Uncovering Corporate Sustainability Trends with Sentiment Analysis: The Nifty 50 Index Perspective

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Abstract

Sustainability reporting is crucial for organizations to document their progress toward objectives and potential environmental, social, and managerial hazards. It allows companies to evaluate their environmental and social impact and financial performance, providing transparency by revealing the impact of their operations on society and the environment. This research evaluated the sustainability reports of 50 companies in the Nifty 50 index, identifying patterns and trends in 2023-2024. The analysis, conducted using Python, showed that many of the explanations in the sustainability reports had a favorable sensitivity, while a low number had an unfavorable sensitivity. This suggests that the companies in the Nifty 50 index exhibit a substantial level of corporate sustainability responsibility. The findings suggest that corporations prioritize sustainability beyond generating profits, prioritizing benefits to society and the environment. The future prosperity of a company is significantly influenced by sustainability, and companies must prioritize sustainability accountability and implement optional initiatives. This study aims to improve the understanding of sustainability report users, such as investors, governments, and communities, about the strategies and concerns of businesses in relation to economic, social, and environmental issues.

Keywords: *Sustainability Report, Nifty 50 index, Indian stock market, Sentiment Analysis,*

Introduction

Sentiment analysis plays a crucial role in understanding financial reports by extracting and evaluating the emotional tone or polarity of the text, which can provide insights into market trends and investor sentiment. This is particularly significant in predicting stock market movements, as the analysis of textual data sources such as news articles, social media posts, and earnings reports can reveal underlying sentiments that drive market behavior (Azhagiri et al., 2023a). The application of machine learning and deep learning algorithms, such as Multinomial Naïve Bayes, Logistic Regression, RNN, LSTM, and GRU, has shown high accuracy in extracting sentiment polarity from financial textual data, thereby aiding in more informed and stable financial decision-making(Ahmad & Umar, 2023). Sentiment analysis is also essential for businesses, government agencies, and researchers to gather and evaluate public opinions, which can influence strategic decisions and policy-making(Azhagiri et al., 2023b; Popoola et al., 2024). Introducing Sustainable Development Goals (SDGs) 7, 11, and 13, these goals focus on ensuring access to affordable, reliable, sustainable, and modern energy for all (SDG 7), making cities inclusive, safe, resilient, and sustainable (SDG 11), and taking urgent action to combat climate change and its impacts (SDG 13). Analyzing sentiment around these topics in financial reports is important because it helps stakeholders understand public and investor perceptions regarding investments in clean energy, sustainable urban development, and climate action. This understanding can drive investments and policies that align with these SDGs, promoting a transition to a more sustainable and resilient economy. By leveraging sentiment analysis, stakeholders can better gauge the market's response to initiatives aimed at achieving these goals, thereby facilitating more effective and targeted actions towards sustainable development.

The main objective of the research is to analyze the sentiment in financial reports using keywords related to SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action) to gain insights into corporate attitudes towards affordable and clean energy. This objective is rooted in the broader context of understanding how companies disclose their contributions to the Sustainable Development Goals (SDGs) and the impact of these disclosures on stakeholders. For instance, a study on European financial institutions' Integrated Reports revealed that SDG 13 (Climate Action) was the most disclosed goal, indicating a strong corporate focus on climate-related issues, followed by SDG 7 (Affordable and Clean Energy)(Hassan et al., 2022). Another research emphasized the role of green innovation and investor sentiment in the relationship between climate change-related risks and sustainability reporting, highlighting the importance of transparent communication of sustainable practices and environmental performance(Siregar et al., 2023). Additionally, the evolution of corporate discourse in non-financial reports, such as those from CaixaBank, shows a shift towards framing sustainability issues, including SDGs, as central themes in recent years(Jiménez-Yáñez & Fontrodona, 2022). The analysis of European energy sector companies' SDG reporting practices further suggests that while SDGs are increasingly integrated into corporate disclosures, there is a tendency towards symbolic rather than substantive changes, calling for more genuine efforts in sustainability reporting(Manes-Rossi & Nicolo', 2022). Finally, a novel BERT model developed to analyze the thematic evolution of European banks' sustainability reports identified climate action as a predominant focus by 2022, underscoring the growing emphasis on SDG 13 in corporate sustainability narratives(Li & Rockinger, 2024). By examining the sentiment and thematic focus on SDGs 7, 11, and 13, this research aims to provide a comprehensive understanding of corporate attitudes towards affordable and clean energy, sustainable urban development, and climate action, thereby informing stakeholders and guiding future sustainability strategies.
This study aims to examine the sentiment of financial reports by focusing on specific terms associated with SDG 7, SDG 11, and SDG 13. The analysis attempts to understand better how companies view and communicate their sustainability efforts.

Literature Review

Sentiment analysis, a subfield of natural language processing (NLP), focuses on extracting and categorizing subjective information from text, such as reviews, social media posts, and news articles, to determine the emotional tone or polarity expressed. In the financial domain, sentiment analysis has gained significant traction, particularly in Financial Sentiment Analysis (FSA), which involves defining tasks and developing techniques to improve performance in financial markets through hypothesis testing and predictive modeling(Du et al., 2024). Techniques in FSA have evolved from traditional machine learning models like Support Vector Machines (SVM) to more advanced methods, including transformer architectures and multimodal classifiers, which integrate text and audio data from corporate earnings calls to enhance sentiment detection(Todd et al., 2024). Despite these advancements, financial sentiment analysis still lags behind state-of-the-art NLP techniques, indicating a need for further research and adoption of cutting-edge methods(Todd et al., 2024). The broader field of sentiment analysis has seen substantial growth, with applications extending beyond finance to areas such as political campaigns, online bullying detection, and mental health monitoring, particularly during transformative events like the COVID-19 pandemic(Rimpy et al., 2024). The integration of sentiment analysis with Sustainable Development Goals (SDGs), such as SDG 7 (Affordable and Clean Energy), is crucial for understanding public opinion and driving policy decisions. Although specific studies linking sentiment analysis directly with SDG 7 are sparse, the methodology's potential to gauge public sentiment on energy policies and innovations is evident.

Previous research has highlighted the importance of sentiment analysis in various domains, emphasizing its role in bridging the gap between academia and industry and its potential for real-world applications(Du et al., 2024; Rimpy et al., 2024). As the field continues to evolve, the integration of sentiment analysis with sustainable development goals will likely become more prominent, offering valuable insights for achieving global sustainability targets.

Sentiment analysis significantly enhances the interpretation of financial reports by providing deeper insights into the underlying emotional tone and subjective expressions within the text, which traditional quantitative analysis might overlook. By leveraging advanced techniques such as natural language processing and machine learning, sentiment analysis can quantify the emotional tendencies in financial reports, thereby offering a more nuanced understanding of a company's performance and future prospects(Zhong & Ren, 2022). For instance, the use of BERT models allows for the consideration of broad word contexts and meanings, eliminating ambiguities and subjective biases, which improves the precision of sentiment predictions and aligns them with market reactions. Additionally, incorporating contextual information and sentiment contagion across multiple platforms, such as news articles and microblogs, can capture implicit sentiments that are not immediately apparent in the text alone, thus providing a more comprehensive sentiment analysis (Daudert, 2021). Prompt engineering and the use of large language models (LLMs) further refine sentiment extraction by enhancing the accuracy and effectiveness of classification models, although the quality of results can vary based on prompt design and task complexity(Ahmed et al., 2024). Moreover, sentiment analysis can serve as a proxy for reporting quality and risk indicators, as seen in the analysis of Corporate Social Responsibility reports, where proportional sentiment scores were linked to reporting quality rather than direct risk assessment. Overall, sentiment analysis enriches the interpretation of financial reports by uncovering hidden emotional cues and providing a multi-dimensional view of a company's financial health, thereby aiding stakeholders in making more informed decisions.

Sentiment analysis in finance offers several key benefits that significantly enhance market understanding and decision-making. Firstly, it provides critical insights into market trends by decoding sentiments from various textual data sources such as news articles, social media posts, and earnings reports, which are essential for risk management and making well-informed financial decisions(Jawale et al., 2023; Shahapur et al., 2024). By leveraging advanced machine learning (ML) and natural language processing (NLP) models, such as Multinomial Naïve Bayes, Logistic Regression, and Random Forest, sentiment analysis can achieve high accuracy in predicting market movements, with some models reaching up to 82% accuracy(Shahapur et al., 2024). Additionally, sentiment analysis helps in understanding the impact of public sentiment on market factors like trading volume, volatility, stock prices, and corporate earnings, thereby enabling investors to make more informed decisions(Kantha et al., 2023; Shahapur et al., 2024). The use of pre-trained NLP models and deep learning architectures further enhances the precision of financial forecasting, although these models require large datasets and computational resources(Jawale et al., 2023). Moreover, the development of specialized lexicons, such as the eXplainable Lexicons (XLex), combines the efficiency of lexicon-based methods with the performance of transformer models, resulting in improved sentiment classification accuracy and better interpretability, which is crucial for financial decision-making (Rizinski et al., 2024). Fine-tuning models specifically for the financial domain, as demonstrated with the Llama 2 7b-hf model, also significantly improves sentiment analysis accuracy, achieving up to 89% accuracy by adapting to the sector's unique linguistic characteristics(Rizinski et al., 2024). Overall, sentiment analysis algorithms provide timely and accurate insights into market conditions, allowing investors to navigate the complex dynamics of financial sentiment and make more strategic and informed investment choices (Kantha et al., 2023).

Methodology

Data Collection

The annual sustainability reports of the Nifty 50 firms were examined, and 11 companies were selected based on the presence of their annual sustainability report for the year 2023-24. The firms included in the list are ITC Limited, HDFC Bank, Unilever, Asian Paints, State Bank of India, Hero Motocorp, Divi's Laboratories, LTIMindtree, Mahindra&MahindraLtd., Sun Pharmaceutical Industries Ltd., and HCL Technologies. The annual sustainability reports were obtained from the companies' official websites.

Keyword Selection

The Sustainable Development Goal 7 (SDG 7) ensures affordable and clean energy access. The objective of SDG 7 is to guarantee universal access to affordable, dependable, sustainable, and contemporary energy. Energy plays a vital role in driving economic growth and development. To achieve this objective, it is necessary to enhance energy efficiency, promote the use of renewable energy sources, and ensure that underserved groups have access to electricity. The use of renewable energy sources not only leads to advancements in health, education, and economic prospects but also holds the promise of a brighter, more sustainable future. It simultaneously decreases greenhouse gas emissions and minimizes the effects of climate change, offering hope for a healthier planet and improved quality of life.

The Sustainable Development Goal 11 (SDG 11) focuses on developing sustainable cities and communities. The primary objective of SDG 11 is to ensure that cities and human settlements are inclusive, safe, resilient, and sustainable. With the expansion of urban populations, cities encounter obstacles such as insufficient infrastructure, pollution, and a scarcity of housing. This objective aims to tackle these challenges by advocating for sustainable urban design, boosting public transportation infrastructure, enhancing air quality, and guaranteeing access to secure and reasonably priced housing. The potential of sustainable urban design to enhance the well-being of urban dwellers is inspiring. SDG 11 seeks to minimize the ecological impact of urban regions and promote the development of sustainable cities, motivating us to work towards a healthier, more sustainable future.

The Sustainable Development Goal 13 (SDG 13) focuses on Climate Action. SDG 13 is specifically focused on addressing the urgent issue of climate change and its consequences. This objective highlights the pressing necessity to enhance the ability to withstand and adjust to climate-related dangers and natural calamities. The urgency of tackling climate change is essential for preserving ecosystems, promoting sustainable livelihoods, and maintaining the health and well-being of populations globally. The gravity of the situation underscores the need for immediate action and the importance of incorporating climate change measures into national policies and strategies, enhancing education and awareness of climate challenges, and gathering financial resources for climate action.

SDG 7, SDG 11, and SDG 13 highlight the interdependence of energy, urban development, and climate action in establishing a sustainable future. By striving to achieve these objectives, we may progress towards a global society characterized by fairness, adaptability, and sustainability.

The keywords 'sustainable development,' 'energy efficiency,' and other relevant terms relating to SDG 7, SDG 11, and SDG 13 were chosen based on their significance and frequency in the literature. Keywords corresponding to each of the aims of the Sustainable Development Goals (SDGs) were selected. The appendix has a comprehensive list of all the keywords.

Text Extraction and Preprocessing

The text was taken and divided into individual sentences. For analysis, sentences with keywords related to SDG 7, SDG 11, and SDG 13 were identified.

Sentiment Analysis

The sentiment of relevant sentences was analyzed using the VADER SentimentIntensityAnalyzer, which provided negative, neutral, positive, and compound feelings scores.

Statistical and Visual Analysis

The sentiment scores were consolidated and displayed using bar charts and pie charts to illustrate the distribution of sentiments.

Results and discussion

Sentence Count

In the consolidated sustainability reports, the keywords SDG7, SDG11, and SDG13 appear 940, 410, and 976 times.

Descriptive statistics of Sentiment Score

Table 1. SDG 7

	Negative	Neutral	Positive	Compound
Count	940	940	940	940
Mean	0.024871	0.7991	0.17596	0.550872
Standard deviation	0.039996	0.111852	0.10983	0.368548
Minimum	0	0.38	0	-0.9796
25%	0	0.743	0.10275	0.2732
50%	0	0.805	0.1665	0.6486
75%	0.042	0.87125	0.231	0.833275
Maximum	0.24	1	0.62	0.9998

Source: Authors own computation

The dataset has 940 observations with diverse amounts of negative, neutral, positive, and compound emotions. The mean negative sentiment score is 0.0249, suggesting a significantly low level of negativity. The sentiment score of 0.7991 suggests that most texts are neutral. The sentiment score is 0.1760, which suggests a relatively low level of positive sentiment. The compound sentiment score is 0.5509, indicating a predominantly favorable sentiment. The standard deviation of the data is 0.3685, indicating a relatively small amount of variation. The lowest score is -0.9796, suggesting some texts exhibit a strong negative attitude. The maximum compound sentiment score is 0.9998, which signifies a highly favorable attitude in specific texts. Most texts have a neutral sentiment, with an average neutral sentiment score of 0.7991. The presence of positive sentiment is relatively low, with an average score of 0.1760, whereas negative sentiment is negligible. The compound sentiment score, aggregating many sentiments into a unified score, has an average of 0.5509, indicating an overall inclination towards positivity in the analyzed texts.

Table 2. SDG 11

	Negative	Neutral	Positive	Compound
Count	410	410	410	410
Mean	0.0737	0.797593	0.128676	0.219099
Standard deviation	0.084887	0.113508	0.105514	0.551513
Minimum	0	0.455	0	-0.9965
25%	0	0.724	0.048	-0.2023
50%	0.051	0.794	0.1205	0.2732
75%	0.118	0.87175	0.192	0.7269
Maximum	0.44	1	0.545	0.9998

Source: Authors own computation

The sentiment analysis data for SDG 11 comprises 410 observations, with an average negative sentiment score of 0.0737, showing a relatively low level of negative emotion. Most texts exhibit a neutral sentiment, with an average score of 0.7976. The sentiment expressed is predominantly positive, albeit relatively low, with an average score of 0.1287. The average score for negative emotion is 0.0737, indicating a low level of negativity. The compound sentiment score, aggregating many sentiments into a unified score, has an average of 0.2191, suggesting a marginally favorable overall sentiment. The compound sentiment has a high standard deviation of 0.5515, indicating that the overall sentiment varies significantly throughout the texts, with some showing strong positive or negative attitudes. The dataset contains a compound sentiment score of 0.9998, which signifies a highly favorable sentiment. The sentiment analysis data for SDG 11 indicates that most texts exhibit a neutral sentiment, with a moderate range of scores.

Table 3. SDG 13

	Negative	Neutral	Positive	Compound
Count	976	976	976	976
Mean	0.037965	0.850541	0.1	0.324665
Standard deviation	0.062379	0.111462	0.1	0.446075
Minimum	0	0.476	0	-0.9918
25%	0	0.77975	0	0
50%	0	0.8585	0.1	0.34
75%	0.061	0.933	0.2	0.7096
Maximum	0.447	1	0.5	0.9998

Source: Authors own computation

The dataset has 976 observations, with an average negative sentiment score of 0.0380, indicating a relatively low level of negative emotion. Most texts have a neutral sentiment, with an average sentiment score of 0.8505, indicating a largely neutral sentiment. The minimum value is 0.0000, which signifies the absence of negative sentiment. The 25th percentile score is also 0.0000, suggesting that 25% of the texts exhibit no negative sentiment. The median score is 0.0000, signifying that exactly half of the texts exhibit no negative sentiment. The 75th percentile is 0.0610, indicating that 75% of the texts have a score equal to or lower than 0.0610. The maximum negative sentiment score is 0.4470. Most texts have a relatively high positive sentiment score, with an average score of 0.1115. The compound sentiment score aggregates many sentiments into a unified score, with an average of 0.3247, suggesting a marginally favorable sentiment overall. The large standard deviation in the compound sentiment indicates significant variability among the texts, with specific texts displaying pronounced positive or negative attitudes.

Sentiment Score Visualizations

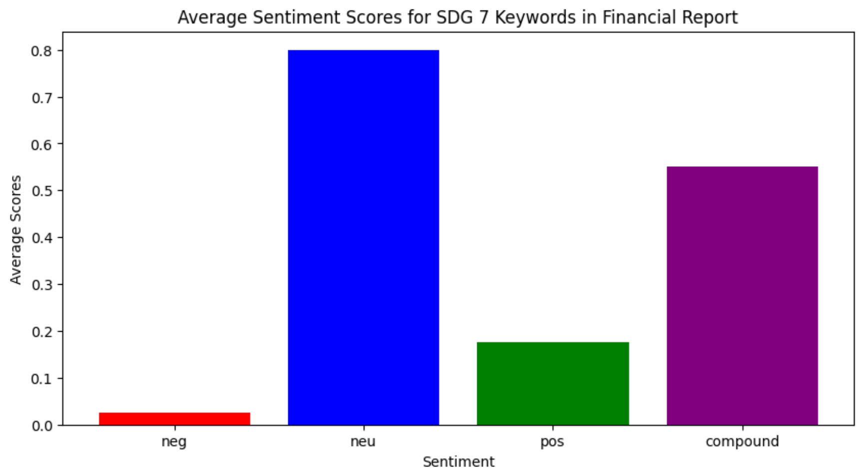

Figure 1: Average Sentiment score: SDG 7

The figure 1 illustrates the mean sentiment scores for SDG 7 phrases in the companies' yearly sustainability report. The sentiment categories consist of negative (neg), neutral (neu), positive (pos), and compound. The average score for the neutral sentiment is approximately 0.8, suggesting that most mentions are neutral. Positive sentiment exhibits a modest average score, but negative sentiment demonstrates a significantly low average score, suggesting a scarcity of unfavorable mentions. The compound score, calculated as a weighted average of the three attitudes, indicates a relatively high level of positivity in the sentiment for SDG 7 keywords.

ISBN code 978-93-83302-70-3

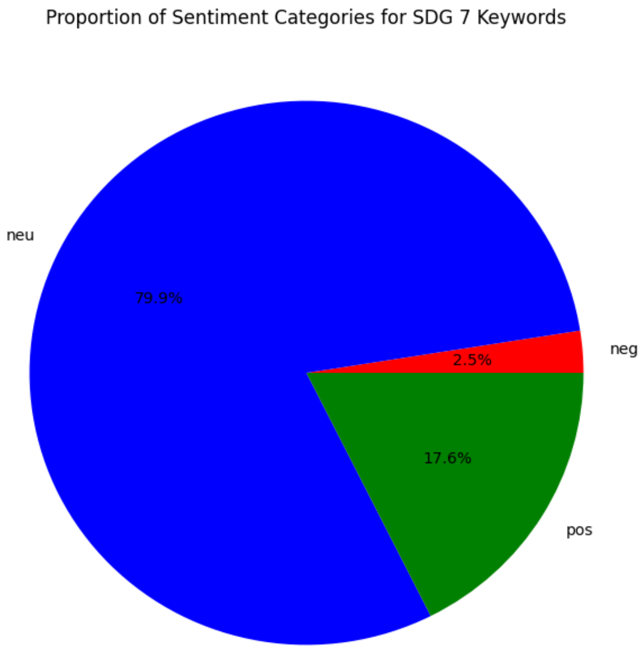

Figure 2: Proportion of sentiment score: SDG 7

The above pie chart figure 2 illustrates the distribution of sentiment categories about SDG 7 keywords in the annual sustainability report. The graphic is segmented into three sentiment categories: neutral (neu), positive (pos), and negative (neg). The neutral category prevails with a majority of 79.9%, signifying that most mentions are neutral. The positive feelings account for 17.6% of the total, indicating a notable yet relatively lesser share of good input. The analysis indicates that negative attitudes account for only 2.5% of the total, suggesting minimal negative utterances.

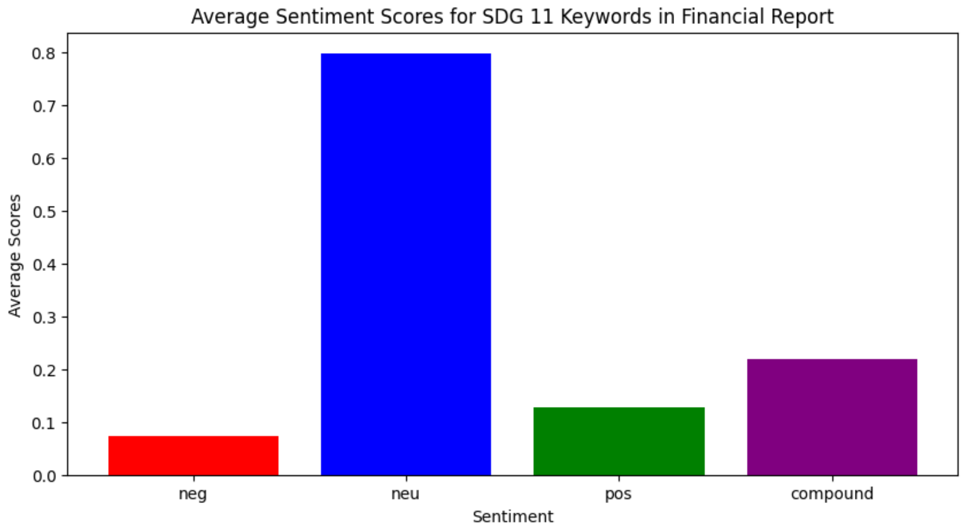

Figure 3. Average Sentiment score: SDG 11

This bar chart figure 3 illustrates the mean sentiment scores for SDG 11 phrases in the companies' yearly sustainability report. The sentiment categories consist of negative (neg), neutral (neu), positive (pos), and compound. The average score for the neutral sentiment is approximately 0.8, suggesting that most mentions are neutral. The average score for positive sentiment is moderate, whereas the average score for negative sentiment is meager, suggesting a scarcity of unfavorable references. The compound score, calculated as a weighted average of the three sentiments, indicates a relatively low sentiment towards SDG 11 keywords, suggesting an overall neutral sentiment.

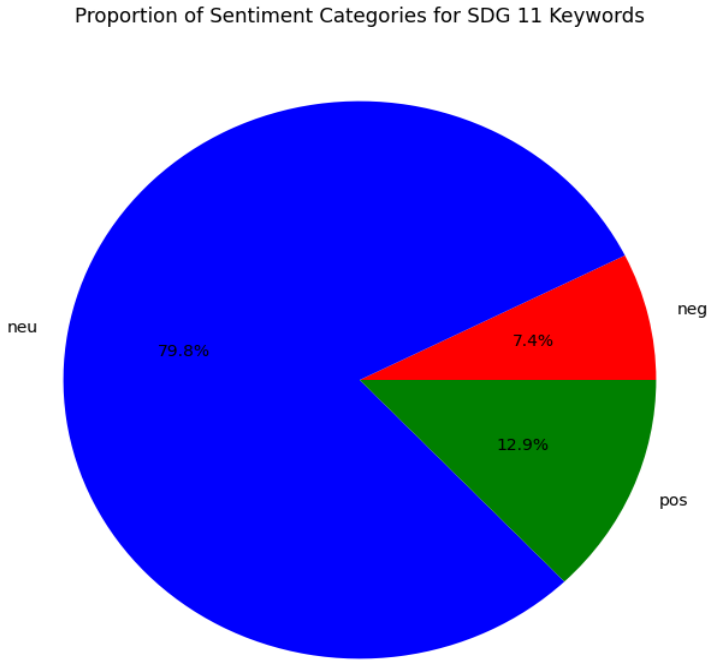

Figure 4. Proportion of sentiment score: SDG 11

The pie chart figure 4 illustrates the distribution of sentiment categories related to SDG 11 keywords in the annual sustainability report. The graphic is segmented into three sentiment categories: neutral (neu), positive (pos), and negative (neg). Most of the mentions, 79.8%, fall into the neutral category, meaning that most are neither positive nor negative. The positive thoughts account for 12.9% of the total, indicating a noteworthy albeit relatively tiny amount of good input. The analysis indicates that negative feelings account for only 7.4% of the total, suggesting minimal negative utterances.

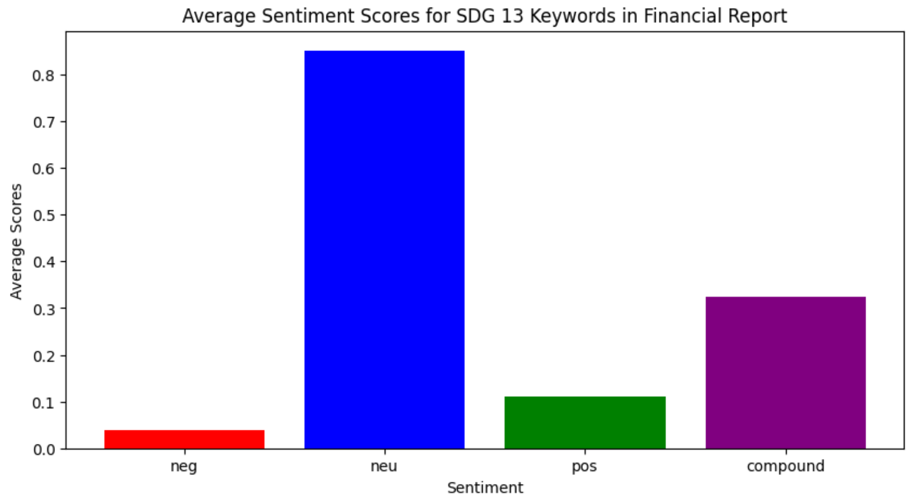

Figure 5. Average sentiment scores: SDG 13

The bar chart figure 5 depicts the mean sentiment scores for SDG 13 phrases in the companies' yearly sustainability report. The sentiment categories consist of negative (neg), neutral (neu), positive (pos), and compound. The average score for the neutral emotion is approximately 0.9, suggesting that most mentions are neutral. The positive sentiment has a modest score. However, the negative sentiment has a significantly low average score, suggesting a scarcity of unfavorable references.

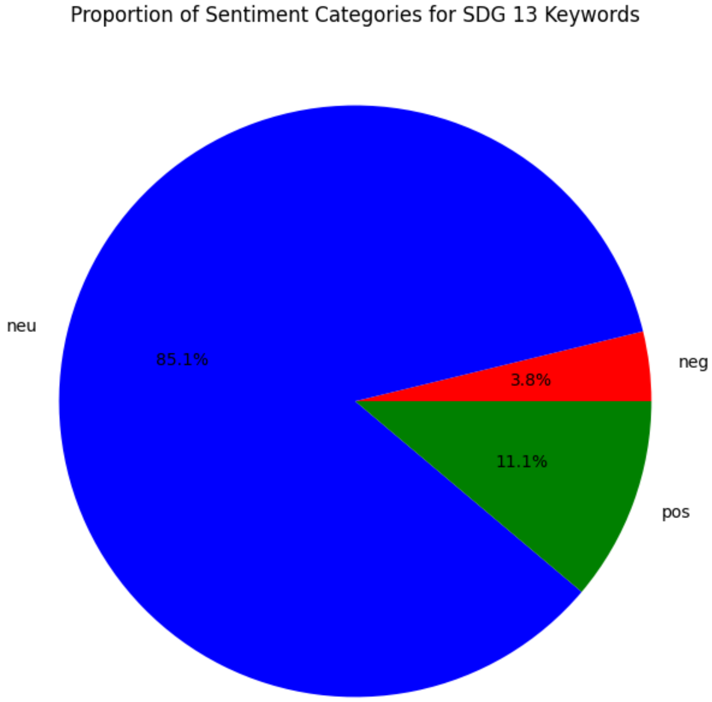

Figure 6. Proportion of sentiment score: SDG 13

The pie chart illustrates the distribution of sentiment categories for SDG 13 keywords in the yearly sustainability report. The graphic is segmented into three sentiment categories: neutral (neu), positive (pos), and negative (neg). The neutral category is the most prevalent, accounting for 85.1% of the mentions, suggesting that most references are neutral. The positive comments account for 11.1% of the total, indicating a noteworthy albeit relatively tiny amount of good input. The analysis indicates that negative attitudes account for only 3.8% of the total, suggesting minimal negative utterances.

Conclusion

This study has yielded significant findings about the sentiment expressed in financial reports regarding SDG 7, SDG 11, and SDG 13. Our analysis uncovered notable trends in how organizations express their sustainability initiatives, which indicate different degrees of dedication and involvement. Comprehending these emotions assists stakeholders in assessing the genuineness of company sustainability assertions and the congruence of business strategies with worldwide sustainability objectives. The results emphasize the significance of clear and authentic communication in advancing sustainable development in the business industry.

An essential aspect of comprehending financial data is sentiment analysis, which offers valuable perspectives on market movements and investor opinion. Machine learning and deep learning

ISBN code 978-93-83302-70-3

algorithms can analyze financial data to determine the sentiment polarity, which can assist in making well-informed decisions. This analysis facilitates the comprehension of public sentiments toward Sustainable Development Goals, including clean energy, sustainable urban development, and climate action, guiding future sustainability plans to corporations, government agencies, and researchers.

Sentiment analysis, a subfield of natural language processing, is employed in financial analysis to comprehend the emotional tone and polarity. Financial Sentiment Analysis (FSA) has become increasingly popular as it uses hypothesis testing and predictive modeling to enhance market performance. Despite progress, the study of financial emotion still needs to catch up to modern techniques in natural language processing (NLP). The applications of this technology go beyond cash and include political campaigns, online bullying detection, and mental health monitoring.

The sustainability reports of the Nifty 50 corporations for the year 2023-24 indicate that 11 companies are specifically prioritizing Sustainable Development Goals 7 (SDG 7) and 11 (SDG 11). Their primary objectives are to promote renewable energy, create sustainable cities, and combat climate change. The aims prioritize the interconnectedness of energy, urban development, and climate action, advocating for equity, flexibility, and durability in a worldwide community.

The dataset has 940 letters exhibiting diverse degrees of negative, neutral, positive, and complex emotions. The average negative sentiment score is 0.0249, indicating that most texts have a neutral attitude. The level of positive sentiment is relatively low, as indicated by an average score of 0.1760. The compound sentiment score is primarily positive, with an average value of 0.5509. The standard deviation value is 0.3685.

The data on sentiment analysis for SDG 11 consists of 410 observations, with an average negative sentiment score of 0.0737, suggesting a low level of negativity. Most texts exhibit a neutral attitude, with a favorable score of 0.1287. The compound sentiment score, which combines many sentiments, has an average value of 0.2191, suggesting a slightly positive sentiment. The general sentiment exhibits substantial variation among passages.

The dataset has 976 observations, with an average negative sentiment score of 0.0380, suggesting a modest level of negative emotion. Most texts exhibit a neutral sentiment, as indicated by an average score of 0.8505. The negative sentiment scores are as follows: the minimum score is 0.0000, the 25th percentile score is 0.0000, the median value is 0.0610, the 75th percentile score is 0.4470, and the maximum score is 0.1115. The compound sentiment score combines sentiments, demonstrating substantial diversity across texts.

The study analyses organizations' financial reporting on SDGs 7, 11, and 13 to gain insights into how they convey information about their sustainability initiatives. It uncovers trends in dedication and involvement, enabling stakeholders to assess the genuineness and conformity of sustainability declarations with worldwide objectives. The Nifty 50 firms prioritized SDGs 7 and 11, emphasizing the significance of clear communication in advancing sustainable development.

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