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Artificial Intelligence for Greenwashing Detection: A Conceptual Analysis of NLP and LLM in Sustainability Reporting

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Abstract

Greenwashing, the practice of making misleading environmental claims, continues to hinder genuine progress toward sustainable development. Studies show that a significant proportion of corporate sustainability claims are exaggerated or unfounded, creating a demand for effective tools to identify such practices. Traditional methods of detecting greenwashing, such as manual reviews and basic keyword analysis, are often insufficient due to the complexity and volume of data involved. This study uses a conceptual and analytical research design to summarize existing evidence on the use of Artificial Intelligence (AI), including Natural Language Processing (NLP) and Large Language Models (LLMs), in detecting greenwashing. By analyzing sustainability reports, press releases, and social media content, these AI tools offer a more efficient and accurate approach to identifying discrepancies between corporate claims and actual practices. The findings demonstrate that AI technologies can significantly advance greenwashing detection, contributing to more reliable and accessible sustainability assessments. However, limitations remain, as the study focuses on only two AI methodologies. Future research should explore a wider range of AI tools and techniques to address industry-specific challenges and regulatory concerns, ensuring a more comprehensive approach to detecting greenwashing in corporate practices.

Keywords Greenwashing, Artificial Intelligence, Natural Language Processing, Large Language Models, Sustainability Reporting.

1. INTRODUCTION

Greenwashing, the practice of making misleading claims about environmental sustainability, remains a major barrier to genuine progress toward sustainable development. The European Commission [1] found that 42% of corporate sustainability claims were exaggerated or unfounded, while a 2025 report noted that 53% of such claims in the EU market were vague or misleading [2]. A Google [3] survey revealed that 58% of executives acknowledged their companies likely overstated their sustainability efforts, with only 36% having the tools to measure their actual impact. These unverified statements and lack of proper measurement underscore the persistence of greenwashing—defined as corporate efforts to mislead stakeholders through deceptive sustainability messaging [4]. In response, the European Union has introduced the Empowering Consumers for the Green Transition Directive (EU)

2024/825, effective from March 26, 2024. This directive amends existing consumer protection laws to prohibit misleading environmental claims, such as unsubstantiated terms like "eco-friendly" or "biodegradable," and requires companies to provide clear, verifiable information about their environmental impact. This regulatory shift aims to curb greenwashing and increase transparency in sustainability claims, addressing the ongoing challenges in holding companies accountable for their environmental assertions [5].

Detecting greenwashing is particularly challenging. Sustainability reports are often excessively long (sometimes reaching 70 pages) making them difficult for stakeholders like investors and policymakers to analyze efficiently [6]. This highlights the growing demand for automated, transparent tools that can streamline and improve the assessment of such documents. One promising approach involves Natural Language Processing (NLP), which facilitates the sorting and interpretation of unstructured sustainability data [7]. With advancements in NLP and the emergence of Large Language Models (LLMs), such as GPT–4 [8] and LLaMA3 [9], these systems can now provide deeper reasoning and textual analysis within ESG disclosures [6].

Building on this, [6] developed CHATREPORT. It is an AI-powered framework designed to analyze corporate sustainability reports based on the TCFD (Task Force on Climate-related Financial Disclosures) recommendations. This AI is to deliver traceable, informative, and accessible insights from complex sustainability documents. By leveraging LLMs like ChatGPT, the system supports not only experts and researchers, but also general users such as students, educators, and professionals seeking clear, reliable assessments of climate-related disclosures.

On the other hand, [7] demonstrates progress in using NLP for greenwashing detection through sentiment analysis and ESG text classification. Natural Language Processing (NLP) enables the detection of greenwashing by analyzing and interpreting textual data related to corporate sustainability. Through techniques like sentiment analysis, topic modeling, and text classification, NLP helps uncover discrepancies between a company's internal communication and public perception, which may indicate exaggerated or misleading ESG claims. By leveraging these techniques on data sources like sustainability reports, press releases, and social media, NLP provides a more robust approach to detecting greenwashing and enhancing transparency and accountability in corporate ESG practices. This approach is commonly favored by researchers and academics due to its analytical depth and complexity, which often surpasses that of large language models (LLMs). In this article we explain the outline of how NLP and LLMs work in the process of detecting greenwashing.

2. METHOD

This research uses a conceptual and analytical research design to summarize existing evidence on the use of Artificial Intelligence (AI) including Natural Language Processing (NLP), and Large Language Models (LLMs) in detecting greenwashing. The goal is to review and analyze the benefits and limitations of these technologies in identifying misleading sustainability claims. Following the approach of [29], the research will systematically review recent academic articles, industry reports, and case studies. By combining theoretical insights and practical applications, this study will provide a clear understanding of how NLP and LLMs can help detect greenwashing and improve sustainability reporting.

3. RESULT AND DISCUSS

In the face of greenwashing, there is a pressing need for advanced analytical tools that can efficiently and accurately detect instances of green-washing, particularly in the complex landscape of financial reporting. However, traditional methods, such as manual review and basic keyword frequency analysis, often fall short due to the sheer volume of data and the sophistication of general green-washing tactics [30]. These methods are time-consuming, prone to human error, and lack the depth required to uncover subtle discrepancies between corporate claims and actual practices. Recent advancements in artificial intelligence, especially Large Language Models (LLMs) and NLP, offer promising solutions to these limitations [31].

A. Application of NLP For Greenwashing Detection

Based on [7] the flow for using NLP for detecting greenwashing as follow:

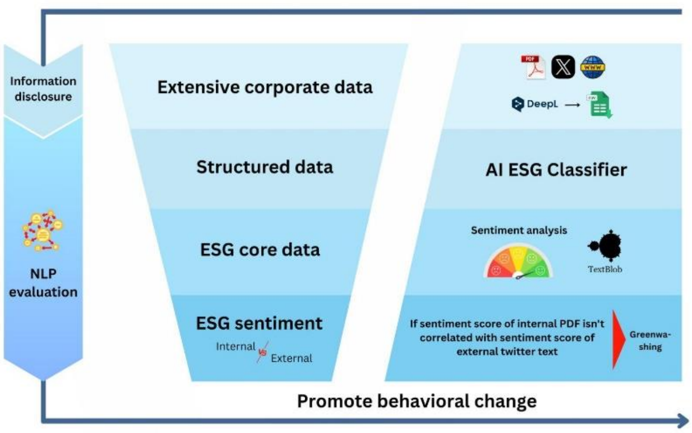

Figure 1. NLP framework in detecting ESG-greenwashing

Source : Adapted by [7], pp. 177

1) Export Data

First we need to collect data that comes from official company documents–internal data sources, typically ESG or sustainability reports available on company websites in PDF format. This data presents internal disclosures related to the company's ESG initiatives and strategies. The second data that need to be collect came from external sources (i.e. X) using web scraping tools and API. This data includes public tweets about the company, which provide a public view of the company's ESG activities.

2) Processing Data

Once the data has been collected, the first step is to process the data to make it ready for analysis. This will include: Tokenization (breaking text), Stopword removal (remove common words), Lemmatization (convert words base for consistency), Text conversion (align the text for consistency.

3) Data Analysis

The FinBERT Classifier utilizes the FinBERT-ESG-9-Categories model to categorize data into relevant ESG themes, including topics such as Climate Change, Natural Capital, Pollution & Waste, Human Capital, and Business Ethics, among others. Once the text is classified, sentiment analysis is conducted using TextBlob, which assigns sentiment scores to indicate whether the content is positive, negative, or neutral.

4) Correlation Sentiment

After obtaining sentiment scores from both internal data (i.e. PDF reports) and external sources (i.e. X), a correlation analysis is conducted to examine whether there is a relationship between the two. For example, it explores whether the sentiment expressed in official company reports aligns with public sentiment on social media platforms like X. A significant discrepancy between these sources may indicate potential greenwashing, where a company presents sustainability claims that do not reflect its actual practices.

B. Application of LLMs for Greenwashing Detection

Based on [6] the flow for using LLM for detecting greenwashing as follow:

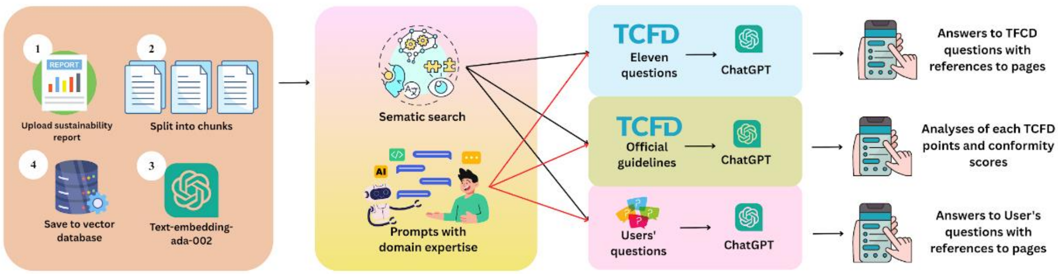

Fig 2. LLMs framework in detecting ESG-greenwashing

Source : Adapted by [6]

1) Report Embedding (RE)

The process begins with Export Data (Report Embedding - RE), which involves retrieving the report to be analyzed, such as a company's sustainability report. The report is then divided into smaller sections (chunks) to make it easier for further processing and analysis. Each section of the report is converted into a vector representation using a text model, such as *text-embedding-ada-002*, allowing the information to be stored in a form that can be easily searched and analyzed in the future.

2) Semantic Search

Performed after the report has been converted into vectors. In this phase, the system is able to search for relevant sections of the report based on the queries or requests provided. The use of domain experts, such as TCFD specialists, helps transform TCFD recommendations into precise queries to be searched within the report.

3) Report Summarization (RS)

To facilitate quicker reading of the report, the system then proceeds with Report Summarization (RS). This system summarizes the report based on the eleven aspects recommended by TCFD. To do so, it searches for relevant sections in the report using pre-defined queries. The retrieved information is then used to create a summary of the report, focusing on each TCFD recommendation and including basic context about the company.

4) TCFD Conformity Assessment (TCA)

Where the system evaluates the extent to which the report follows the guidelines set by TCFD. Each TCFD recommendation is analyzed to determine whether the report complies with the guidelines related to the information that needs to be disclosed. This analysis results in a conformity score between 0 and 100, indicating how closely the report aligns with the prescribed TCFD guidelines.

5) Customized Question Answering (CQA)

Finally, Customized Question Answering (CQA) allows users to ask more specific or customized questions based on their needs. To answer these questions, the system first retrieves relevant context from the report using the search module. Then, the system uses a large language model (LLM) to provide answers to the user's query. These answers are also tailored to the guidelines in place to address the variations in user questions.

CONCLUSIONS

This study explored the use of Artificial Intelligence (AI) technologies, specifically Natural Language Processing (NLP) and Large Language Model (LLM), in detecting greenwashing in corporate sustainability claims. The findings highlight the growing issue of greenwashing, where companies make misleading environmental claims without verifiable proof, which misleads consumers and undermines genuine sustainability efforts. AI tools, such as NLP and LLM, can significantly improve the detection of greenwashing by analyzing large volumes of data from sustainability reports, product descriptions, and consumer reviews, offering a more efficient and reliable method than traditional manual reviews. This research contributes to corporate sustainability by demonstrating how AI can enhance the detection of discrepancies between corporate claims and actual practices, fostering genuine sustainable practices. However, the study has limitations, as it only utilized two methodologies (NLP and LLM), which may not cover the full range of AI tools available for greenwashing detection. Future research should explore the use of a broader range of AI tools and techniques to further improve greenwashing detection, refine their effectiveness across different industries, and address ethical and regulatory considerations to ensure fair and transparent use..

DAFTAR PUSTAKA

[1] European Commission, "Screening of websites for 'greenwashing': half of green claims lack evidence," Press Release, Jan. 28, 2021. [Online]. Available: https://ec.europa.eu/commission/presscorner/detail/en/ip_21_269European Commission.

[2] European Commission, "Green claims," Environment, Apr. 30, 2025. [Online]. Available: https://environment.ec.europa.eu/topics/circular-economy/green-claims_en.

[3] Google, Report: What It Will Take for CEOs to Fund a Sustainable Transformation [Online]. 2022. Available: https://sustainability.google/ceo-sustainable-transformation/.

[4] S. V. De Freitas Netto, M. F. F. Sobral, A. R. B. Ribeiro, and G. R. Da Luz Soares, "Concepts and forms of greenwashing: a systematic review," Environmental Sciences Europe, vol. 32, no. 1, 2020. doi: 10.1186/s12302-020-0300-3.

[5] European Union, Directive (EU) 2024/825, Official Journal of the European Union, 2024. [Online]. Available: http://data.europa.eu/eli/dir/2024/825/oj.

[6] J. Ni, J. Bingler, C. Colesanti-Senni, et al. CHATREPORT: Democratizing Sustainability Disclosure Analysis through LLM-based Tools. ArXiv, 2023.

[7] Y. Zhao, L. Kroher, M. Engler, and K. Schnattinger, "Detecting Greenwashing in the Environmental, Social, and Governance Domains Using Natural Language Processing," in Proc. 15th Int. Joint Conf. on Knowledge Discovery, Knowledge Engineering and Knowledge Management (KDIR), vol. 1, SciTePress, 2023, pp. 175–181. doi: 10.5220/0012155400003598.

[8] OpenAI J. Achiam, S. Adler, S. Agarwal, et al. GPT-4 Technical Report. ArXiv, 2023.

[9] A. Grattafiori, A. Dubey, A. Jauhri, et al. The llama 3 Herd of Models, 2024.

[10] I. Abouelwafa, “Climate change and legal responsibility for greenwashing,” in Advances in Human Services and Public Health (AHSPH) Book Series, pp. 67–84, Sep. 2024, doi: 10.4018/979-8-3693-2987-0.ch005.

[11] M. Verma and U. Bharti, “Combating greenwashing tactics and embracing the economic success of sustainability,” Veethika: An International Interdisciplinary Research Journal, Sep. 2023, doi: 10.48001/veethika.2023.09.03.002.

[12] J. K. Shanmugam, I. M. Saidon, M. M. Noor, K. Lokanathan, and W. K. H. W. Ya,

"Unmasking greenwashing: A brief note to consumers," Int. J. Res. Innov. Soc. Sci., vol. 8, no. 10, pp. 353–358, 2024. [Online]. Available: https://doi.org/10.47772/ijriss.2024.8100029.

[13] TerraChoice Environmental Marketing, The Seven Sins of Greenwashing: Environmental Claims in Consumer Markets, Summary Report: North America, Apr. 2009.

[14] M. Chudinovskikh, Y. Gudoshnikova, and N. Boronenkova, "Greenwashing: Deceptive Marketing Practices, trends and facts," E3S web of conferences, vol. 537, p. 02007, Jan. 2024, doi: 10.1051/e3sconf/202453702007.

[15] D. Jamali, C. Karam, J. Yin, and V. Soundararajan, "CSR logics in developing countries: Translation, adaptation and stalled development," J. World Bus., vol. 52, no. 3, pp. 343–359, Mar. 2017, doi: 10.1016/j.jwb.2017.02.001.

[16] D. B. Turban and D. W. Greening, "Corporate social performance and organizational attractiveness to prospective employees," Acad. Manage. J., vol. 40, no. 3, pp. 658–672, 1997.

[17] H. A. Irigaray and F. Stocker, "ESG: Novo conceito para velhos problemas," Cadernos Ebape.Br, vol. 20, no. 4, pp. 1–4, 2022. [Online]. Available: https://doi.org/10.1590/1679-395186096

[18] N. Kapur, Building block for sustainable success: Environmental, social and governance through good governance, 2023. [Online]. Available: https://doi.org/10.33516/maj.v58i6.77-81p

[19] L. Zhang, "The impact of environmental, social and governance (ESG) on corporate value enhancement," J. Educ. Humanit. Soc. Sci., vol. 24, pp. 792–797, 2023. [Online]. Available: https://doi.org/10.54097/4mvdkn40

[20] S. Peari, "The combination of environmental, social and corporate governance factors has an important place in business today," Alternative Law Journal, Oct. 2023, doi: 10.1177/1037969x231205912.

[21] E. A. Chidera and C. G. Kenechukwu, "Green marketing and sustainability: A critical review of environmental, consumer, corporate, and regulatory perspectives," Preprints, Oct. 2024. [Online]. Available: https://doi.org/10.20944/preprints202410.1495.v1.

[22] J. Wang, "Utilizing AI-based models to detect greenwashing behavior in corporations," in Handbook of Research on Managing Green Economies and

Environmental Sustainability, IGI Global, 2024, pp. 43–74, doi: 10.4018/979-8-3693-1331-2.ch003.

[23] M. Fornasiero, “Exploring the effectiveness of large language models in greenwashing detection,” Business Economics, Sep. 9, 2024. [Online]. Available: http://hdl.handle.net/2105/72537.

[24] A. Kantor, Trust Media and the Economy, "Greenwashing," pp. 259-269, 2025.

[25] R. Simion, “Eco-frauds: The ethics and impact of corporate greenwashing,” Studia Universitatis Babeș-Bolyai Philosophia, vol. 69, no. 2, pp. 7–26, Aug. 2024, doi: 10.24193/subbphil.2024.2.01.

[26] C. L. Spash, “The Paris Agreement to Ignore Reality,” Research Papers in Economics, Jan. 2016, [Online]. Available: https://epub.wu.ac.at/4802/

[27] Z. Huang, Y. Shi, and M. Jia, “Greenwashing: A systematic literature review,” Accounting and Finance, Nov. 2024, doi: 10.1111/acfi.13352.

[28] L. Wu, S. Liu, L. Qi, dan D. Lin, “Mandatory disclosure and corporate ESG performance: Evidence from China’s ‘explanation for nondisclosure’ requirement,” Corporate Social Responsibility and Environmental Management, vol. 32, no. 1, pp. 176–191, Jan. 2025, doi: 10.1002/csr.2944.

[29] B. A. Kitchenham, Procedures for Performing Systematic Reviews: Guidelines for Performing Systematic Reviews in Software Engineering, Tech. Rep. EBSE-2004-01, 2004.

[30] F. Bernini, M. Giuliani, and F. La Rosa, "Measuring greenwashing: A systematic methodological literature review," Business Ethics, the Environment & Responsibility, vol. 33, no. 4, pp. 649–667, 2023. doi: 10.1111/beer.12631.

[31] F. J. O. Boedijanto and L. L. Delina, "Potentials and challenges of artificial intelligence-supported greenwashing detection in the energy sector," Energy Research & Social Science, vol. 115, p. 103638, Sep. 2024. doi: 10.1016/j.erss.2024.103638..

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