Sentiment Analysis of Sustainability Disclosures in the Tech Sector: An AI-Based Assessment of Environmental Accountability[1]

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Abstract

The technology acts as both a driver of environmental solutions through AI-driven climate modelling and a source of pressure via high energy consumption and carbon emissions. This study employs a BERT-based Natural Language Processing (NLP) architecture to conduct a sentiment analysis of environmental sustainability reports from leading technology firms. By evaluating the consistency of these disclosures and their alignment with sector-specific indicators, the research assesses the reliability of "green" narratives in high-growth sectors. The findings demonstrate that sentiment-based analysis can effectively identify patterns of reporting quality, which is essential for ensuring the financial sustainability and accountability of tech-driven economies. This study offers a structural framework for regulators and investors to utilize AI in verifying the integrity of sustainability reporting, particularly in transitional markets where transparency is a prerequisite for long-term economic stability.

Introduction

Environmental factors reflect on the company's impact on the natural environment and its relationship with the investment decisions. Indicators that are greenhouse gas emissions, carbon footprint, water usage, and energy efficiency become key evaluation criteria in terms of both investors and customers. Companies obeying sustainable practices and adapting to climate change have a tendency to increase the confidence of investors and attract more long-term capital (Arunkumar et al., 2025). Additionally, not only the level of these indicators but also how companies communicate and convey these issues to the public becomes a key component of sustainability performance.

The relationship between digital transformation and sustainability is gaining importance in terms of academic and business literature. (Lodhia et al., 2025). The increasing visibility and dynamic structure of technology companies make it particularly meaningful and necessary to analyse the content of sustainability reports in terms of the accuracy, depth and impact of the environmental information disclosed (Marsdenia, 2018). Through resource optimization, energy efficiency, and intelligent industrial processes, digital technologies promote sustainable development. However, rising their energy consumption and the generation of their electronic waste pose a challenge for environmental sustainability objectives (Deng et al., 2017). Increasing carbon emissions and growing e-waste volumes have become key focal points in environmental sustainability policies (Stocker et al., 2024). Recent studies emphasise that digital applications such as Industry 4.0 and smart factories have the potential for reducing their environmental impacts, but introduce new environmental and social risks (Jones & Wynn, 2021).

The technology sector has become one of the main drivers of global economic growth by shaping innovation and digital transformation processes (Abdullah et al., 2024). Rapid developments in the field of Information and Communication Technologies (ICT) have accelerated the integration of innovative tools such as cloud computing, the Internet of Things (IoT), big data analytics and artificial intelligence into production and management systems.

These technologies improve production systems' sensing, decision-making, and communication capacities, which makes industries more intelligent, adaptable, and productive. (Zheng et al., 2018). Real-time data sharing facilitates faster and more accurate decision-making and also this situation forms the basis of Industry 4.0. Digitalisation enables the

effective use of information by making data sharing open, accessible and centralized, which facilitates both access to information and the ability to make comparisons. Briefly, a new approach to reporting and management is emerging that supports the transformation of economic activities and technological tools in line with Industry 4.0 (Mehedințu & Șoavă, 2023).

The fast growth of the technology sector has also brought new debates to the forefront on social and environmental issues such as data privacy, energy consumption, and working conditions (Chen & Mai, 2024). For this reason, technology companies are now seen not only as symbols of progress, but also as strategic actors at the centre of sustainability risks and opportunities. Therefore, it can be said that the relationship between ICT and sustainability is approached from a dual perspective. (Egorova et al., 2022; Stocker et al., 2024; Hasnaoui, 2025). ICT has the ability to provide sustainable solutions in areas like resource efficiency, environmental monitoring, and energy management, even if it also puts pressure on the environment through the creation of hardware, energy consumption, and electronic trash. (Batool et al., 2022; Kavathatzopoulos, 2015). Due to these two bidirectional effects, while the technology industry plays a transformative role in solving environmental problems, it also has a harmful effect on the environment. Therefore, the design, production, use, and post-use processes have a directly impact on the environment as well on social sustainability. From the perspective of this view, the working procedures of technology companies are as important as how they communicate these challenges to their stakeholders. It is also important for evaluating their environmental performance. Therefore, an impartial, reliable, and globally recognized benchmark is necessary to understand and compare corporate sustainability leadership.

In this context, the main reference source for this research is the Sustainability Leaders 2024 Report published by the ERM Sustainability Institute and GlobeScan. Five hundred sustainability experts from 65 countries participated in the preparation of the report that evaluates business sustainability leadership using expert opinions rather than financial performance metrics. (GlobeScan & ERM Sustainability Institute, 2024). In this respect, the report offers a thorough worldwide standard evaluating the sustainable leadership based on the strategic coherence, openness, and company reputation in addition to stated aims.

According to the report's 2024 findings, technology companies have getting strengthened their position as sustainability leaders, Companies that stand out for their ability to innovate, open reporting, and environmental commitments include Microsoft, Google, Apple, Amazon, Samsung, and Siemens. As a result, the research focuses on these global technology leaders' sustainability reports.

As for this study evaluating the tone, emphasis, and thematic distribution of the corporations' environmental discourse by applying sentiment analysis to their 2024 sustainability reports (Saxena et al., 2024).

The architecture based on Transformers' Bidirectional Encoder Representations (BERT) was methodically used to filter all environmental statements, which were then categorized into three emotional categories for analysis: positive, neutral, and negative. The sentiment distribution of the reports was interpreted as the Environmental Discourse Strength (EDS) indicator, which is used to measure the intensity and orientation of environmental discourse. The EDS indicator enables the tone of the language and the intensity of environmental themes to combine the strength of companies' environmental discourse into a quantitative measure.

This study aims to contribute to the literature in two ways. One of these is sentiment analysis and environmental discourse density of reports used with EDS model. There exist studies about the measurement of tone and volume of corporate environmental discourse, however, combining the tone of report and density of environmental discourse and then we obtain a structure that measures this combination in simultaneously. The second one is eliminating the length bias with density component. It allows for comparable result to be obtained without considering the size of the report and also makes different companies comparable. This enables the assessment of not only the presence of environmental discourse, but also density, tone and consistency through the text.

Thanks to this holistic approach, sustainability reports have been made comparable within a standard methodology framework; differences and consistencies in technology companies' environmental discourse have been objectively evaluated. The Environmental Discourse Strength (EDS) model used in the study offers an innovative framework that measures companies' sustainability communication power by integrating the emotional tone of language and the intensity of environmental themes. Thus, not only the presence of environmental discourse but also its intensity, orientation, and consistency can be analysed. In this respect, the study contributes to the literature examining the strategic function of linguistic tone in environmental reporting at both the methodological and conceptual levels.

The remainder of the article is structured as follows: the second section covers the relevant literature and theoretical framework; the third section details the data set and methodological approach used in the research; and the final section presents the findings, conclusions, and discussions. One of these is sentiment analysis and environmental discourse density of reports used with EDS model. There exist studies about the measurement of tone and volume of corporate environmental discourse (Rodrigue et al., 2015; Villacampa-Porta et al., 2025). However, combining the tone of report and density of environmental discourse and then we obtain a structure that measures this combination in simultaneously.

1. Literature Review

Environmental reports are one of the most important communication tools through which businesses communicate their environmental performance to their stakeholders. In recent years, examining the content of these reports not only through quantitative indicators but also through the language and tone used has become a significant area of research. In this context, sentiment analysis is considered an important method for revealing the credibility, transparency, and potential greenwashing tendencies of sustainability reports. Sentiment analysis can provide valuable information about how greenwashing allegations affect a company (Lagasio, 2023).

Sentiment analysis is an approach to identifying and categorizing opinions expressed in text to determine attitudes toward a specific topic. It aims to identify the contextual polarity of language and classify it as positive, negative, or neutral (Devika et al., 2016). In other words, sentiment analysis, based on Natural Language Processing (NLP), is an analysis method that enables machines to interpret emotions embedded in text data. Different techniques are used in sentiment analysis, known as rule-based, machine learning-based, and deep learning-based methods.

In this article, sentiment analysis was performed using the BERT (Bidirectional Encoder Representations from Transformers) based models. BERT, the Google AI language introduced by Devlin et al. (2019), emerged as an NLP method. Unlike traditional language models that process text in a single direction, BERT ensures semantic integrity by capturing contextual information from both sides. The BERT framework employs a two-phase training procedure consisting of pre-training and fine-tuning. In the pre-training stage, the model is trained with unlabelled data for different pre-training tasks. During the fine-tuning stage, BERT is initialized with the pre-trained parameters and adjusted with labelled data from specific downstream tasks (Devlin et al., 2019).

Early studies used mostly general-purpose methods to classify the tone of reports into categories of positive, negative, or neutral. The released language models are trained on general documents. While fine-tuning is easy, it has been shown that pre-training language models on a specific domain for large-scale of documents improve the performance. For this purpose, various domain-specific BERT models are trained and put into use (Yang et al., 2020).

Special general-purpose models are to be ineffective due to the specialized language used in the financial context. Pre-trained language models can address this problem because they require fewer labelled examples. For this purpose, FinBERT model is proposed to tackle NLP tasks in financial domain (Araci, 2019).

Researchers working on sustainability issues are increasingly using NLP to automatically extract relevant information from textual data. The emotional nature of language, particularly in climate and environmental reports, is prominent to increases the transparency. This has led to the need for pre-trained language processing models related to the environment.

Webersinke et al. (2021) introduced CLIMATEBERT, a natural language processing (NLP) model specifically pre-trained on climate-related text from a variety of sources, such as news, corporate statements, and scientific articles. EnvBert is an NLP method focused on Environmental Due Diligence (EDD) developed using the Environmental dataset to fine-tune the performance of DistilBERT (Aman & Reji, 2022b).

There are different studies in the literature for sentiment analysis of sustainability reports. Kang & Kim (2022) investigated the sustainability reports of Global Sustainability Leaders companies between 2011 and 2020 using sentence similarity and sentiment analysis. The study identified thematic trends and compared the positive and negative tones across companies. They concluded that the companies actively use sustainability reports to improve their positive image during crises periods.

Lu & Jagoda (2023) analysed whether the positive or negative tone in the sustainability reports of extractive companies (mining, quarrying, oil and gas extraction) that published voluntary sustainability reports in the US between 2010 and 2018 is associated with their future environmental performance. They find that the relation between the tone in sustainability reports and future environmental performance is negative. This supports the greenwashing theories since the companies with lower environmental performance use a more optimistic tone to influence stakeholders.

Kumari et al. (2024) used the NLP method to analyse the sustainability reports of financial institutions that implement the GRI guidelines. The aim of this study is to identify general trends and, in particular, perspectives on sustainability. While the vast majority of financial institutions place significant importance on sustainability, their results show that the reporting needs to be improved to capture the diversity of perspectives.

Mohammadrezaei et al. (2024) conducted a study on the use of Text Mining (TM) and NLP methods for evaluating the sustainability reports. They investigated which methods were emphasized and for what purposes the methods were used. They concluded that studies were used to identify the themes of the reports, assess their compatibility with existing frameworks, and evaluate the sentiment and tone of the message.

2. Research Methodology

The aim of this study is to develop a two-stage language model for measuring both the volume and sentiment tone of environmental discourse in long corporate texts such as sustainability or environmental reports.

The proposed framework consists of two sequential stages:

- In the first stage, Environmental BERT is applied as a filtering mechanism to identify sentences that contain environmental content.
- In the second stage, the extracted environmental sentences are analysed using ClimateBERT to determine the sentiment orientation of the climate discourse.

Based on the outputs of these two stages, an interpretable indicator called Environmental Discourse Strength (EDS) is constructed. This indicator combines three components: coverage, density, and sentiment tone (positive, neutral, or negative).

The BERT model converts textual inputs into numerical representations prior to analysis. During this process, tokenization, segmentation, and embedding operations are applied to capture contextual relationships within the text (Wilkho et al., 2023). Contextual dependencies between words are modelled through the self-attention mechanism, which evaluates the relationships between words within a sequence using vector representations, as originally proposed in the transformer architecture (Vaswani et al., 2017).

The attention mechanism is mathematically expressed as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^{\mathsf{T}}}{\sqrt{d_k}}\right)V \tag{1}$$

where: Query (Q), Key (K), and Value (V) vectors are obtained through linear transformations of the input embeddings. These transformations enable the model to represent each word within different vector spaces, with learnable parameters determining the attention weights (Kowsher et al., 2024).

$$K = XW_k, Q = XW_q, V = XW_v, \ X \in \mathbb{R}^{(nxd)} \tag{2}$$

where: the input vector *X* is considered as a token embeddings and query vector *Q* is existing knowledge of the sequence that is pair of multiple key and value *(K, V)* vectors.

The relationships between tokens are normalized using the SoftMax function, which converts attention scores into probability distributions (Wilkho et al., 2023). The resulting probabilities are then multiplied by the value vectors to generate context-aware representations of the input sequence (Vaswani et al., 2017).

The structure of this self-attention mechanism is illustrated in Figure 1, which presents an example based on the Amazon Sustainability Report.

Figure 1: Amazon Sustainability Report Single Head Self-Attention
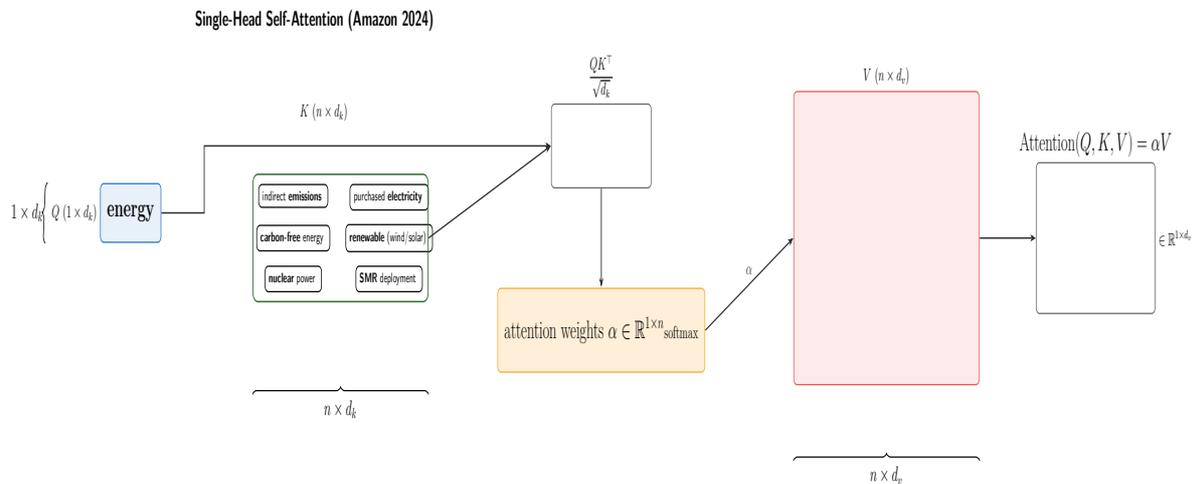
Source: Wu et al. (2024)

With the help of BERT Transformers architecture, simultaneously learning is made possible by multi-head attention. The term as an example "carbon emission rate is declined" and "emissions" can be captured in the semantic concepts and also there will be also a high attention weights in the sentence. Multi-head attention is used in BERT pre-processing model to perform better in different heads and representations. The attention of head is represented in Equation 3 and multi-head is represented in Equation 4. Results of the *head_i* are added and projected with W matrix (Zhang et al., 2024).

$$head_i = Attention\big(QW_i^Q, KW_i^K, VW_i^V\big)\text{head}_\text{i} \tag{3}$$

MultiHead(Q, K, V) = Concate(head₁ …, headₕ)W $\tag{4}$

Additionally, the pre-processing applied to the input data text is an important component of BERT. The text has a special token classification labelled as CLS at the start and other token used for separator labelled as SEP at the end Clark et al. (2019). CLS interacts with other tokens with the help of multi-head attention mechanism and also collects the contextual relationships of the sequence. The aim of the study is to detect the sentences actually contains environmental content and to determine the tone of discourse.

Environmental is a pipeline solution that predicts the likelihood of a given sentence or article falling into a set of categories. It is used to determine whether the sentences in the report are environmental or not (Aman & Reji, 2022a). It is used as gatekeeper because it filters the sentences related to environmental and non-environmental.

In equation 5 and 6, where *i* = 2 means that environmental or non-environmental and *p* is the probability of the classification, so *p* is interpreted as the probability of being environmental.

$$h_{(CLS)} \in \mathbb{R}^d, \; logit = h_{(CLS)}W_i + b_i \tag{5}$$

$$p = softmax(logit) \tag{6}$$

The decision rule is used as follows the sentence is environmental if and only if p is greater than or equal to the threshold value of 0.5 (neutral equilibrium at the outset). If the value of the p is less than 0.5, the sentence is accepted as unrelated to environmental. Only

environmental sentences are filtered in this way. These filtered sentences are subjected to sentiment analysis using the ClimateBERT method.

ClimateBERT gives the three results that are probability of opportunity, neutral and risk. Opportunity is interpreted as a positive signal and risk is negative signal. It classifies the sentences according to probability results and also determines the tone of the statement.

This study builds conceptually on two approaches identified in the literature, including the ClimateBERT-based Cheap Talk Index (CTI) model developed by Bingler et al. (2024). To measure the consistency of companies' statements on climate change, it reduces textual information to a single quantitative index. The other is Stander (2025) article's that analyses the sentiment tone (risk, opportunity, neutral) of climate discourse in integrated reports and relates it to investor reactions. Based on these two approaches, the EDS model aims to measure the quantitative indicator and consistency of environmental discourse by combining discourse coverage, tone positivity/negativity and density normalization under a single mathematical structure.

Moreover, it enables to understand the quantitative approach for how much and how company mentions about environment in the report.

$$EDS = 100 * (0.25C + 0.2P + 0.2D - 0.1N) \tag{7}$$

$$Coverage(C) = \frac{(number\ of\ enviromental\ sentences)}{(number\ of\ total\ sentences)} \tag{8}$$

where: N = all sentences, $N_{enviroment}$ = all environmental sentences, P = $\frac{N_{(positive)}}{N_{(enviroment)}}$, N = $\frac{N_{(negative)}}{N_{(enviroment)}}$.

$$Density(D) = min(20 * C, 1) \tag{9}$$

$$density = \begin{cases} \frac{1000*C}{50} & if\ C < 0.05 \\ 1 & if\ C \geq 0.05 \end{cases} \tag{10}$$

Density is used for standardization of the report because it measures the environmental density of the report without the taking report length, thereby content density of 50 environmental expressions per 1,000 sentences and above if the content has a full density, then it will get maximum value (1.0).

EDS enables to differentiate incompatibility between the coverage and sentiment result. Assuming that, the coverage is high, but the tone is neutral or else the sentiment result is positive and the coverage is low. To prevent this unbalanced result, EDS combines the coverage and density with a balanced structure.

In mathematically neutral terms have not been directly in the equation of EDS, as the sum of probability of neutral, risk and opportunity equal 1 and neutral terms taken into consideration indirectly.

$$p_{(opportunity)} + p_{(neutral)} + p_{(risk)} = 1 \tag{11}$$

The overall methodological pipeline of the two-stage transformer architecture used in this study is illustrated in Figure 2.

Figure 2: Two-Stage Transformers Architecture
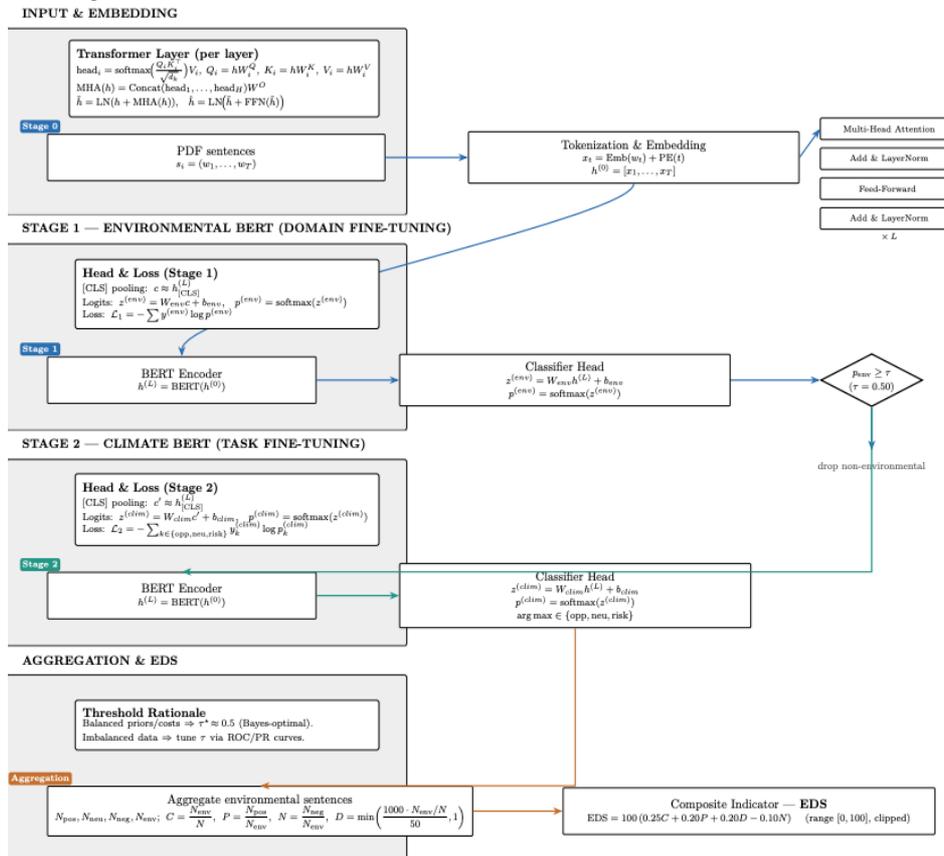
Source: Adapted from Chitty-Venkata et al. (2023).

The dataset used in this study consists of the sustainability and environmental reports for 2024 from six global companies operating in the technology sector. The companies included in the analysis are Google, Apple, Microsoft, Amazon, Samsung and Siemens. Google publishes environment-focused reports titled 'Environmental Report', Apple publishes 'Environmental Progress Report' and Microsoft publishes 'Environmental Sustainability Report'; Samsung, Siemens and Amazon prepare reports in the 'Sustainability Report' format. Environmental reports mostly focus on environmental performance indicators such as climate change, carbon footprint, energy efficiency, water management, and waste reduction, while sustainability reports include social (employee rights, community relations) and governance elements in addition to these themes. Therefore, environmental reports generally exhibit higher environmental discourse density, while environmental content in sustainability reports is shared with social and governance themes. The EDS indicator evaluated in the subsequent stages of the study is significantly influenced by this difference. This is due to corporate preferences and regional regulatory frameworks. European-based companies (such as Siemens and Samsung's European operations) report in accordance with their legal obligations under the EU's CSRD and ESRS.

Therefore, these companies have adopted the 'Sustainability Report' format, which brings together environmental, social and governance (ESG) indicators. On the other hand, it is not compulsory for US technology companies (Google, Apple, Microsoft and Amazon and so on etc.) to provide sustainability reports, so these reports are generally voluntary. This makes companies write reports about how they are doing on the environment, which are then used to measure their performance.

The name given to these reports is "Environmental Report". In short, European companies are adopting a comprehensive approach to sustainability. Regulation is the driving force behind this. Meanwhile, US-based firms have a tendency to concentrate on environmental reporting, so this is founded on the expectations of investors, and the methods companies use to share information. Amazon's report is called "Sustainability". Its content, however, focuses heavily on environmental themes. These include climate, energy, waste management and water. There is less attention given to social issues. Employee rights and community activities are both covered. The investigation of this issue requires an examination of the environmental debate from perspectives of both the manner of its expression and its depth.

The primary reference framework used in the study is the Sustainability Leaders 2024 Report published by GlobeScan and the ERM Sustainability Institute. This report was prepared with the participation of 500 sustainability professionals from 65 countries representing academia, the private sector, public institutions, and civil society organizations. Participants were asked, "Which companies demonstrated leadership in sustainability over the past year?" and the responses were systematically analysed. Thus, the report provides an independent, reliable, and comparable measure of corporate leadership based not on companies' own statements or financial indicators, but on global expert assessments (GlobeScan & ERM Sustainability Institute, 2024).

Although the report has been used in previous studies covering all sectors (Kang & Kim, 2022), this research focuses solely on the technology sector. This focus allows for a more in-depth and comparative examination of the environmental discourse and reporting strategies of technology companies recognized as global sustainability leaders. The next section details the processing of texts obtained from these reports and the methodological framework used in sentiment analysis. In this context, the filtering of texts in terms of environmental content, the determination of sentiment orientation, and the EDS indicator are explained.

3. Research Results

In this section evaluates the results of an environmental discourse analysis of the 2024 sustainability reports of six global companies operating in the technology sector (Amazon, Apple, Google, Microsoft, Samsung, and Siemens).

The comparative environmental coverage ratios across companies are presented in Figure 3. The analyses period is restricted to a single year of 2024 because choosing the single year enables us to align with the findings of GlobeScan & ERM Sustainability Leaders Report 2024 and also to focus of assessing the current trends in technological sector discourse. The analyses focus on two fundamental concepts of environmental communication: one is content scope (the portion of the report devoted to the environment), and the other is the tone of the report. The results are detailed under four subheadings to facilitate comparative evaluation. First of all, the extent to which companies addressed environmental issues in their reports (scope analysis) was examined. Second, the tone used to convey these issues (sentiment analysis) was evaluated. Third, an analysis based on the EDS indicator derived from the combination of coverage and tone variables was presented. Lastly, the importance companies attach to different environmental themes was examined through thematic content distribution. The extent to which companies mention environmental issues in their sustainability reports is the first indicator of their corporate environmental communication strategies. Coverage

measures the proportion of the sentences that relates to environmental and climate themes in the total text of the reports.

Figure 3: Environmental Scope Ratios by Company
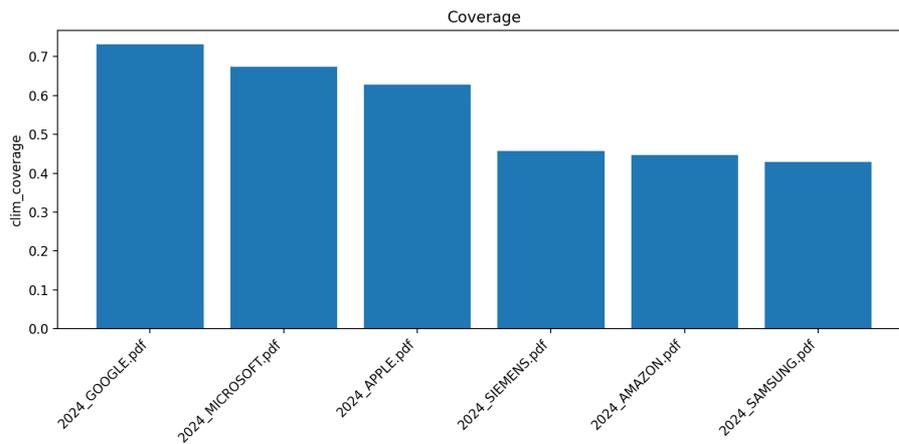
Source: Authors' calculations based on corporate sustainability and environmental reports (2024).

When it comes to talk about the analysis results, there exists significant differences between companies in terms of environmental coverage. Google (73%) and Microsoft (67%) have the highest coverage rates. More than two-thirds of their reports address environmental issues. Apple ranks third with 63%, while Siemens (46%), Amazon (45%), and Samsung (43%) have addressed environmental issues to a more limited extent. This distribution quantitatively demonstrates the priority companies give to environmental issues in their corporate reporting. With the help of sentiment analysis whether the language used in environmental topics was positive (opportunity, progress, success-oriented), negative (risk, challenge, problem-oriented), or neutral evaluated. The sentiment distribution of environmental discourse across companies is illustrated in Figure 4.

Figure 4: Distribution of Positive and Negative Tone by Company
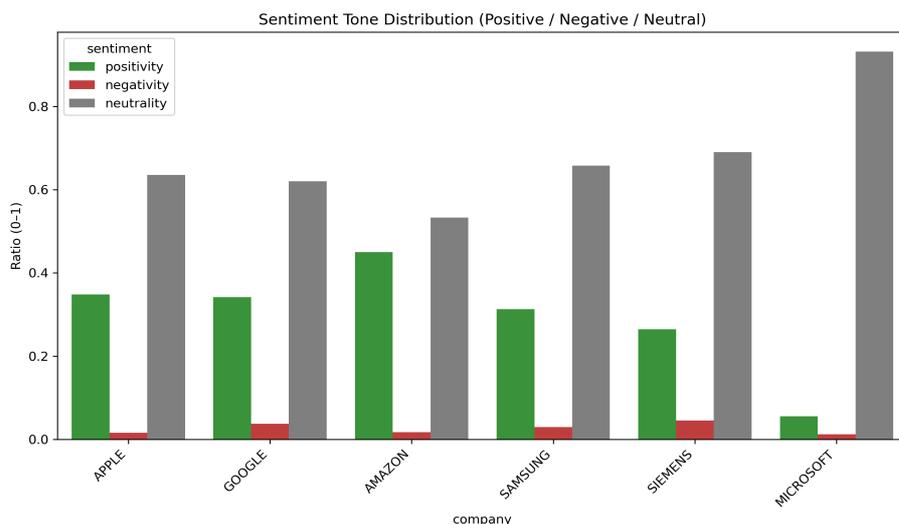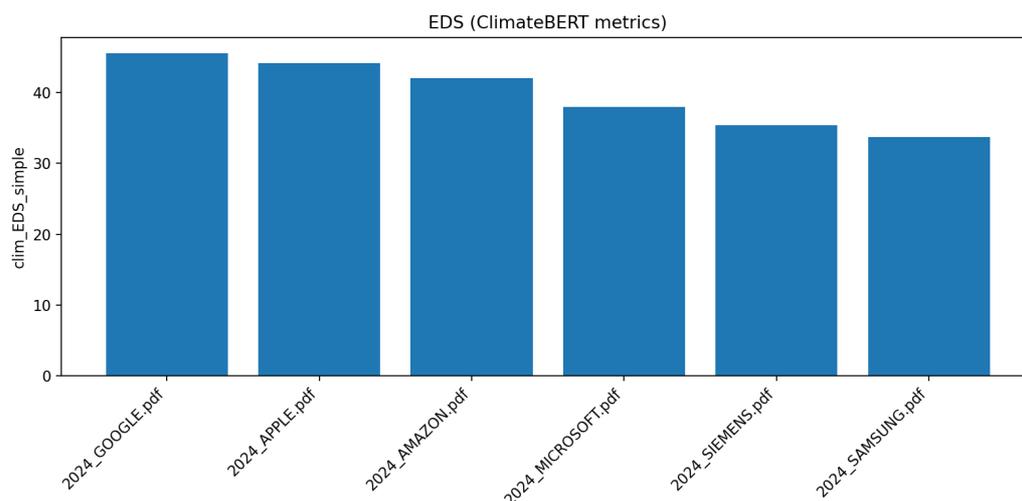

Source: Authors' calculations based on ClimateBERT sentiment analysis of corporate sustainability reports (2024).

The results of the sentiment analysis demonstrated that companies show three different profiles in their discursive orientations. The predominantly positive discourse group consists of Amazon (56% positive, 4% negative), Apple (44% positive, 3% negative) and Google (40%

positive, 7% negative). These companies predominantly address environmental issues in terms of opportunity, commitment and progress. Microsoft (6% positive, 1% negative) is in the balanced/neutral discourse group; the company's language is largely information-reporting focused and devoid of emotional orientation. The cautious discourse group includes Siemens (24% positive, 9% negative) and, notably, Samsung (23% positive, 17% negative). Samsung's 17% negative tone ratio represents the highest emphasis on risk and challenge in the sample. The composite Environmental Discourse Strength (EDS) scores are summarized in Figure 5.

Figure 5: Environmental Discourse Strength (EDS) Scores and Dimensional Distribution

Source: Authors' calculations based on Environmental BERT and ClimateBERT outputs.

The EDS metric is a composite indicator that combines scope and tone dimensions to measure the strength of environmental discourse. A high EDS score indicates both broad environmental coverage and a positive discourse orientation. Table 1 summarizes the environmental discourse density and EDS scores calculated for the six companies.

Table 1: Environmental Discourse Density and Environmental Discourse Strength (EDS) Scores

| Company	Environmental Sentences	Total Sentences	Coverage (%)	Positive Tone (%)	Negative Tone (%)	EDS Score
Google	1,297	1,774	73	40	7	45.54
Apple	1,029	1,641	63	44	3	44.18
Amazon	660	1,479	45	56	4	42.00
Microsoft	273	405	67	6	1	37.99
Siemens	1,276	2793	46	24	9	35.43
Samsung	410	956	43	23	17	33.72

Source: Authors' calculations based on corporate sustainability and environmental reports (2024).

The EDS score is a normalised metric that jointly evaluates the proportion of environmental topics within a text (scope) and the orientation of the language (tone). Values are scaled between 0 and 100.

Results evaluated using the EDS indicator show that companies do not have a homogeneous structure in their environmental discourse strategies. According to the results of this indicator, Google (45.54) received the highest score, followed by Apple (44.18) and Amazon (42.00). Samsung (33.72) has the lowest EDS value.

The interaction between coverage and sentiment plays a decisive role in EDS. Although Microsoft has a high coverage rate of 67%, its EDS score (37.99) is average because it uses neutral language. In contrast, Amazon's ranking is at the top, with a positive sentiment rate of 56% compensating for its medium coverage rate of 45%. The findings of the analysis demonstrate that the manner in which environmental discourse or emphasis is articulated is of equal significance to its intensity. To understand which environmental topics companies, prioritise, a thematic content analysis was conducted. The analysis covers seven categories: climate and greenhouse gas emissions, energy efficiency, waste management and circular economy, water resources management, biodiversity, targets and adaptation strategies, and reporting frameworks. The thematic distribution of environmental topics across companies is visualized in the heat map presented in Figure 6.

Figure 6: Distribution of Environmental Themes by Company (Heat Map)
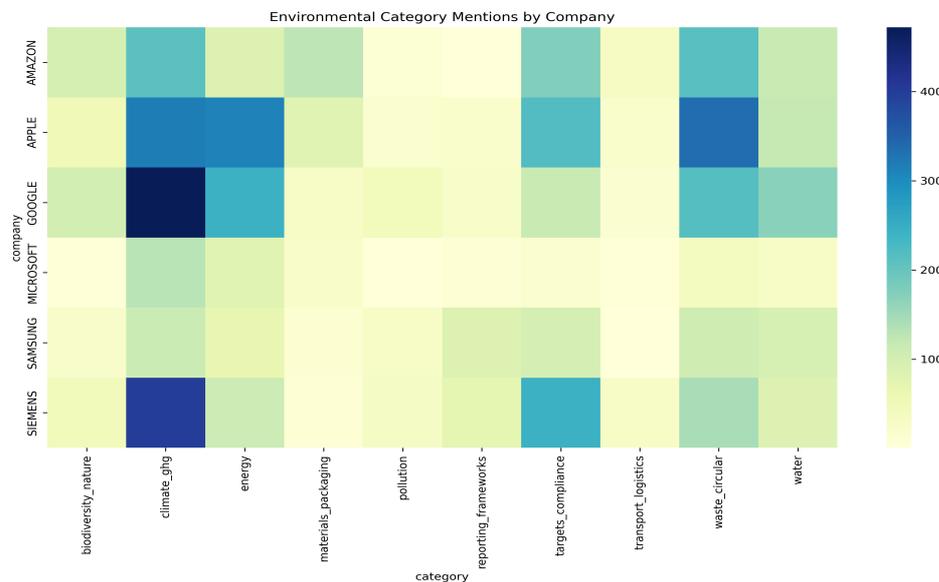
Source: Authors' work based on thematic content analysis of corporate sustainability reports (2024).

The heat map analysis showed three important things. Firstly, the most important topics for all companies are climate change and energy management. This shows that companies are working hard to reduce their carbon emissions. Secondly, companies do not pay as much attention to biodiversity and water management. Only briefly touched on in the Samsung and Amazon reports, these two subjects are addressed in greater depth in the Google/Apple report, where a strong environmental ethos is demonstrated. Samsung and Siemens adopt a more selective approach.

The categorisation of subject headings mirrors the companies' industry positions and strategic objectives. Samsung, a hardware manufacturer, demonstrates its consideration of legal regulations for product life cycle management through its strong emphasis on waste and the circular economy. On the other hand, companies that make software and provide services, like Google and Microsoft, are working on ways to show the environmental impact of their data centre operations. These companies are doing this by looking at how much energy is used and the amount of carbon that is produced. Technology companies' approaches to environmental sustainability were analysed, finding that they employ three distinct strategies.

Conclusion

In this study, the sentiment trends in the sustainability reports of technology companies are consistent with ESG-based market signalling mechanisms, which are gaining increasing importance in the literature. According to signalling theory, companies with high ESG performance adopt a more positive sentiment in their reports, and this sentiment provides information about the company's sustainability quality (Sun et al., 2024). The impact of this signal on markets has brought about significant effects on investor behaviour and financial market dynamics. There is empirical evidence that a positive ESG discourse tone increases stock liquidity, strengthens institutional investor participation, and reduces companies' cost of equity through these channels (Deng et al., 2026). In a similar way, it has been observed that information asymmetry has weakened and financing costs have declined in companies where the flow of ESG-related information has increased (Yu et al., 2025). Results from European capital markets demonstrate that mandatory ESG disclosures have a positive impact on earnings quality and cost of capital; the results indicate that ESG regulations are a defining structural element of the financial information environment (Akin & Akin, 2025). As well as its impact on the cost of equity, ESG performance has also been demonstrated to increase the efficiency of pricing by reducing investor sensitivity and alleviating information asymmetry (Chen & Wu, 2025). It has been noted that ESG-specific tone and sentiment indicators can predict stock returns more strongly than general news indicators (Goutte et al., 2023). Evaluating these findings as a whole, our study reveals that the discourse tone patterns identified in technology companies' sustainability reports reflect the multidimensional market effects of ESG disclosures, ranging from investor behaviour to capital allocation, pricing efficiency to financial stability, at the sector level.

When it comes to talk about the findings of this study, it indicates that there are significant differences in the environmental discourse strategies of technology companies. These differences may stem primarily from structural factors such as business model, corporate communication strategy, legal regulations, and stakeholder expectations. First, companies' business models and activities directly influence the importance they place on environmental issues and the language they use. Production and product-focused companies (e.g., Apple and Siemens) use more concrete, positive language by linking environmental impact to physical processes. In contrast, service and digital infrastructure-focused companies (e.g., Microsoft and Samsung) address environmental issues in terms of efficiency, technology, and compliance, which makes the language more neutral and technical. Secondly, corporate communication strategy and brand identity significantly influence the tone of discourse. Brands aiming for global leadership (such as Google and Apple) present the environment as part of innovation and transformation. Therefore, they adopt a broad, solution-oriented style in their reports. In contrast, companies with high operational risks (Amazon, Samsung) have a more cautious and process-oriented environmental discourse. Thirdly, regulatory and reporting culture reinforce these differences. European-based companies (such as Siemens, Samsung etc.) are more measurable due to the influence of CSRD-ESRS standards.

As for the examples, given that Samsung and Siemens demonstrate that environmental discourse in European-based companies is produced within a different corporate context in terms of content. The reports of these companies prepared in compliance with the principle of double materiality, which means that defining under the European Union's CSRD and ESRS. From the view of comprehensive point, besides the measuring environmental impacts, reporting of social and governance become compulsory.

Therefore, European-based reports comprising environmental issues not as a separate heading, but also as an integral part of corporate strategy, ethical governance and social impact. In contrast with the European-based reports, United States (US) based on technology companies (Google, Apple, Microsoft, Amazon) often prepare environmentally theme reports that are mostly in the form of an Environmental Report or Environmental Progress Report, without any legal obligation to do so. This difference appears as a significant variable affecting the density and sentiment distribution of environmental discourse strength in EDS analysis. Whereas European companies' reports make use of environmental language that is more corporate, measured and strategic in tone, US-based reports feature a more pronounced, positive and communicative emphasis on environmental issues.

In consequently, the EDS analysis is more than just a tool for measuring the sentiment of the report and it also reveals differences in corporate discourse emerging from different regulatory contexts. Regarding to this context, EDS provides an analytical contribution to understanding the formal diversity in sustainability reporting and offering a comparable discourse analysis framework for researchers, investors and policymakers. EDS indicator measuring the consistency, sentiment tone balance and coverage of environmental discourse can help to identify the risk of greenwashing at an early stage for investors. In this way, EDS can serve as a behavioural indicator that could support investment decisions by analysing non-financial indicators through linguistic data. From the perspective of policymakers, it can be used to monitor how reporting formats change across different regulatory domains and to assess the need for linguistic standardisation in reporting. NLP tools are being evaluated not only as technical solutions that reduce text volume under regulatory supervision with the increase in sustainability reporting, but also as analytical mechanisms that provide trend monitoring, model identification, and the structuring of risk-focused audit priorities. These tools play a complementary role to human assessments in the early detection of possibly misleading statements (ESMA, 2024).

Particularly within the context of European Union regulations such as CSRD and ESRS, it is likely that metrics similar to EDS will contribute to future standards of comparability and transparency. The limitation of this research is that the scope of analysis 2024 reports, which partially restricts the generalised of findings up to years or trends. Yet, the selected year provides a synchronised context with the GlobeScan & ERM Sustainability Leaders Report (2024), which enables to asses consistently current environmental discourse trends in the technology sector. Text-based sentiment measurements can provide information for decision-makers and generate signals related to market/behavioural responses, consistent with the literature (Tetlock, 2007). Within this framework, "emotional consistency" in technology companies' environmental sustainability reports can be interpreted as a complementary indicator of reporting quality. Therefore, the tone of reporting remaining consistent with performance indicators over time can be considered a factor that strengthens the reliable reporting infrastructure, which is a prerequisite for long-term financial and environmental sustainability. For future research, applying the EDS method across different sectors, past and upcoming years data and cultural contexts, and inter-annual changes will be valuable for understanding the evolution of environmental discourse. In addition to this, EDS could become a measurable awareness tool for investor confidence, stakeholder relations, and corporate reputation management by quantifying not only the content but also the strategic and ethical dimensions of sustainability communication.

Credit Authorship Contribution Statement

Çardak, B. R. contributed to the conceptualization of the study, research design, supervision, and critical revision of the manuscript. Çardak, H. was responsible for methodology development, data collection, and formal analysis. Alp, Ö. S. conducted the sentiment analysis using AI-based techniques and contributed to data interpretation. Hazar, A. supported data curation, validation, and visualization of the empirical results. Babuşcu, S. contributed to the literature review, drafting of the manuscript, and editing for intellectual content. All authors reviewed and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. There are no patents and copyrights to be declared in relation to this work.

Data Availability Statement

Data Availability Statement: The reports used in this work available on the company website.

Ethical Approval Statement

This study uses publicly available corporate sustainability and environmental reports as the primary data source. No human participants or confidential data were involved in the research process. Therefore, formal ethical approval was not required. All data were obtained from publicly accessible company reports and used solely for academic research purposes.

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