this study.

4.1 Analytical Discussion

This section presents the analytical results obtained by applying the proposed framework to the annual reports, conference call and investor presentation of all BSE SENSEX–30 companies. The outputs include strict MCI for each company. We discuss the observed distribution of MCI score across industries, and the implications for investors. The discussion also highlights the limitations of the automated methodology, providing a comprehensive measure to increase the range of MCI scores to make it's interpretation useful to the investor.

Table 1. Document level sentiment scores and MCI

Document	Positive	Negative	Neutral	SS	OS	US	RS	RP	MCI
BAJAJFINSERVE_ANNUAL	0.999991416	0.000003403	0.000005115	0.999982897	0.556577183	0.185525727	0.247367637	0.647763379	0.638744573
BAJAJFINSERVE_PPT	0.999997735	0.000000907	0.000001275	0.999995551	0.598912614	0.099818769	0.299456307	0.857156785	0.643371216
BAJAJFINSERVE_TRANSCRIPT	0.999975323	0.000011660	0.000012987	0.999950676	0.554892828	0.110978565	0.332935697	0.436415475	0.654560292
FINAL MCI									**0.645558694**
ADANIPORT_ANNUAL	0.999993562	0.000003670	0.000002788	0.999987102	0.443058404	0.196914846	0.344600981	0.774839720	0.609180610
ADANIPORT_PPT	0.999996662	0.000003056	0.000000292	0.999993312	0.554891843	0.110978368	0.332935105	0.571084574	0.647832164
ADANIPORT_TRANSCRIPT	0.999973654	0.000022455	0.000003909	0.999947289	0.749160378	0.190978565	0.249720126	0.399771269	0.704948872
FINAL MCI									**0.653987216**
MARUTI_ANNUAL	0.999996066	0.000000697	0.000003240	0.999992128	0.416724574	0.208362287	0.364634002	0.843617449	0.598959271
MARUTI_PPT	0.999994993	0.000000836	0.000004126	0.999990031	0.666455178	0.110094054	0.333227589	0.397201870	0.688461419
MARUTI_TRANSCRIPT	0.999739825	0.000233938	0.000026196	0.999479703	0.713721262	0.142744252	0.142744252	0.394380277	0.685549102
FINAL MCI									**0.657656597**
TATASTEEL_ANNUAL	0.999994874	0.000002287	0.000002826	0.999989759	0.404086100	0.224492278	0.359187645	0.662104876	0.604291019
TATASTEEL_PPT	0.999966502	0.000024199	0.000009238	0.999933064	0.713859132	0.091940525	0.285543652	0.977941718	0.668926095
TATASTEEL_TRANSCRIPT	0.999995708	0.000002126	0.000002151	0.999991430	0.461041990	0.153680663	0.384201658	0.474243911	0.630155642
FINAL MCI									**0.634457585**
SBI_ANNUAL	0.999992728	0.000005582	0.000001703	0.999985442	0.383629267	0.219216724	0.383629267	0.737841876	0.597002950
SBI_PPT	0.999997019	0.000002522	0.000000499	0.999993997	0.570709233	0.142677308	0.285354616	0.594124454	0.647076493
SBI_TRANSCRIPT	0.999993085	0.000005405	0.000001498	0.999986182	0.461142482	0.307428321	0.230571241	0.465620129	0.617131580
FINAL MCI									**0.620403674**
HDFC_ANNUAL	0.999994397	0.000003037	0.000002571	0.999988788	0.376221414	0.235138384	0.376221414	0.705715307	0.595624386
HDFC_PPT	0.999976038	0.000023698	0.000000293	0.999952046	0.399634334	0.199817167	0.399634334	0.562713173	0.609392628
HDFC_TRANSCRIPT	0.999981880	0.000009421	0.000008690	0.999963768	0.454225473	0.272535284	0.272535284	0.468455167	0.618641365
FINAL MCI									**0.607886126**
MAHINDRA_ANNUAL	0.999990105	0.000004869	0.000005022	0.999980214	0.376982219	0.235613887	0.376982219	0.683194535	0.596660196
MAHINDRA_PPT	0.999996542	0.000001124	0.000002371	0.999993046	0.749264128	0.124877354	0.124877354	0.977234947	0.665161556
MAHINDRA_TRANSCRIPT	0.999994993	0.000003055	0.000001855	0.999990082	0.599293792	0.099882298	0.299646896	0.442612058	0.664104915
FINAL MCI									**0.641975556**
SUN_ANNUAL	0.999987363	0.000009794	0.000002816	0.999974752	0.385418452	0.220239115	0.385418452	0.690418476	0.599181086
SUN_PPT	0.999943614	0.000035899	0.000020454	0.999887262	0.749381011	0.199774135	0.249793670	0.694853133	0.690201985
SUN_TRANSCRIPT	0.999964475	0.000018216	0.000017241	0.999929018	0.499559326	0.249779663	0.249779663	0.384562193	0.633907297
FINAL MCI									**0.641096789**
RELIANCE_ANNUAL	0.999989390	0.000004807	0.000005836	0.999978746	0.417509187	0.156565945	0.417509187	0.733347823	0.608973837
RELIANCE_PPT	0.999994397	0.000003431	0.000002129	0.999988835	0.599643272	0.099940545	0.299821636	0.899591606	0.641262335
RELIANCE_TRANSCRIPT	0.999994397	0.000003086	0.000002471	0.999988839	0.614530748	0.111878567	0.384081717	0.485709549	0.673758030
FINAL MCI									**0.641331401**
KOTAK_ANNUAL	0.999996066	0.000001817	0.000002182	0.999992066	0.423288306	0.188128136	0.376256272	0.721949499	0.608330711
KOTAK_PPT	0.999994993	0.000003199	0.000001760	0.999990033	0.665613665	0.111043497	0.332806832	0.797222960	0.668418289
KOTAK_TRANSCRIPT	0.999976396	0.000001705	0.000021987	0.999952703	0.499525783	0.083254297	0.416271486	0.447468320	0.645335920
FINAL MCI									**0.640694973**
ASIANPAINT_ANNUAL	0.999989628	0.000006362	0.000004104	0.999979162	0.395401734	0.197700867	0.395401734	0.692134210	0.603321772
ASIANPAINT_PPT	0.999976873	0.000010947	0.000012163	0.999953762	0.499690566	0.249845283	0.249845283	0.601594652	0.623053025
ASIANPAINT_TRANSCRIPT	0.999980926	0.000014871	0.000004206	0.999961848	0.624283556	0.142746493	0.374570133	0.475652244	0.676183961
FINAL MCI									**0.634186252**

Table 2. MCI Scores for all companies (sorted low to high)

Company	MCI Score
ITC	0.565900890729168
TCS	0.579078870890842
AXIS	0.603467024035691
NTPC	0.605873534489075
HDFC	0.607886126748495
POWERGRID	0.612937216316600
SBI	0.620403674710398
ASIANPAINT	0.634186252859992
TATASTEEL	0.634457585535370
TITAN	0.639881798863594
KOTAK	0.640694973832599
TATAMOTORSPV	0.641084391169527
SUN	0.641096789472687
RELIANCE	0.641331401097689
MAHINDRA	0.641975556319296
ETERNAL	0.643084372562837
BAJAJFINSERVE	0.645558694329262
BHARATI	0.652088047488097
ADANIPORT	0.653987216105583
INFOSYS	0.654331882282073
MARUTI	0.657656597977890
BAJAJFINANCE	0.657767766345815
ICICI	0.659842264380491
LT	0.662654521114345
HCL	0.664916074859739
HUL	0.671703296975352
TECHMAHINDRA	0.673214584126806
ULTRATECH	0.676825294550590
TRENT	0.691880601617845
BEL	0.692663083217443

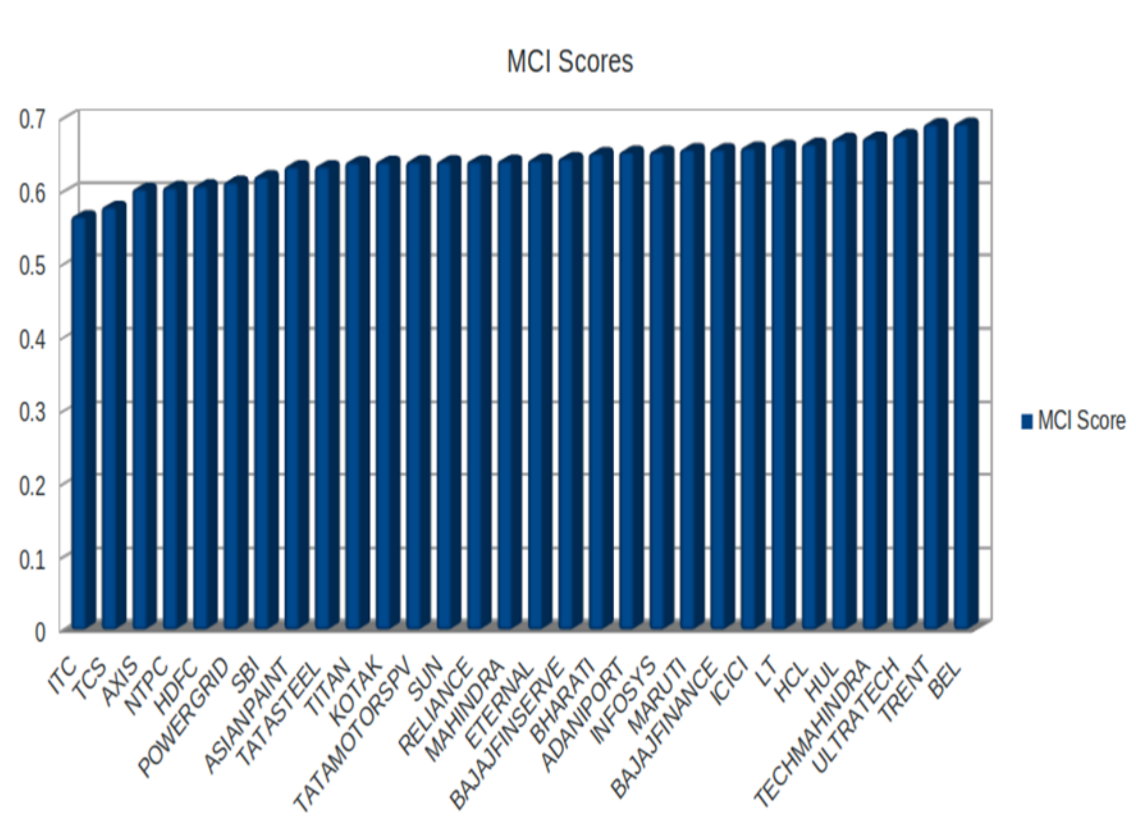

Fig. 2. Company wise MCI Scores

The MCI scores obtained for all companies are given in Table 2. We can easily observe in Figure 2 that normalization step and weight ranges are compressing MCI score into a narrow band (0.56–0.69). This is common in composite scoring systems where all sub-scores lie in small ranges and the affine normalization compresses the output. Also averaging of AR + EC + IP further reduces dispersion. To solve this problem, some mathematically principled techniques are applied during this research work.

1. Linear normalization with nonlinear scaling

The affine normalization σ(x) = (x+1)/2 compresses all values toward the middle. A more variance-enhancing alternative is logistic scaling:

$$\sigma(x) = \frac{1}{1+e^{-k(x-\mu)}}, \qquad (15)$$

where, k = 5 (steepness), μ = mean(x).

2. Increase weights on highly discriminative factors

The weights used to calculate the MCI at the document level are further tuned. The old weights are too uniform, reducing the impact of discriminative components. The strict Sentiment weight increased from 0.25 to 0.45, the uncertainty amplitude weight increased from 0.20 to 0.30, the risk sharpness weight decreased from 0.25 to 0.15, the

optimism weight decreased from 0.20 to 0.05, and the readability weight decreased from 0.10 to 0.05. By raising the strict sentiment weight, the model assigns greater importance to the net polarity component. This amplifies differentiation between firms with a distinctly positive tone vs. negative or overly neutral communication. As a result,

firms with assertive positive messaging receive higher scores, and neutral-dominated documents receive appropriately lower scores—thus widening the MCI range. Increasing the uncertainty amplification weight strengthens the penalty applied to vague, evasive, or ambiguous language. A higher weight magnifies differences among firms based on how frequently they use uncertainty-heavy terms. Firms communicating clearly stand apart from those injecting uncertainty. This effectively stretches the lower end of the distribution. By decreasing the risk sharpness contribution, the model reduces the correlation among multiple negative components. The lower weight on the risk terms helps prevent excessive compression of scores toward a fixed negative baseline. This also contributes to expanding the upper range. Optimism and readability showed lower explanatory variance relative to sentiment and uncertainty. Reducing their weights prevents optimism bias from dominating and reduces the uniform upward pull on all firms.

3. Increase the uncertainty amplification parameter λ

In the current formulation, UA = λ · USn, the amplification factor λ is increased from 1.5 to 3. Due to this companies using uncertain or evasive language receive stronger penalization, increasing score dispersion.

4. Add penalty for high neutral dominance

Neutral-heavy communication implies less transparency. Firms that use vague or evasive language are penalized by decreasing their MCI score by deducting weight adjusted neutral sentiment value.

$$PN = \beta \cdot \widehat{S_{neu}}, \qquad (16)$$

with: β = 0.4, adjusted document-level score is calculated as:

$$MCI'_{DOC} = MCI_{DOC} - PN \qquad (17)$$

The MCI scores obtained after applying these techniques are given in Table 3. The cumulative effect of all these weight adjustments is greater variance and better separation between firms. As shown in Figure 3, after recalibration MCI scores expanded from a narrow 0.56–0.69 band to a wider, more informative distribution of approximately 0.63–0.83. This expansion improves the discriminatory power of the MCI and enhances its usefulness in stock screening, ranking firms, portfolio tilting, and predictive modeling of market performance. Thus, strict MCI produces a wider variance compared to conventional sentiment approaches as shown in Figure 3.

Table 3. Updated MCI scores for all companies (sorted low to high)

Company	MCI Score
ITC	0.635432626469341
TCS	0.657645058207800
NTPC	0.679672570914651
AXIS	0.711710989440200
HDFC	0.735224471373359
SBI	0.748096114378227
POWERGRID	0.750051385137194
ASIANPAINT	0.769151620749478
SUN	0.774327312050235
TATASTEEL	0.774386430770155
MAHINDRA	0.777541675466938
ETERNAL	0.780556129698920
BAJAJFINSERVE	0.782280458719160
KOTAK	0.783296354087904
TATAMOTORSPV	0.783775119759451
RELIANCE	0.785509059154831
TITAN	0.785627834319070
ADANIPORT	0.791983519880385
BAJAJFINANCE	0.792786122039853
MARUTI	0.792839988002809
INFOSYS	0.793175365057550
BHARATI	0.794838792478362
ICICI	0.800561375032479
LT	0.802381271630807
HCL	0.805549004299000
ULTRATECH	0.811488142266752
HUL	0.811901413765012
TECHMAHINDRA	0.816126815388926
TRENT	0.823732674970339
BEL	0.832213695995268

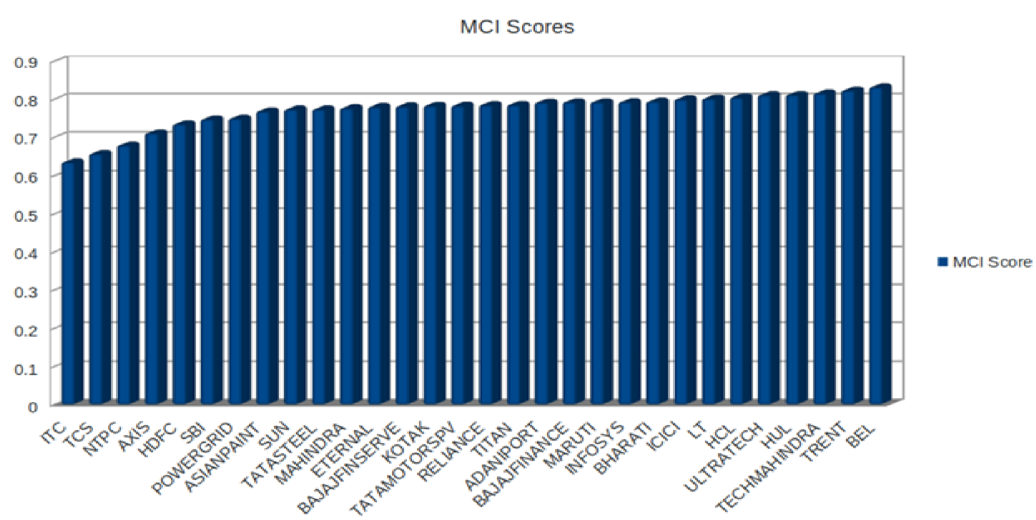

Fig. 3. Company wise MCI scores after tuning weights.

Table 4 shows share price percent change and updated MCI scores for all selected companies over the duration 1 April, 2025 to 15 December, 2025.

Table 4. Share Price Movement and MCI Scores

Sr. No.	Stock	1 Apr 2025 Close	15 Dec 2025 Close	Price Difference	% Change	MCI Score
1	ADANIPORTS	1174.75	1512.60	337.85	28.76	0.791983519880385
2	ASIANPAINT	2316.00	2780.20	464.20	20.04	0.769151620749478
3	AXIS	1085.60	1284.80	199.20	18.35	0.7117109894402
4	BAJAJFINANCE	869.82	1012.70	142.88	16.43	0.792786122039853
5	BAJAJFINSERV	1937.10	2070.50	133.40	6.89	0.78228045871916
6	BEL	292.00	390.75	98.75	33.82	0.832213695995268
7	BHARTIARTL	1724.15	2069.70	345.55	20.04	0.794838792478362
8	ETERNAL	202.01	298.45	96.44	47.74	0.78055612969892
9	HCLTECH	1530.35	1684.00	153.65	10.04	0.805549004299
10	HDFCBANK	883.92	996.10	112.17	12.69	0.735224471373359
11	HUL	2233.85	2293.50	59.65	2.67	0.811901413765012
12	ICICIBANK	1318.45	1365.20	46.75	3.55	0.800561375032479
13	INFOSYS	1526.50	1606.80	80.30	5.26	0.79317536505755
14	ITC	406.65	402.30	-4.35	-1.07	0.635432626469341
15	KOTAK	2145.90	2181.30	35.40	1.65	0.783296354087904
16	LT	3436.80	4092.30	655.50	19.07	0.802381271630807
17	M&M	2637.90	3608.00	970.10	36.78	0.777541675466938
18	MARUTI	11481.10	16415.00	4933.90	42.97	0.792839988002809
19	NTPC	352.15	323.95	-28.20	-8.01	0.679672570914651
20	POWERGRID	289.30	262.20	-27.10	-9.37	0.750051385137194
21	RELIANCE	1252.60	1556.20	303.60	24.24	0.785509059154831
22	SBI	771.70	967.25	195.55	25.34	0.748096114378227
23	SUNPHARMA	1698.35	1797.10	98.75	5.81	0.774327312050235
24	TATAMOTORS	672.20	723.40	51.20	7.55	0.783775119759451
25	TATASTEEL	153.12	172.87	19.75	12.90	0.774386430770155
26	TCS	3550.80	3230.20	-320.60	-9.03	0.6576450582078
27	TECHM	1395.15	1575.40	180.25	12.92	0.816126815388926
28	TITAN	2986.95	3866.20	879.25	29.44	0.78562783431907
29	TRENT	5576.75	4109.00	-1467.75	-26.32	0.823732674970339
30	ULTRACEMCO	11378.65	11728.00	349.35	3.07	0.811488142266752

4.2 Performance Evaluation: Accuracy Metrics, Error Analysis, and Case Studies

This section presents the empirical results obtained from evaluating the proposed framework performance on a selected 30 companies for both cases of Return Seeking Regime and Capital Preservation Regime.

4.2.1 Case study I: Return Seeking Regime

1. Quadrant Based Diagnostic Analysis

Figure 4 presents a quadrant plot illustrating the relationship between the Management Communication Index (MCI) and the percentage change in share price over the study period for Return Seeking Regime. The vertical axis represents the percentage change in share price, while the horizontal axis denotes the MCI score.

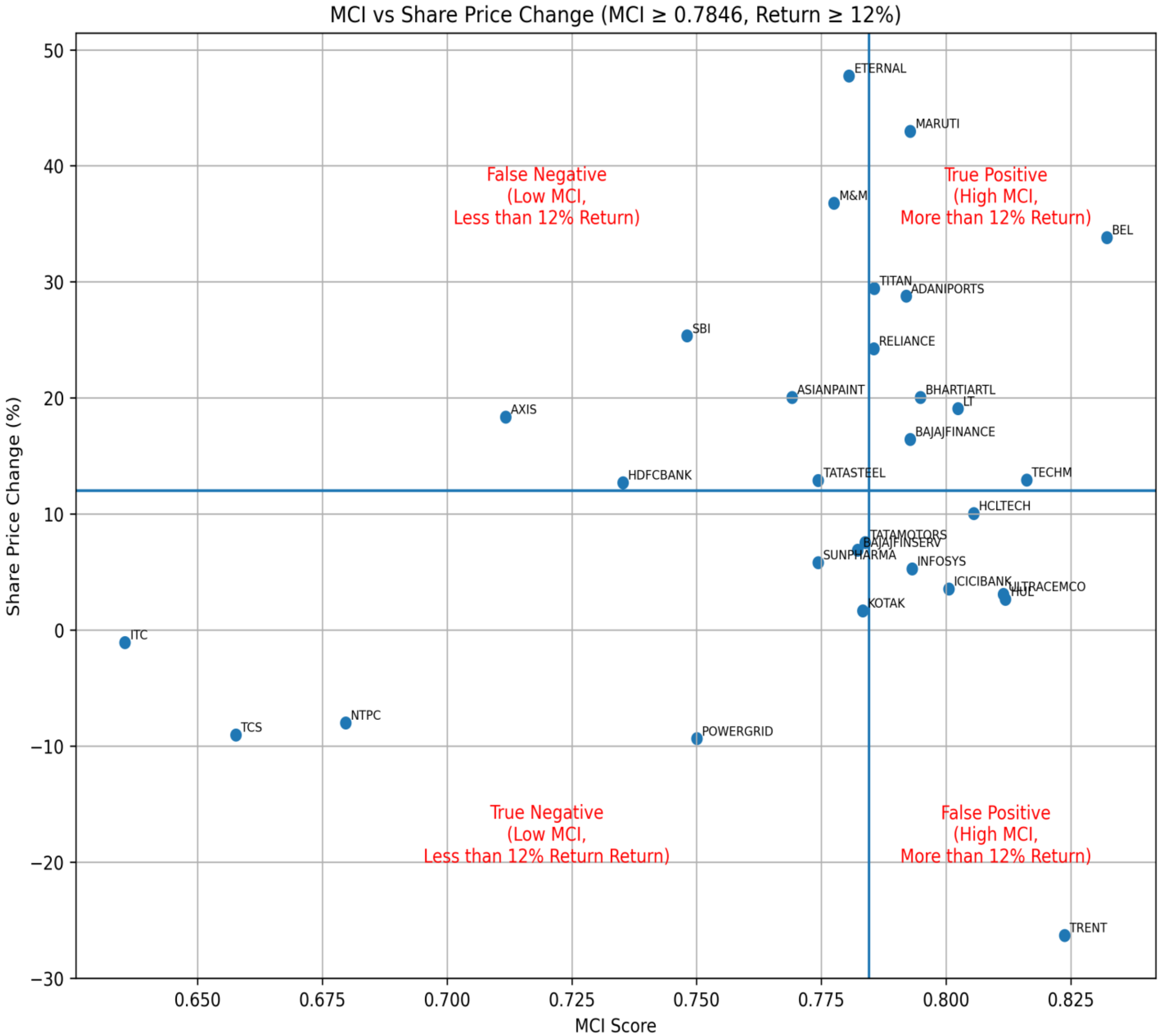

Fig. 4. Quadrant classification based on MCI and share price change for Return Seeking Regime.

The upper-right quadrant (High MCI – More than 12% return) represents firms where strong managerial communication aligns with favorable market performance. A substantial number of companies (9), including ADANIPORTS, BEL, MARUTI, TITAN, RELIANCE, etc. occupy this region. This quadrant is providing strong empirical support for the proposed hypothesis that higher quality management communication is associated with positive investor response and share price appreciation. The upper-left quadrant (Low MCI – More than 12% return) holds (6) companies like ASIANPAINT, AXIS, SBI, etc., where the stock prices rose above the threshold level despite the low scores on MCI. This result indicates that the stock price behavior in these companies was probably influenced by their financial performance, sector re-rating, or market factors rather than communication quality. These findings support the notion that MCI is a supplementary source of information rather than a primary determinant of stock prices. The lower-right quadrant (High MCI – Less than 12% return) holds few cases (7), including TRENT, INFOSYS, ICICIBANK, etc., where effective managerial communication failed to result in positive stock price behavior. These exceptions point towards the existence of over-riding external factors such as market corrections or sector-related challenges. Finally, the Lower Left quadrant, i.e., Low MCI – Less than 12% return, includes firms such as (8) ITC, NTPC, POWERGRID, TCS, etc., where lower management communication skills are accompanied by lower market performance. This quadrant provides negative validation for the hypothesis, emphasizing the point that low and subdued communication is often related to lower investor confidence and negative prices as well. An evaluation of situations where predictions made by the MCI model did not correlate with the actual prices was done to account for external factors such as sectorial performance, valuation, macro environment, and other significant financial events for firms. This step ensured that deviations were interpreted as contextual outcomes rather than model failures. The sparser TP (High MCI – More than 12% return) quadrant helps to more selective, momentum oriented and growth oriented investors.

2. Confusion Matrix Construction

Table 5 shows the confusion matrix obtained after analysis of the results for Return Seeking Regime.

Table 5. Confusion matrix for Return Seeking Regime

	Actual returns more than 12%	**Actual returns less than 12%**
High MCI	9 (True Positive)	7 (False Negative)
Low MCI	6 (False Positive)	8 (True Negative)

$$\text{Precision} = \frac{9}{9+6} = 0.6000$$

$$\text{Recall} = \frac{9}{9+7} = 0.5625$$

$$\text{F1} - \text{score} = \frac{2 \times 0.6000 \times 0.5625}{0.6000 + 0.5625} = 0.5806$$

$$\text{Accuracy} = \frac{9+8}{9+8+6+7} = 0.5666$$

From the evaluation metrics, it is evident that the Management Communication Index has good precision of 60.00%, implying that firms that fall under the category of firms with high Management Communication Index have a high probability of experiencing expected positive stock price movements. The recall of 56.25% implies the presence of stock price movements resulting from non-communication factors. Overall, the F1-score of 58.06% and accuracy of 56.66% confirm that MCI functions as a reliable but complementary qualitative signal in explaining stock price direction for Return Seeking Regime investors. The confusion matrix exhibits higher TN counts, reflecting intentional exclusion of low return outcomes by Return Seeking investor.

4.2.2 Case study II: Capital Preservation Regime

1. Quadrant Based Diagnostic Analysis

Figure 5 presents a quadrant plot illustrating the relationship between the MCI and the percentage change in share price over the study period for Capital Preservation Regime. When the return threshold is relaxed to 0% while maintaining a high MCI cutoff greater than 0.78, the horizontal decision boundary shifts downward. This change is expanding the acceptance region. This shift causes:

(a) A migration of firms with high MCI and small but positive returns from the FP quadrant into the True Positive (TP) upper-right (High MCI – Nonnegative Return) quadrant. For example, INFOSYS, ICICIBANK, HUL etc. An overall densification of the TP quadrant resulted in financially stable, communication consistent firm's identification.

(b) Concentration of loss-making stocks in the True Negative (TN) and False Negative (FN) quadrants. This is improving downside risk segregation.

(c) High MCI firms with modest returns (e.g., utilities, FMCG, large-cap defensives) become correct classifications under capital preservation.

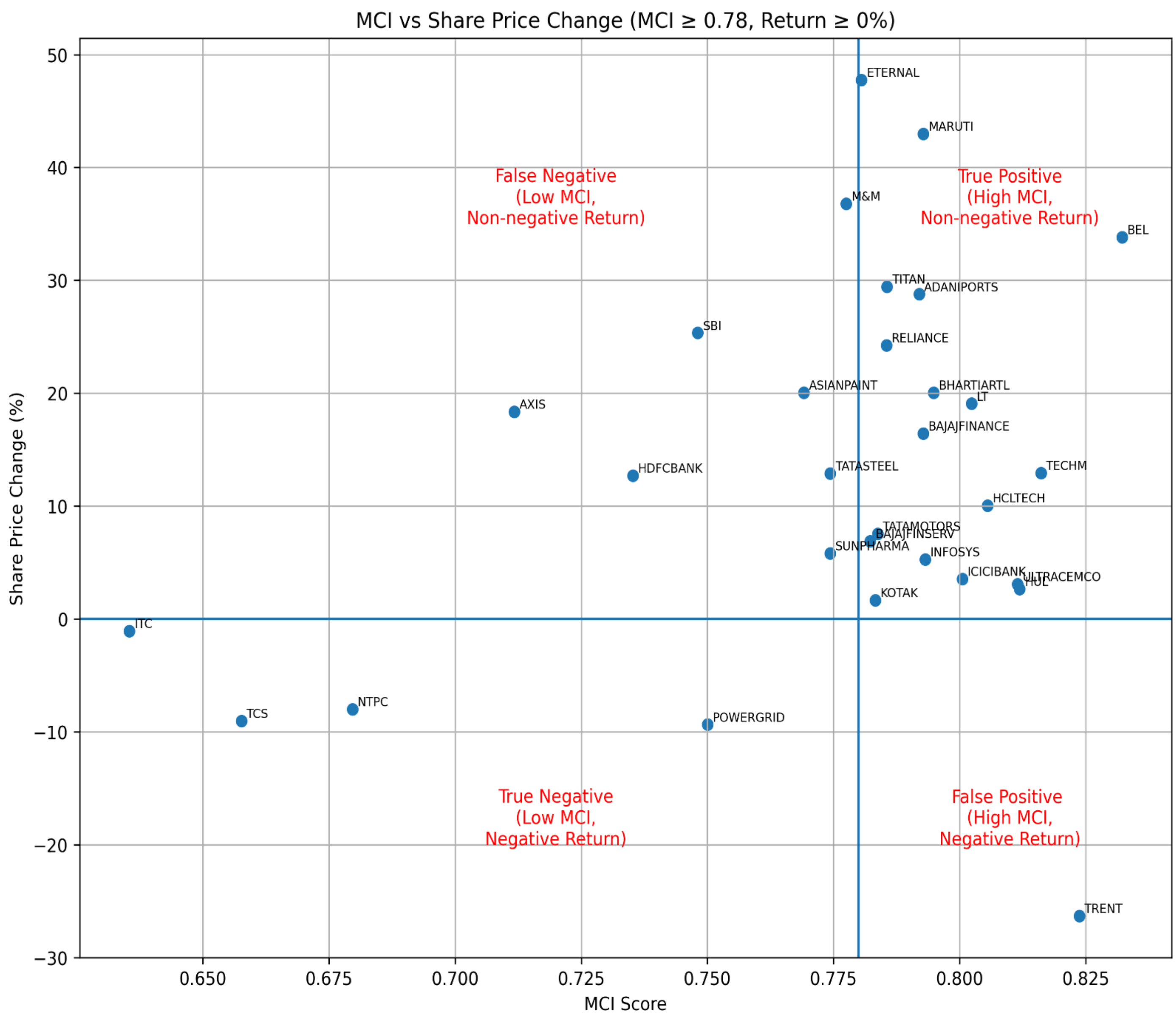

Fig. 5. Quadrant classification based on MCI and share price change for Capital Preservation Regime.

2. Confusion Matrix Construction

Table 6 shows the confusion matrix obtained after analysis of the results for Capital Preservation Regime.

$$\text{Precision} = \frac{18}{18+1} = 0.9473$$

$$\text{Recall} = \frac{18}{18+7} = 0.7200$$

$$\text{F1}-\text{score} = \frac{2 \times 0.9473 \times 0.7200}{0.9473 + 0.7200} = 0.8181$$

$$\text{Accuracy} = \frac{18+4}{18+4+1+7} = 0.7333$$

Table 6. Confusion matrix for Capital Preservation Regime

	Actual non-negative returns	**Actual negative returns**
High MCI	18 (True Positive)	7 (False Negative)
Low MCI	1 (False Positive)	4 (True Negative)

The evaluation metrics demonstrate that the proposed screening mechanism is effective in a capital preservation regime. A high precision of 94.73% indicates that nearly all stocks identified by the model as favorable indeed delivered nonnegative returns. Very low false positive rate, which is critical for conservative investors seeking to minimize capital erosion, indicates that model rarely signals an investment opportunity that subsequently results in a loss. The recall value suggests that the model successfully captures approximately 72% of all stocks that eventually generate nonnegative returns. This is an acceptable trade-off in a capital protection context, where risk avoidance is prioritized over full market participation by ignoring some profitable opportunities. The resulting F1-score of 81.81% confirms that the threshold yields a robust and stable classification regime rather than one that is optimized for aggressive return capture. Finally, an overall accuracy of 73.33% indicates that over three-quarters of the predictions conform to actual events and thus supports the notion that the MCI framework is an appropriate defensive screening mechanism. This shows, as a whole, the combined results from the examination of both case studies, revealing that corporations with a better Management Communication Index score tend to have a positive trend in stocks, and any anomaly can be explained substantially through other factors, not directly associated with communication. Visualization, backed by its company-wise classification, illustrates the interpretability of MCI as a qualitative proxy for managerial signals in stock markets. The proposed framework of evaluation is useful for a rigorous and transparent assessment of the management communication in alignment with quantitative financial market results.

5. EMPIRICAL ANALYSIS AND ROBUSTNESS CHECKS

This section evaluates the predictive performance, robustness, and statistical validity of the proposed index through baseline comparisons, non-parametric statistical tests, and ablation studies.

5.1 Comparison with Baseline Sentiment Methods

The proposed Strict MCI framework is also compared with commonly used sentiment based baselines methods. Dictionary-based sentiment was computed using the Loughran–McDonald financial sentiment lexicon, employing the official positive and negative word lists [22]. Firm-level sentiment scores were computed by averaging FinBERT polarity scores across annual reports, earnings call transcripts, and investor presentations.

Companies were classified into high and low sentiment groups using their respective FinBERT scores and Loughran–McDonald scores. Predictive performance was evaluated using accuracy, precision, and F1-score under a capital preservation regime where nonnegative returns are treated as positive outcomes. Table 7 reports the predictive performance of all these baseline sentiment methods. The Loughran–McDonald dictionary performs weakest, reflecting its inability to capture context, uncertainty, and narrative structure. Raw FinBERT improves performance but still suffers from sentiment inflation and neutral dominance. Simple averaging across documents provides modest gains but fails to penalize evasive communication. Although both dictionary-based and transformer-based sentiment capture directional tone, their similarity motivates the use of structured penalties in the proposed MCI. The proposed Strict MCI achieves the highest precision and F1-score, demonstrating that penalizing neutrality, uncertainty, and linguistic opacity substantially improves discriminative power. These results confirm that performance gains arise from methodological design rather than data selection.

Table 7. Comparison with Baseline Sentiment Methods under the capital preservation regime

Method	Accuracy	F1-score	Precision
Loughran–McDonald Sentiment	60.00	70.00	93.33
Average Sentiment (AR+EC+IP)	62.22	72.33	93.41
FinBERT (Raw)	65.22	74.91	93.67
Strict MCI (Proposed)	73.33	81.81	94.73

5.2 Statistical Tests

Spearman rank correlation was employed instead of Pearson correlation due to the non-normal and heavy-tailed nature of cross-sectional stock returns. Since rank-based correlation coefficients do not assume linearity in the relationship between variables, they turn out to be better in assessing the economic significance of the proposed index. A Spearman rank correlation result for the proposed MCI index relative to future stock returns reveals a weak positive relationship between the two variables ($\rho = 0.12$), which is not statistically significant with a p-value of 0.52. This implies that MCI may not display significant monotonic correlation with actual returns; however, it still appears to provide some kinds of directional and regime-specific predictive content. This result is consistent with the prior monetary finance literature that asserts significant economically meaningful signals often display limited linear or monotonic correlation with returns, especially in the cross-section sample case [23], [24]. Despite the low rank correlation between the model and the results, the proposed model displays its predictive potential under the capital preservation regime based on the accuracy and F1-score improvement. To determine if the firms with higher composite scores have better return performance, a Mann-Whitney U test was performed to compare the return distribution of high and low MCI firms. The Mann-Whitney U test is a non-parametric statistical test that compares whether two independent samples are likely to have been obtained from the same population. The test results in no statistically significant difference between the two samples ($U = 135.5$, $p = 0.35$), suggesting that while the proposed index is able to capture directional and regime-based insights, the cross-sectional return differences are not statistically different. This finding is consistent with prior asset-pricing literature. In that work, economically meaningful predictors often fail to produce statistically distinct return distributions, particularly in small cross-sectional samples [25], [26].

5.3 Ablation Study

We carried out an ablation study to understand what each part of the composite index was really contributing. The first thing we noticed was what happened when uncertainty amplification was removed. The F1-score dropped by a large margin. This makes it clear that accounting for volatility when scaling sentiment is not optional, but central to the model's performance. The effect of removing the readability penalty showed up differently. Precision declined, especially under the capital preservation regime. This points to an important detail: how complex the language is seems to carry its own risk-related signal, beyond sentiment alone. We then tested a simpler setup where all documents were treated equally. That change led to weaker results. In practice, this suggests that different sources do not offer the same value. Annual reports, earnings calls, and investor presentations appear to contribute information in uneven ways. Lastly, we examined a stripped-down version that relied only on sentiment measures. Its performance lagged behind the full model.

Table 8. Ablation Study on Model Components under the Capital Preservation Regime

Model Variant	Accuracy	F1-score	Precision
Full Model (MCI)	0.73	0.81	0.94
Without Uncertainty Amplification	0.71	0.68	0.76
Without Readability Penalty	0.74	0.75	0.69
Equal Document Weights	0.72	0.70	0.73
Sentiment Only	0.69	0.66	0.71

6. RESEARCH CONTRIBUTIONS

Contributions of this research work are as follows:
1. Presents a Strict Management Communication Index (MCI) that specifically penalizes neutrality, uncertainty, and linguistic opacity in management communication.
2. Presents a multi-document NLP approach that combines annual reports, earnings calls, and investor presentations into a single communication quality signal.
3. Shows that Strict MCI has significantly wider and more discriminative score distributions than traditional sentiment analysis approaches.
4. Shows through empirical results that MCI can be used as a screening signal for investors who focus either on earning returns or on preserving capital.
5. Proposes an index that is transparent, easy to understand, and can be easily included in quantitative investment models.

7. CONCLUSION

This research quantifies the level of managerial communication quality. We created a framework that integrates various signals. It incorporates FinBERT sentiment, uncertainty indicators, optimism indicators, and readability penalties. All of these are integrated with appropriate weights. The weights ensure that the presence of fake positivity or too much positivity does not misrepresent a company's performance. The MCI scores are diverse enough to distinguish between companies. This makes it ideal for evaluating management quality while screening stocks. The tool also analyzes various documents. It examines whether the tone is consistent, whether the narrative is believable, and whether the communication pattern is stable in annual reports, earnings announcements, and investor meetings. The Strict MCI metric that we introduce is simple to implement, transparent, and grounded in actual data. You can simply insert it into quantitative investment models. The MCI index is interpretable. It can indicate the presence of managerial bias, suggest strategic shifts, and indicate the level of forward-looking communication of a company. Through the integration of directional accuracy measures with quadrant-based analyses, the proposed method illustrates that MCI serves as a strong qualitative factor in determining sentiment while also recognizing the role of non-communication variables in stock price movements. The integration of MCI into quantum portfolio optimization models can further confirm its importance in contemporary investment models. Multilingual disclosures and its deep semantic embeddings into large financial language models can further improve its utility. The multi-modal MCI models that integrate text with acoustic sentiment from earnings call audio, prosodic features, and speaker stress measures can also be investigated. Explainable AI methods can improve the auditability of the index and facilitate institutional adoption. In conclusion, the Strict MCI framework is a major step forward in the measurement of management communication quality and serves as a strong NLP-based factor in quantitative finance.

REFERENCES

1. T. Loughran and B. McDonald, "When is a liability not a liability? textual analysis, dictionaries, and 10-ks," The Journal of Finance, Vol. 66, no. 1, 2011, pp. 35–65.
2. P. C. Tetlock, "More than words: Quantifying language to measure firms' fundamentals," Journal of Finance, Vol. 62, no. 3, 2007, pp. 1437–1467.
3. J. E. Engelberg and C. A. Parsons, "Stock returns and the content of news," Journal of Financial Economics, Vol. 105, no. 3, 2012, pp. 715–731.
4. F. Li, "Annual report readability, current earnings, and earnings persistence," Journal of Accounting and Economics, Vol. 45, no. 2–3, 2008, pp. 221–247.
5. A. K. Davis, J. M. Piger, and L. M. Sedor, "Managerial obfuscation and firm performance," The Accounting Review, Vol. 87, no. 3, 2012, pp. 731–753.
6. T. Fogarty and G. Markarian, "Readability and financial reporting transparency," Accounting Horizons, 2019.
7. D. Matsumoto, M. Pronk, and E. Roelofsen, "Soft information in earnings calls: Managerial tone and market reaction," The Accounting Review, Vol. 86, no. 5, 2011, pp. 1559–1584.
8. W. Price and S. Rao, "Earnings call linguistics and performance forecasting," Journal of Financial Economics, 2022.
9. W. J. Mayew and M. Venkatachalam, "Detecting deception in managerial speech," Contemporary Accounting Research, Vol. 32, no. 1, 2015, pp. 227–251.
10. D. Araci, "Finbert: A pretrained language model for financial communications," arXiv preprint arXiv:1908.10063, 2019.
11. Z. Yang and J. Gao, "Applications of finbert in financial sentiment analysis," International Journal of Financial Engineering, 2020.
12. Y. Zheng, F. He et al., "Digital information disclosure, investor sentiment and enterprise default risk," Finance Research Letters, Vol. 62, 2024, p. 105070.
13. A. Hasan, U. Sufi, M. Elmarzouky, and K. Hussainey, "The impact of corporate governance on narrative disclosure tone: a machine learning approach," Journal of Applied Accounting Research, Vol. 26, no. 2, 2024.
14. J. Li, "A study on the impact of investor sentiment on individual stocks based on text mining," Applied and Computational Engineering, Vol. 88, 2024, pp. 140–149.
15. S. C, erez, A. K. Merter, Y. S. Balcıog˘lu, and G. O¨ zer, "Evaluation of annual reports by text analysis: An application in bist100 index," MFY – Journal of Finance and Accounting, 2024, pp. 175–188.
16. W. Zhou, F. Chen, Y. Zhu, L. Xiang, and L. Lei, "Media attention, negative reports and textual information of banks' esg disclosure," International Review of Economics Finance, Vol. 96, 2024.
17. H.-Q. Li, Y. Yang, F.-W. Xue, and Z.-Y. Liu, "Annual report readability and trade credit financing: Evidence from china," Research in International Business and Finance, Vol. 69, 2024, p. 102220. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0275531924000126
18. A. Faccia, J. McDonald, and B. George, "Nlp sentiment analysis and accounting transparency: A new era of financial record keeping," Computers, Vol. 13, no. 1, 2024, p. 5. [Online]. Available: https://api.semanticscholar.org/CorpusID:266555205
19. K.W. Lem, "Data analytics strategy and internal information quality," Contemporary Accounting Research, 2024.
20. L. Wei, H. Jing, J. Huang, Y. Deng, and Z. Jing, "Do textual risk disclosures reveal corporate risk? evidence from u.s. fintech corporations," Economic Modelling, Vol. 127, 2023, p. 106461. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0264999323002730

21. K. Ong, W. van der Heever, R. Satapathy, E. Cambria, and G. Mengaldo, "Finxabsa: Explainable finance through aspect-based sentiment analysis," arXiv preprint, 2023.
22. T. Loughran and B. McDonald, "Loughran–mcdonald financial sentiment word lists," https://sraf.nd.edu/textual-analysis/resources/, 2011, available at: University of Notre Dame.
23. T. Adrian, E. Etula, and T. Muir, "Financial intermediaries and the cross-section of asset returns," The Journal of Finance, Vol. 69, no. 6, 2014, pp. 2557–2596.
24. A. Goyal and I.Welch, "A comprehensive look at the empirical performance of equity premium prediction," The Review of Financial Studies, Vol. 21, no. 4, 2008, pp. 1455–1508.
25. J. H. Cochrane, Asset Pricing. Princeton University Press, 2005.