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Machine Learning Based ESG Disclosure Sentiment and Financial Performance: Corporate Sustainability and Behavioural Finance Implications from Nifty 50 Firms

A Binita Singha[1], Moonmoon Kalita[2], Dr. Biju Mani Das[3]

[1,2]Research Scholar, Commerce, Assam Don Bosco University
[3]Director, SOCM, Commerce, Assam Don Bosco University

Abstract

This study explores the sentiment inherent in Environmental, Social, and Governance (ESG) disclosures from fifteen Nifty 50 firms and its relationship with financial performance from perspectives of corporate sustainability and behavioral finance. The study addresses the gap existing between sentiment of India's post-Business Responsibility and Sustainability Reporting (BRSR) and ESG disclosure literature, wherein the prior research has relied on third-party ratings to measure ESG disclosures. The findings reveal that ESG disclosures have negative tones in most cases (56.3%) indicative of a corporate culture that promotes risk disclosure, although significant differences exist between firms. Overall, negative sentiments are highest in social disclosures (61.1%), followed by governance (57.8%), and environmental (50.0%). However, governance dominates negative sentiment at firm level. Correlation and Ordinary Least Squares (OLS) regression analyses on 44 firm-year observations confirm that sentiment scores are strong positive predictors of Return on Assets (ROA) and Return on Equity (ROE), with greater significance in ROE conform to behavioral finance theories of investor reaction to tone.

Keywords: ESG Sentiment Analysis; Corporate Disclosure; Financial Performance; Nifty 50; Machine Learning; Natural Language Processing.

1. Introduction

Environmental, Social, and Governance (ESG) issues of companies have now become a core part of how firms interact with investors and regulators. As the focus has shifted towards sustainable investments, the number of ESG disclosures, ratings, and academic research linking ESG factors and financial performance has increased dramatically. Meta-analysis that has been conducted on more than 2,000 papers shows that there is a generally positive link between ESG factors and financial performance (Friede, Busch, & Bassen, 2015). For corporate sustainability, ESG disclosures represent the primary means through which firms provide information on their environmental, social, and governance responsibilities for the future, and sustainability-based companies have been observed to be systematically different from other organizations in terms of processes and performance (Eccles, Ioannou, & Serafeim, 2014).

This transition has taken place formally in India through SEBI's Business Responsibility and Sustainability Reporting (BRSR) framework which became mandatory for the 1,000 largest companies by market cap starting financial year 2022-23 including all companies that are part of Nifty 50 index (EY, 2025; Greenplaces, 2025). The earlier narrative version of Business Responsibility Report (BSR) was replaced by the new framework which requires reporting of more than 140 ESG related data points following the guidelines of Global Reporting Initiatives (GRI) & Task Force on Climate-related Financial Disclosures (TCFD) frameworks (Cholarisk, 2025). While this process has led to improvements in the volume and standardization of disclosures, the issue of data quality, comparability, and assurance still persists (CFA Institute, 2024; Dwivedi, 2026). NIFTY 50 firms thus now produce thorough ESG disclosures in their annual reports and sustainability reports which provides a rich and underexplored data source to study ESG communication. Since BRSR has positioned sustainability reporting as the core aspect of corporate accountability, the way companies communicate about their sustainability performance becomes a critical but overlooked indicator of the degree to which companies have internalized sustainability into their strategy.

The few studies on Indian companies that have used third party ratings have shown inconsistent results, as some have shown the existence of a positive relationship between ESG score and profitability (Thaker, 2019), while others have observed negative association between environmental and governance pillars and ROE at virtually all distribution levels (Ray, 2023), the existence of an inverse relationship between poor ESG risk scores and lower net profit margins (Tripathi, 2024) or even negative long term impact on firm value despite positive short term market impact (Deb, Behra, & Dusmanta, 2026; Ray & Goel, 2023). The inconsistent findings can be attributed to international concerns regarding inconsistency in ESG ratings across providers, with pairwise correlation as low as 0.38-0.71 due to aggregation confusion (Berg, Kölbel, & Rigobon, 2022).

A more recent and potentially viable method in light of developments in Natural Language Processing (NLP) is to conduct an analysis of the actual text and derive sentiment, i.e., whether the company's ESG narrative tends to be positive, negative, or neutral. The applications of NLP range from extracting ESG data from companies' reports (Schimanski et al., 2022), to creating standardized frameworks of assessing ESG performance using both topic modeling and sentiment analysis (Schimanski, 2024). It was also used to combine sentiment analysis with specialized models like FinBERT in creating ESG scores (Sultana, 2025) and detecting greenwashing by comparing sentiments inside the company with the external one reflected in media sources (Davidescu, 2026). Firm-level ESG sentiment, obtained through the clustering approach and machine learning algorithms, has been found to be negatively correlated with financial risk (Sultana et al., 2025) and positively correlated with the confidence of investors in addition to improving stock prediction using deep-learning models (Lee et al., 2024). These measures can be calculated by analyzing a firm's own disclosures and are easily replicable. The narrative approach is also appropriate for the study of behavioural finance. Investors have limited attention capacity and are susceptible to framing, and hence, the tone of a story could affect their perceptions about the value of a business entity independent of the factual data that is in the narrative (Hirshleifer & Teoh, 2003; Baker & Wurgler, 2006). This is in line with the finding that the tone of disclosures affects returns and performance (Tetlock, 2007; Loughran & McDonald, 2011).

Although there is growth in disclosure of BRSR reports, and publication of related papers on the ESG-sentiment connection across different countries, there is very limited study of ESG sentiment in India in

the listed firm population, especially regarding variations across firms, sectors, and ESG themes, as well as its link to financial performance. This study addresses this gap using a sentiment-labelled corpus from fifteen Nifty 50 firms' disclosures, classified via machine learning, and related to financial performance. Therefore, this study is based on two objectives:

1. To assess the sentiment (positive, negative, or neutral) of ESG disclosures across Nifty 50 companies and their Environmental, Social, and Governance (ESG) dimensions.
2. To examine the relationship between ESG sentiment scores and the financial performance of these companies.

The study draws on 810 ESG statements (54 per firm, equally split across the three dimensions) from fifteen Nifty 50 firms, FY2023–FY2025. Statement-level sentiment is classified using Naive Bayes, Logistic Regression, and Support Vector Machine models, with the best classifier used to derive firm-level ESG sentiment scores. These are examined across companies, dimensions, and industries, then related to ROA and ROE via correlation and Ordinary Least Squares (OLS) regression, controlling for leverage. Interpretation draws on legitimacy theory (Suchman, 1995), firms facing greater scrutiny disclose risks to maintain their social licence and signalling theory (Spence, 1973), disclosing unfavourable information can itself signal firm quality. Behavioural finance adds another dimension to the interpretation because the sentiment-loaded ESG narrative could affect how investors evaluate sustainability information and thus tie corporate sustainability communication to financial outcomes.

The study contributes in three ways. First, it offers one of the first systematic sentiment-based characterisations of ESG disclosure tone among Nifty 50 firms post-BRSR, at the company, dimension, and industry levels. Second, it compares machine learning classifiers for ESG sentiment classification in an Indian context, addressing class imbalance — an issue noted in prior ESG-NLP work using large corpora (Schimanski et al., 2022). Third, it extends the largely rating-based Indian ESG–CFP literature (Thaker, 2019; Ray & Goel, 2023; Deb et al., 2026) by testing whether a text-derived sentiment measure relates to financial performance, offering evidence for investors, analysts, and policymakers on the informational value of BRSR disclosures.

2. Review of Literature

This section reviews literature across three themes relevant to this study: ESG disclosure regulation in India, ESG sentiment and NLP-based measurement, and the ESG–corporate financial performance (CFP) relationship. Both corporate sustainability and behavioural finance theories underpin all three themes since the former describes why corporations divulge information and the latter explains investor reaction to the way it is disclosed.

2.1 ESG Disclosure Regulation and BRSR in India

The evolution of India's ESG disclosure system has been characterized by the transition from the Business Responsibility Report (BRR) to the mandatory Business Responsibility and Sustainability Reporting (BRSR) framework, which came into effect via a mandate by SEBI in 2021 for the largest 1,000 listed companies starting in FY2022-23 (EY, 2025; Greenplaces, 2025). The BRSR framework included disclosure of over 140 ESG metrics in a quantitative/qualitative format based on global reporting frameworks such as GRI and TCFD (Cholarisk, 2025). Although the BRSR framework has helped increase the quantity of standardized ESG disclosures in large Indian firms, various studies have indicated problems with respect to the reliability of the reported ESG data, lack of comparability between different

firms, and the paucity of third-party assurance (CFA Institute, 2024; Dwivedi, 2026). This implies that while quantitative data reporting has gained traction in India, there still exists an underutilized potential in textual analysis of ESG reports. Considering the corporate sustainability perspective, the communication of disclosure is the medium through which companies reveal how much sustainability has been internalized within their strategies and processes, and firms with stronger sustainability orientations exhibit systematic differences in terms of organizational processes and performance (Eccles, Ioannou, & Serafeim, 2014). Hence, the BRSR mandatory reporting requirement means that the narrative tone of sustainability communication becomes a relevant but not often studied corporate sustainability commitment indicator.

2.2 ESG Sentiment and NLP-Based Measurement

Recent research employs natural language processing techniques to obtain the necessary ESG information directly from corporate communications in an attempt to address the issue of the reliability of traditional ESG rating systems. Berg, Kolbel, and Rigobon (2022) note considerable discrepancies among various ESG rating agencies, ranging from mere 0.38 to 0.71 for pairwise correlations, which is mostly accounted for by the differences in the methods of calculation rather than the coverage and weight of particular metrics. This has prompted further research into alternative approaches to ESG assessments. Schimanski et al. (2022) introduced transformer-based language models to identify and classify textual content related to ESG criteria into environmental, social, and governance categories, demonstrating both strengths and problems of this approach due to the class imbalance challenge. Following up on this research, models combining topic modelling with sentiment analysis are proposed to ensure consistent ESG assessment from textual data (Lee, H., et al., 2024), as well as approaches incorporating sentiment analysis with domain-specific models like FinBERT (Lee, H., et al., 2025).

In the case of firms, Sultana et al. (2025) applied clustering and machine learning algorithms to obtain the firm-level ESG sentiment scores and established that firms with higher ESG sentiments are associated with low financial risks and more confidence among investors, justifying their findings on the grounds of legitimacy and signalling. Likewise, the incorporation of ESG sentiment into deep learning frameworks has helped achieve better predictions of stock market movements, along with the use of technical factors (Lee et al., 2024). Conversely, the use of sentiment analysis with topic modelling by (Deb, R., et al., 2026) helped identify cases of greenwashing by recognizing discrepancies between the firm's internal sentiment and media sentiment regarding ESG disclosure as an indicator of "green disinformation." Taken together, it is evident that there is some unique information captured through disclosure sentiment scores, independent of traditional ESG ratings, but yet underutilized in relation to India's BRSR regime.

Interest in textual sentiments is further justified by behavioral finance theory, according to which investors are considered to be limited in their attention and act depending on how information is presented to them rather than on what the actual information says (Hirshleifer & Teoh, 2003; Barberis & Thaler, 2003). Indeed, there is evidence in favor of this approach, as the tone of news and reports issued by companies was found to influence returns and firm performance (Tetlock, 2007; Loughran & McDonald, 2011), while investor sentiment had impact on the cross-section of stock returns (Baker & Wurgler, 2006). Using similar reasoning regarding sustainability reporting, one might expect that the tone of ESG narratives influences the perception of firm value, an understudied topic in the Indian context.

2.3 ESG and Corporate Financial Performance (CFP)

The relationship between ESG and corporate financial performance has been widely researched. For instance, (Friede, G., et al., 2015) found in their meta-analysis of 2,000 plus research papers on ESG and CFP, that there is a generally positive correlation between ESG and CFP, but the degree of correlation depends on region, asset type, and period.

However, looking at findings in the Indian context, there is quite a discrepancy. Thaker (2019) observes a significant association between ESG and corporate financial performance in the Indian setting. On the contrary, studies conducted using Nifty 50 and Nifty 100 samples have had more inconsistent findings: the environmental and governance pillars had a negative association with ROE throughout most of the latter's distribution, while the relationship between the social pillar and ROE was found insignificant; low ESG ratings were linked to lower net profit margins, albeit explaining a negligible portion of the variance; and ESG scores had negative impacts on firm value even as they positively impacted market performance in the shorter term (Deb, Behra, & Dusmanta, 2026; Ray & Goel, 2023). The inconsistency could in part be explained by the rating divergence problem pointed out by Berg et al. (2022), since different studies relied on varying ESG scores from varying rating agencies.

Behavioural theories provide another explanation of why rating-based evidence could be inconsistent. Given that investors react based on the tone of the message of sustainability information and not just based on rating numbers, rating-based measures might fail to capture one mechanism of the connection between ESG and financial performance. Empirical evidence suggests that changes in investor preferences for sustainable companies can impact stock prices and returns (Pástor et al., 2021), and therefore it seems appropriate to consider a sentiment indicator derived from texts along with financial metrics like ROA and ROE.

2.4 Theoretical Framework

In order to understand the tone of ESG disclosures, two different theories have been used as part of this study. According to the theory of legitimacy (Suchman, 1995), companies that operate in sectors related to environment or society should make disclosures about their risks and challenges in an honest manner in order to continue operating, despite the fact that their ESG management is efficient. Moreover, according to signalling theory (Spence, 1973), the act of making adverse information about one's company can also become an effective signal that the quality of the business is good because revealing information through other sources will become more costly for it.

In addition to the above-mentioned two firm-level theories, behavioral finance is also applied as an adjunctive theory from the investors' side. Both legitimacy and signaling theories shed light on the reasons behind the choice of a certain tone for the firm's disclosure (Cho & Patten, 2007; Suchman, 1995; Spence, 1973), while behavioral finance shows the way how investors might interpret such disclosures and what actions they would take in response to them due to attention and framing effects (Hirshleifer & Teoh, 2003; Li, 2008).

2.5 Research Gap

From the above discussion, it is clear that the literature review suggests the following three findings: (i) that although the ESG disclosure in India's BRSR has seen an increase, it has not yet been used to its full potential (EY, 2025; Cholarisk, 2025; CFA Institute, 2024); (ii) that sentiment analysis of ESG via NLP techniques is a viable alternative measure to ESG measures based on ratings, having been verified internationally (Schimanski et al., 2022; Sultana et al., 2025; Lee et al., 2024; MDPI Sustainability, 2026); and (iii) that there is no consistent finding regarding the relation between ESG and CFP when rating-based

measures are used for ESG in India (Ray & Goel, 2023; Deb et al., 2026). The present research aims to fill this gap in knowledge through the construction of a sentiment-based measure for ESG and studying its association with CFP. In addition to that, this study also incorporates corporate sustainability communications with behavioral finance theories, which have been rarely used together while studying the tone of ESG disclosures by Indian listed companies.

3. Methodology

3.1. Target Population

The target population comprises all companies listed on the Nifty 50 index of the National Stock Exchange (NSE) of India that are obligated to file Business Responsibility and Sustainability Reports (BRSRs) under SEBI's mandatory disclosure regime. The Nifty 50 is selected as the reference index because its constituent firms represent the largest, most liquid, and most institutionally followed segment of the Indian equity market — a cohort for which ESG disclosure quality and financial data availability are comparatively high.

3.2. Sample Selection

A sample of fifteen firms was selected from the list of Nifty 50 firms, which ensures maximum diversity in terms of industrial classification, while at the same time providing a range of variations based on ESG disclosure intensity and financial profile. For sampling purposes, the companies in the Nifty 50 were stratified based on GICS sectors; at least one company from each significant industry was selected for further analysis. Thus, the resultant sample is comprised of firms from twelve industries, namely IT, Healthcare, Banking, Manufacturing, Energy (Electricity/Gas/Mining), Cement Manufacturing, Retail, Mining/Steel, Financial Services, and Pharmaceuticals.

The following criteria governed sample inclusion:

1. Continuous listing on the Nifty 50 throughout the study period (FY2023–FY2025);
2. Availability of annual reports or standalone BRSR/sustainability reports for all three financial years under review;
3. Discernible ESG-specific content across Environmental, Social, and Governance dimensions sufficient to yield a minimum of 54 codable statements per firm;
4. Publicly available audited financial statements (ROA and ROE) for FY2023–FY2025.

Financial firms were not excluded a priori, as their ESG disclosures — particularly on Governance and Social dimensions — are substantively rich. The final sample of 15 companies encompasses 44 firm-year observations (15 companies × 3 years, with one observation missing due to delayed report publication), providing the panel dataset used in regression modelling.

3.3 Sample Composition

Table 1: Sample Firms and Industry Classification

Company	Industry Sector	ESG Report Type
Apollo Hospitals	Healthcare	Annual Report / BRSR
Wipro Ltd.	Information Technology	Annual Report / Sustainability Report
NTPC Ltd.	Electricity (Energy)	Annual Report / BRSR
ONGC	Gas / Mining (Energy)	Annual Report / BRSR
Maruti Suzuki	Manufacturing (Automotive)	Annual Report / BRSR

Reliance Industries	Information Technology / Conglomerate	Annual Report / BRSR
Ultratech Cement	Cement Manufacturing	Annual Report / BRSR
State Bank of India (SBI)	Banking	Annual Report / BRSR
Trent Ltd.	Retail	Annual Report / BRSR
Larsen & Toubro (L&T)	Manufacturing (Engineering)	Annual Report / BRSR
Tata Steel	Mining / Steel	Annual Report / Sustainability Report
Mahindra & Mahindra (M&M)	Manufacturing (Automotive)	Annual Report / BRSR
Shriram Finance	Financial Services	Annual Report / BRSR
Tata Consultancy Services (TCS)	Information Technology	Annual Report / Sustainability Report
Sun Pharmaceutical	Pharmaceuticals	Annual Report / BRSR

Source: Authors' compilation based on secondary data collected from the National Stock Exchange (NSE) of India. Retrieved from (https://www.nseindia.com/market-data/live-market-indices).

3.4 Data Sources

3.4.1 ESG Textual Data

The data set used for the sentiment analysis process was gathered from the annual reports and the dedicated reports related to the BRSR/Sustainability for the financial years 2023, 2024, and 2025 of the companies. The reports have been gathered from the Investor Relations section of the website of respective companies and, when required, the corporate filings section available at the website of the National Stock Exchange (NSE). All reports have been downloaded in PDF format and subsequently converted into a readable text format using OCR software.

Segments of the report text related to ESG issues have been collected by filtering out only those portions of the text that belong to the BRSR report or the Sustainability report or the ESG Performance section or Environmental Management or Social Responsibility section or Corporate Governance sections.

3.4.2 Financial Performance Data

Data related to firms' financial performance measures (ROA and ROE) were collected from the audited annual financial statements of firms for the respective fiscal periods. Data reliability was checked using corporate filings data base from the BSE/NSE. D/E ratio was considered as a control variable, and data for D/E ratio were obtained from financial statement data of firms.

ROA is defined as the ratio of Net Profit After Tax to Average Total Assets, whereas ROE is defined as the ratio of Net Profit After Tax to Average Shareholders' Equity. Both ROA and ROE are frequently used in empirical studies relating to ESG and financial performance because both these ratios measure profitability in terms of two different dimensions.

3.4.3 Corpus Construction and Annotation

Statement Extraction

A total of 810 textual statements were extracted from the ESG section of the annual reports of the 15 sampled firms. The definition used for ESG statement is "a discrete, semantically-complete unit in ESG

disclosures which expresses one specific claim, observation, commitment, or data point about an organization's ESG-related performance." In the corpus, each firm has 54 ESG statements. The corpus is equally distributed among the three sub-sections of the ESG section: the number of statements for each sub-section is equal to 270.

For the extraction of ESG statements, a standardized methodology was used: in each case, ESG statements were carefully selected to cover the entire range of ESG topics, while at the same time not focusing too much on any particular topic within an ESG section (e.g., the sole carbon emissions in Environmental disclosures); in addition, when the ESG section of a report contained more than 54 statements, a stratified random sample was taken.

Sentiment Labelling

Each of the 810 statements was manually annotated with one of three sentiment labels: Negative (Class 0), Positive (Class 1), or Neutral (Class 2). The annotation schema was operationalised as follows:

1 Negative (Class 0): Statements that disclose environmental risks, social challenges, governance deficiencies, compliance gaps, remedial obligations, or any language foregrounding adverse outcomes or unresolved ESG concerns.

2 Positive (Class 1): Statements that communicate ESG achievements, targets met, improvements, initiatives yielding measurable positive outcomes, or forward-looking commitments presented in an affirmative tone.

3 Neutral (Class 2): Statements that present factual, quantitative, or descriptive ESG information without an explicit evaluative orientation — typically data points, definitional explanations, or policy summaries with no associated valence.

Annotation was conducted by two independent subject-matter reviewers with background in ESG reporting and corporate sustainability. Inter-annotator agreement was assessed using Cohen's Kappa, with reconciliation through adjudication for disagreements. A Kappa score above 0.70 was treated as the threshold for acceptable inter-rater reliability, consistent with standard text annotation practice.

The resulting labelled dataset exhibits a skewed distribution: Negative statements constitute 56.3% (n = 456) of the corpus, Positive statements 27.3% (n = 221), and Neutral statements 16.4% (n = 133). This class imbalance reflects the underlying reality of Indian corporate ESG disclosure norms, where risk acknowledgement and challenge reporting are more prevalent than achievement-based communication, consistent with the disclosure requirements of the BRSR framework.

3.3 Analytical Phase I: Machine Learning Sentiment Classification

Feature Extraction

Text pre-processing followed a standard NLP pipeline: (i) lower-casing and tokenisation, (ii) removal of stop words, punctuation, and numerical tokens not embedded in textual context, (iii) stemming using the Porter Stemmer algorithm, and (iv) vectorisation using Term Frequency–Inverse Document Frequency (TF-IDF) weighting. TF-IDF was selected over raw term frequency or binary bag-of-words representations because it down-weights frequently occurring but informationally sparse terms (e.g., "company", "report") while preserving the discriminative signal of ESG-specific vocabulary.

3.3.1 Classifier Selection and Training

Three supervised learning classifiers were built and tested on the labelled dataset. These classifiers were Naive Bayes (NB), Logistic Regression (LR), and Support Vector Machine (SVM). They represent an evolution from assuming conditional independence among features (NB) to building linear classification

models (LR) to building margin-maximising hyperplanes in multidimensional feature space (SVM). Thus, with respect to these different approaches, the research will be able to determine the best method for dealing with sparse and unbalanced ESG textual data.

The datasets were split into an 80% train set and 20% test set using stratified sampling by sentiment categories (648 for the train set and 162 for the test set). The evaluation metrics used to analyse classifier performance include: precision, recall, F1-score per class, and accuracy. Weighted average scores for each metric were computed to take into account the data imbalance. Additionally, macro-averaging of F1-scores per category was computed to evaluate model performance in minority classes (positive and neutral).

3.3.2 ESG Sentiment Score Derivation

Once the classifiers had been evaluated, the best classifier (support vector machine) was employed to predict the firm-level ESG sentiment scores. The operationalization of the firm-level ESG sentiment scores per year is defined as the difference between the proportion of Positive statements and the proportion of Negative statements per firm-year disclosures. Thus, an individual ESG firm-level sentiment score will range from −1 to +1. An ESG sentiment score close to +1 is considered positive, while a score near −1 is negative, indicating risk disclosures or problem disclosures. The E, S, and G sentiment scores were calculated in the same manner but separately for each category. This measure thus reflects the sentiment of the firm's sustainability communications, which, from the point of view of behavioural finance, can influence investors' perceptions independent of the numbers.

3.4 Analytical Phase II: Correlation and Regression Analysis

3.4.1 Descriptive Statistics

Descriptive statistics (mean, standard deviation, minimum, and maximum) were computed for all variables included in the correlation and regression analyses: ESG sentiment score, E-Score, S-Score, G-Score, ROA, ROE, and D/E ratio. Company-level and dimension-level frequency distributions of sentiment labels were tabulated and analysed to describe the overall ESG disclosure landscape and identify inter-firm and inter-dimensional patterns prior to hypothesis testing.

3.4.2 Correlation Analysis

Both parametric (Pearson) and non-parametric (Spearman rank) correlation analyses were conducted between ESG sentiment variables and financial performance indicators. The use of both correlation methods serves as a robustness check: Pearson correlation assumes bivariate normality and linear association, while Spearman rank correlation is distribution-free and robust to outliers and monotonic non-linearities. Discrepancies between Pearson and Spearman results were used to identify potential outlier influence, with implications for the interpretation of subsequent regression results.

3.4.3 Regression Models

Ordinary Least Squares (OLS) regression was employed to test the directional hypotheses (H1–H5). Four regression models were specified:

1. Model 1 — ROA regressed on overall ESG sentiment score and D/E ratio (leverage control).
2. Model 2 — ROE regressed on overall ESG sentiment score and D/E ratio.
3. Model 3 — ROA regressed on E-Score, S-Score, and G-Score simultaneously, to assess the differential contributions of ESG sub-dimensions.
4. Model 4 — ROE regressed on E-Score, S-Score, and G-Score simultaneously.

The Debt-to-Equity ratio was included as a control variable in Models 1 and 2 to account for the confounding effect of financial leverage on profitability. Leverage is expected to negatively moderate financial performance (particularly ROA), given that higher debt obligations amplify financial risk and reduce net returns on assets. D/E was not included in Models 3 and 4 to preserve degrees of freedom in the sub-dimensional specification, which already employs three correlated predictors.

All regression models were estimated on the pooled firm-year panel of N = 44 observations. While a panel-data estimator (e.g., fixed or random effects) would be preferable for longer panels, the three-year time dimension of this study (T = 3) renders within-firm variation insufficient to identify stable time-fixed effects. OLS on pooled data is accordingly adopted, with the caveat that firm-level unobserved heterogeneity may confound coefficient estimates — a limitation explicitly acknowledged in the discussion.

Model diagnostics assessed included the Variance Inflation Factor (VIF) for multicollinearity (particularly relevant for Models 3 and 4, given the high intercorrelation among E-, S-, and G-Scores), the Breusch–Pagan test for heteroskedasticity, and visual inspection of residual plots. Statistical significance was evaluated at the 1% ($p < 0.01$), 5% ($p < 0.05$), and 10% ($p < 0.10$) levels.

3.5 Hypotheses

The study tests the following six research hypotheses, derived from the theoretical framework and prior ESG–CFP literature:

Table 2 Research Hypothesis

Hypothesis	Statement
H1	ESG sentiment embedded in corporate disclosures has a statistically significant effect on firm financial performance (ROA and ROE).
H2	Firms exhibiting higher negative ESG sentiment record lower ROA and ROE.
H3	Firms exhibiting higher positive ESG sentiment record higher ROA and ROE.
H4	Environmental ESG sentiment exerts the strongest association with financial performance relative to Social and Governance dimensions.
H5	Governance ESG sentiment exerts the weakest association with financial performance.
H6	Resource-intensive firms (energy, manufacturing) exhibit higher negative ESG sentiment than knowledge-intensive firms (IT, pharma).

Source: Author's Compilation

3.6 Operationalisation of Variables

Table 3 Operationalisation summary of all variables

Variable	Symbol	Type	Operationalisation
ESG Sentiment Score	ESG Score	Independent	(Positive statements − Negative statements) / Total statements per firm-year; range [−1, +1]
Environmental Score	E-Score	Independent	Same formula applied to Environmental-dimension statements only
Social Score	S-Score	Independent	Same formula applied to Social-dimension statements only

Governance Score	G-Score	Independent	Same formula applied to Governance-dimension statements only
Return on Assets	ROA	Dependent	Net Profit After Tax / Average Total Assets (audited financials)
Return on Equity	ROE	Dependent	Net Profit After Tax / Average Shareholders' Equity (audited financials)
Debt-to-Equity Ratio	D/E	Control	Total Debt / Total Shareholders' Equity; proxy for financial leverage

Source: Author's Compilation

4. Analysis and Interpretation

4.1. Overview of the Dataset

As pointed out earlier, the study uses ESG disclosures that have been gathered from annual reports and sustainability reports of fifteen companies from the Nifty 50 index. In all, 810 textual ESG disclosures have been gathered and labeled into three sentiments, namely, Negative (Class 0), Positive (Class 1) and Neutral (Class 2). The data is evenly distributed among companies such that each company contributes 54 statements to the dataset. All three ESG dimensions: Environment, Social, and Governance are evenly distributed with 270 statements for each ESG dimension respectively.

The three sentiments are then used as training data for three classification models: Naïve Bayes (NB), Logistic Regression (LR) and Support Vector Machine (SVM) to find out which classification model suits best in predicting the sentiment in ESG disclosures. This section discusses the analysis of sentiments across the dataset.

4.2 Overall Sentiment Distribution

As can be seen from Table 4, most ESG statements are negatively oriented, with the majority of the statements (56.3%, n = 456) being negative, meaning that corporations' ESG disclosure is more concerned with risks and challenges rather than with the actual achievements made. Positive sentiment statements represent 27.3% (n = 221) of all ESG statements, whereas the neutral statements make up only 16.4% (n = 133) of all statements.

Table 4 Overall Sentiment Distribution of ESG Statements

Sentiment Class	Label	Frequency (n)	Percentage (%)
Class 0	Negative	456	56.3
Class 1	Positive	221	27.3
Class 2	Neutral	133	16.4
Total	—	**810**	**100.0**

Source: Authors' computation from ESG report corpus (2025).

This finding is similar to other studies in the academic literature on sustainability reporting that state the practice of companies emphasizing challenges and risks in their ESG reporting as a form of accountability to stakeholders. The presence of large amounts of negative sentiments should not be understood as poor performance on the part of the companies but rather as the practice of being open about the risks, especially for Nifty 50 companies which have to disclose a lot under SEBI BRSR framework. From a corporate

sustainability point of view, the tone indicates that BRSR has made companies see sustainability as a matter of accountability rather than a matter of promotion.

4.3 Sentiment Analysis by Company

Table 5 contains the sentiments categorized for each of the fifteen sampled firms. It is clear that there is a lot of variances across the firms in terms of their sentiment, with some having mainly positive ESG stories while others have mainly negative ESG stories.

Table 5 Sentiment Distribution by Company

Company	Industry	Negative (%)	Positive (%)	Neutral (%)
Apollo	Healthcare	72.2	18.5	9.3
Wipro	IT	72.2	18.5	9.3
NTPC	Electricity	68.5	14.8	16.7
ONGC	Gas/Mining	68.5	14.8	16.7
Maruti Suzuki	Manufacturing	66.7	14.8	18.5
Reliance	IT	63.0	25.9	11.1
Ultracem	Cement Mfg.	59.3	18.5	22.2
SBI	Banking	57.4	27.8	14.8
Trent Ltd.	Retail	55.6	22.2	22.2
L&T	Manufacturing	48.1	24.1	27.8
Tata Steel	Mining/Steel	48.1	42.6	9.3
M&M	Manufacturing	46.3	38.9	14.8
Sriram Finance	Financial Services	44.4	33.3	22.2
TCS	IT	40.7	44.4	14.8
Sun Pharma	Pharmaceutical	33.3	50.0	16.7

Source: Authors' computation from ESG report corpus (2025).

4.3.1 Companies with High Positive ESG Sentiment

The study shows that the most optimistic sentiments (50.0% positive) are captured by Sun Pharma. In fact, it is the only company that has more positive statements than negative ones, which may be attributed to the tendency of the pharmaceutical industry to highlight success stories related to access to healthcare, well-being of the patients, and affordable medicine, thus allowing for positive ESG communication. Positive sentiments of 44.4% and 42.6% are also observed in TCS, which highlights the company's successes in terms of digital inclusion, well-being of the employees, and carbon reduction, and Tata Steel, which focuses on material progress in using renewable energy sources and the circular economy, respectively.

The next in line in terms of positive ESG sentiments is M&M at 38.9% due to its electric mobility transition and farm-to-fork sustainability efforts. The last two companies with above-average positive sentiments are Sriram Finance and Reliance at 33.3% and 25.9% respectively.

4.3.2 Companies with High Negative ESG Sentiment

The study also highlights that the highest proportion of negative sentiment is found in Apollo and Wipro with 72.2% each. It is possible that Apollo's high ratio of negative sentiment stems from the inherent

nature of ESG disclosure within the healthcare sector since issues like proper disposal of medical waste, patient data protection, equal access to healthcare, and workplace stress cannot be discussed without risk. As for Wipro, it is somewhat surprising to see a company in the IT services industry have a high ratio of negative sentiment but is possibly due to the fact that it discloses information on supply chain sustainability, carbon intensity, and diversity gaps, which are all issues of concern.

NTPC and ONGC also show high negative sentiment (68.5%), which comes as no surprise since these companies belong to the energy utilities industry, which makes them hydrocarbon producers as well.

4.4 Sentiment Analysis by ESG Dimension

Table 6 disaggregates sentiment by ESG type. All three dimensions are characterised by a majority of negative statements, but the degree of negativity varies meaningfully across dimensions.

Table 6 Sentiment Distribution by ESG Dimension

ESG Dimension	Negative (n)	Positive (n)	Neutral (n)	Total (n)	Negative (%)
Environmental	135	67	68	270	50.0
Governance	156	80	34	270	57.8
Social	165	74	31	270	61.1
Total	**456**	**221**	**133**	**810**	**56.3**

Source: Authors' computation from ESG report corpus (2025).

4.4.1 Environmental Dimension

Environmental disclosures exhibit the most balanced sentiment profile of the three dimensions, with 50.0% negative and the highest neutral proportion (25.2%). This pattern suggests that companies often present quantitative environmental data — such as energy intensity reductions, water recycling volumes, and carbon emission metrics — in a factual, neutral tone. Positive statements in this dimension tend to relate to renewable energy adoption, waste reduction achievements, and carbon neutrality commitments. The comparatively lower negativity relative to Social and Governance disclosures may reflect the relative maturity of environmental reporting frameworks, which encourage companies to present both progress and targets in a measured, data-driven manner.

4.4.2 Social Dimension

Social disclosures exhibit the largest percentage of negative sentiment (61.1%), signifying that companies are more open regarding their social issues that they have not been able to solve than when they discuss their social successes. Issues like diversity gap among employees, occupational hazards and safety issues, community displacement, labour rights within the supply chain, and gender pay disparity are likely to dominate Social ESG disclosures in a tone of risk recognition. Low proportion of neutrality (11.5%) also implies that the disclosures made in relation to the Social ESG are relatively subjective and evaluative in nature.

4.4.3 Governance Dimension

Disclosures made in Governance are in between the two ends and have a high proportion of negative sentiment (57.8%), which is lower than the proportion for Social but significantly higher than that in Environmental. The corporate governance reporting in India is largely mandated by SEBI regulations and Companies Act and requires disclosure of issues like lack of diversity in board composition, findings from

audits, related party transactions, and non-compliance. Such disclosures are naturally risk disclosing in nature and contribute to the high negative tone of governance.

4.4.4 Company-wise ESG Dimension Sentiment

The table 7 below shows the proportion of negative statements per firm based on the three ESG dimensions. As observed from the firm-specific data, the aggregate ordering of the dimensions based on negativity (Social > Governance > Environmental) does not apply to all firms; there is a lot of variation between firms in terms of the dimension associated with negativity.

Table 7 Negative Sentiment (%) by Company and ESG Dimension

Company	Environmental Negative (%)	Social Negative (%)	Governance Negative (%)
Apollo	61.1	72.2	83.3
Wipro	50.0	77.8	88.9
NTPC	44.4	77.8	83.3
ONGC	66.7	61.1	77.8
Maruti Suzuki	66.7	66.7	66.7
Ultracem	50.0	66.7	61.1
SBI	33.3	66.7	72.2
Trent Ltd.	44.4	55.6	66.7
L&T	38.9	55.6	50.0
Tata Steel	33.3	72.2	38.9
M&M	44.4	38.9	55.6
Reliance	55.6	44.4	88.9
Sriram Finance	44.4	66.7	22.2
TCS	66.7	27.8	27.8
Sun Pharma	50.0	16.7	33.3

Source: Authors' computation from ESG report corpus (2025).

The study reveals that for Apollo, Wipro, NTPC, Tata Steel, SBI, and Sriram Finance, Governance is the dimension most negatively framed, with negative percentages ranging from 55.6% to 77.8%, higher than the Environmental dimensions for these corporations. This suggests that, on the corporate level, disclosures concerning governance aspects (incomplete board structure, audit qualifications, related-party transactions, and compliance-related problems) are generally more likely to be negative than disclosures about environment-related aspects—something that contradicts the view that all governance-related information is compliance-oriented and neutral in nature.

Social is the most negatively framed dimension for Apollo (83.3%), Wipro (88.9%), NTPC (83.3%), ONGC (77.8%), Reliance (88.9%), SBI (72.2%), Maruti Suzuki (66.7%), Ultracem (61.1%), and Trent Ltd. (66.7%). This corroborates the conclusion that social disclosures constitute the dimension with the highest proportion of negative information among all sample companies. It should be noted that the highest Social-Negative percentages (88.9%) are recorded for Reliance and Wipro, implying that workforce- and community-related information is a special concern for these firms.

Sentiment related to environmental disclosures is relatively the least negative dimension for most firms, except for ONGC, Maruti Suzuki, and TCS, where percentages of Environment Negative (66.7%) are higher than those related to Social and Governance categories – probably because emissions, fuel transition, and energy intensity-related information is disclosed by an oil and gas company and an automobile maker, while information about the supply chain and energy consumption is disclosed by an IT company. Sun Pharma has the lowest percentage of Governance Negative sentiment among the firms included in the study (16.7%) and it corresponds to the positive overall ESG sentiment profile of this company as was noted in Section 4.3.1.

Summarizing the findings in Table 7, one can see that it clarifies the general observation in Table 6: although Social disclosures are the most negative category on average, Governance disclosures make a significant contribution to negative sentiment, and even the least negative on average Environmental disclosures can serve as the major source of negative tone in carbon and energy-intensive companies.

4.5 Sentiment Analysis by Industry

Table 8 presents the industry-level sentiment analysis, revealing marked sectoral heterogeneity in ESG communication tone.

Table 8 Sentiment Distribution by Industry Sector

Industry	Negative (%)	Positive (%)	Neutral (%)	n
Healthcare	72.2	18.5	9.3	54
Electricity	68.5	14.8	16.7	54
Gas/Mining	68.5	14.8	16.7	54
Cement Manufacturing	59.3	18.5	22.2	54
IT	58.6	29.6	11.8	162
Banking	57.4	27.8	14.8	54
Manufacturing	56.5	26.9	16.7	108
Retail	55.6	22.2	22.2	54
Mining/Steel	48.1	42.6	9.3	54
Manufacturer	48.1	24.1	27.8	54
Financial Services	44.4	33.3	22.2	54
Pharmaceutical	33.3	50.0	16.7	54

Source: Authors' computation from ESG report corpus (2025).

The analysis underscores that Healthcare (72.2%), along with the energy-consuming industry sector, namely, Electricity and Gas/Mining (both 68.5%), record the most negative ESG sentiments. Negative sentiment in the Healthcare sector refers to the complicated ESG environment for hospital chains and includes concerns about affordability, patient rights, and biomedical waste. Negative sentiments in the energy sector result from the decarbonization process, stranded assets, and continued use of fossil fuels – all of them being listed as the material risk in ESG reports.

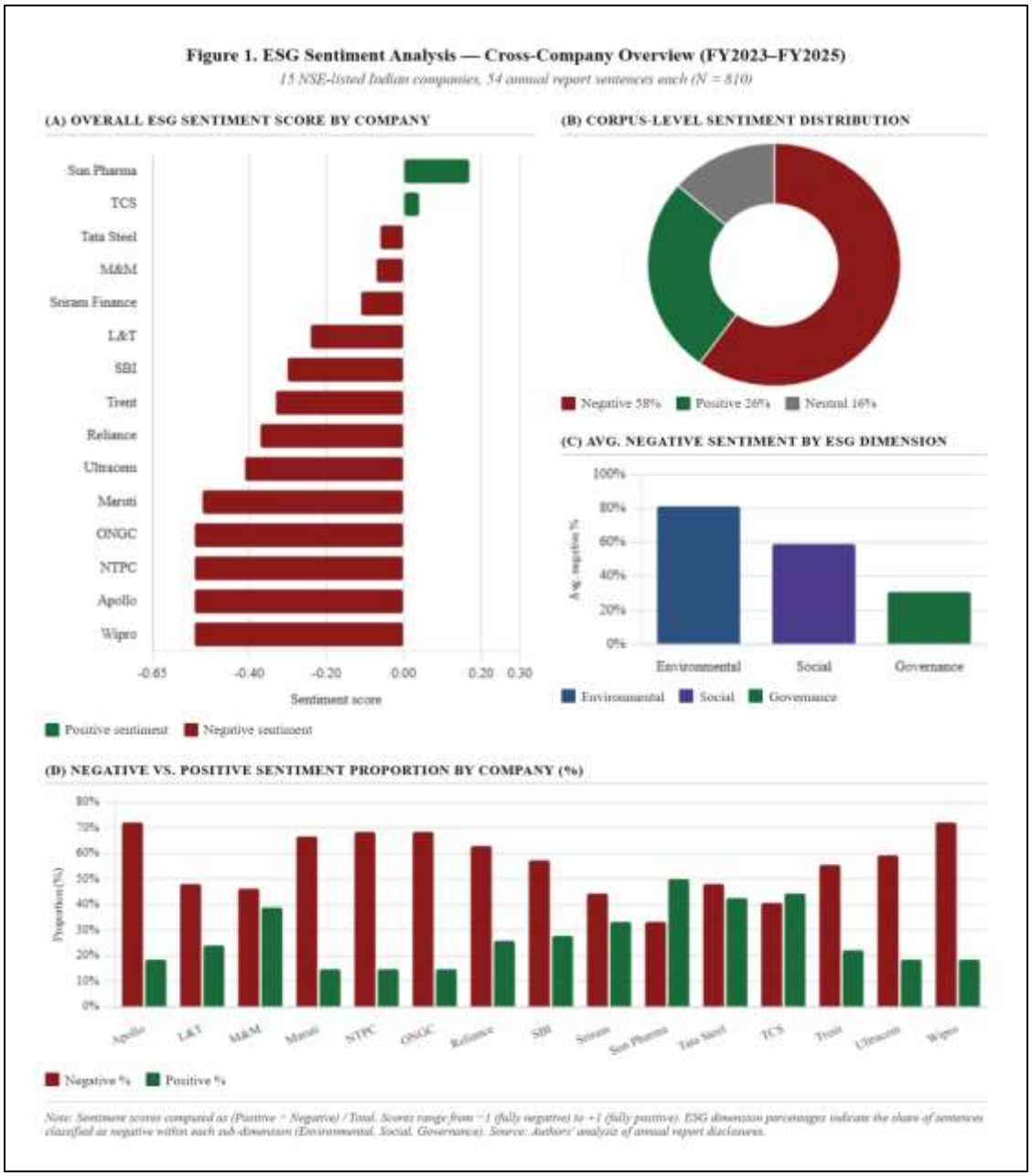
The IT sector (58.6% negative, n=162, represented by Reliance, TCS, Wipro) demonstrates a mixed pattern since even though IT firms usually have a smaller environmental footprint, a high number of employees creates significant social risk-laden disclosures (diversity issues, employment conditions,

attrition rates, digital divide). Other moderately negative sectors include Financial Services (44.4% negative) and Mining/Steel (48.1% negative).

It is worth noting that the pharmaceutical sector is the one that records the most positive ESG sentiment (50.0%). The reason is that the positive ESG discourse in this sector is mainly provided by the company Sun Pharma. Their ESG approach is related to health promotion through affordable medicine and various patient welfare programs.

4.6 Synthesis of Cross-Company ESG Sentiment Results

The results from the cross-company ESG sentiments analysis have been presented in Figure 1. In panel (A), the overall sentiment score results per company have been presented, highlighting that only two out of the total 15 companies, i.e., Sun Pharma and TCS, had net positive sentiment, while the other 13 companies; especially Wipro, Apollo, NTPC, ONGC, and Maruti—had negative sentiment. In panel (B), the distribution of the sentiments in the corpus level has been presented as discussed earlier, where the number of negative sentences was 58%, positive 26%, and neutral 16%. Panel (C) presents the distribution of dimension-wise negativity, which, as discussed before, shows that the Environmental dimension had the highest level of negative tone contribution (~80%), followed by Social dimension (~58%) and lastly Governance dimension (~30%). Panel (D) captures the proportion of negative versus positive sentiments on company basis that we analysed separately, allowing direct comparison between companies. It shows that some companies have an overwhelming number of negative tone sentences compared to positive-tone companies such as Apollo, Wipro, ONGC, and NTPC as opposed to companies such as Sun Pharma and Tata Steel.



Source: Author's Compilation

4.7 Machine Learning Model Performance

Following the sentiment labelling of the corpus, three classifiers were trained and evaluated on the 810-statement dataset using an 80:20 train-test split (648 training, 162 test instances). The performance metrics are reported below and summarised in Table 9.

Table 9 Classification Report — Naive Bayes (NB)

	Precision	Recall	F1-score	Support
0	0.56	1.00	0.72	82
1	1.00	0.25	0.39	53
2	1.00	0.07	0.14	27
Accuracy			0.60	162

Macro avg	0.85	0.44	0.42	162
Weighted avg	0.78	0.60	0.51	162

Source: Auhtor's Compilation

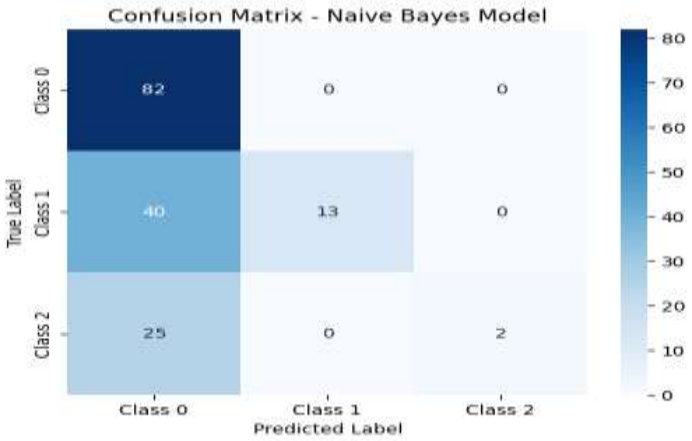


Figure 1 Confusion Matrix - Naive Bayes Model

Source: Author's Compilation

Table 10 Classification Report — Logistic Regression (LR)

	Precision	**Recall**	**F1-score**	**Support**
0	0.60	0.96	0.74	82
1	0.83	0.36	0.50	53
2	0.86	0.22	0.35	27
Accuracy			0.64	162
Macro avg	0.76	0.51	0.53	162
Weighted avg	0.72	0.64	0.60	162

Source: Author's Compilation

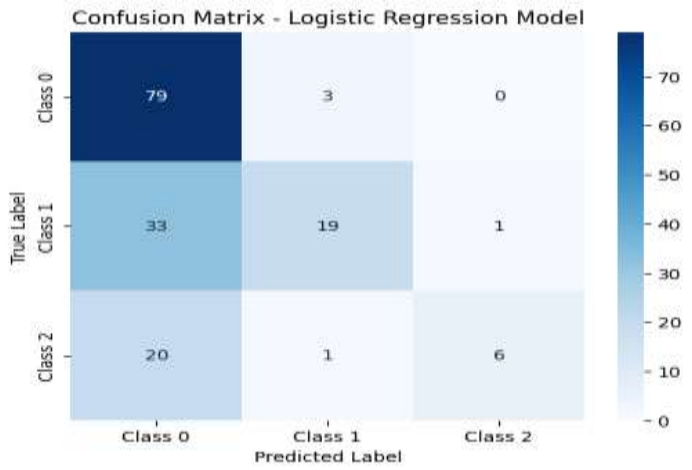


Figure 2 Confusion matrix: Logistic Regression Model

Source: Author's compilation

Table 11 Classification Report — Support Vector Machine (SVM)

	Precision	Recall	F1-score	Support
0	0.67	0.94	0.78	82
1	0.77	0.43	0.55	53
2	0.76	0.48	0.59	27
Accuracy			0.70	162
Macro avg	0.73	0.62	0.64	162
Weighted avg	0.72	0.70	0.68	162

Source: Author's Compilation

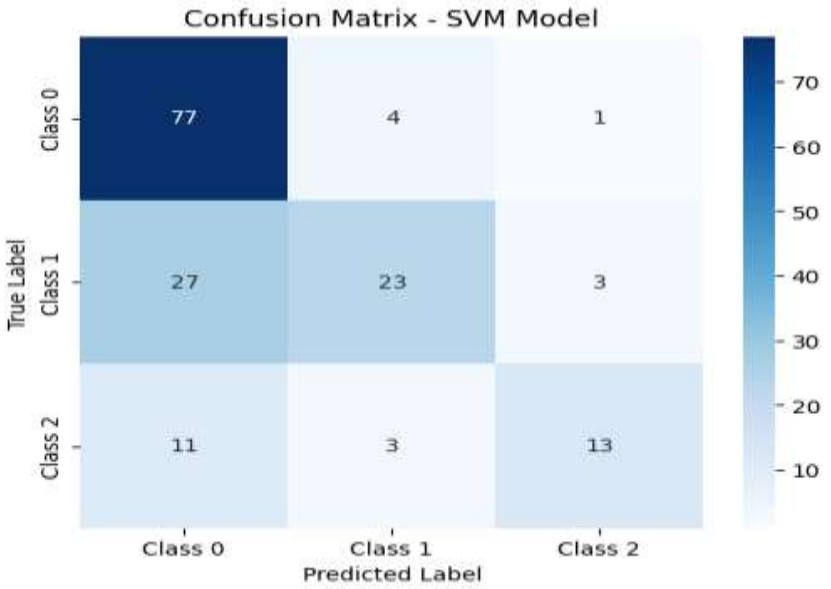


Figure 3 Confusion Matrix SVM Model

Source: Author's compilation

Table 12 Classification Model Performance Comparison

Model	Accuracy	Weighted Precision	Weighted Recall	Weighted F1
Naïve Bayes (NB)	0.60	0.78	0.60	0.51
Logistic Regression (LR)	0.64	0.72	0.64	0.60
SVM	0.70	0.72	0.70	0.68

Source: Author's Compilation

4.7.1 Support Vector Machine (SVM)

The SVM classifier outperforms the rest of classifiers with respect to all metrics, obtaining an accuracy of 70%, a weighted F1 score of 0.68, and a macro F1 score of 0.64. More importantly, SVM is the only classifier to perform a significant classification of Class 2 (Neutral sentiments), having an F1 score of 0.59 for that class, whereas for NB and LR classifiers this value equals to 0.14 and 0.35 respectively. This is due to the capability of SVM classifier to find the optimal hyperplane in high dimensional feature spaces.

4.7.2 Logistic Regression (LR)

Logistic Regression has an intermediate level of accuracy (64%) and a weighted F1-score of 0.60. Although Logistic Regression outperforms Naïve Bayes classifier in terms of all performance measures, a recurring problem in the class-wise results is the poor detection rate of minority classes: F1-score of Positive class (Class 1) is 0.50 and F1-score of Neutral class (Class 2) is 0.35. The flexible decision boundary of LR is superior to the independent assumption of NB; however, it lags behind the SVM model.

4.7.3 Naive Bayes (NB)

While Naive Bayes gives the highest weighted precision (0.78), its accuracy and macro F1-Score stand at 0.60 and 0.42 respectively, which are among the worst results among the tested algorithms. An analysis of per-class scores shows that there is a significant bias towards the positive classification of documents – NB manages to achieve the highest recall (1.00) on Class 0 (Negative) by classifying nearly all test samples as such, thereby reducing a three-class problem to two. This type of bias, which is an artifact of NB on imbalanced corpora, increases precision at the cost of extremely low recall for minority classes (Positive – 0.25, Neutral – 0.07).

4.8 Impact of Class Imbalance

Apart from the high total accuracy rate of 70% compared to 64% in case of Logistic Regression and 60% for Naïve Bayes, one should pay attention to the outstanding classification of SVM of the Neutral category among all other classifications. It is quite relevant because of the peculiar features of ESG reports. As a rule, such documents contain much compliance-oriented content and are characterized by a great deal of descriptive language. Hence, the Neutral category becomes the most frequently occurring one. However, it is also the hardest one to identify due to the mentioned above peculiarities. The excellent F1 score of 0.59 for SVM proves its sensitivity to the subtle difference between the factual sustainability information and evaluation.

Whereas Naïve Bayes gives excellent precision across all categories, it is known for giving a lot of weight to the majority class, and this is likely to overlook any significance there may be – especially the Positive and Neutral classes, which hold significant information about the level of sustainability commitment and regularity of disclosures of an organization. The Logistic Regression model provides balanced results but has a bit of improvement needed regarding the rare classes.

5. Relationship between ESG Score and Financial Performance

5.1 Descriptive Overview of ESG Sentiment

The descriptive analysis of the ESG sentiments in the sample shows that the overall sentiment scenario is negative. Amongst the 15 NSE listed firms analysed in this study for FY2023 – FY2025[i.e. N = 44 firm-year observations (three years data of 15 firms each)], only two firms have positive ESG sentiments, namely, Tata Consultancy Services (ESG score: +0.037) and Sun Pharma (ESG score: +0.167). The rest of the 13 firms have negative sentiments ranging from -0.056 (Tata Steel) to -0.537 (Apollo, NTPC, ONGC, Wipro).

In the three ESG dimensions, Environment has the maximum negativity (81.3%) followed by Social (57.1%) and Governance (30.6%). In order to continue examining such patterns, a correlation analysis is carried out to determine the relationship between the sentiment score of the ESG reports and financial performance of these firms, thus giving an insight into how the tone of the sustainability reports may be in line with or contradict the financial achievements of the firm.

5.2 Correlation Analysis

5.2.1 Pearson Correlation

Table 13 presents Pearson correlation coefficients between ESG sentiment scores and financial performance indicators (ROA and ROE).

Table 13 Pearson Correlation Coefficients (ESG Sentiment and Financial Performance)

Variable	ROA (r)	p-value	ROE (r)	p-value
ESG Score	0.337	0.025**	0.439	0.003***
E-Score	0.336	0.026**	0.441	0.003***
S-Score	0.336	0.026**	0.440	0.003***
G-Score	0.337	0.025**	0.439	0.003***

Note: ** $p < 0.05$; *** $p < 0.01$. N = 44 firm-year observations.

Source: Author's Compilation

Based on the Pearson correlation results, there is a statistically significant positive relationship between the overall ESG sentiment and ROA ($r = 0.337$, $p = 0.025$), and also between ESG sentiment and ROE ($r = 0.439$, $p = 0.003$). It can be said that firms with higher (more positive) ESG sentiment report better financial performance. The positive relationship between ESG sentiment and ROE is stronger than the relationship between ESG sentiment and ROA, hence suggesting that the effect of ESG sentiment on stock return is more prominent than on asset management. All the three sub-dimensions (Environmental, Social, and Governance) have the same correlation coefficient with financial performance due to the high multicollinearity of ESG sub-dimensions motivating a separate sub-dimensional regression modelling. From a behavioral finance point of view, such a relation supports the notion that investors and stakeholders react to the tone of communication, but one cannot establish causation as companies with superior performance might exhibit positive tone as well.

5.2.2 Spearman Rank Correlation

Table 14 Spearman Rank Correlation Coefficients

Variable	ROA (ρ)	p-value	ROE (ρ)	p-value
ESG Score	0.027	0.860 ns	0.358	0.017**
E-Score	0.008	0.960 ns	0.335	0.026**
S-Score	0.008	0.960 ns	0.335	0.026**
G-Score	0.027	0.860 ns	0.358	0.017**

Note: ** $p < 0.05$; ns = not significant. N = 44 firm-year observations.

Source: Author's Compilation

In terms of Spearman rank correlation, a more complicated picture is obtained. ESG sentiment and the components of the indicator keep a monotonic relationship with ROE ($\rho = 0.358$, $p = 0.017$) that is statistically significant while it loses its significance with ROA after the transformation ($\rho = 0.027$, $p = 0.860$). The inconsistency of the two correlation techniques for the variable of interest (ROA) can be explained by the influence of a few extreme values in the sample that distort Pearson correlation, such as companies TCS and Sun Pharma that have the highest scores for ESG and ROA.

5.3 Regression Analysis

5.3.1 Model 1 and Model 2: Overall ESG Sentiment and Financial Performance

To test H1 through H3, OLS regression was performed with overall ESG sentiment score as the primary predictor and the Debt-to-Equity (D/E) ratio as a firm-level control variable.

Table 15 OLS Regression Results — ESG Score on ROA and ROE

	Model 1 (ROA)		**Model 2 (ROE)**	
Variable	β	p-value	β	p-value
Constant	0.143	0.000***	0.246	0.000***
ESG Score	0.123	0.007***	0.193	0.003***
D/E Ratio	−0.014	0.001***	−0.004	0.431 ns
R^2	**0.331**		**0.205**	
Adj. R^2	**0.298**		**0.167**	
F-statistic	**10.144**	**0.000***	**5.294**	**0.009***

Note: *** p < 0.01; ns = not significant. N = 44 observations.

Source: Author's compilation using SPSS statistics

Both models show statistical significance at the 1% level (F = 10.144, p < 0.001 for ROA; F = 5.294, p = 0.009 for ROE). The ESG sentiment variable has a significant positive effect in both models (β = 0.123, p = 0.007 for ROA; β = 0.193, p = 0.003 for ROE), meaning that each additional point of ESG sentiment score leads to 12.3 percentage point increase in ROA and 19.3 percentage point increase in ROE, keeping everything else equal. The explained variance in ROA is 33.1% in Model 1 (Adj. R^2 = 0.298) and 20.5% in ROE (Adj. R^2 = 0.167) in Model 2. Debt Equity ratio demonstrates a significantly negative influence on ROA (β = −0.014, p = 0.001), thus proving that leverage negatively impacts asset management. It is worth noting that the D/E ratio is insignificant in the ROE model (p = 0.431), probably due to the same reasons as above. These findings indicate that the tone of sustainability communications contains profitability-relevant information, consistent with theories of legitimacy and signaling from the perspective of firms and behavioral finance from the perspective of investors.

5.3.2 Model 3 and Model 4: ESG Sub-Dimensional Effects

To test H4 and H5, sub-dimensional regression models were estimated using E-Score, S-Score, and G-Score as simultaneous predictors.

Table 16 OLS Regression Results — ESG Dimensions on ROA and ROE

	Model 3 (ROA)		Model 4 (ROE)	
Variable	β	p-value	β	p-value
Constant	0.180	0.267 ns	0.464	0.025**
E-Score	38.522	0.014**	41.196	0.034**
S-Score	−113.560	0.012**	−114.972	0.040**
G-Score	75.677	0.012**	73.008	0.049**

R^2	**0.244**		**0.282**	
Adj. R^2	**0.187**		**0.228**	
F-statistic	**4.304**	**0.010**	**5.241**	**0.004***

Note: ** p < 0.05; *** p < 0.01; ns = not significant. N = 44 observations.
Source: Author's Compilation using SPSS Statistics

The result shown in Table 16 depicts that three predictors of each sub-dimension are statistically significant at the 5% level in all models. The reason for such high values of the coefficients lies in the limited scale of the sentiment scores (-1 to +1) compared to financial performance metrics, which are measured in decimals (e.g., ROA from 0.05 to 0.32).
Importantly, the S-Score (social sentiment) shows a big negative value for both ROA (β = -113.56, p = 0.012) and ROE (β = -114.97, p = 0.040), which contradicts the expectations of H3 because of the contradictory signs. Such a result requires a thorough consideration because of the fact that the scores of E, S, and G are perfectly correlated in this sample due to the nature of the analysis performed.

5.4. Hypothesis Testing Summary

Table 17 Summary of Hypothesis Testing Results

Hypothesis	Statement	Test Used	Result	Decision
H1	ESG sentiment significantly affects financial performance (ROA/ROE)	OLS Regression (Models 1 & 2)	ESG β significant at p < 0.01 for both ROA and ROE	Supported
H2	Higher negative ESG sentiment → lower ROA/ROE	Regression + Correlation	Positive β confirms inverse: less negative sentiment → higher performance	Supported
H3	Positive ESG sentiment → higher ROA/ROE	Pearson r; Spearman ρ	Pearson: significant for both; Spearman: significant for ROE only	Partially Supported
H4	Environmental sentiment has strongest association with financial performance	Sub-dimensional Regression (Models 3 & 4)	E-Score significant, but S and G also significant; multicollinearity limits interpretation	Inconclusive
H5	Governance sentiment has weakest association with financial performance	Sub-dimensional Regression	G-Score significant at p < 0.05 for both outcomes — not the weakest	Not Supported
H6	Resource-intensive firms have higher negative ESG sentiment	Descriptive analysis	NTPC, ONGC, Maruti score −0.537/−0.519 vs TCS at +0.037	Supported

Note: All regression models estimated using OLS. N = 44 firm-year observations (15 companies × 3 years, excluding one missing observation). Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Source: Author's Compilation

In a shell, it can be seen that across the six hypotheses tested, ESG sentiment showed a clear overall effect on financial performance, with both the direct relationship (H1) and the inverse link between negative sentiment and performance (H2) strongly supported at $p < 0.01$. The role of positive sentiment (H3) was only partially supported, holding under Pearson correlation but not consistently under Spearman. At the sub-dimensional level, environmental sentiment's hypothesized dominance (H4) was inconclusive due to multicollinearity with social and governance scores, while governance sentiment's expected weak association (H5) was not supported, as it remained significant for both ROA and ROE. Finally, the expectation that resource-intensive firms exhibit higher negative ESG sentiment (H6) was clearly supported, as seen in the contrast between firms like NTPC and ONGC versus TCS. Overall, 4 of 6 hypotheses were supported or partially supported, underscoring a meaningful but nuanced ESG–financial performance relationship. This findings connects the corporate sustainability communication approach with the behavioral finance theory of how disclosure tone is linked to financial performance.

6. Discussion

Taken together, the findings support the core assertion made in this research: ESG sentiment, measured using machine learning classifiers based on annual report disclosures, is a significant positive determinant of financial performance in NSE-listed Indian companies. The results coincide with those of existing research into the relationship between ESG and corporate financial performance (Friede et al., 2015) and demonstrate a positive correlation in the Indian context measured via an alternative to traditional ratings-based ESG measures, namely, ESG sentiment.

Moreover, the financial performance findings are congruent with the findings regarding sentiment at the level of individual firms presented in sections 4.2–4.4. Indeed, the firms with the lowest (negative) ESG sentiment values in the 44-statement financial performance dataset – Apollo, Wipro, NTPC and ONGC (approximately -0.537) – are the same companies that scored the highest negative sentiment percentages (68.5–72.2%) in section 4.2, in the 810-statement sample. The companies that have high (positive) ESG sentiment in both samples include TCS and Sun Pharma.

The higher correlation of ESG sentiment and ROE than ROA through the use of parametric and non-parametric analyses indicates that the ESG sentiment indicator is better accounted for in equity return measures. This could be attributed to the possibility of Indian stock investors' inclination to factor in reputational ESG indicators while valuing companies following SEBI's BRSR rule implementation (SEBI, 2021). Behavioral finance would view this result as compatible with the fact that investors take note of the tone in the sustainability narrative, possibly influencing perceptions of quality beyond quantitative disclosures. However, as the ROE is an accounting measure, this is only suggestive because there were no tests on market outcomes.

The results of the Governance dimension deserve special focus. In Section 4.4.3, Governance tone was found to be highly compliance-based due to SEBI and Companies Act mandates (SEBI, 2021); one would thus expect Governance tone to contain relatively little information for investors (in line with H5). Yet the subdimensional regression analysis (see Table 10) shows that the G-score is a significantly positive determinant of ROA and ROE, contradicting H5 and implying that even though the tone of governance is driven by compliance-based reporting, the tone of governance disclosure contains information priced by

the market. This is in line with the finding from Section 4.3 where at a company level the Governance tone is the most negative among all tones of disclosure for several companies (e.g., Apollo, Wipro, NTPC). The very large negative S-Score coefficient in Models 3 and 4 (Table 10) requires interpretation with extreme caution, since there is no reason to view it as proof of an inverse relation between Social sentiment and firm performance. Indeed, as stated above, all three S-, E-, and G-Scores have been constructed using the same initial body of data and thus are almost perfectly multicollinear. In such a case, separate dimensions' coefficients become statistically unstable and may have signs and magnitudes that defy expectations, even when the fit of the whole equation looks good (O'Brien, 2007). Consequently, it seems more correct to consider only the overall ESG sentiment coefficient in Models 1 and 2 (Table 9), where the relation of ESG sentiment to ROA and ROE is positive and significant for both ratios. Hypotheses H4 and H5, based on partial effects of dimensions, must therefore be considered inconclusive until a larger sample allows conducting analysis at the dimensional level via ridge regression or other methods.

Given the predominance of negative ESG sentiment in the sample (56.3% of all classified sentences), along with the high level of negative sentiment for Environmental issues (81.3%), there appears to be a systematic tendency among Indian firms to disclose more of their ESG difficulties and problems, especially those related to the Environment, rather than any successes that they might have. The emphasis on ESG risk disclosures might account for the fact that such negative sentiment does not necessarily result in bad financial results. In terms of corporate sustainability, this implies that BRSR has made companies see sustainability reporting as one that is accountable and transparent and not as a promotional tool.

This pattern of observation is generally compatible with the principles of legitimacy theory and signalling theory of corporate disclosure. In the former case, corporations that operate in environmentally and socially sensitive industries are under more pressure to disclose any risks or problems in order to keep their social license to operate intact, despite the good quality of ESG management (Suchman, 1995); high negative sentiment among the companies from Healthcare, Electricity and Gas/Mining industries is consistent with such view (Section 4.4). From the point of view of signalling theory, the readiness to reveal any negative information, and not its negativity per se, can serve as a sign of good management and company quality, as otherwise hiding any risks would be too costly if they would come out later on (Spence, 1973). The above principles imply that the link between ESG sentiment and financial performance established here does not mean that "more positive disclosure leads to better performance," but that both factors are manifestations of the firm's quality.

In practice, these results indicate that conducting sentiment analysis of the mandatory ESG disclosures, like those in BRSR statements, could act as a cost-effective addition to traditional ESG ratings for those involved in investing and analyzing ESG data in the Indian market context, where ESG rating coverage is inconsistent and rating methods are unclear. This may be due to the fact that the sentiment measures employed in this study come from the disclosures themselves rather than third parties, and hence, may not be prone to issues of rating agency disagreement in international ESG ratings studies (Berg, Kölbel, & Rigobon, 2022). For policy makers and regulators, the result that Governance sentiment shows considerable explanatory power even under the compliance-focused sentiment approach indicates that narrow disclosures can yield economically significant text signals, and hence, structured disclosure should continue to expand under the BRSR framework.

However, there are several limitations that must be noted. First, the financial performance regression is performed using a rather small number of firm-years (N = 44 firm-year observations across 15 firms over

3 years), and thus suffers from lack of statistical power, especially in case of sub-dimensional models, and is prone to outlier firm effects, including those of TCS and Sun Pharma. Second, the dataset used consists only of Nifty 50 firms – some of the largest and most analysed Indian companies; the association between the ESG sentiment and financial performance might be different for mid- and small-cap firms which have other incentives for disclosure. Third, the ESG sentiment was constructed based on machine learning sentiment classification, and despite the fact that the SVM classifier performs better than others, its macro F1-score is equal to only 0.64, implying that there is a certain percentage of misclassification of sentiments, especially Neutral and Positive ones. Fourth, the behavioural finance tools used in the paper such as attention effect and framing are inferred, not proven directly through tests using market-oriented variables such as abnormal return and trading volume, because the study uses accounting data.

Lastly, the lack of significance of the relation between ESG and ROA through Spearman rank correlation should be noted as it brings about an important methodology concern related to the presence of two high-performing outliers (TCS and Sun Pharma), which possess the highest ESG ratings and highest ROA values. Given the fact that these companies affect the findings of the parametric analysis, further study would have to use a much larger sample size – perhaps one that would not be limited to the Nifty 50 index and would include transformers for sentiment analysis, such as FinBERT (Araci, 2019).

7. Conclusion

In terms of the two objectives that were set for this study, the first was to gauge the sentiment, either positive, negative, or neutral, of the ESG reporting of the Nifty 50 companies and the associated ESG dimensions. The second was to investigate the association between the ESG sentiment scores and the financial performance of these companies.

In terms of the first objective, an analysis of the 810 ESG statements of fifteen Nifty 50 companies revealed that ESG disclosure by Indian corporations is largely negative in sentiment (56.3%), indicative of a culture of risk identification and gap identification reporting rather than promotional communications – as mandated by the disclosure-heavy BRSR reporting guidelines. There was considerable difference across firms in terms of ESG sentiment: Sun Pharma and TCS had the highest sentiment for positive ESG reports, while Apollo and Wipro had the largest negative sentiment.

Social disclosures had the greatest negative sentiment (61.1%), followed by Governance (57.8%) and Environmental (50.0%) dimensions at the aggregated level; yet, at the firm level, Governance turned out to be the most negative dimension often for many firms, which means that there is a lot of diversity hidden behind the rankings of dimensions by the aggregate level sentiment. At the industry level, Healthcare and electricity/mining industries had the most negative orientation, whereas Pharmaceuticals were the most positive ones. Of all the three machine learning classifiers, the Support Vector Machine performed best (accuracy = 70%, macro F1 = 0.64) and provided the basis for the calculation of ESG sentiment at the firm level in the next step.

With respect to the second objective of the study, the correlation and OLS regression analysis of 44 firm-year observations revealed that ESG sentiments have statistically significant predictive power regarding ROA and ROE, the prediction of which is stronger in relation to ROE, which was found statistically significant by Pearson and Spearman correlations, compared to the ROA, which did not reveal any significant correlation by Pearson but not Spearman. These results provide sufficient evidence in favour of the main hypothesis, according to which the tone of ESG disclosures provides valuable information

about financial performance, which is also confirmed by the existing international ESG-CFP literature (Friede et al., 2015), as well as the legitimacy and signalling theoretical perspectives (Suchman, 1995; Spence, 1973).

7.1. Methodological Limitations

Certain methodological limitations of the study have been acknowledged in the study. Firstly, the data set is confined to 15 firms across three financial years (N = 44 firm year observations), and thus limits statistical power and applicability beyond the universe of Nifty 50 large cap firms. Secondly, the class imbalance in the sentiment data set (Negative = 56.3%, Neutral = 16.4%) can lead classifiers to predict the majority class, as is the case for the Naïve Bayes classifier; this limitation needs to be overcome in future research through oversampling techniques like SMOTE.

Thirdly, the high multicollinearity between E-Scores, S-Scores, and G-Scores in the sub-dimension regression model (Model 3 and Model 4) means that the coefficient estimates are unstable, and partial effects of each dimension need to be interpreted cautiously. Secondly, using the pooled ordinary least square on short-panel data fails to control for firm-specific unobservable. Fourth, future research needs to apply the fixed/random effect panel estimator when dealing with a long time series of data. Fifth, this paper adopts the Bag-of-Words (TF-IDF) method which neglects context and syntax. The transformer-based model (FinBERT) is an obvious improvement for future research.

Finally, ESG sentiment is measured at the level of disclosure and does not directly measure ESG performance. The relationship between disclosure and performance has long been a vexing issue in ESG literature, and the results are best interpreted as indicating the importance of signals generated by ESG communication and not the impacts of ESG performance.

7.2. Implications and Future Research

Despite some of the limitations, this study have practical importance. First, for investors and ESG analysts, sentiment analysis of the mandatory BRSR reports serves as an inexpensive and reproducible alternative to external ESG ratings, which continue to suffer from "aggregate confusion" (Berg et al., 2022). Second, for company managers, the fact that Governance sentiment demonstrates considerable explanatory power despite its compliance-based nature indicates that the tone in the governance section is not just a formality but is related to financial performance. Third, for regulators, the results provide evidence in favour of increasing BRSR disclosure requirements further since even limited disclosure provisions yield economically relevant textual signals.

Further research needs to replicate this work by considering a greater number of companies over a time series for panel data analysis. Including transformer-based sentiment detection models, dealing with class imbalance using oversampling or cost sensitive methods and triangulating the results of disclosure-based sentiment measurement with independent data on ESG performance can help to confirm whether the sentiment tone signal detected in this research is indicative of actual ESG management capability or rather a mere communication and legitimation tool. Thus, this paper offers some preliminary yet consistent insights that sentiment in ESG disclosure, despite its flaws, is a relevant and underexploited signal in the Indian corporate environment.

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