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Abstract

Despite widespread pledges to tackle climate change, the credibility and comparability of country and corporate commitments remain limited. This impact paper draws on two recent AI-based studies: one analysing over 300 climate pledges (Nationally Determined Contributions, or NDCs) submitted under the Paris Agreement, and another examining almost 1,500 Environmental, Social, and Governance (ESG) reports of STOXX Europe 600 companies. Using methods from natural language processing (NLP), the studies reveal which themes are emphasised, how they vary across countries and firms, and how they relate to actual emissions reductions and environmental performance. This paper discusses how AI can highlight gaps between discourse and action, and proposes ways in which NLP techniques, including topic modelling and large language models (LLMs) such as ChatGPT, can improve transparency and comparability in sustainability reporting.

Keywords: AI, NLP, topic modelling, climate policy, ESG

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From narratives to action: leveraging AI to decode and advance sustainability commitments

Introduction

Climate change mitigation depends not only on ambition but also on the clarity, credibility, and comparability of commitments. Governments and companies increasingly publish strategic documents—such as Nationally Determined Contributions (NDCs) or Environmental, Social, and Governance (ESG) reports—to outline their climate goals. Yet these documents often vary greatly in format and focus, limiting their utility for tracking progress or holding actors accountable.

This paper argues that tools from artificial intelligence (AI), and in particular natural language processing (NLP), are critical to addressing this gap. By enabling scalable, interpretable, and replicable analysis of large text corpora, AI can help identify misalignments between narratives and actual performance, assess credibility, and improve transparency. The goal is not only to highlight recent academic applications of these methods, but also to promote their broader adoption by policymakers, regulatory bodies, and international institutions as part of a systemic push toward more standardized and actionable climate communication. To illustrate this potential, the paper reflects on two recent applications of NLP to sustainability texts and outlines key insights for better climate governance.

AI and climate narratives: two applications

A recent study by Savin et al. (2025) analysed the full content of 309 NDCs submitted to the United Nations Framework Convention on Climate Change (UNFCCC) using structural topic modelling (STM), a technique that lies at the intersection of machine learning, computer science and linguistics. STM identifies hidden thematic structures in large corpora by clustering frequently co-occurring words into distinct topics. The study identified 21 topics grouped into seven broader thematic areas, such as development, mitigation targets, implementation processes, policies and technologies, climate impacts, AFOLU (standing for Agriculture, Forestry and Other Land Use), and stakeholders. These were not evenly distributed. The most prevalent group was development (25%), followed by implementation (21.5%), mitigation targets (20.3%), and policies and technologies (11.3%). The least discussed themes were stakeholders (3.8%) and AFOLU (7.4%).

Clustering countries based on their topic profiles revealed nine distinct clusters (see Figure 1). For instance, high-income countries such as the United States, Japan and the EU member states formed a cluster (C2) focusing primarily on emission targets but providing little detail on implementation. Countries like Brazil, Russia and some countries from the Middle East formed a cluster (C3) with a strong emphasis on economic development. Another cluster, mainly India and small island developing states (C5), stressed sustainable development and climate vulnerability. Venezuela stood alone (C4), with a highly idiosyncratic pledge shaped by its national political context. Exceeding 76,000 words, the document is the longest of all submissions and incorporates climate action into a wider eco-socialist “political vision of sustainable development of the country.” These clusters align in part with established negotiation blocs under the UNFCCC, such as the Umbrella Group or LMDCs (Like-Minded Developing Countries), but they also show content-specific alignment that transcends geography or income.

This variation and lack of standardisation in how countries report on climate goals has long been recognised as an obstacle to global climate governance (Pauw et al., 2018; King & van den Bergh, 2019). Yet, until now little has been done to fix this problem.

Another recent paper by Savin and López Carel (2025) analysed 1,477 ESG reports published by companies in the STOXX Europe 600 index between 2010 and 2023. This index covers 600 large companies from 17 European countries, representing approximately 90% of the market capitalisation of the European stock market. ESG reports were processed using STM, revealing 34 recurring topics, grouped into six broader themes: governance (G1, 33.2%), environment (G2, 18.5%), sector-specific issues (G3, 15.8%), social and community aspects (G4, 13.1%), finance (G5, 11.6%), and public regulation (G6, 7.3%).

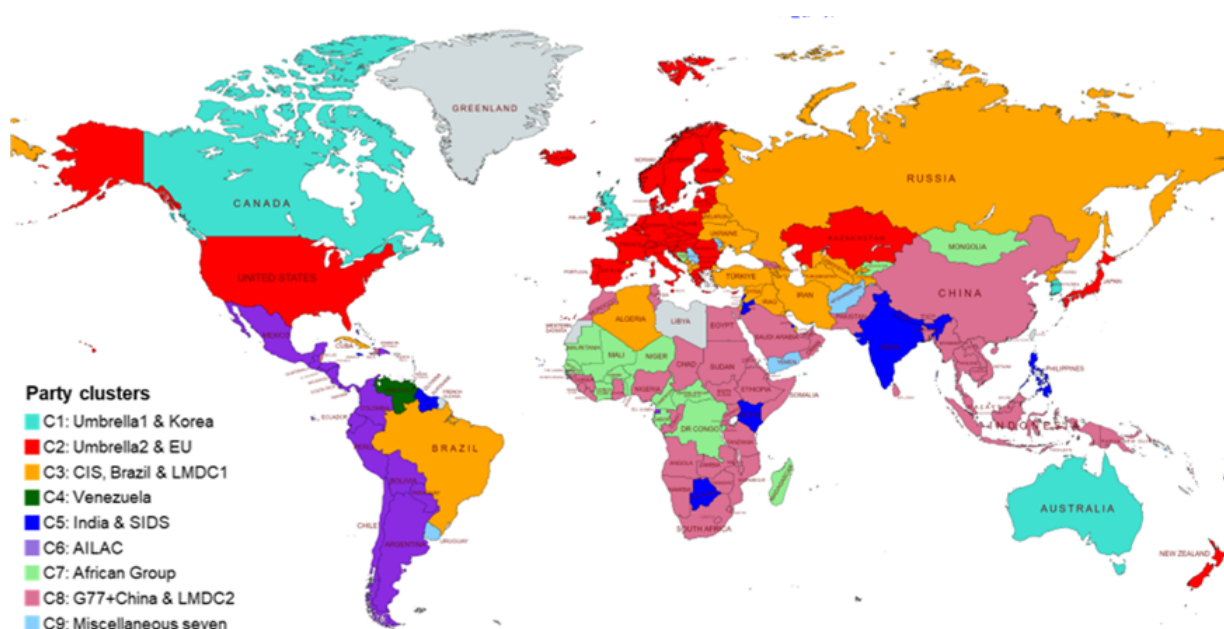


Figure 1. Clusters of parties to the Paris Agreement by NDC topic prevalences.

Note: CIS = Commonwealth of Independent States. LMDC1 and 2 = Least Medium Developed Countries group 1 and 2. SIDS = Small Island Developing States. AILAC = Independent Alliance of Latin America and the Caribbean. See the study for more details on the clusters. Source: Savin et al., 2025.

Within the environmental theme, six key topics were identified: greenhouse gas (GHG) emissions (T3), sustainable value chains (T8), electric vehicles (T14), renewable energy (T20), energy sources (T27), and subsidies & environment (T28). Notably, discussions of GHG emissions and electric vehicles, although frequent, showed no significant correlation with companies' environmental key performance indicators (KPIs). In contrast, stronger focus on sustainable value chains and renewable energy was positively associated with improvements in emissions intensity and environmental innovation. Clustering companies based on these topics revealed groupings consistent with sectoral patterns: energy firms like Enel focused on renewables, while industrial firms like Siemens emphasised value chains.

Structurally, ESG reports vary widely in length and organisation. Some are stand-alone sustainability reports, others integrated with financial reporting. While many follow frameworks like the Global Reporting Initiative (GRI) or the Sustainability Accounting Standards Board (SASB), the depth and specificity of environmental sections differ greatly. The lack of common structure complicates comparability and may mask discrepancies between claims and performance. A systematic review by Dugoua et al. (2022) highlights this issue and shows how text-as-data approaches can help navigate these inconsistencies.

Topic modelling and beyond: the promise of AI

Topic modelling, such as STM, enables fast, transparent, and reproducible identification of themes across large document corpora such as policy documents, patents, presidential speeches, academic publications, but also open-ended survey responses and posts on social networks such as Twitter/X (Savin et al., 2024; Savin et al., 2023; Savin and Teplyakov, 2022; Savin and van den Bergh, 2021). It helps quantify which issues are discussed and compare across documents or over time. Roberts et al. (2014) introduced STM as a valuable method for exploring unstructured texts in a statistically grounded way, improving over traditional Latent Dirichlet Allocation (LDA) models.

However, topic models have limited contextual understanding, i.e. you can classify the textual data but cannot infer its conclusions and implications. Large language models (LLMs) such as ChatGPT offer more nuanced text interpretation, enabling tasks like sentiment analysis.

Larosa et al. (2025) applied Gemini to classify NDC paragraphs according to their relevance to the UN Sustainable Development Goals (SDGs). While only 1% of NDC content explicitly referenced SDGs, the LLM identified implicit alignment in many paragraphs, uncovering overlooked synergies and trade-offs. For example, low-income countries emphasized the water-energy-food nexus (SDGs 6-7-12), while high-income nations stressed SDGs related to health (SDG3) and inequality (SDG10). The study also revealed that narratives in fossil-dependent economies framed SDGs as a pathway for just transition. These findings build on previous research by Larosa et al. (2022), which used similar NLP tools to reveal inequality patterns in climate-related investment strategies.

This kind of AI-assisted analysis, especially when structured through an NLP pipeline combining STM and LLMs, can generate both breadth and semantic depth—scaling to thousands of documents while retaining interpretative power.

Three lessons from applying AI to sustainability discourse

- **Mismatch between focus and action:** Many documents devote extensive space to themes only loosely connected to actual emissions reduction. In the ESG reports, popular topics like GHG emissions and electric vehicles lacked statistical association with environmental KPIs, suggesting superficial engagement. Similarly, in NDCs, many developing countries devote most of the text to broader development themes. As a separate test in the NDC analysis, we summed the prevalence of topic groups directly related to mitigation targets (mitigation targets, policies and technologies, and AFOLU) and tested its correlation with pledge ambition. The resulting correlation was positive and significant ($r=0.113$, $t=2.00$, $p=0.046$), meaning that countries focusing more on core mitigation topics like green energy policies tend to make more ambitious pledges. This suggests that discourse content—not just numerical targets—matters.
- **Need for standardisation:** Both NDCs and ESG reports suffer from wide variation in structure and content. Some NDCs contain fewer than 100 words, others exceed 70,000. ESG reports, in their turn, can be even longer and vary in whether they follow GRI, SASB, or other frameworks. Such a format could include standardized emissions baselines, sector-specific reduction targets, timelines for policy implementation and clear methodologies for measuring progress. It could also require countries to report on the financial and technological support they need – or provide – to ensure a just transition. These elements would not only make NDCs more comparable but also help identify gaps, best practices and potential areas for international cooperation.

- **AI enables systemic analysis:** With thousands of sustainability documents published annually, manual analysis is infeasible. AI methods such as topic modelling and LLMs allow scalable and replicable assessments. They help identify recurring themes, detect inconsistencies or omissions, and track changes over time. For instance, Larosa et al. used Gemini to assess sentiment and tone in NDC paragraphs and found that most references to SDG linkages are positive, but trade-offs were more prominent in low-income countries. This type of assessment can feed into early-warning systems for implementation gaps.

Outlook: toward smart, comparable, and actionable climate reporting

Looking ahead, AI has the potential to be embedded within sustainability disclosure practices, both at the country and company level. National authorities and companies could use NLP pipelines to analyse past reports and guide drafting of future ones. Reports could be structured into machine-readable components, improving transparency.

International bodies like the UNFCCC or EU could promote the adoption of minimal reporting templates, augmented by AI-based validation tools. LLMs like ChatGPT could also be used to provide draft text, summarise submissions, or generate executive summaries across hundreds of reports. These tools can help shift sustainability discourse from aspiration to accountability.

A few real-world initiatives already demonstrate how AI and NLP can be effectively applied to climate and sustainability disclosures:

- The Net-Zero Tracker (<https://zerotracker.net/>) , coordinated by the Energy & Climate Intelligence Unit, University of Oxford, Data-Driven EnviroLab, and NewClimate Institute, uses automated NLP methods to monitor and analyse net-zero commitments by countries, regions, cities, and companies. The platform extracts data from official statements and reports to assess the credibility of net-zero pledges.
- Climate Policy Radar (<https://www.climatepolicyradar.org/>) is a non-profit public initiative developed in collaboration with the Grantham Research Institute at the London School of Economics, the UK Department for Energy Security and Net Zero, and the ClimateWorks Foundation. It uses NLP and large language models to make climate policies machine-readable, searchable, and analysable. Their tool processes thousands of policy documents and scientific articles to help policymakers and researchers explore climate legislation and identify gaps.
- The Corporate Sustainability Reporting Directive (CSRD, https://finance.ec.europa.eu/capital-markets-union-and-financial-markets/company-reporting-and-auditing/company-reporting/corporate-sustainability-reporting_en), administered by the European Commission, mandates that large companies disclose sustainability information in a standardized and machine-readable format using the XBRL taxonomy. This provides a foundation for integrating AI-based systems to parse and assess corporate sustainability disclosures.

Policymakers can build on these models to operationalize AI in sustainability governance. National ministries and climate authorities could deploy NLP pipelines to screen and benchmark sustainability documents—such as NDCs or ESG reports—against prior commitments or peer-country submissions. For example, LLMs trained on historical NDCs could highlight missing implementation pathways or ambiguous targets in new pledges. International bodies such as the UNFCCC, the European Commission, or multilateral development banks like the World Bank could also use AI dashboards to track trends in discourse, monitor alignment with global goals, and identify implementation gaps early.

This would improve transparency, enable better coordination, and support more effective allocation of climate finance and technical assistance

Conclusion

AI, and particularly NLP methods like topic modelling and LLMs, are transforming how we analyse climate communication. As demonstrated by studies of Paris Agreement pledges and European ESG reporting, these tools help uncover key themes, detect misalignments, and assess credibility. To fully harness their potential, reporting systems need to move toward standardisation and machine readability. Only then can we ensure that sustainability commitments are not only declared, but also comparable, actionable, and aligned with global goals. Without clearer commitments and greater accountability, the goals of particular companies and entire countries risk remaining only on paper.

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