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MORALITY BEFORE KNOWLEDGE

PRISMA systematic review: The application of Natural Language Processing (NLP) to identify greenwashing in sustainability reports within the oil and gas industry

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ABSTRACT

Background: Greenwashing refers to misleading sustainability claims not backed by real actions, commonly seen in the oil and gas industry due to its dependence on fossil fuels. While companies may publicly commit to sustainability, their investments often contradict these claims, obstructing global renewable energy efforts. This mismatch between statements and actions misleads stakeholders and complicates audit processes. As demands for transparency grow, there is a pressing need for systematic tools to detect greenwashing. Prior research highlights that the narrative format of sustainability reports makes manual detection difficult, underscoring the need for technology-based solutions. **Methods**: This study aims to examine the application of Natural Language Processing (NLP), particularly the N-Gram model, in identifying indications of greenwashing in the oil and gas industry. The research uses a qualitative approach with a Systematic Literature Review (SLR) method and applies the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. **Findings:** The N-Gram model aids in feature extraction by converting raw text from sustainability reports into structured representations and detecting linguistic patterns commonly found in overstated sustainability claims. When combined with classification methods like Support Vector Machine (SVM), it improves the accuracy of greenwashing detection. Key findings show that NLP can support auditors in assessing greenwashing risks and improving the efficiency of sustainability audits. Moreover, the integration of this technology promotes greater transparency in corporate disclosures. **Conclusion**: The application of the N-Gram model in the NLP context is effective in detecting greenwashing practices that were previously difficult to identify manually. **Novelty/Originality of this article:** This study offers novelty through the application of the N-Gram NLP model within the oil and gas industry context, which has been rarely explored in previous research. The practical implications of this study open opportunities for cross-sectoral implementation and the development of data-driven greenwashing identification standards in the future.

KEYWORDS: greenwashing; natural language processing; oil and gas industry.

1. Introduction

Amid growing awareness of the climate crisis, a global shift toward renewable energy, and increasing international regulatory pressure for decarbonization, the oil and gas sector faces complex and long-term challenges. Changing investor preferences—now increasingly focused on environmental, social, and governance (ESG) factors—along with rapid

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advancements in clean energy technologies, have further accelerated the decline in long-term prospects for fossil fuel-based industries. Specifically, oil and gas companies must confront the reality that their traditional business models are no longer aligned with the trajectory of the global energy transition, compelling them to adapt or risk losing relevance and market support.

Currently, oil and gas companies face significant challenges in substantially reducing carbon dioxide (CO_2) emissions, due to the inherently fossil fuel-dependent nature of their operations. According to Statista (2023), the oil and gas sector is considered the most difficult to decarbonize, often categorized as a 'hard-to-abate' emissions source. In 2022, global consumption reached approximately 97 million barrels per day (mb/d) of oil and 5,150 billion cubic meters of natural gas (IEA, 2023a), resulting in an estimated 18 gigatons of CO_2 emissions—accounting for nearly half of global energy-related CO_2 emissions (IEA, 2023b). At the same time, the emergence of environmentally friendly technologies such as electric vehicles (EVs) has the potential to induce a kinked demand curve phenomenon, wherein fossil fuel demand becomes inelastic and increasingly vulnerable to sudden declines. When fossil fuel prices—such as crude oil or natural gas—drop, demand does not necessarily rebound significantly, as both consumers and industries begin shifting toward renewable energy alternatives, including solar and wind power or electric mobility. Moreover, as renewable energy technologies become more cost-effective and supported by public policy, this demand shift may accelerate. According to the International Energy Agency (IEA, 2025), the adoption of electric vehicles alone has reduced global oil demand by approximately 1.3 million barrels per day in 2024.

The growing urgency for clean energy poses a threat to the going concern status of oil and gas companies. In addition, climate-related risks can create material uncertainties that affect a company's ability to continue its operations, particularly if it fails to adapt to rapidly evolving market dynamics and regulatory frameworks (Deloitte, 2023; KPMG, 2023). In response, companies worldwide have increasingly incorporated sustainability into their business processes. Notably, 96% of the world's 250 largest companies (the G250) and 80% of the N100—a sample of 5,200 companies consisting of the top 100 firms across 52 countries—have published sustainability reports (KPMG Survey of Sustainability Reporting, 2020). These reports serve as tools for investors to evaluate corporate performance in environmental, social, and governance (ESG) dimensions over time (Bernow et al., 2019). However, 85% of investors report that sustainability disclosures contain misleading statements. The discrepancy between sustainability claims and actual practices is referred to as greenwashing. Spence's (1973) signaling theory explains how a signal sender conveys information to a signal receiver in order to influence the latter's perceptions or decisions. Companies possess complete knowledge of their own operations—including both the actions taken and those omitted in pursuit of sustainability. Stakeholders, on the other hand, rely solely on externally communicated information, such as sustainability reports or public disclosures. Given their limited access to internal activities, stakeholders cannot independently verify such data, increasing the likelihood of information distortion.

According to Klynveld Peat Marwick Goerdeler's 2024 report, the oil and gas sector is the industry most frequently associated with greenwashing, accounting for 19% of all reported cases in 2023. This sector is particularly susceptible to greenwashing practices due to the existential threat posed by renewable energy sources, which have the potential to substitute fossil fuels. In response, oil and gas companies engage in greenwashing strategies to maintain trust among the public, investors, and regulators (Carrington, 2023). This aligns with legitimacy theory, which posits that organizations seek to align themselves with prevailing social norms to preserve public support (Suchman, 1955). Within the context of greenwashing, companies employ sustainability narratives as symbolic tools to construct legitimacy. By publishing environmentally friendly claims, firms attempt to demonstrate alignment with societal values (moral legitimacy) and/or to foster stakeholder belief in their responsibility and accountability (pragmatic legitimacy). An example of greenwashing is the case involving Shell in 2021 (Shell plc, 2021). According to an article by The Guardian, Shell claimed that 12% of its capital expenditure was allocated to its Renewable and Energy Solutions division. However, investigative findings by Global Witness reveal that only approximately 1.5 % of Shell's capital expenditure went towards genuine renewable energy projects (such as wind and solar) in 2021. Another instance of discrepancies between corporate sustainability claims and actual practices within the oil and gas industry can be observed in Table 1.

Table 1. Claims and realities of implementing oil and gas companies' sustainability efforts

Claim	Reality
Commitment to reduce carbon emissions and increase investment in low-carbon energy	Despite their stated commitment to the energy transition, companies such as ExxonMobil, Shell and BP are expanding their oil and gas expansion after making record profits in 2022. Large acquisitions such as Exxon's USD 60 billion purchase of Pioneer emphasize the climate-defying direction of their investments (Global Wittness, 2022, 2023; IEA, 2023b).
Claiming to be a leader in climate solutions and clean energy transition	Oil and gas companies actively promote their image as climate leaders through advertising, but data shows that their actual investment in clean energy only accounts for 1-2.5% of total capital expenditure. This is far from the 50% recommended by the International Energy Agency to achieve the Paris Agreement targets (IEA, 2023c; InfluenceMap, 2021).
Supporting the Paris Agreement and net-zero targets	Despite publicly expressing support for the Paris Agreement, internal Exxon documents show systematic efforts to avoid formal commitments. In fact, Exxon refused to set Scope 3 emissions targets and sued the shareholder who proposed them.
Natural gas as a "low carbon" solution and transition bridge	Natural gas is often positioned as a low-carbon solution. However, when methane leakage is taken into account, its total emissions can be equivalent to coal. Without a clear transition plan, this narrative reinforces dependence on fossil fuels (UNEP, 2023)
Highlighting investment in biofuels, such as algae	Exxon once promoted plans to produce 10,000 barrels per day of algae biofuel. However, the project was quietly halted in 2023 because the technology was deemed unfeasible, making the earlier claims more of a marketing tool than a serious climate strategy.
Relying on Carbon Capture and Storage (CCS) as the main solution	Data shows that around 80% of existing CCS facilities are used to increase oil extraction through enhanced oil recovery (EOR), which involves injecting CO_2 into oil wells. In addition, this technology is still relatively expensive, has not been widely implemented, and has not been proven to have a significant impact as a long-term climate change mitigation solution (Larson, 2021; IEA, 2023a).
Encourage the use of personal carbon footprint calculators for public awareness	Through campaigns such as BP's "Target Neutral", companies encourage individuals to calculate and compensate for their carbon footprint. However, this strategy is seen as shifting structural responsibility from corporations to consumers, even though industrial emissions remain a major contributor (Supran & Oreskes, 2021; ClientEarth, 2019).

Greenwashing practices not only mislead the public but also pose significant risks to a company's long-term sustainability. Agency theory, as proposed by Jensen and Meckling (1976), outlines the relationship between principals and agents, and how to manage conflicts of interest and information asymmetry between the two parties (Eisenhardt, 1989). From the perspective of agency theory, greenwashing in oil and gas companies reflects a conflict between managerial interests and those of stakeholders who demand genuine transparency and sustainability. Management often exploits information asymmetry to construct an environmentally friendly image through symbolic claims, without making substantive changes to core operations that remain heavily reliant on fossil fuels (Rousseau, 2006). While such strategies may protect short-term reputational interests, greenwashing risks deceiving the public and eroding trust. In the long run, this may threaten a firm's viability through loss of legitimacy, increased regulatory pressure, and declining market value. The sustainability audit process is not an easy process. There are unique challenges in each process, as shown in Table 2.

Table 2. Challenges on sustainability auditing process

Key steps in the auditing process	Representative challenges	Issue (Adapted from Pendyla (2018))
Data collection	Use of past data (retrospective), use of limited samples, and use of 'preselected data' by management.	Accuracy; Precision; Completeness; Consistency; Timeliness
Data recording and sharing	Auditors are responsible for data management (external auditors keep the data e used for generating audit reports) and the data is not available to firms.	Transparency; Traceability; Timeliness
Data analysis	Audits unable to fully process large amounts of data due to limited resources or time; analysis could also be compromised due to conflicts of interest.	Bias, Process errors; Timeliness

(Castka et al., 2020)

The main problem with sustainability audits is data inconsistency (Hazaea et al., 2022). For example, while industries such as manufacturing have established specific benchmarks for emissions and resource consumption, other sectors still lack such standards, resulting in inconsistent and fragmented reporting practices (Braig & Edinger-Schons, 2020). These challenges include the lack of uniform methods and indicators for measuring environmental performance, the complexity of environmental regulations that vary from region to region, and the unavoidable subjectivity when assessing the qualitative dimensions of sustainability (Pramukti, 2024). Additionally, auditors often encounter management teams that are reluctant to share sensitive environmental data or allocate resources to sustainability efforts (Pramukti, 2024).

As a response to rising concerns over misleading sustainability disclosure, global regulators have developed a regulatory framework to increase accountability. The European Union's Corporate Sustainability Reporting Directive (CSRD) introduced European Sustainability Reporting Standards (ESRS) to provide a framework for companies to report consistent and comparable sustainability matters. Through CSRD, companies are required to provide detailed information on a wide range of ESG matters such as data on climate change impact, emissions reduction strategies, human right practices, and more.

To address this issue, sustainability audits can play a crucial role in conducting risk assessments of materially significant sustainability disclosures, thereby reducing the potential for greenwashing. However, the effectiveness of such audits remains limited due to the predominantly narrative nature of disclosures and their reliance on managerial subjectivity (IAASB, 2023). In such conditions, auditors often struggle to assess the extent to which sustainability claims accurately reflect a company's actual practices. As a result, a technology-based approach is needed to systematically identify linguistic patterns and signs of inconsistency. In this context, technology-driven methods can be employed to assess disclosure materiality, detect inconsistencies, and uncover potential material misstatements indicative of greenwashing. One such approach involves the application of Natural Language Processing (NLP), particularly through the use of N-Gram models. These models enable the extraction of linguistic features from narrative texts, allowing for the identification of characteristic language patterns frequently found in sustainability claims lacking substantive evidence. By integrating managerial subjectivity, historical data, and benchmarking against peer companies, auditors can use N-Gram models to detect anomalies within sustainability narratives and enhance risk-based audit procedures. This approach has the potential to serve as a systematic solution for addressing increasingly complex and concealed greenwashing practices, while promoting more transparent and reliable sustainability reporting.

Accordingly, this study aims to explore the application of the N-gram NLP model in detecting linguistic patterns of greenwashing, as a tool to support auditors in conducting more objective and accurate sustainability audits. The research specifically focuses on the oil and gas sector, which exhibits the highest risk of greenwashing and faces significant challenges in the transition to clean energy. The primary contribution of this study lies in addressing the gap in the literature concerning the limited empirical research on the use of NLP in the context of sustainability auditing. Additionally, it seeks to develop a technical framework that enhances the transparency and credibility of audit processes amid the increasing complexity of sustainability narratives. This study is expected to broaden the understanding of greenwashing detection and provide a practical foundation for both auditors and regulators in fostering more accountable sustainability governance.

2. Methods

2.1 Types and sources of research

This study adopts a qualitative approach utilizing the Systematic Literature Review (SLR) method to examine the application of Natural Language Processing (NLP) technology in detecting greenwashing practices within the oil and gas industry. The SLR method enables researchers to systematically identify, evaluate, and synthesize relevant literature, thereby generating a comprehensive and structured understanding of the research topic. The SLR process in this study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, which consist of four main stages: identification, screening, eligibility, and inclusion. The identification stage involved searching for relevant literature using keywords such as 'greenwashing,' 'oil and gas industry,' 'sustainability reporting,' 'natural language processing,' 'N-Gram,' and 'support vector machine.' Literature sources were drawn from leading scientific databases including Scopus, ResearchGate, and ScienceDirect, covering publications from 2019 to 2025. Additional supporting data were obtained from institutional publications, including those from the International Energy Agency (IEA), KPMG, EY, and corporate sustainability reports (EY, 2024).

2.2 Analysis method

A systematic review is conducted to gather all relevant scientific evidence based on predefined inclusion criteria in order to answer a specific research question. In this study, the researcher adopts the PRISMA model (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), an approach originally developed in the healthcare field to support clinical practice guidelines and evidence-based decision-making through a structured methodological framework and accompanying protocols (Moher et al., 2009). The adoption of a systematic review method—particularly the PRISMA model—is driven by the need for a highly structured and rigorous research approach (Tranfield et al., 2003). This method enables researchers to summarize existing literature through a meticulous, explicit, and transparent process across iterative stages (Liberati et al., 2009). A comprehensive systematic review strengthens the justification for the final research question, including when the aim is to replicate or extend previous studies (Tranfield et al., 2003). The focus on greenwashing in the oil and gas sector reflects an initial assessment of the relevance of the literature gap in this topic area. Accordingly, a systematic literature review is employed as a methodological approach to evaluate the significance of this gap.

The PRISMA model has now been widely adopted, not only in evidence-based medical research but also across various other disciplines. Although originally developed within healthcare and later applied to management studies, the model has also been utilized in systematic reviews within financial literature (Hammad et al., 2024). The PRISMA flow diagram used in this study follows four main phases. The first phase, identification, involves formulating the research question and systematically locating relevant studies. This process is conducted comprehensively, guided by clearly defined inclusion and exclusion criteria. The second and third phases—screening and eligibility—focus on filtering the identified studies based on their relevance to the research question and the predetermined criteria. This involves an initial review of titles and abstracts, followed by a full-text assessment of articles that meet the initial requirements. The studies that pass this stage are then evaluated for their quality and relevance to determine their eligibility. Finally, in the inclusion phase, eligible articles are incorporated into the systematic review. Data from these studies are extracted, analyzed, and synthesized to inform the research findings.

The PRISMA model ensures replicability, transparency, and traceability of the review protocol employed. In alignment with the PRISMA checklist, all relevant aspects were carefully addressed, as summarized in the following table. At the initial stage, a review plan was developed by establishing specific inclusion and exclusion criteria. To obtain the necessary literature sources, a keyword-based search expression was constructed, including terms such as “green wash or greenwash,” “oil and gas,” and “audit.” The inclusion criteria encompassed full-text articles available online, written in either Indonesian or English, and directly relevant to the study topic. The exclusion criteria consisted of books, conference proceedings, editorials, articles written in languages other than Indonesian or English, and gray literature such as non-academic industry reports or documents that did not meet the inclusion requirements.

The next stage involved conducting the systematic literature review in accordance with the PRISMA protocol. The previously constructed search expressions were applied to access documents from the selected academic databases. No publication date restrictions were imposed at the outset to ensure that all relevant materials published up to May 20, 2025, could be included. The inclusion focused on the area that examines greenwashing practices, particularly in the oil and gas industry and within the sustainability and environmental, social, and governance (ESG) context. Furthermore, research discussing natural language processing, artificial intelligence, or machine learning techniques, particularly those aimed at detecting greenwashing, was included. In contrast, research was excluded if it discussed NLP without linking it to ESG, greenwashing, or sustainability. Furthermore, research that was not in English and was not an academic document was also excluded. The initial search yielded 116 documents. Following the removal of duplicates, non-English articles, and non-academic documents, a total of 102 articles remained. The abstracts of these articles were then analyzed to determine their relevance to the scope of the study. Through this process, 13 articles were selected as the final sample. All selected articles were thoroughly reviewed, and key information was tabulated and categorized based on their central objectives or themes. The result of the entire screening and selection process followed the PRISMA stages illustrated in Fig. 1.

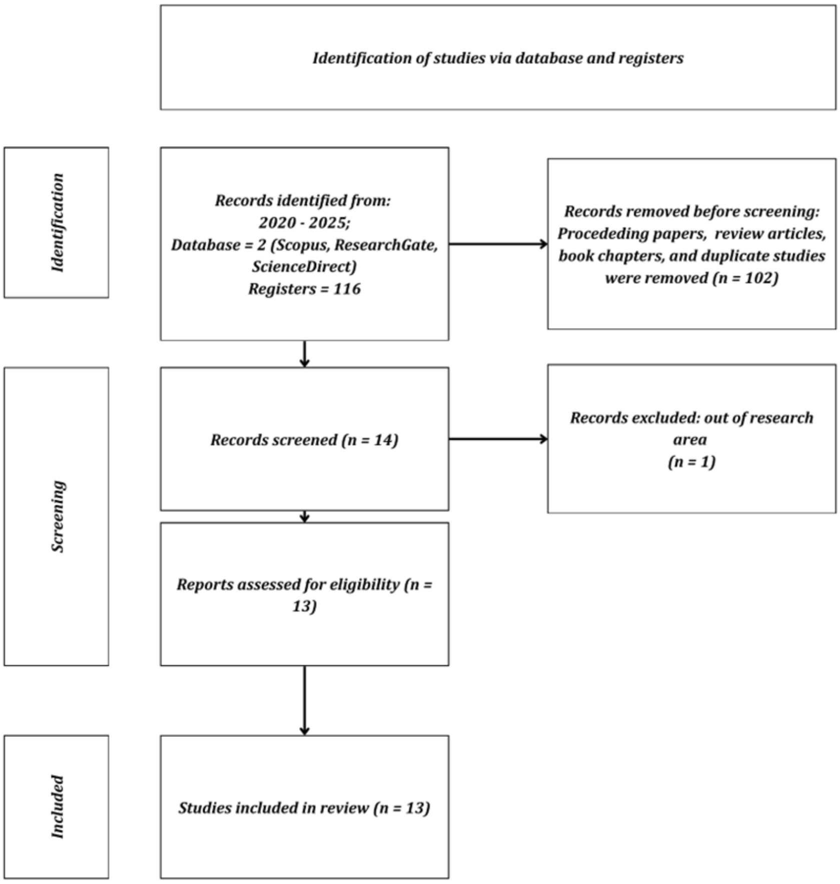

Fig. 1. PRISMA process literature review

3. Results and Discussion

3.1 Description of data and research objects

This study examines sustainability reports published by companies in the global oil and gas sector. These documents serve as official disclosures containing narratives on corporate commitments to sustainability issues, strategic initiatives, and achievements related to environmental impact reduction, as well as improvements in social and governance practices. The sustainability reports analyzed in this study were published within the last five years, from 2020 to 2025, and were selected based on market capitalization and the companies' membership in industry associations such as the Oil and Gas Climate Initiative (OGCI).

To obtain the sustainability reports, this study adopted a web scraping method—an automated process for systematically downloading documents from websites. This technique enables researchers to collect large volumes of data efficiently and in a structured manner, eliminating the need for manual downloads. The scraping process was applied to the official websites of oil and gas companies, where links to PDF files of sustainability reports were identified. Once these links were located, the scraping software automatically downloaded the PDF files into a local database. The PDF links were accessible on the scraped webpages and were not obstructed by technical barriers such as CAPTCHA (Completely Automated Public Turing Test to Tell Computers and Humans Apart) protection, user authentication, or access restrictions based on user-agent headers. The implementation used Python programming libraries, specifically the requests module to send HTTP (Hypertext Transfer Protocol) requests to the websites and BeautifulSoup to extract and parse the HTML (HyperText Markup Language) structure for locating the PDF links.

A key characteristic of the data is the presence of sentences containing claims in the form of strategic statements or sustainability commitments, alongside sentences describing actions—concrete activities that have been undertaken, are in progress, or are planned by the company. This study focuses on identifying and analyzing discrepancies between such claims and actions, specifically situations in which sustainability claims are not proportionally supported by tangible efforts. Theoretically, such discrepancies can be interpreted as indications of greenwashing practices.

3.2 Theoretical framework and text analysis process

3.2.1 Identification of claims and actions in texts

In the context of sustainability reports, *claims* refer to promises, commitments, or targets made by companies regarding their sustainability efforts—such as statements about reducing carbon emissions, adopting renewable energy, or achieving net-zero emissions by a specified year. These claims are strategic in nature and are often conveyed using persuasive and optimistic language to build a positive image of the company in the eyes of stakeholders (Goh & Jie, 2019). In contrast, actions refer to more concrete descriptions of the steps that companies have taken or are currently undertaking to fulfill those claims. Examples include reports of investments in clean energy projects, the implementation of environmentally friendly technologies, or the achievement of measurable environmental indicators.

The mismatch between claims and actions is a central focus in detecting greenwashing practices within sustainability reports, emphasizing the need to analyze the logical connection and coherence between the two. For instance, a company may claim strong commitment to carbon reduction, but the reported actions may reveal minimal or irrelevant investments toward that goal. From a theoretical standpoint, mismatch detection involves analyzing contextual alignment between claim and action sentences using NLP techniques capable of capturing the semantic relationships between them. This approach also requires an understanding of temporal context—namely, whether the reported actions occurred within an appropriate timeframe relative to the claim—as well as the proportionality between the intensity of the claim and the scale of the disclosed actions.

3.2.2 Greenwashing detection using NLP Based on other methodologies

As part of our approach to detecting greenwashing using Natural Language Processing (NLP), we refer to the methodology proposed by Suyash Saxena. The study conducted by Saxena (2024) offers valuable insights into how NLP techniques can be applied to identify greenwashing indicators within sustainability reports, as well as how these models can be used to construct portfolios with a focus on social and environmental impact. In his research, Saxena developed a framework based on two primary metrics: Focus Scores and *Action Scores* (Saxena, 2024). Focus Scores measure the extent to which a company emphasizes environmental issues in its sustainability reporting. This metric is calculated by assigning higher weights to words associated with environmental commitment, utilizing NLP models such as TF-IDF and BERT.

While Focus Scores provide an overview of how much emphasis a company places on environmental issues in its reports, they do not confirm whether the company actually follows through on these commitments (Saxena, 2024). To build on this analysis, Saxena introduced Action Scores, which measure the extent to which a company's claims are supported by concrete, measurable, and relevant actions (Saxena, 2024). These scores are calculated using techniques such as Relation Extraction and Named Entity Recognition (NER) to identify the link between stated claims and the actual steps taken or being undertaken by the company. Saxena also proposed the concept of Net Action Direction to assess whether a company’s actions align with its stated commitments. When Action Scores are significantly lower than Focus Scores, this serves as a potential indicator of greenwashing, suggesting that the company may be overstating its sustainability commitment without taking proportional action. In his study, NLP models such as BERT and RoBERTa—fine-tuned on sustainability report data—were used to support this framework. For instance, EnvBERT and EnvRoBERTa were employed to calculate Environment Scores, which measure how much a company's claims pertain to genuine environmental issues. Additionally, EnvClaims and EnvAction scores were derived to assess the coherence between stated claims and actual initiatives, as well as how these elements contribute to detecting potential greenwashing. This analytical approach offers critical insight into whether companies are genuinely committed to sustainability or merely leveraging environmental narratives for reputational gain without corresponding action.

Table 3. Greenwashing indicators

Company	ICB Industry	Relative Focus Score	Environment Score	Claims Score	Actions Score	Net Action Direction
Ashtead Group Plc	Industrials	85.23	59.14	34.93	35.19	Positive
BAE Systems Plc	Industrials	44.01	12.23	57.33	26.72	Negative
Bunzl Plc	Industrials	88.67	88.4	48.53	86.93	Positive
DCC Plc	Industrials	2441	70.16	69.16	5.83	Negative
Diploma Plc	Industrials	29.00	27.97	79.8	81.66	Positive
Experian Plc	Industrials	26.67	5.12	30.81	36.58	Positive
Halma Plc	Industrials	34.52	14.39	11.27	11.47	Positive
IMI Plc	Industrials	39.05	25.44	68.51	88.94	Positive
Intertek Group Plc	Industrials	35.24	43.08	27.37	21.44	Negative
Mondi Plc	Industrials	85.06	92.83	97.71	88.93	Negative
Melrose Industries	Industrials	73.67	89.6	73.74	57.77	Negative
Rolls-Royce Holdings	Industrials	35.37	14.35	26.85	8.87	Negative
Rentokil Initial Plc	Industrials	13.71	7.00	53.6	25.42	Negative
Smurfit Kappa Group Plc	Industrials	91.61	95.37	96.01	55.87	Negative
DS Smith Plc	Industrials	94.5	95.98	96.66	83.99	Negative
Smith & Nephew Plc	Industrials	75.58	53.75	58.55	56.21	Positive
Severn Trent Plc	Industrials	36.41	97.45	83.51	97.25	Positive
The Weir Group Plc	Industrials	26.35	17.74	39.22	38.54	Positive

(Saxena, 2024)

Table 3 provides a comparative evaluation of the sustainability performance of several industrial companies based on five key indicators; relative focus score, environment score, claims score, action score, and net action direction. Each indicator offers a distinct perspective on how companies communicate their sustainability commitments, articulate claims, and implement concrete actions. The Relative Focus Score reflects the degree of emphasis placed on sustainability issues in corporate communications, while the Claims Score measures the frequency and intensity of sustainability-related claims. In contrast, the Action Score represents the extent to which tangible actions are taken to support these claims, and the Net Action Direction indicates the overall tendency of corporate actions—whether they align with or contradict the sustainability rhetoric being conveyed. In this context, companies such as Mondi Plc and Smurfit Kappa Group Plc stand out with high Relative Focus Scores (85.06 and 94.50, respectively), indicating a strong emphasis on sustainability issues in their communication strategies. However, the relatively low Action Scores these companies received point to a discrepancy between narrative and implementation, suggesting a potential for greenwashing—that is, a tendency to portray themselves as environmentally committed without sufficient substantive action to support such claims. Conversely, Ashtead Group Plc demonstrates a relatively balanced alignment between its Focus and Action Scores, indicating coherence between public statements and corporate actions. This consistency reinforces the credibility of the company's ESG (Environmental, Social, and Governance) efforts in the eyes of stakeholders, including investors and regulators. Such an integrated approach suggests the company is not merely pursuing symbolic legitimacy but is also showing genuine commitment to sustainability goals. Overall, this analysis highlights the importance of a more nuanced evaluation of corporate sustainability—not solely based on the quantity of claims or the intensity of the narrative, but also on the extent to which those claims are supported by verifiable, objective actions.

3.2.3 Natural language processing techniques for claims and action analysis

Natural Language Processing (NLP) is employed to process narrative texts so that claims and actions can be systematically identified and analyzed. To enhance the accuracy of greenwashing detection, we introduce the use of more efficient N-Gram techniques. As in Saxena's approach, we continue to utilize two primary metrics: Focus Scores and Action Scores (Saxena, 2024). Focus Scores measure the extent to which a company emphasizes environmental issues in its reports, while Action Scores assess how strongly the company's claims are supported by concrete actions.

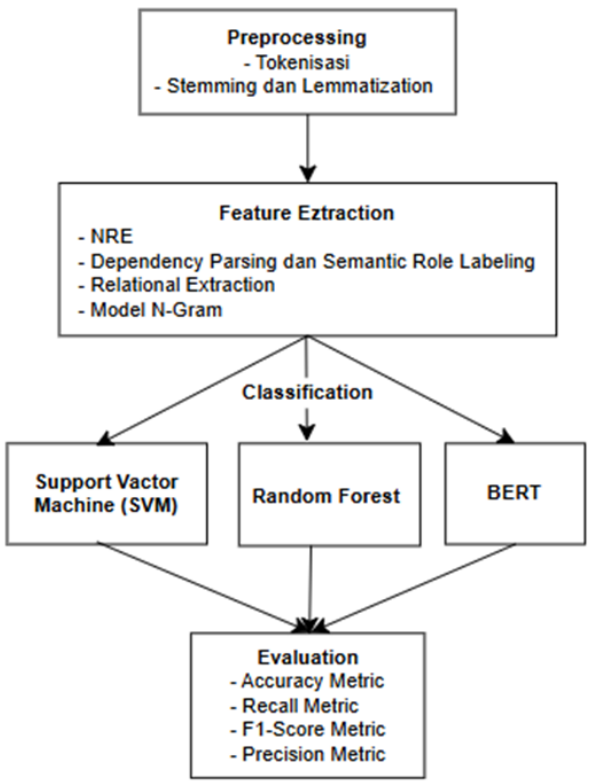

Fig. 2. Flowchart process of NLP

The first stage in the NLP process is text preprocessing, which involves several key steps. Tokenization is the initial step, where the text is broken down into individual word units known as tokens. In this context, the concept of unique tokens is applied, meaning each word is counted only once regardless of how many times it appears in the text. Following tokenization, stopwords are removed—these are common words that do not contribute significant meaning, such as conjunctions or prepositions that are irrelevant to the analytical context. Next, stemming and lemmatization are performed to convert words to their base or root forms. This ensures that different variations of a word with the same core meaning can be analyzed consistently (Pant et al., 2024). For example, words like "invest," "investing," and "invested" would all be standardized to the root form "invest."

After the preprocessing stage, feature extraction is carried out to transform the processed text into numerical representations or features that can be further analyzed by NLP models. Word embeddings convert words in the text into numerical vectors that can be understood by the model. This technique enables the model to capture semantic relationships between words, so that words with similar meanings are represented by similar vectors. The processed words are transformed into vector representations using models such as Word2Vec, GloVe, or fastText (Arianto et al., 2024). These embeddings serve as inputs for further NLP analysis. Named Entity Recognition (NER) is applied to identify key entities in the text, such as investment amounts, time targets, types of activities, and environmental performance indicators. NER enables the mapping of both quantitative and qualitative information relevant to claims and actions (Zhao et al., 2024). Dependency parsing and semantic role labeling are used to understand the syntactic structure and semantic roles of words in a sentence—for example, identifying the subject, the object, and the actions performed. These techniques are essential for distinguishing between sentences that express claims, which usually contain promises or goals, and those that describe concrete actions. They are particularly useful for linking claims and actions that may be textually separated but contextually related. N-Gram models are employed to analyze sequential patterns of words and recognize key phrases that frequently appear in sustainability claims (Nguyen & Grishman). These words are delivering claims and promises for sustainability initiatives, such as “reduced carbon emissions,” “transition to renewable energy,” “net zero”, etc. To improve the accuracy of the analysis, we introduce weighted N-Grams, which assign higher weights to phrases that frequently occur in sustainability claims while also considering the semantic context of those phrases. For instance, using models like BERT, N-Grams can be leveraged to analyze inter-sentence relationships and capture claim–action inconsistencies more effectively (Nguyen & Grishman). This enhancement improves upon earlier methods that relied solely on keywords, by capturing more complex context-based patterns. To calculate Action Scores, we combine Relation Extraction techniques with N-Gram models to identify logical relationships between claims and actions. Relation Extraction determines whether a concrete action corresponds to a specific sustainability claim made by a company (Nguyen & Grishman). Meanwhile, N-Gram analysis reinforces this process by detecting common sequential patterns in claims and actions, thus strengthening the output of the relation extraction model.

By integrating N-Gram analysis into the evaluation of Action Scores, we are able to identify whether the actions taken by a company truly support the claims it makes. For example, a claim such as “reducing carbon emissions by 50% by 2030” would be assessed for consistency with sentences describing actual investments or the implementation of environmentally friendly technologies aimed at achieving that goal.

As illustrated on Figure 2, after we extract all of the data by structured step, including N-Gram Model, the next stage is classification. In this stage, supervised learning models are used to categorize sentences in the documents as claims, actions, or potential greenwashing. One of the algorithms employed in this classification process is the Support Vector Machine (SVM). SVM works by finding a hyperplane that best separates data points from two different classes with the largest possible margin, allowing the model to predict the class (claim, action, or greenwashing) more accurately. In addition to SVM, Random Forest—a model based on an ensemble of decision trees—can handle complex features and is capable of reducing overfitting, making it more robust for classifying text with highly varied features. On the other hand, transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) are capable of understanding sentence context at a deeper level. BERT uses a self-attention mechanism to capture the relationships between words in a sentence without being limited by word order, enabling it to grasp more complex semantics and long-range dependencies between sentences. BERT is particularly effective at detecting inconsistencies between claims and actions, as well as identifying ambiguous claims that frequently appear in sustainability reports. Once the model has been trained, the final step is model evaluation to assess classification performance. The metrics used in this evaluation include accuracy, which measures the percentage of correct predictions; precision, which evaluates how well the model identifies appropriate claims or actions; recall, which assesses the model's ability to detect all relevant sentences classified as claims or actions; and the F1-score, which balances precision and recall. This evaluation is critical to ensure that the model can accurately distinguish between claims, actions, and potential greenwashing present in the text.

3.3 The application of NLP to audit procedures

Audit governance has a significant influence on the transparency of information disclosure in ESG reports (Wang, 2024; Wang & Zhi, 2022). The ESG report itself is a type of sustainability report that shares a similar narrative format with traditional sustainability reports. Both types of reports are structured as narrative texts that communicate a company's sustainability strategies, which must be analyzed to assess the alignment between the claims made and their actual implementation. NLP supports audit procedures in the risk assessment process by enhancing the speed and accuracy of analyzing and classifying discrepancies between sustainability claims and their actual implementation. Before applying NLP, auditors must identify mismatch indicators and key terms that significantly influence the determination of claim-action alignment. By employing NLP techniques—from preprocessing to processing—auditors can systematically detect and classify risks within the narrative text of sustainability reports. The resulting classifications are then converted into risk scores and mapped into a risk matrix, allowing auditors to quickly prioritize areas with the highest misalignment for further examination (Kokina et al., 2025). During the audit reporting phase, NLP output is used to automatically generate summaries of findings and draft clarification questions. Text generation systems produce standardized narratives for key findings, mitigation recommendations, and highlights of critical indicators. This enables auditors to efficiently prepare audit workpapers and interactive dashboards, supporting transparency and consistency in the reporting of sustainability audit results (Kokina et al., 2025; Wang, 2024).

The use of NLP as a supporting tool for audit risk assessment processes aimed at increasing efficiency faces challenges due to the diversity of client information systems. Clients implement information systems tailored to their business needs, resulting in varying systems or programs. This presents a challenge in the data adjustment process. The diverse landscape of ERP and finance systems used by clients means it is nearly impossible to have a universal audit tool fitting all contexts. To address this, auditors need to readjust client data to fit a format that can be translated and processed by the developed NLP system. This adjustment process can result in time savings that fall short of the initial expectations of NLP use, which is intended to expedite the risk assessment process.

Audit client companies welcome the use of AI, including NLP, in the audit process to improve audit efficiency and quality, thereby gaining increasingly valuable business insights. However, concerns remain about data privacy. Clients are concerned about providing auditors with access to vast amounts of their data, fearing privacy and being audited around the clock (Kokina et al., 2025). Furthermore, clients are aware that their data might be used beyond the purpose of delivering the audit engagement, possibly for training machines and even for other audit engagements. Furthermore, client data is crucial during the training phase, and the more data provided, the better the accuracy of the results. Therefore, audit firms must reassure clients by transparently explaining the purposes for which the data will be used and demonstrating strong governance to ensure clients are willing to provide sufficient data.

The detection of greenwashing through the use of NLP in audits is still limited to the identification stage. This is due to the limited identification based on company reports and the limited real-time monitoring of the company's activities. These limitations make it difficult to verify the alignment between claims and actions after detecting indications of greenwashing. This means that further review of the post-processing of greenwashing indications through NLP is necessary. To support the eradication of greenwashing, NLP cannot stand alone; other innovations are needed that can monitor and report data in real time regarding the alignment of the sustainability roadmap communicated by the company with implementation in the field.

4. Conclusions

The findings of this study indicate that N-gram-based Natural Language Processing (NLP) can be effectively used to identify potentially ambitious claims, such as emission reduction targets and net-zero commitments. N-gram models are capable of detecting mismatches between claims and actions—specifically, situations where the scale of sustainability promises is not proportionally reflected in the company's actual steps. The mismatch detection methodology employs Natural Language Processing (NLP) techniques, including TF-IDF/BERT for calculating Focus Scores, Relation Extraction and Named Entity Recognition (NER) for Action Scores, and the Net Action Direction metric to assess proportionality, temporal context, and semantic alignment between sentences. Preliminary results reveal that some companies exhibit high focus scores but low action scores—indicating potential greenwashing—while others demonstrate a more balanced alignment between stated commitments and actual actions.

The application of NLP has also been integrated into ESG audit procedures in previous studies. Findings from these studies revealed that NLP accelerates risk assessment and the classification of mismatches between claims and realizations. Supervised models (such as SVM and Random Forest) and transformer-based models (like BERT and RoBERTa) were used to classify sentences as claims, actions, or potential greenwashing. Model performance was evaluated using metrics such as accuracy, precision, recall, and F1-score. The classification output was converted into risk scores and automated summary findings, helping auditors prioritize audit areas and compile workpapers more efficiently, consistently, and transparently. This research opens up opportunities for future studies, particularly the need to enhance the impact and relevance of the findings through experimental research, which can provide stronger empirical evidence for the models used. Through an experimental approach, future studies are expected to directly observe the impact of NLP implementation on analysis outcomes, resulting in more accurate and validated conclusions. Furthermore, future research may compare the effectiveness of N-gram-based NLP models with other methods. Such comparisons could offer deeper insights into the strengths and limitations of each method applied.

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Author Contribution

All authors collaboratively developed the research framework and contributed to data collection and analysis. Each author participated in interpreting the findings and refining the manuscript. All authors approved the final version of the article for submission.

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