Villacampa-Porta *et al.*
Environmental Sciences Europe (2025) 37:29
https://doi.org/10.1186/s12302-025-01067-z

Environmental Sciences Europe

RESEARCH

Open Access

Impact of EU non-financial reporting regulation on Spanish companies' environmental disclosure: a cutting-edge natural language processing approach

Javier Villacampa-Porta[1,2], María Coronado-Vaca[1*] and Eduardo C. Garrido-Merchán[1,3]

Abstract

Background A debate exists about the effects of environmental disclosure becoming mandatory on the quality and the actual commitment of such reporting. This study seeks to assess whether differences exist when comparing the disclosure quality and comprehensiveness of Spanish companies' non-financial reports under voluntary and mandatory reporting regimes spanning the period 2015–2022.

Methods We present a novel approach by utilizing cutting-edge Natural Language Processing (NLP) techniques, chiefly *ClimateBERT* (a transformer-LLM—Large Language Model) and *ClimateBERT* fine-tuned on *ClimaText* (a public database for climate change topic detection), to scrutinize and compare 729 voluntary and mandatory non-financial corporate reports from 96 Spanish companies spanning multiple sectors. Since transformers can only be accurately estimated by organizations with lots of computing power, but not by small organizations, we have also fine-tuned the transformer, something cheaper in computational terms, thus making it affordable to all companies, investors, regulators, policymakers, and other stakeholders.

Results Our results document interesting patterns and strong trends of enhancement in specificity and commitment, particularly in risk-related texts, spanning the period 2015–2022. We provide descriptive evidence and an explorative appeal that underscores the regulations' influence, among many other factors also identified by prior literature (other stakeholders' requirements and expectations from companies, aside from the regulatory stakeholders), in fostering a higher quality and more comprehensive approach to climate risk reporting by Spanish companies, with enhanced alignment to internationally recognized reporting guidelines. In addition, the comparative analysis between the transformer model and the fine-tuned transformer model revealed subtle yet insightful differences in how climate disclosures are interpreted. The fine-tuned model exhibited an increased sensitivity to elements of commitment, specificity, and neutrality in climate texts.

Conclusions Our findings highlight the potential of cutting-edge NLP techniques, like fine-tuned transformers, in the quantitative assessment of the evolution and quality of environmental disclosures, either mandatory or voluntary. It is the first paper applying a fine-tuned transformer-LLM to compare the currently in force European mandatory environmental disclosure regulation's impact on Spanish companies' environmental disclosure versus previous voluntary reporting.

*Correspondence:
María Coronado-Vaca
mcoronado@comillas.edu
Full list of author information is available at the end of the article

Keywords Environmental disclosure, Climate-related risks impact, Environmental corporate reports, Sustainability reporting, Mandatory disclosure, Voluntary disclosure, Large Language Models (LLM), ClimateBERT, ClimaText, Pre-trained transformer

Introduction

The increasing concern for climate change and its potential impacts on the global economy has intensified the growing demand from financial agents, especially from particular and institutional investors, for companies to report on climate-related financial risks [1–3]. This is relevant not only for the companies themselves but also for investors, regulators, policymakers, intergovernmental institutions, other stakeholders, and academics who recognize the need to understand better how to identify, mitigate, and disclose their environmental impacts [4].

There is also a recent trend toward mandatory rather than voluntary reporting worldwide [5]. In the European Union (EU), the Non-Financial Reporting Directive 2014/95/EU (NFRD) [6] entered into force on 5 December 2014 and was effective on 1 January 2017 and obliges companies subject to it to prepare a Report of Non-Financial Information (NFIR), through which to provide this information. Spain transposed this NFRD into its national regulation through Law 11/2018 [7]. Due to NFRD shortcomings regarding comparability, consistency, and reliability of the information it requires and the limited number of companies in scope, a new Directive, the Corporate Sustainability Reporting Directive (CSRD) [8], was adopted in December 2022 and replaces the NFRD with regard to the disclosure of sustainability information. CSRD will enter into force for the reporting year 2024, with the first submissions due in 2025. CSRD expands the content of the NFRD and the number of entities required to report information on sustainability, although Spanish Law 11/2018 already contemplated a greater scope than the NFRD and requires a mandatory assurance of sustainability information to increase its reliability and comparability. The content of this information must take as a reference the European Sustainability Reporting Standards (ESRS) developed by the European Financial Reporting Advisory Group (EFRAG) [9]. ESRS were approved by the European Parliament in July 2023 and published in the EU Official Journal in December 2023 [10]. They will be applicable for the reporting year 2024, with the first submissions due in 2025. The adoption of sectoral ESRS and standards for non-EU companies with a significant presence in this territory were postponed for 2 years (from June 2024 to June 2026).

However, a debate exists about the effects of environmental disclosure becoming mandatory on the quality and the actual commitment of such reporting, as a common critique of organizations' communication practices is that they do not demonstrate genuine accountability nor represent a commitment to sustainability [11–18]. On the other hand, other studies found an overall disclosure quality after the introduction of mandatory environmental reporting, thus considering it as value-relevant to firms' external stakeholders [19–27].

The quality of voluntary and mandatory disclosure in company reports is not a strictly defined concept [22], and the previous studies use different approaches to measure it [28], as we will review in "Prior research on climate-related corporate disclosures and reporting: specific focus on the quality and transparency of environmental disclosures" subsection.

As summarized by [22], most studies use (a) a scale to assess the reporting quality of sustainability disclosure, (b) other studies simply assess whether different sustainability items are disclosed or (c) use a self-develop more sophisticated measurement tool, which includes a range of different qualitative aspects.

Hence, with the introduction of regulatory frameworks mandating non-financial disclosures, companies are now required to report on their environmental impacts, including climate change-related risks. The growing importance of these disclosures, with their intrinsic characteristic of heterogeneity and dispersed features, makes the task of studying and analyzing these types of financial and non-financial reports worthy of automation. As a result, in recent years, a growing literature has emerged that relies on Artificial Intelligence (AI) for the identification and analysis of climate-related information [10, 20, 29–34]. In the industry, NLP and LLMs can help automate the process of analyzing financial reports and extracting key insights that can aid businesses in understanding better how to identify, mitigate, and disclose their environmental impacts and in making informed decisions. However, this field is experiencing an enormous revolution, since the implementation of transformer models has been possible due to the rise of computing and we apply cutting-edge NLP techniques in our paper.

Thus, our study is framed within this threefold context of a) growing awareness and demand for reporting climate-related risks, and the recent trend toward mandatory rather than voluntary reporting worldwide [1–3, 5, 19–28], b) the tension between signaling theory and legitimacy theory as to whether sustainability reports indicate actual sustainability performance, also related with the quality reporting measurement [21, 35–40], and c) the enormous advances in NLP techniques [10, 20, 29–34]. Three research fields associated with our work and whose state of the art will be provided in "Theoretical foundation and context of the research and Literature review" sections.

In this paper, we study the voluntary and mandatory reporting of climate-related risks among public-listed Spanish companies spanning multiple sectors over the period 2015–2022 (4 years before and after the implementation of the NFRD, which came into force in 2017, and the Spanish *Law 11/2018*). Spain presents a unique case for analysis due to its implementation of the NFRD via Spanish *Law 11/2018*, which not only transposed the Directive but also expanded its scope by lowering the reporting thresholds for companies. This makes Spain an ideal jurisdiction to study the impact of mandatory environmental disclosure requirements within the EU.

We assess whether differences exist when comparing the disclosure quality and comprehensiveness of Spanish companies' non-financial reports under voluntary and mandatory reporting regimes and among sectors. We focus primarily on the sentiment scores, specificity indices, and commitment levels within the disclosure texts. Moreover, this study explores the climate-related topics disclosed and how they are addressed in the NFIRs, which are aligned with environmental reporting frameworks, including a focus on risk management in accordance with the TCFD categories. We aim to ascertain whether companies actually depict their climate-related strategies, commitments, and actions in their NFIRs.

To this end, this paper presents a novel approach to evaluating environmental disclosure by utilizing cutting-edge NLP techniques, chiefly *ClimateBERT* (a transformer-LLM developed by Webersinke et al. [41]) and *ClimateBERT* fine-tuned on *ClimaText* (a public database for climate change topic detection) developed by Garrido-Merchán et al. [42], to scrutinize and compare 729 voluntary and mandatory corporate reports from 96 Spanish companies spanning multiple sectors. To the best of our knowledge, it is the first paper applying a fine-tuned transformer-LLM to identify patterns and trends, including nuanced analyses on the development of the specificity and commitment of firms' environmental disclosures. We provide a technical quantitative definition of what does quality and transparency really mean in the context of climate change texts, regulation, and our analysis done by transformers in "Problem modelisation" subsections and "The fine-tuned ClimateBERT model".

Our paper contributes both to practitioners and to the academic field. The insights gained from this research are valuable for investors, regulators or policymakers, and other stakeholders, improving their informed decision-making processes in the context of climate change and sustainability. In the academic field, we add to the literature regarding the enormous advances in NLP and LLMs highlighting the potential of cutting-edge NLP techniques, like fine-tuned transformers, in the assessment of the evolution and quality of environmental disclosures, either mandatory or voluntary. We also contribute to the debate and to the strand of the literature on the recent trend toward mandatory rather than voluntary reporting worldwide.

The main limitation of this study is that the geographical and sectoral focus of this study, centered on Spanish financial and non-financial companies, yields results that may not be extrapolated to companies operating in different regulatory environments or corporate cultures.

The remainder of this paper is organized as follows: "Theoretical foundation and context of the research" section provides the theoretical foundation and frameworks for the context of our research, with a special focus on the debate on mandatory vs voluntary environmental disclosure and the recent trend toward mandatory rather than voluntary reporting worldwide. "Literature review" section provides a literature review on the two research fields related to our work: the quality measurement of climate-related corporate disclosure, and the huge advances in NLP techniques and LLMs and their application to climate risk disclosure analysis. "Materials and methods" section details the empirical study, beginning with the data selection process. We then present the problem modelisation, where we provide a technical description of how transformers can be used to annotate, providing features, a corpus dataset of texts by performing mappings from texts to different labels generated as a result of performing classification of those texts. Next, we introduce our fine-tuned *ClimateBERT* model and explain the motivation for and advantages of fine-tuning the *ClimateBERT* model and discussing its differences and comparative advantages/disadvantages relative to *ClimateBERT*. Finally, in this empirical section, we describe the pre-processing techniques and the approach for tokenization and inference using the *ClimateBERT* model. "Results and discussion" section presents and discusses the results obtained by applying the two models: the original *ClimateBERT* and the fine-tuned *ClimateBERT* on *ClimaText*. The results analysis from the original *ClimateBERT* unfolds, in turn, in two segments: first offering a global perspective, then proceeding to a sector-based examination. In a third subsection, we make a comparative analysis of results obtained by applying both the original and the fine-tuned models. Finally, we close our paper with the conclusions and further work in "Conclusion" section.

Theoretical foundation and context of the research

Theoretical foundation

Accounting reporting research has two schools of thought concerning disclosure: one assumes that voluntary disclosure is *value-relevant*, and the other assumes such disclosure to be *opportunistic* [40]. When applied to environmental disclosure, these two streams have opposite views on whether sustainability reports indicate actual sustainability performance [35]. The value-relevant stream of research considers companies providing external stakeholders with value-relevant, credible, and comparable information on firms' climate performance through their environmental reports [21, 38, 43]. In the opposing view, the opportunistic school considers companies use these reports mainly to influence stakeholder perceptions to improve the company's reputation through greenwashing [11, 14, 16]. There are several theories that consider this relation between voluntary environmental disclosures and actual environmental performance, such as signaling [36], legitimacy [11], stakeholder [44], stewardship, and institutional [45] theories. However, all of them are, in brief, consistent with either a discretionary/voluntary disclosure perspective to which signaling theory belongs [46, 47], or theories grounded in a socio-political perspective, such as legitimacy theory [48], to which greenwashing belongs.

Signaling theory has been successively applied in a number of corporate studies, including corporate communication, to explain that management may signal "something" about the company through different aspects of corporate information disclosure, as a signal for investors and/or other stakeholders (employees, customers and suppliers, regulators, and the broader community within which a firm operates) [39]. Under the voluntary/discretionary-signaling perspective, firms with good environmental information make the most exhaustive disclosures and thus voluntarily disclose such information to reduce information asymmetry and avoid adverse selection [40]. Signaling theory suggests that firms may attempt to signal "good news" using mandatory and voluntary reporting of non-financial information. Thus, in compliance with signaling theory, good firms (those with high sustainability performance) differentiate themselves from bad firms (those with low sustainability performance) and signal their sustainability as good corporate citizens [36–39].

Legitimacy theory posits that corporate disclosures are made as reactions to environmental pressures (economic, social, and political) and to legitimize the corporation's existence and actions [12]. Greenwashing is a legitimation strategy that occurs when firms voluntarily issue environmental reports to promote an impression of legitimate environmental values, which may or may not be substantiated [16]. Under the greenwashing explanation, firms use environmental reports to just try to appear to be good corporate citizens with strong sustainability performance, but they are not in fact [11–18].

There is a supported generally held notion that socio-political theories (which include stakeholder theory) predict a negative relation between sustainability disclosure and performance, but some authors find that, on balance, stakeholder theory predicts a positive relation [44]. These are not competing but complementary or even overlapping theories when applied to corporate social reporting [11].

Some authors use the lens of a single theory in their research [12, 44], while it is the coupling of two theories (or more) that other authors' models are built on [14, 49]. Our paper is informed mainly by these three theories: signaling, legitimacy, and stakeholder theories, and our results contribute to both value relevance and opportunistic perspectives (see "Results and discussion" section).

Mandatory versus voluntary disclosure debate

In the context of our study, the nature of the debate between voluntary and mandatory reporting may be framed into these questions: Does legal pressure increase comparability and/or quality of non-financial reporting [17]? Does the passage from voluntary to mandatory environmental reporting (ER) have a positive impact on environmental disclosure (ED) quality (and quantity)? Of course, many other variables, not only ED quality (and quantity), may be affected by mandatory ED (such as firm stock price, and liquidity, firm default risk, and have also been investigated in prior literature), but we focus the debate, primarily, on quality. While the quantity of disclosure seems to be easier measured, reporting quality is no strictly defined concept [22] and the previous studies use different approaches to measure it, as we will review in "Prior research on climate-related corporate disclosures and reporting: specific focus on the quality and transparency of environmental disclosures" subsection.

Summarizing the empirical literature on the debate between voluntary and mandatory ER, several studies provide evidence of the positive impact of mandatory ER on ED quality [19–27], others document a negative impact [18, 50, 51], and some find no significant influence [52–57].

Many prior studies that find evidence in favor of mandatory ER cover EU individual countries after the implementation of different disclosures in Europe and only consider specific EU Member States, such as Sweden [21], Denmark [24], or Spain [25], while other researchers examine the effects of the introduction of mandatory ED through NFRD at the whole European level [22]. Other works compare mandatory (EU firms) and voluntary (US companies) ESG disclosures and find that EU firms outperform US firms under voluntary disclosure requirements (2007–2016), and the ESG disclosure of EU firms further improves relative to US firms after the implementation of the mandatory disclosure in Europe in 2017 [19].

Besides the research providing evidence of the positive impact of mandatory ER on ED quality in European and North American countries, other authors find the evidence of the positive impact of mandatory non-financial disclosure regulations emerging in other countries such as China or South Africa [24], or Malaysia [23, 24].

Müller et al. [20] also contribute to this literature that studies the interplay of mandatory and voluntary disclosure. They state that *"in contrast to the largely voluntary, unaudited disclosures made elsewhere, climate disclosures in financial statements more strongly reflect firms' fundamental climate exposure, in line with their role of grounding the corporate information environment in reliable 'hard facts'"*. In their comprehensive overview of contemporary sustainability accounting research, comprising 1,283 academic articles published in 54 journals (2014– 2020), Hsiao et al. [27] found that there is undisputed evidence of national policies and regulations (e.g., mandatory CSR disclosure, environmental regulations, and emission trading schemes) and regulatory pressure being positive stimuli for sustainability systems, disclosure, assurance, and certification.

On the other hand, there also exist studies that document a negative impact of mandatory sustainability reporting only considering specific EU individual countries after the implementation of different mandatory disclosures in Europe, such as Italy [18] or Norway [51].

Finally, other researchers show that the quality of NFR does not increase when moving from a voluntary to a mandatory basis (with the introduction of NFRD) both at a European level [53] and considering only individual countries such as Italy [54] or Czech Republic [56]. Fiechter et al. [50] point to pronounced anticipation effects related to the NFRD, introducing uncertainty about the timing of the treatment effect after the enforcement of the mandatory disclosure requirements. They find that firms already began their CSR reporting before the NFRD came into effect, firms' inclusion of climate-related matters into their financial statements occurred later.

Thus, although most studies emphasize the need for mandatory reporting regimes and regulatory policy for better quality of ED, the debate between voluntary and mandatory ER in Europe remains inconclusive and further research is welcome. Our paper contributes new insights into this debate.

Regarding the case of Spain, prior studies on mandatory sustainability reporting found a positive effect on the number of firms reporting on sustainability topics in comparison to the respective preceding voluntary regime [58, 59]. Criado-Jiménez et al. [25] state that voluntary Corporate, Social, Ethical, and Environmental reporting has been characterized by a dearth of neutral and objective information and recommend that it be made compulsory. Their underlying rationale is that legally specified disclosure requirements and enforcement mechanisms would enhance the volume and quality of such reporting. They analyze the reporting patterns of 78 of the largest Spanish companies between 2001 and 2003 and examine the extent of their compliance with the existing normative standard at this time in Spain (ICAC-2002), which obliged them to make environmental disclosures in their financial statements. Their results suggest that progressive and improved regulation could increase the volume and quality of Corporate, Social, Ethical and Environmental Disclosures.

In 2017, the Task Force on Climate-Related Financial Disclosures (TCFD) released climate-related financial disclosure recommendations designed to help companies provide better information to support informed capital allocation [60]. Furthermore, several governments, regulators, and standard setters have implemented the TCFD recommendations in developing climate-related reporting requirements and standards. Even more, after the International Sustainability Standards Board (ISSB)'s release of its climate-related and general sustainability-related disclosure standards on June 2023 and concurrent with the TCFD's release of its 2023 Status Report on October 2023 [61] Appendix, the TCFD has fulfilled its remit and disbanded, handing over the reins to ISSB. The ISSB's work is backed by the G7, the G20, International Organization of Securities Commissions (IOSCO), the Financial Stability Board (FSB), African Finance Ministers and by Finance Ministers and Central Bank Governors from over 40 jurisdictions. Most of the jurisdictions with final or proposed climate-related disclosure requirements specify that such disclosures be reported in financial filings or annual reports. This reveals the recent trend toward mandatory rather than voluntary reporting worldwide.

At the EU level, the CSRD [8] and ESRS [10] mandatory regulation is in the midst of climate-related disclosures and will foreseeably make a big impact on sustainability reporting. The ESRS comprise three categories of standards: (i) cross-cutting standards, (ii) topical standards, and (iii) sector-specific standards. The adopted first set of ESRS consists of cross-cutting standards (ESRS 1 and

ESRS 2) and topical standards (ESRS E1 to E5, ESRS S1 to S4, ESRS G1), and is sector agnostic. The topical standards contain additional disclosure requirements for material sustainability topics and are divided into environmental (ESRS E1 to E5), social (ESRS S1 to S4), and governance (ESRS G1) matters. ESRS (E1) is the specific climate-related ESRS [5]. Prior to this new regulation, our study analyzes NFRD as the insights from the current regulation will help analyze future regulation impact.

For a deeper analysis of CSRD and ESRS, we refer to the recent study of Hummel and Jobst [5] that provides a comprehensive overview of corporate sustainability reporting legislation in the EU.

From an international perspective, the International Sustainability Standards Board (ISSB), which was created by the International Financial Reporting Standards (IFRS) Foundation, issued the IFRS S1 General Sustainability Disclosures and IFRS S2 Climate-related Disclosures on 26 June 2023, based on the TCFD recommendations. This IFRs S2 sets out the requirements for an entity to disclose information about its climate-related risks and opportunities [62], and it has been included in the IFRS Sustainability Disclosure Taxonomy published on 30 April 2024 [63]. As companies around the world are increasingly mandated to disclose sustainability-related information through the ISSB Standards and ESRS, EFRAG, and the ISSB are committed to creating efficiencies where possible to advance transparency, comparability, and accountability. Thus, the IFRS Foundation and EFRAG have just published on 5 May 2024 guidance material to illustrate the high level of alignment achieved between the IFRS Sustainability Disclosure Standards and the ESRS and how a company can apply both sets of standards, including detailed analysis of the alignment in climate-related disclosures [64].

On the side of voluntary guidelines, many international organizations have developed over recent decades various frameworks to help companies in their disclosure of environmental issues, including the Global Reporting Initiative (GRI) [65], Carbon Disclosure Project (CDP) [66], United Nations Global Compact (UNGC) [67], Workforce Disclosure Initiative (WDI) [68], Sustainability Accounting Standards Board (SASB) [69, 70], TCFD [71], and some others. The TCFD guides companies on how to disclose climate-related financial risks and opportunities across four key dimensions: Governance, Strategy, Risk Management, and Metrics and Targets [72]. Unerman et al. [73] provide a detailed comparison of the qualitative characteristics of SASB, GRI, and other reporting frameworks. We show a comparative table of voluntary frameworks (Table 1) and a summary of the sequence of voluntary and mandatory disclosures distinguishing between European and international levels (Fig. 1).

Other factors influencing non-financial information disclosure

Not only voluntary vs. mandatory but also other stakeholders' requirements and expectations from companies (clients, investors, financial institutions, etc.), aside from the regulatory stakeholders, may influence reporting quality, as previous research shows [74–80]. Some authors find the relationship of companies with their stakeholders affects the transparency of sustainability reporting [77] and explain the diversity in sustainability

Table 1 ESG frameworks comparative table

Framework	Description	Works well with
GRI	Comprehensive international framework for sustainability reporting with guidelines and modules	TCFD, UNGC, ISSB
CDP	Standardized questionnaire for reporting climate-related risks and opportunities across different sectors	GRI, TCFD, WDI
UNGC	Voluntary initiative promoting corporate sustainability through 10 principles in four main areas	GRI, TCFD, SASB
WDI	Data gathering on employee and supply chain worker management for institutional investors	CDP, GRI
SASB	Industry-tailored sustainability accounting standards, including climate-related disclosure obligations	GRI, TCFD, UNGC, ISSB
TCFD	Guidance on disclosing climate-related financial risks and opportunities across four key dimensions	GRI, SASB, UNGC, ISSB

Source: Authors' own creation

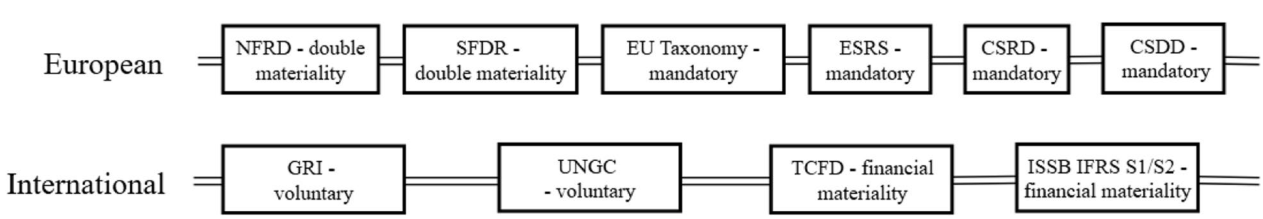


Fig. 1 Sequence of voluntary and mandatory disclosures. Source: Authors' own creation

reporting by studying how it is used to engage stakeholders [76]. Michelon [75] highlights the importance of reputation and media exposure in driving sustainability disclosures, particularly in times of heightened external pressure. Helfaya and Moussa [74] emphasize the role of board-level CSR strategy in shaping the quality of environmental sustainability disclosures. Firms with strong CSR committees and sustainability-oriented leadership are more likely to provide detailed, high-quality disclosures, particularly in environmentally sensitive sectors. Recently, some studies support the COVID-19 pandemic's influence on companies' climate disclosure practices [78–80], noting that the pandemic forced many companies to adjust their climate-related reporting practices due to the heightened uncertainties in the business environment, particularly as they prioritized short-term survival. Previous research has shown that obtaining independent assurance of environmental reporting helps to prevent the threat of lack of credibility-greenwashing [81–84] and obtain evidence on how sustainability assurance improves the quality of non-financial reporting [85].

Literature review

We divide the relevant literature for this topic into two strands: (1) prior research on climate-related corporate disclosures and reporting with a specific focus on previous research on the quality and transparency of environmental disclosures, and (2) reporting and NLP methods for analyzing environmental disclosure.

Prior research on climate-related corporate disclosures and reporting: specific focus on the quality and transparency of environmental disclosures

A vast body of literature exists on the disclosure of climate-related information [86], and we will focus on the specific strand on the quality and transparency of environmental disclosures. The quality and transparency of environmental disclosures are critical dimensions for evaluating the credibility and usefulness of sustainability reporting. Despite a proliferation of regulatory frameworks and voluntary guidelines designed to enhance disclosure practices, the literature still debates how best to measure and assess the quality of this information.

Quality in environmental disclosures is multidimensional, typically encompassing completeness, specificity, accuracy, materiality, and assurance. According to Fernández-Feijóo et al. [87], the GRI provides a widely accepted framework for evaluating sustainability reports. The GRI focuses on transparency, relevance, and the inclusion of assurance statements to validate the information provided. The quality of sustainability reports is often measured by assessing adherence to GRI guidelines, which emphasize the application of reporting standards, third-party validation, and data comprehensiveness.

Hahn and Kühnen [17] emphasize the importance of reflecting both positive and negative aspects of a company's environmental performance. However, many sustainability reports continue to prioritize positive outcomes, creating an imbalanced representation of corporate sustainability. This selective disclosure undermines transparency, a point also highlighted by Criado-Jiménez et al. [25], who argue for more thorough reporting on negative incidents as a crucial element of accountability and by Hahn and Lülfs [26] who advocate negative aspect first has to be objectively described and, this step should be regarded as mandatory minimum requirement in future guidelines, aiming at balance, impartiality, and, in sum, transparency, in a reporting company.

Emerging research further stresses the importance of industry-specific factors in determining disclosure quality. Herz and Rogers [88] from the SASB argue that applying industry-specific Key Performance Indicators (KPIs) enhances the materiality and relevance of disclosures, particularly in sectors with significant environmental risks. Transparency in environmental disclosure is not simply about providing large amounts of data; it is about ensuring that the information is clear, complete, and accessible to stakeholders. Unerman et al. [73] highlight three critical dimensions of transparency: relevance, reliability, and comparability. Reports that lack transparency often use ambiguous or boilerplate language, failing to provide meaningful insights into a company's environmental performance.

A key challenge in enhancing transparency is balancing specificity with comprehensibility. Paananen et al. [29] introduce the concept of Specificity Indices, which assess the level of detail in narrative disclosures by focusing on entity-specific terms rather than generic statements. Specificity has been validated as a robust measure of transparency, as it reflects the level of concrete, decision-useful information provided by companies. For instance, environmental liability disclosures that mention specific pollutants, affected regions, and regulatory frameworks are seen as more transparent and valuable for stakeholders. Additionally, media exposure can serve as a proxy for disclosure transparency. Samani et al. [89] demonstrate that media coverage, especially when negative, prompts firms to disclose more detailed and relevant environmental information, thereby enhancing transparency.

Third-party assurance is pivotal in improving the credibility of environmental disclosures. Ballou et al. [85] and Lock and Seele [53] highlight the value of assurance services, particularly when provided by reputable Big Four auditors, in enhancing transparency and accuracy. However, the quality of assurance varies depending on the provider. Auditors generally issue higher quality assurance reports than consultants, with Fernández-Feijóo et al.'s [87] finding that Big Four auditors are particularly associated with higher quality assurance statements. These findings underscore the importance of selecting credible assurance providers to ensure the reliability and transparency of environmental disclosures. Moreover, Ballou et al. [85] suggest that firms seeking assurance are more likely to revise and improve their disclosures over time. This iterative process, where firms issue restatements to correct errors or omissions, reflects a commitment to transparency and continuous improvement in reporting quality.

The application of industry-specific standards, such as those developed by SASB, is gaining traction as a method for improving the relevance and comparability of environmental disclosures. Herz and Rogers [88] argue that generic sustainability frameworks like GRI, while comprehensive, may lack the precision needed to address the unique environmental challenges of different sectors. For example, climate-related disclosures are critical for the oil and gas industry but may be less relevant for the tech sector, which might prioritize issues like energy efficiency and electronic waste management. By focusing on materiality within specific industries, SASB and other sector-focused frameworks offer a more tailored approach to sustainability reporting. Gao et al. [90] further support this view, finding that firms with higher quality ESG disclosures attract more sustainable investments, especially when adhering to industry-specific metrics. Despite progress in enhancing the quality and transparency of environmental disclosures, the literature still challenges how best to measure and assess the quality of this information [91]. Our paper adds to this challenging literature.

Natural Language Processing (NLP) techniques for analyzing environmental disclosure

As we have seen, the growing demand for sustainable and responsible investments has led to an increased emphasis on climate risk disclosures [3]. NLP techniques can help them in this context. Its primary objective is to enable computers to understand, interpret, and generate human language in a manner that is both meaningful and useful [92]. By leveraging advanced NLP techniques, researchers and practitioners can automatically process, analyze, and extract relevant information from climate risk disclosures, facilitating a more comprehensive assessment of a company's sustainability practices and performance [33, 93–95]. The evolution of NLP techniques and models can be divided into three main eras: rule-based systems, statistical methods, and deep learning-based approaches (Fig. 2). By reviewing them, we will conclude that no previous study has applied fine-tuned transformers in the quantitative assessment of the evolution and quality of environmental disclosures, either mandatory or voluntary.

In the early days of NLP, heuristic techniques were employed to solve problems. These methods, while not guaranteed to be optimal or perfect, were sufficient for achieving immediate, short-term goals. Examples of heuristic methods in NLP include regular expressions for pattern matching and Wordnet, a lexical database for the English language [96]. However, they are sometimes time-consuming, rely on expert knowledge, and often

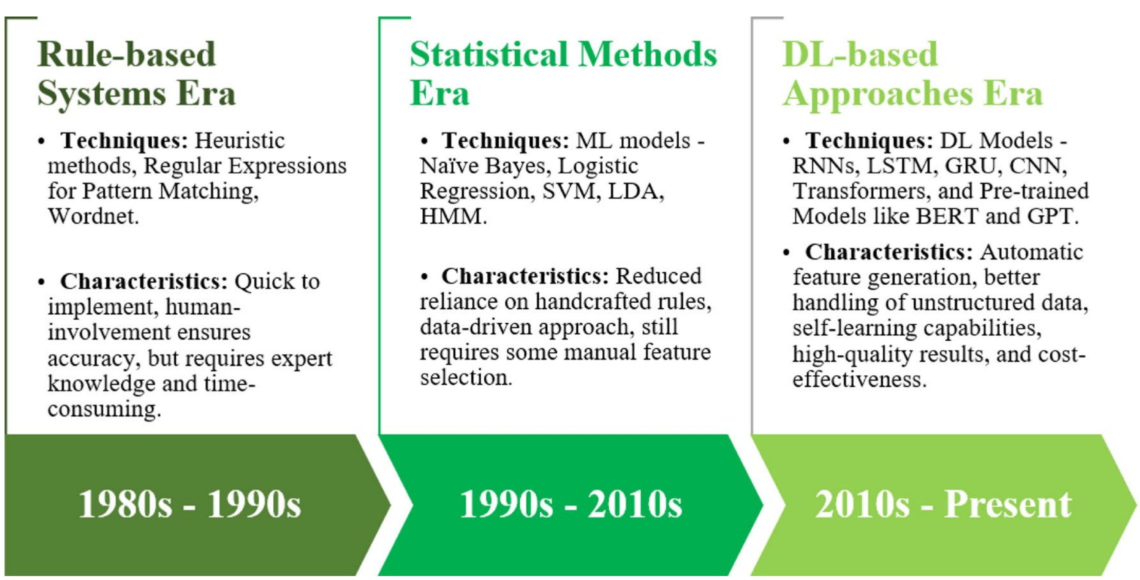


Fig. 2 NLP evolution timeline. Source: Authors' own creation

require the aggregation of multiple experts' results. The limitations of heuristic methods in addressing open-ended problems led to the adoption of machine learning (ML) techniques in the 1990s. ML models are trained on existing data to generate accurate predictions or classifications. The typical ML workflow in NLP includes problem statement, data gathering, text pre-processing, feature engineering, model building, model evaluation, and model deployment [97]. Popular ML models used in NLP include Naïve Bayes, Logistic Regression, Support Vector Machines (SVM), Latent Dirichlet Allocation (LDA), and Hidden Markov Models (HMM).

The advent of deep learning (DL) in the 2010s revolutionized NLP, offering numerous advantages over traditional ML methods, such as automatic feature generation, better handling of unstructured data, self-learning capabilities, high-quality results, and cost-effectiveness. These models can retain sequential information in text, eliminating the need for manual feature selection. DL models commonly used in NLP include the Transformers, that are large language models that capture the dependencies between words, that are encoded in word embeddings whose space represents the meaning of the words. Specifically, transformers' empirical results dramatically outperform the classical pipeline of machine learning models with a bag-of-words representation of the most common and relevant words of the texts according to algorithms such as Term Frequency-Inverse Document Frequency (TF-IDF) [98].

Consequently, we apply a cutting-edge NLP technique: a transformer model; a BERT-related model called *ClimateBERT* [41], that has been specifically tailored for climate text classification. This model reads a whole sequence of words at once, allowing it to learn the context of a word from its surroundings. More specifically, *ClimateBERT* is the state-of-the-art NLP model based on the Transformer architecture which has been specifically pre-trained on climate-related text corpora of over 1.6 billion paragraphs in relation to climate change consisting of news articles, corporate climate reports, and research abstracts. Moreover, *ClimateBERT* is the first climate domain adaptive pre-trained model which has been made available to the public.

Prior literature applying NLP techniques for analyzing environmental disclosures or financial matters still apply NLP techniques belonging to the second era of ML models and only two studies apply transformers [20, 94]. However, we differentiate from the two studies applying transformers: [94] proposes FinBERT (a financial domain-specific adaptation of the BERT model), instead of our applied transformer, *ClimateBERT* by [41] which has been pre-trained specifically tailored for climate text classification and outperforms FinBERT for climate-related tasks. Moreover, they do not apply FinBERT to compare the quality of mandatory vs voluntary reports. And [20] only apply NLP techniques when previously obtaining climate disclosures data from financial statements (concretely they first use a bag-of-words approach, and also, to capture climate-related disclosures more comprehensively, they use the number of climate-related paragraphs identified by *ClimateBERT*). They subsequently apply OLS regressions. Thus, to the best of our knowledge, our study is the first paper applying a fine-tuned transformer-LLM to compare the currently in force European mandatory Environmental disclosure requirements' impact on Spanish companies' environmental disclosure versus previous voluntary reporting. We summarize all the studies in Table 2 (studies applying NLP techniques of the 2nd era) and Table 3 (studies applying NLP techniques of the third era).

Thus, based on the context of the research, its theoretical foundation, and the literature review discussed so far, we address three research questions in this paper:

RQ1: *Are there differences when comparing the disclosure quality and comprehensiveness of firms' non-financial reports under voluntary and mandatory reporting regimes?*

RQ2: *Does transformer-LLM processing of companies' NFIRs allow us to ascertain whether firms actually depict their climate-related strategies, commitments, and actions in them?*

RQ3: *Is our proposed novel fine-tuned CimateBERT model able to outperform the standard ClimateBERT model in these diverse climate-related text classification tasks?*

Materials and methods

This section will deal with the materials and methods that have been used to provide an answer to our research questions and generate an enhanced description of the regulatory texts with transformer models. We start the section with the data that has been used as we believe that it is the most critical information for practitioners, explaining the information flux that we have followed to obtain the enhanced regulatory texts with information provided by transformers. Then, we explain how we have pre-processed the data as, in practice, is the most expensive step, and we continue, logically following the presented information flux, with how we did inference using transformers. We show the methodology flowchart in Fig. 4.

Data

Various types of reports were collected for our analysis during the data extraction process. These include: annual

Table 2 Summary of studies applying NLP-ML techniques for environmental disclosure analysis

Author	Summary	Classified era/technique
Dyer et al. (2017) [107]	This study investigates changes in the textual characteristics of 10-K disclosures over the period 1996–2013, noting significant increases in document length, boilerplate, and redundancy, with decreases in specificity and readability	Statistical Methods Era/Latent Dirichlet Allocation (LDA)
Ertugrul et al. (2017) [108]	The study investigates how readability and tone ambiguity in annual reports impact borrowing costs, showing that less readable and more ambiguous reports lead to stricter loan terms and higher future stock price crash risk	Statistical Methods Era/Econometric models, Textual Analysis
Ehrmann et al. (2019) [109]	This study investigates the effects of semantic similarity in central bank press releases on market volatility, focusing on how the predictability of statement style influences market reactions	Statistical Methods Era/ARCH models, Semantic similarity measures
Paananen et al. (2021) [29]	The study explores how media exposure influences the specificity and comprehensiveness of environmental liability disclosures among European-listed firms, assessing market implications of these disclosures	Statistical Methods Era/Econometric models, computerized textual analysis
Moreno and Caminero (2022) [30]	They apply text-mining techniques to analyze the TCFD recommendations on climate-related disclosures of the 12 significant Spanish financial institutions and of the companies comprising the IBEX1 35 stock market index using publicly available corporate reports from 2014 until 2020	Statistical Methods Era/Econometric models, Textual Analysis
Samani et al. (2023) [89]	The study examines how the EU Directive on Non-Financial Reporting and the presence of employee representatives on boards affect the quality and extent of employee-related disclosures in Swedish firms	Statistical Methods Era/Econometric models, Quantitative Analysis, Textual Analysis
Debener et al. (2023) [110]	The study examines how the quality and quantity of textual disclosures in issuance prospectuses affect investors' security pricing, highlighting that more detailed and less boilerplate content can lead to higher yield demands by investors	Statistical Methods Era/Econometric models, Textual Analysis
Sautner et al. (2023) [31]	This study develops a method to identify the attention paid to firms' climate change exposures using earnings call transcripts and a machine learning keyword discovery algorithm, covering over 10,000 firms from 34 countries between 2002 and 2020	Statistical Methods Era/Machine Learning, Keyword Discovery
Düsterhöft et al. (2023) [32]	This study analyzes the impact of climate risk disclosures on stock market volatility among European energy utilities, focusing on the period from 2007 to 2017, using unsupervised machine learning to categorize risk topics within financial disclosures	Statistical Methods Era/Unsupervised machine learning (Latent Dirichlet Allocation)

Source: Authors' own creation

reports, ESG reports, and Corporate Sustainability reports (see Appendix 1. *Data*).

To select the companies for our analysis, we applied the following criteria based on the Spanish *Law 11/2018*:

1. Companies that meet at least two of the following conditions for two consecutive fiscal years:
    a. Total assets exceeding 20 million euros.
    b. Annual net business volume exceeding 40 million euros.
    c. A workforce of more than 250 employees.
2. Financial companies, such as banks, insurance companies, and funds.

These criteria allowed us to identify the financial and non-financial companies that are required to prepare an NFIR according to the Spanish *Law 11/2018*. The sample was limited to publicly traded firms to ensure the availability and consistency of data, as these companies are obligated to disclose detailed reports accessible to the public and investors.

Using the Bloomberg EQS function, we initially identified 120 Spanish companies that met these criteria. We

Table 3 Summary of studies applying NLP DL-based techniques for environmental disclosure analysis

Author	Summary	Classified era/technique
Kraus and Feuerriegel (2017) [93]	This study examines the use of deep learning, specifically LSTM models, to improve financial decision-making processes by analyzing the textual content of financial disclosures and predicting stock price movements	DL-based Approaches Era/Deep Neural Networks, LSTM, Transfer Learning
Hsu and Rauber (2021) [33]	This study uses NLP and network analysis to evaluate the coordination among diverse climate actors based on their strategy documents. The analysis covers 9,326 documents from various global actors	DL-based Approaches Era/Natural Language Processing, Network Analysis
Mohamad Sham and Mohamed (2022) [34]	This study explores various sentiment analysis techniques including lexicon-based, machine learning, and hybrid approaches to analyze climate change sentiment on Twitter, aiming to identify the most effective methods	DL-based Approaches Era/Hybrid methods incorporating lexicons and machine learning classifiers
Huang et al. (2023) [94]	This study introduces FINBERT, a financial domain-specific adaptation of the BERT model, which outperforms traditional machine learning algorithms and other NLP models in sentiment classification of financial texts	DL-based Approaches Era/Large Language Model, BERT adaptations
Vestrelli et al. (2024) [95]	The study explores how climate risk disclosures in 10-K and 10-Q reports and earnings conference calls affect firm market value, emphasizing a generally positive impact that becomes complex under high climate attention	DL-based Approaches Era/Text Mining, Semantic Network Analysis
Müller et al. (2024) [20]	This paper studies climate exposure' reflection in financial statements from EU and US firms. Although it uses OLS regressions, it previously applies NLP techniques when obtaining climate disclosures data from financial statements (concretely it first uses a bag-of-words approach, and also, to capture climate-related disclosures more comprehensively, it uses the number of climate-relayed paragraphs identified by ClimateBERT)	DL-based Approaches Era/Large Language Model (ClimateBERT), and Statistical Methods Era/Econometric models, Textual Analysis

Source: Authors' own creation

then gathered their annual reports from Bloomberg and FactSet. Additionally, the corporate websites of these companies were checked for any supplementary reports that discuss climate or other ESG factors, including previous voluntary disclosures and recommendations from organizations, such as the TCFD, SASB, and GRI.

However, while our selection criteria initially yielded a broad range of companies, there was a significant subset that had to be subsequently excluded. Specifically, 24 companies were excluded, because their reports were not available in English. This exclusion was necessary, because the *ClimateBERT* models we employed are pretrained on English-language corpora, and thus require input data in English for accurate analysis. Utilizing reports in other languages could have compromised the effectiveness and reliability of our NLP analysis, as the model's linguistic and contextual understanding is optimized for the English text.

Furthermore, some companies lacked complete reports for the entire period under study, resulting in the exclusion of certain firm-years due to insufficient data.

After applying these filters, our final dataset incorporated 729 reports from 96 companies, spanning multiple sectors such as Construction, Real Estate, Energy, Financial Services, Media, and Healthcare, among others (see Appendix 1). Table 1 summarizes the number of companies and reports from each of the 16 sectors analyzed). This selection process is illustrated in Fig. 3, which details the filtering stages leading to the final sample.

The timespan chosen for this analysis is the period between 2015 and 2022. The selection of this interval was not arbitrary but was purposefully designed to capture a significant shift in environmental reporting practices. The year 2015 was selected as the starting point, since it was a time when climate-related reporting was still largely voluntary. As we progress toward 2022, we enter the era post the implementation of the NFRD, which came into force in 2017, and the Spanish *Law 11/2018*. This period, hence, represents the transition from voluntary to mandatory climate-related disclosures, offering an excellent opportunity to observe and analyze the changes that occurred due to this shift in regulation. The 2018 cut-off gave us 4 years of mandatory reports to compare against voluntary ones. This period was deemed sufficiently long to identify any early impacts of the regulation

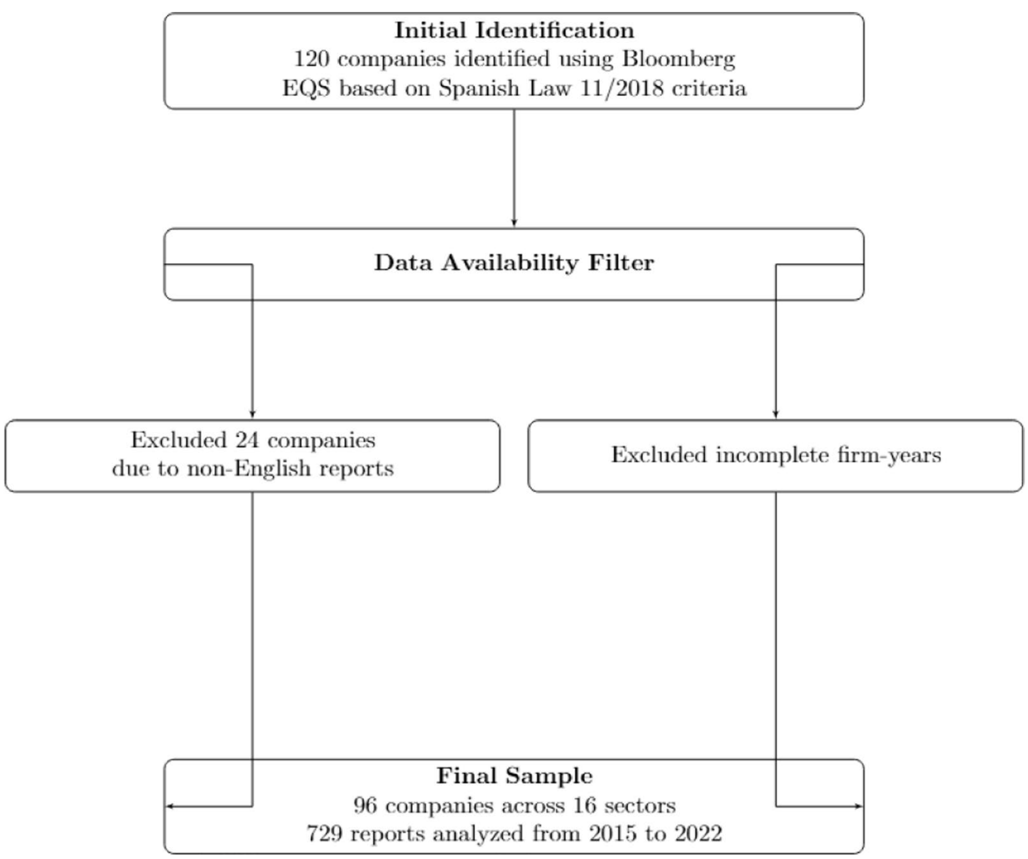


Fig. 3 Sample selection flowchart. Source: Authors' own creation

while still being recent enough to reflect contemporary disclosure practices.

We focused on comprehensive reports such as annual reports, corporate sustainability reports, and ESG reports, and excluded "non-traditional" publications like ESG fact sheets or brief summaries. This decision was made to ensure consistency and depth in the data analyzed, as these comprehensive reports provide detailed and standardized information necessary for our NLP techniques.

By focusing on Spain, we aimed to provide insights into how mandatory disclosure requirements influence corporate reporting in a specific national context within the EU jurisdiction. Spain presents a unique case for analysis due to its implementation of the NFRD via Spanish Law 11/2018, which not only transposed the Directive but also expanded its scope by lowering the reporting thresholds for companies. Moreover, as we mentioned in "Theoretical foundation and context of the research" section, Spanish Law 11/2018 requires that the information contained in the NFIR be verified by an independent assurance provider to increase its reliability and comparability. This verification was an important step forward as it was not compulsory in the NFRD but optional for each Member State. This made Spain an ideal jurisdiction to study the impact of mandatory environmental disclosure requirements within the EU. While the findings may not be fully or directly generalizable to other EU or non-EU jurisdictions due to variations in regulatory implementation and cultural factors, the study offers a valuable basis for comparative analyses and can inform policy development in similar contexts.

We show the methodology flowchart in Fig. 4, and once the collected data are described, we proceed to explain the subsequent steps: data pre-processing, tokenization and inference, and finally, climate disclosure analysis.

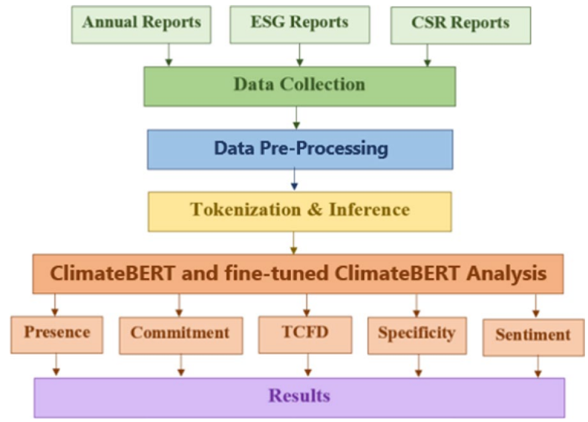


Fig. 4 Methodology flowchart. Source: Authors' own creation

Problem modelisation

We find in the literature vast evidence that modern transformers such as GPT and BERT provide state-of-the-art results in text classification tasks with respect to classic techniques or traditional machine learning classification in general [98] and also in particular regarding climate change text classification tasks [99] like the Paris agreement climate action plans [100].

Concretely, a classification task can be seen as approximating the mapping $y = f(X)$ between a categorical or binary variable y with respect to the word embedding representation of a text **X** to create a new feature of the text, such as, for example, if its topic is climate change. As we will further see, our five applications of transformers **f**, a vector of feature mappings, create features of the text **y**, a vector of these variables of features, following these mappings $y = f(X)$ and hence providing a more accurate descriptive and exploratory representation of the climate change topic that is mentioned in the texts, that have been converted into a tuple (**X,y**), where the features y can be interpreted in a business manner a posteriori by combining its values.

For example, given a new text, we can measure whether the climate change transparency of the organization has improved if the number of texts where climate change is mentioned increases and they include actions undertaken, targets achieved, or future activities likely to be implemented. Interestingly, the *distilroberta-base-climate-detector* and the *distilroberta-base-climate-commitment* transformers classify the texts precisely if the presence of those two features is detected, and, as it is presented in the results section, by observing whether the relative frequency of this variable increases, we can interpret that the transparency of the organization regarding climate change also increases. Similarly, we could interpret whether the quality of the climate change texts has improved if the texts that mention climate change are specific, tailoring concrete problems and providing descriptions of current, past, or future climate change events that could specifically impact the firm's operations, strategy, or overall business activities, which is captured by the *distilroberta-base-climate-specificity transformer*. If we assume that, for a certain business, these interpretations of quality and transparency are pertinent, then they could be quantitatively measured by the features extracted from the texts by the transformers. If, on the other hand, the business needs another quantitative definition of quality and transparency based on a linear combination of the features extracted by our transformers or another features, it could also be tracked in this way, making the transformer classification model a critical application for climate change quantitative monitoring.

The fine-tuned ClimateBERT model

For this study, we have fine-tuned the *ClimateBERT* model with the *ClimaText* database [5]. From now on, we refer to this model as fine-tuned *ClimateBERT*. The *ClimateBERT* model [41] is a *DistillRoBERTa-based* [101] model that has been specifically tailored for climate text classification. Recall that the *DistillROBERTa-based* model is a smaller version of the *ROBERTa* model, which is a derivation of the BERT transformer model. For more technical details of the transformer model, a complete understanding of them can be acquired by reading the book by Bishop [102] and for a complete visualization of the transformer model family the survey by Lin [103]. In this work, we just need to know that the fine-tuned *ClimateBERT* methodology provides, nowadays, the best approximator of the mapping $y = f(\boldsymbol{X})$ [42] for financial texts $\mathbf{X}$ regarding climate change, independently on how the model represents that mapping in its parameters.

Technically, our fine-tuned *ClimateBERT* model has been created using the *ClimaText* database [104], that consists on data collected from Wikipedia, 10 K Files Reports and web-based claims about climate change, improving the results of the standard *ClimateBERT* model in a set of specific problems, obtaining state-of-the-art results [42]. Our motivation, hence, to use the fine-tuned *ClimateBERT* model is just to obtain the best results, using the tool that we believe that better solves the problem of climate change text classification that is described in the problem modelization section. We assume in our decision to use the fine-tuned *ClimateBERT* model that the scenario described in this paper is similar to the problems where the fine-tuned *ClimateBERT* model is used. Consequently, the behavior obtained by the fine-tuned *ClimateBERT* model is going to be approximately similar to the one displayed in its paper [42], where it outperforms the performance displayed by the *ClimateBERT* model. Moreover, the size of the fine-tuned *ClimateBERT* model is the same than the one of the *ClimateBERT* model, as the only feature that changes is the weights of the last layers of the fine-tuned *ClimateBERT* model, whose weights have been modified to improve the loss function of the problem by representing the knowledge of the *ClimaText* database. Hence, both models are equally complex, not being any of those more prone to overfitting, but being the fine-tuned *ClimateBERT* model a better representation of the features regarding climate change than the *ClimateBERT* model, as its sample of texts is bigger than the one used by the *ClimateBERT* model. Consequently, the sample used for the fine-tuned version has more probability of being representative of the climate change theoretical population of texts and, hence, which converts the fine-tuned version of the *ClimateBERT* model to a better choice with the same complexity than the standard *ClimateBERT* Model.

To evaluate the performance and comparative advantages of the fine-tuned ClimateBERT model, we introduce the following key metrics used in this study:

- Average disclosure volume: Measures the average number of paragraphs identified as climate-related by each model across all analyzed reports.
- Disclosure volume growth: Captures the growth rate in the number of climate-related disclosures over the study period.
- Average proportional commitment: Reflects the average proportion of climate-related paragraphs expressing a commitment to climate action.
- Proportional commitment growth: Indicates the growth in the proportion of committed climate-related disclosures over time.
- Average proportional specificity: Quantifies the average proportion of climate-related paragraphs providing specific details or actions.
- Proportional specificity growth: Tracks the increase in the specificity of climate disclosures during the analyzed period.

Pre-processing

The company reports were pre-processed to transform raw data into a structured format that could be effectively analyzed. The procedure is iterative and multi-layered, consisting of techniques, such as Optical Character Recognition (OCR) extraction, data cleaning, text normalization, and structuring.

OCR[1] was required for some reports, particularly those available only as scanned PDFs. This process converts scanned text into machine-readable data. However, OCR is prone to recognition errors, especially in cases of poor image quality or complex document layouts. These errors were corrected in the subsequent manual data-cleaning phase to ensure accuracy in the extracted text. Once extracted, the text underwent rigorous data cleaning to maintain structural integrity. This involved removing unnecessary line breaks and other inconsistencies that resulted from the OCR process.

[1] The OCR engine used in this research was Tesseract. For further information about this technology: https://github.com/tesseract-ocr/tesseract.

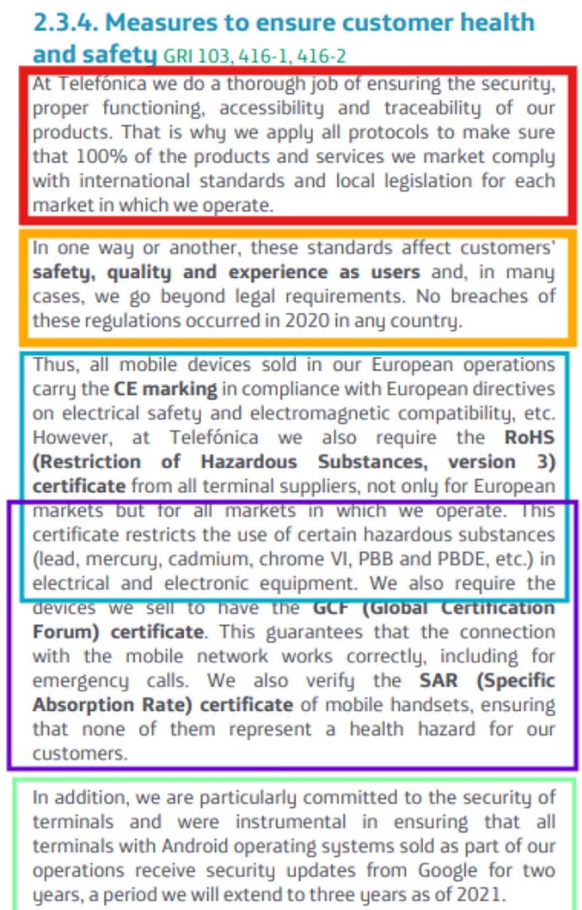
Rather than separating the reports into predefined sections like "introduction" or "climate impact discussion," the entire text was organized by company and year using a Python script, preserving the full narrative of each report. This method provided a holistic perspective on a company's overall climate-related discourse, ensuring that the reports' narrative structure was retained for subsequent analysis. Importantly, the full text was later segmented into distinct paragraphs for further processing, aligning with the *ClimateBERT* models, which are designed to operate at the paragraph level. Each paragraph served as an individual unit for classification, ensuring that granular analysis could be conducted without sacrificing the broader narrative.

Tokenization and inference

To effectively process and analyze the climate-related disclosures in the company reports, we undertook a two-fold methodology of tokenization and inference with the *ClimateBERT* model. Before exploring the specifics of our methodology, it is essential to understand the framework we have used. Our analysis of the climate-related disclosures in the selected sample of companies' reports (Appendix 1. Table A2) employs several variants of the *ClimateBERT* model, each fine-tuned to accomplish a specific task. These tasks range from (1) detecting climate-related paragraphs, (2) classifying their sentiment, (3) identifying commitments and actions toward climate change, (4) assessing their specificity, to (5) categorizing them based on the TCFD recommendations. This comprehensive approach, made possible through the adaptability and precision of the *ClimateBERT* models, allows for a nuanced understanding of the companies' disclosures and their alignment with recognized guidelines. The subsequent sections detail the application of each model to the tokenization and inference of the data and the insights they provide.

The foremost step in our text analysis pipeline was Tokenization—a process that disassembles text into atomic units of meaning, referred to as 'tokens'. This approach provides a nuanced interpretation of text data, capturing semantic essence at a granular level.

For this task, we adopted a transformer-based approach utilizing the different fine-tuned versions of the *ClimateBERT* model, built on top of *RobertaTokenizer*.[2] These tokenizers were trained on the company reports, segmented into distinct paragraphs. Each paragraph was passed through the tokenizers, transforming the contained text into a sequence of tokens. These tokens



2.3.4. Measures to ensure customer health and safety GRI 103, 416-1, 416-2

At Telefónica we do a thorough job of ensuring the security, proper functioning, accessibility and traceability of our products. That is why we apply all protocols to make sure that 100% of the products and services we market comply with international standards and local legislation for each market in which we operate.

In one way or another, these standards affect customers' **safety, quality and experience as users** and, in many cases, we go beyond legal requirements. No breaches of these regulations occurred in 2020 in any country.

Thus, all mobile devices sold in our European operations carry the **CE marking** in compliance with European directives on electrical safety and electromagnetic compatibility, etc. However, at Telefónica we also require the **RoHS (Restriction of Hazardous Substances, version 3) certificate** from all terminal suppliers, not only for European markets but for all markets in which we operate. This certificate restricts the use of certain hazardous substances (lead, mercury, cadmium, chrome VI, PBB and PBDE, etc.) in electrical and electronic equipment. We also require the devices we sell to have the **GCF (Global Certification Forum) certificate**. This guarantees that the connection with the mobile network works correctly, including for emergency calls. We also verify the **SAR (Specific Absorption Rate) certificate** of mobile handsets, ensuring that none of them represent a health hazard for our customers.

In addition, we are particularly committed to the security of terminals and were instrumental in ensuring that all terminals with Android operating systems sold as part of our operations receive security updates from Google for two years, a period we will extend to three years as of 2021.

Fig. 5 Sliding-window approach example. Source: Authors' own creation from "Consolidated Annual Report 2020 Telefónica", S. A. 2. Chapter 2: Non-Financial Information Statement p. 96

serve as the primary input for the models, allowing them to understand and process the semantic content of the paragraph.

To facilitate certain classification tasks, special tokens—'CLS' (classifier) and 'SEP' (separator)—were introduced by the tokenizers. The 'CLS' token is placed at the start of the token sequence, acting as a summarization of the entire sequence. The 'SEP' token delineates the end of one sentence and the start of another within the same sequence, which is crucial in tasks that require understanding the relationship between multiple sentences.

However, a significant challenge arises when dealing with paragraphs that are longer than the model's maximum input length. In transformer-based models like *ClimateBERT*, there is a strict limit to the number of tokens that can be processed in one pass, often set at 512 tokens. To mitigate this issue, we applied a 'sliding window' approach. This technique divides the token sequence of a paragraph into multiple smaller segments

[2] For more information: https://huggingface.co/docs/transformers/model_doc/roberta.

of a fixed size, with a small overlap between adjacent segments (see Fig. 5, where we show this technique graphically on a text from Telefonica in our dataset, concretely from "Consolidated Annual Report 2020 Telefónica", S.A. Chapter 2: Non-Financial Information Statement p. 96). By doing this, we ensured that no token was abruptly cut-off, and that semantic continuity was preserved across segments. This approach effectively allows the model to process longer texts without losing important contextual information.

It can be expressed in analytical notation.

- $\mathbf{L_{max}}$ = maximum token length of the model (e.g., 512 tokens)
- $\mathbf{w}$ = window size (length of each segment, $\leq \mathbf{L_{max}}$)
- $\mathbf{o}$ = overlap size (number of tokens repeated between two adjacent windows).

The total number of tokens in the paragraph is $\mathbf{T}$.

The first segment processes tokens $\mathbf{[1, w]}$, the second segment processes tokens $\mathbf{[w—o+1, w+w—o]}$, and so on, until all tokens in the paragraph have been processed. The general formula for determining the tokens in segment i can be expressed as

$$s_i = [(i—1) \times (w—o) + 1, min(i \times (w—o) + o, T)],$$

where $\mathbf{S_i}$ is the token range for segment i. $\mathbf{w}$ is the window size. $\mathbf{o}$ is the overlap size. $\mathbf{T}$ is the total number of tokens in the text.

After the process of tokenization, we moved toward the next critical phase: inference. This is a crucial step wherein the models utilize the tokenized inputs to yield an output, which is typically a classification or prediction in nature. It was at this juncture that the pre-trained *ClimateBERT* models, tailored to detect and classify various aspects of climate-related information, were leveraged. Each chunk of tokens, processed and primed in the previous phase, was introduced to these models.

The inference stage necessitated the reshaping of tokenized input to make it compatible with the models' requirements. We put an emphasis on enhancing computational speed and minimizing memory utilization during this process. To accomplish this, the *autograd* engine, which provides capabilities for performing automatic differentiation and gradient-based optimization, was deactivated. This allowed us to manage computational resources more efficiently.

Each segment of text was then processed by the models, and the outputs were preserved, supplanting the original content within our data construct. This mechanism was fundamental to the overall pipeline and sets the stage for detailed interpretation and evaluation of each model's inference process.

- Climate detection (*'distilroberta-base-climate-detector'*)[3]: The inference process with this model involves analyzing a given text paragraph and assigning a binary label of 'Yes' or 'No'. The criteria for 'Yes' are that the paragraph discusses climate change, environmental issues, or any related topics such as clean energy, emissions, fossil fuels, and more. 'No' label is assigned if the paragraph does not relate to climate policy, climate change, or any environmental topics.
- Climate sentiment analysis (*'distilroberta-base-climate-sentiment'*)[4]: The inference here involves analyzing the sentiment in a climate-related paragraph and classifying it as 'Risk', 'Opportunity', or 'Neutral'. The 'Risk' label is assigned if the paragraph discusses negative impacts on an entity or the environment. The 'Opportunity' label is for discussions of potential benefits arising from climate change mitigation or adaptation strategies. The 'Neutral' label is assigned when the paragraph mainly states facts without attaching any positive or negative perspectives to them.
- Climate commitments and actions classification (*'distilroberta-base-climate-commitment'*)[5]: This model takes a paragraph as input and assigns a binary label of 'Yes' or 'No', depending on whether the paragraph contains information on actions and/or targets related to climate or business activities. 'Yes' is assigned if the paragraph includes actions undertaken, targets achieved, or future activities likely to be implemented. 'No' is assigned if the paragraph does not contain any information on such actions and/or targets.
- Climate specificity classification (*'distilroberta-base-climate-specificity'*)[6]: The model determines the specificity of a paragraph, assigning it as 'specific' or 'non-specific'. The 'specific' label is assigned when the paragraph gives clear and precise information on current, past, or future events that could specifically impact the firm's operations, strategy, or overall business activities. The 'non-specific' label is assigned

[3] For more information: https://huggingface.co/climatebert/distilroberta-base-climate-detector.

[4] For more information: https://huggingface.co/climatebert/distilroberta-base-climate-sentiment.

[5] For more information: https://huggingface.co/climatebert/distilroberta-base-climate-commitment.

[6] For more information: https://huggingface.co/climatebert/distilroberta-base-climate-specificity.

when the paragraph provides general facts and explanations or discusses general policies and regulations without mentioning specific implementation plans.

- Climate TCFD recommendations classification (*'distilroberta-base-climate-tcfd'*)[7]: This model's inference process involves classifying climate-related paragraphs into one of the four TCFD recommendation categories. The categories correspond to the guidelines provided by the TCFD for climate-related financial disclosures and they are organized in:

    - Governance: Involves the organization's governance and approach toward climate-related risks and opportunities.
    - Strategy: Entails the actual and potential impacts of climate-related risks and opportunities on the organization's businesses, strategy, and financial planning.
    - Risk management: Describes how the organization identifies, assesses, and manages climate-related risks.
    - Metrics and targets: Relates to the metrics and targets used by the organization to assess and manage relevant climate-related risks and opportunities.

During the inference stage, each model processes the input paragraph and generates an output based on the specific classification task for which it was trained. This is achieved by applying the fine-tuned models to the input data, which results in a *softmax* output—a probability distribution across the possible classes. The *softmax* function converts the raw model logits into probabilities, ensuring that the sum of probabilities across all classes equals one.

For binary classification tasks—such as climate detection, specificity level detection, and commitment level detection—an output threshold is employed to determine the final classification label. Specifically, the model assigns a "Yes" label when the probability of the 'Yes' class exceeds a predefined threshold; otherwise, it assigns a "No" label.

In our research, we set the threshold at 0.7. This threshold was selected following a systematic, iterative process in which we tested a range of threshold values using a representative subset of our data. The goal was to find an optimal balance between precision (i.e., the model's ability to correctly identify climate-related content, minimizing false positives) and recall (i.e., the model's ability to capture all relevant climate-related text, minimizing false negatives).

Given the nature of our study, particularly the critical implications of misclassifying climate-related content, the 0.7 threshold was identified as the most effective compromise between precision and recall, ensuring robust performance for the analysis at hand. For instance, for the following paragraph from a Telefonica report:

> *"Telefónica is committed to reducing its environmental impact through its decarbonization strategy, targeting a 50% reduction in greenhouse gas emissions by 2030. [...]"*

This paragraph received a "Yes" label from the climate detection model, because it mentions specific terms such as "decarbonization strategy" and "50% reduction in greenhouse gas emissions." These are clear indicators of climate-related discourse, which the model has learned to associate with the "Yes" class. In this case, the assigned probability was 0.85, comfortably exceeding the 0.7 threshold.

The high probability suggests that the model is confident that the paragraph discusses climate-related issues. However, it is important to remember that, as a black-box model, we cannot fully dissect how individual terms or phrases contributed to this score. While the presence of specific terminology aligns with climate-related content, the model's internal weighting remains opaque.

For multiclass classification tasks, such as sentiment analysis and TCFD recommendation categorization, we adopted a different approach. Since multiclass problems involve more than two classes, applying a binary threshold would be insufficient. Instead, the model assigns the class with the highest probability as the output label. This decision is based on the model's confidence in classifying the input into the most probable category, allowing for the straightforward selection of the class with the highest predicted likelihood.

For instance, for the following paragraph from an Endesa report:

> *"Endesa is committed to a sustainable business model based on the development of innovative products in areas where energy enables greater transformations, such as electric mobility and industrial electrification. [...]"*

The model classified this paragraph under "Opportunity" with a probability of 0.75, due to the forward-looking, positive framing of sustainable innovation and electrification. The use of terms like "sustainable business model" and "innovative products" signals potential benefits, which the model has been trained to interpret as opportunities for the business and the environment.

[7] For more information: https://huggingface.co/climatebert/distilroberta-base-climate-tcfd.

This high probability suggests a confident classification, though again, as a black box, we can only infer how the model weighs specific terms. The positive framing and the focus on future transformation likely influenced the "Opportunity" label, but we cannot pinpoint the exact feature that tipped the scales in favor of this classification.

The tokenization and inference results for each company are stored in pickle files. This ensures efficient data storage, enabling quick retrieval of results for subsequent analysis while preserving the integrity of the inference outcomes across all stages of the study. These preserved outputs form the basis for subsequent evaluations, ensuring that all inference steps are traceable and reproducible.

Results and discussion

We briefly describe the flux followed to undertake the climate disclosure analysis. Following the inference stage, we shifted our focus toward understanding and interpreting the results from each model. This stage entailed a deeper examination of the classification tasks, each of which expanded upon the foundational climate-related content detection. These tasks aimed to provide a multifaceted analysis of corporate climate disclosures, reflecting key dimensions such as commitment, specificity, and alignment with established reporting frameworks (Fig. 6). This approach directly addresses RQ2, which investigates whether transformer-LLM processing can discern firms' climate-related strategies, commitments, and actions.

The first step involved classifying paragraphs into climate-relevant and non-climate-relevant categories. This binary classification aligns with the theoretical perspectives of signaling theory and legitimacy theory by distinguishing between disclosures potentially aimed at signaling transparency and those that might lack substantial content. This initial step enabled the streamlining of our analysis, allowing us to focus exclusively on paragraphs that could offer insights into climate-related activities, commitments, and strategies. By isolating relevant content, we aimed to discern whether firms were engaging in substantive reporting or potentially leveraging disclosures as a reputational tool. This supports RQ1 by analyzing whether disclosure quality and comprehensiveness vary between regulatory regimes.

Building on this classification, we conducted a sentiment analysis to categorize the tone of climate-related paragraphs into 'Risk,' 'Opportunity,' or 'Neutral.' Sentiment analysis is particularly relevant for understanding the strategic framing of disclosures, as it captures how firms portray their climate-related activities to external stakeholders. For instance, the 'Risk' category encapsulated discussions on the potential negative impacts of climate change on business operations, aligning with

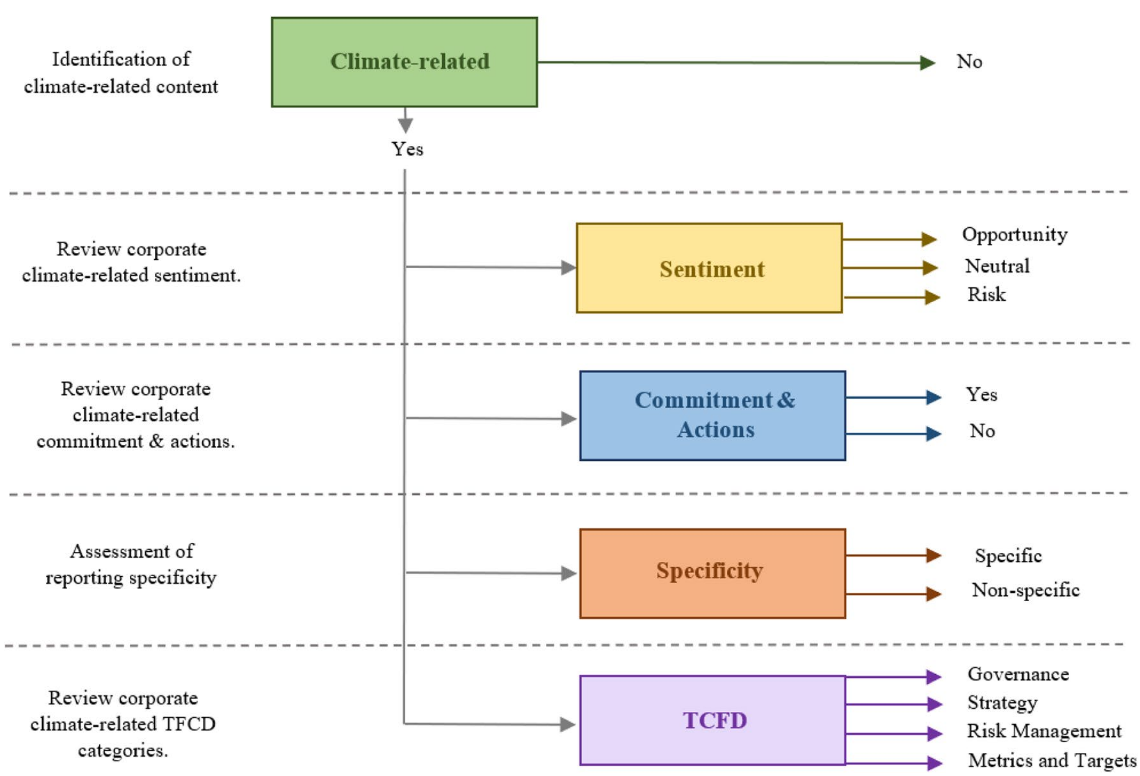


Fig. 6 Task setup with a classification hierarchy. Source: Authors' own creation

legitimacy theory's focus on managing external perceptions of vulnerability. Conversely, the 'Opportunity' category highlighted the potential benefits or positive outcomes of climate change mitigation or adaptation, reflecting a signaling strategy aimed at demonstrating proactive engagement. The 'Neutral' category captured objective statements devoid of subjective framing, often reflecting baseline compliance with reporting frameworks. This layer of analysis expanded our understanding beyond content detection, illuminating the strategic narratives embedded in disclosures and providing nuanced insights into RQ2.

Next, we assessed corporate commitments and actions related to climate change, a key dimension for evaluating the quality and transparency of disclosures. This task distinguished between general descriptions of climate awareness and concrete, action-oriented commitments. By identifying and classifying corporate commitments toward climate mitigation and adaptation, we evaluated the extent to which firms demonstrated active engagement in climate strategies. This step resonates with signaling theory's proposition that firms with higher environmental performance may use disclosures to differentiate themselves. Simultaneously, it allowed us to examine the credibility of these commitments, addressing concerns from legitimacy theory about the potential for greenwashing. These findings align with the broader focus of RQ1 on disclosure comprehensiveness and RQ2 on evaluating corporate actions.

A further dimension of our analysis focused on the specificity of corporate statements regarding climate actions. Specificity, a critical measure of disclosure quality, involves distinguishing factual, precise content from vague or generic statements. By categorizing paragraphs as 'specific' or 'non-specific,' our models assessed whether firms provided detailed, decision-useful information or relied on ambiguous language that might obscure substantive actions. Specificity is central to the broader debate on disclosure quality, as it reflects the capacity of disclosures to support informed decision-making by stakeholders. Moreover, the focus on specificity addressed calls in the literature for transparency and accountability in sustainability reporting, emphasizing the importance of detailed, actionable disclosures. This directly addresses RQ1 by examining differences in the quality of voluntary and mandatory disclosures.

In addition to these tasks, we examined the alignment of texts with the TCFD recommendations, which serve as a benchmark for high-quality climate-related financial disclosures. By mapping texts to the four pillars of the TCFD guidelines—Governance, Strategy, Risk Management, and Metrics and Targets—we assessed the extent to which corporate disclosures adhered to recognized reporting standards. This alignment adds a layer of standard compliance to our analysis, highlighting how firms navigate evolving regulatory and voluntary frameworks and contributing to RQ2 by assessing how disclosures reflect actionable strategies.

The results from the original *ClimateBERT* model unfolded in two significant segments. First, the global analysis provided a broad perspective on trends and patterns across all studied firms, examining the evolution of disclosure volume, commitment, and specificity. This macro-level perspective illuminated how companies' climate reporting practices evolved over time, influenced by regulatory pressures and societal expectations. Second, the sector analysis drilled down into industry-specific nuances, offering a more granular understanding of disclosure practices within distinct sectors. This dual approach allowed us to explore both overarching trends and sector-specific dynamics, addressing the complexity of climate disclosures across diverse corporate contexts and offering empirical insights into RQ1.

Finally, we conducted a comparative analysis using the fine-tuned version of *ClimateBERT*, tailored with the *ClimaText* dataset [42]. This comparative analysis highlighted the enhanced performance of the fine-tuned model in detecting and classifying climate-related content, commitments, and specificity. The fine-tuned model's stricter focusing on climate-relevant content enabled us to address the nuanced distinction between meaningful transparency and symbolic disclosures, reinforcing the study's theoretical foundation. This directly supports RQ3 by demonstrating the superior efficacy of the fine-tuned model in analyzing diverse climate-related text classification tasks. These results bridge the methodological advancements with the overarching theoretical debate on disclosure quality and transparency.

Global analysis

Our research begins with an extensive global analysis, focusing on understanding the breadth and depth of climate risk disclosures across company reports. This initial stage measures the volume of climate-related discourse, helping us gauge if there has been an increase in such discussions over time. This panoramic view is crucial as it affords us the opportunity to identify broad trends and patterns within the domain of climate risk disclosures and directly addresses RQ1 by examining how these disclosures evolve under varying regulatory pressures.

Commencing our discussion with the assessment of the evolution of the volume of climate-related text submitted by various companies, it is clear that since 2016, there has been a perceptible uptick in the volume of climate-associated discourse (Fig. 7). This trend can be attributed to several factors, with increased regulatory measures

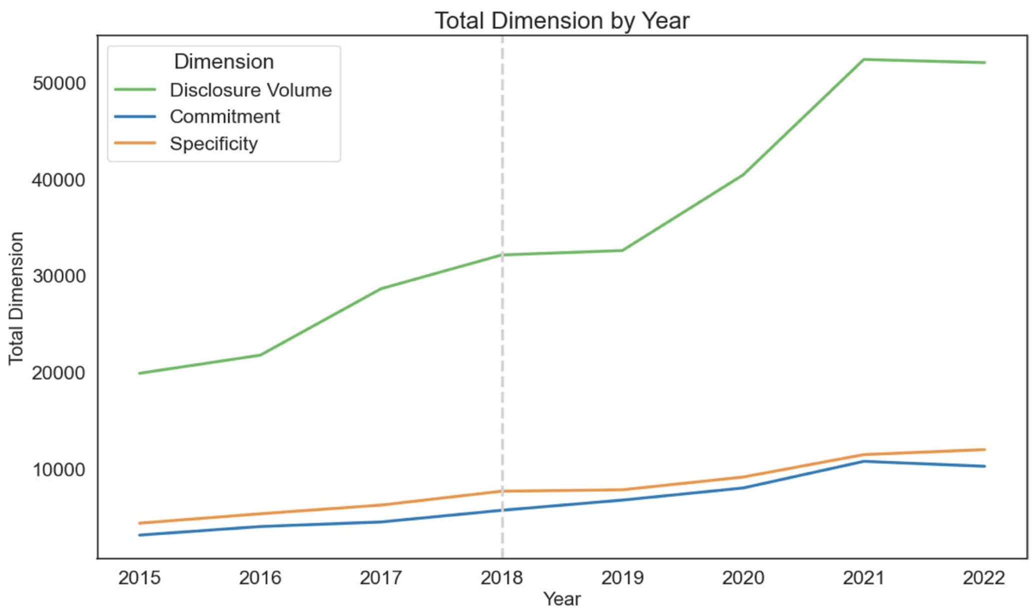


Fig. 7 Aggregated total climate disclosure volume, commitment, and specificity of the studied companies by year. Source: Authors' own creation

playing a crucial role. Regulatory bodies across jurisdictions, such as the EU with its NFRD and the more recent CSRD, have been instrumental in pushing firms to disclose more comprehensive climate-related information [20]. This regulatory shift aligns with growing public concern regarding climate issues and the escalating demands from investors for more transparency in ESG matters, emphasizing the interplay between voluntary and mandatory reporting regimes.

Despite the marked increase in the overall volume of climate-related texts, a closer examination reveals that the portion demonstrating explicit commitment and action-oriented disclosures, along with a high degree of specificity, remains less substantial. This distinction between the volume of discourse and its actionable substance is critical. Commitment in this context refers to concrete, action-oriented pledges made by corporations toward climate change mitigation and adaptation, aligning with signaling theory as firms attempt to convey credible environmental performance. Such commitments may encompass strategic initiatives like investments in green technologies, policy implementations, or explicit emissions reduction targets. Specificity, on the other hand, refers to the detail and precision with which these actions are described—whether companies provide quantifiable targets, timelines, or descriptions of specific programs.

Therefore, while commitment often signals a company's intent to address climate risks, specificity transforms these broad statements into measurable, actionable strategies. The distinction between commitment and specificity is crucial for evaluating the credibility of corporate climate disclosures. For instance, broad statements of intent may align with external pressures, but without specificity, they risk being perceived as symbolic gestures or "greenwashing", a tactic highlighted in legitimacy theory where firms seek to maintain societal approval without substantive action.

As Fig. 8 (Appendix 4) shows, the aggregated total climate disclosure volume has risen sharply, yet specificity—particularly in climate texts demonstrating commitment—has not kept pace at the same rate. A trend across the data is the divergence between increasing commitment levels and fluctuating specificity. From 2018 onwards, the proportion of disclosures that exhibited concrete commitment stabilized at around 20%, reflecting the growing societal and regulatory demand for companies to take a stand on climate change. This stabilization in commitment could be attributed to enhanced pressure from regulators like the European Securities and Markets Authority (ESMA), as well as broader frameworks such as the TCFD.

However, the evolution of specificity within these climate texts followed a more complex trajectory. Initially, it mirrored the rise in commitment but diverged post-2018. The specificity of climate-related disclosures began to decline, dropping back to pre-2018 levels of 22% before recovering in 2021 to reach 24%. This pattern suggests that while firms were increasingly pledging to address climate risks, providing concrete, detailed information on how they would achieve these goals proved more challenging. Regulatory adjustments and corporate adaptation likely played a role here, as firms needed time to internalize new standards and frameworks. As Müller et al. [20] have noted in their work, firms often face internal hurdles in translating high-level commitments into specific, measurable actions, particularly when dealing with emerging regulatory demands.

The pandemic-induced disruptions of 2020 also warrant consideration in this context. COVID-19 created unprecedented operational and reporting challenges for companies globally. Many firms had to prioritize immediate risks and contingencies over long-term strategic disclosures, which likely contributed to the temporary dip in the specificity of climate-related texts during this period. The recovery observed in 2021 could reflect a normalization of business operations as firms regained focus on long-term climate strategies. This finding aligns with broader research on the pandemic's impact on corporate ESG behavior, which shows that while the immediate focus shifted away from climate, the broader societal momentum for corporate transparency and responsibility quickly resumed as the pandemic's initial shock subsided [79]. These results also echo legitimacy theory, as firms faced heightened external pressures during the pandemic to maintain reputational standing, even while their capacity for detailed action planning was constrained.

Figure 9 (Appendix 4) further illustrates the upward trend in the total volume of climate-related texts across key dimensions—overall climate breakdown, commitment, and specificity. Between 2015 and 2022, the total volume of climate discourse increased significantly, with a 2.5-fold amplification by 2022 compared to earlier periods. The period from 2020 to 2021, in particular, saw a pronounced 50% surge in the total volume of climate-related disclosures. This reflects the combined impact of regulatory pressures and companies' need to reassure stakeholders of their proactive responses to climate change amid global uncertainty. Regulatory frameworks like the NFRD and the development of ESG reporting standards likely provided the foundation for this accelerated growth in climate discourse, supporting the view that external pressures influence disclosure quality, as posited by legitimacy theory.

The increase in commitment across these disclosures was equally striking, suggesting that companies are recognizing the importance of aligning their public statements with societal and regulatory expectations. As Müller et al. [20] have demonstrated in their study, companies with higher exposure to climate-related risks, particularly those in high-carbon industries, tend to show greater engagement in climate reporting. The same trend is evident in our data: firms are more likely to make broad commitments as they face mounting regulatory scrutiny and societal pressure. From the signaling perspective, this increase in commitment could reflect efforts by firms with stronger climate strategies to differentiate themselves by signaling their alignment with sustainability priorities.

However, as we explore the specificity of these commitments, a more nuanced picture emerges. Specificity has grown at a slower rate than commitment, indicating that while companies are increasingly vocal about their climate goals, translating these commitments into precise, actionable plans remains a challenge. This gap between commitment and specificity may partly reflect the evolving nature of climate-related regulations and the growing pains firms experience when adapting to new reporting frameworks [20].

To further understand this gap, we investigated the specificity of the texts showing commitment. The relevance of this inquiry stems from the necessity to differentiate between vague commitments and concrete, actionable pledges made by corporations. It adds a layer of validation to the commitments, gauging their feasibility and credibility. From the combined analysis of these aspects, it is evident that only a fraction of the commitment-indicating texts, ranging between 44 and 51%, offer specificity regarding the actions undertaken by the companies (Figure 10 in Appendix 4). This limited specificity could reflect symbolic gestures intended to meet regulatory or societal expectations without substantial action, a tactic often highlighted in legitimacy theory as greenwashing.

As displayed in Figure 11 (Appendix 4), an upward trend, with minor exceptions, in both commitment-indicating texts and their specificity is observed from 2015 to 2022, confirming the shift documented by O'Dwyer and Unerman [72]. Their research underscores the increasing integration of climate risks into corporate strategies, largely driven by frameworks such as the TCFD. Our findings align with this, particularly in the post-2015 period, as companies increasingly adopted structured approaches to climate-related disclosures. The adoption of frameworks like the TCFD likely played a pivotal role in narrowing the gap between commitment and specificity over time.

Interestingly, the specificity within these commitment-related texts grew at a marginally superior rate compared to commitment levels up until 2020. However, post-2020, specificity growth decelerated, while commitment growth continued, a trend highlighted in Figure 10 (Appendix 4). This inversion likely reflects the unique challenges introduced by the COVID-19 pandemic, as noted by Abhayawansa and Adams [80]. The pandemic created a complex environment for companies, where they felt compelled to enhance their climate-related commitments—possibly to maintain reputational standing—while the rapidly changing business landscape prevented equally detailed or actionable plans. This divergence indicates that while firms made pledges to address climate issues, the volatile circumstances limited their ability to provide specific, concrete action plans. Such findings align with broader studies, suggesting that periods of external turbulence often exacerbate gaps in disclosure quality [75, 80].

In Fig. 8, which presents the variance in specificity across companies, the boxplots provide additional insights into the dispersion of specificity values over time. The consistent mean of approximately 40% specificity across the years suggests that, on average, companies provided relatively actionable climate commitments. However, the variability in disclosure practices, as indicated by the interquartile ranges, points to significant differences between companies. As Kim et al. [105] noted, sectors facing more direct exposure to climate risks, such as energy and transportation, tend to produce more specific and detailed climate-related disclosures, which our analysis corroborates. Companies operating under regulatory and environmental pressures are likely to offer more granular climate-related information, whereas sectors with less perceived climate risk exhibit broader variability in disclosure practices.

Before 2018, there was a wider dispersion in specificity, reflected in larger interquartile ranges. This broader spread indicates that some companies provided very detailed climate-related information, while others lagged behind. Post-2018, the dispersion narrowed, likely due to the adoption of climate risk disclosure standards such as the TCFD, which drove more standardized and actionable climate-related reporting across sectors. This shift toward more uniform disclosure practices points to the increasing role of regulatory frameworks in shaping corporate transparency, as firms sought to meet growing stakeholder expectations and align with the international reporting standards.

Delving into the sentiment analysis of the climate-related texts, we observed consistent growth in the volume of texts classified under 'Opportunity', 'Risk', and 'Neutral' categories, as shown in Fig. 9. Despite this growth, the proportional representation of each sentiment within relatively overall disclosures remained stable over the years. Notably, 70–80% of climate-related disclosures were associated with 'Opportunity', emphasizing companies' tendency to frame climate-related initiatives as strategic growth opportunities. This finding aligns with Halkos and Nomikos [106], who highlight that firms often use sustainability reporting to portray themselves as proactive and innovative, thereby enhancing their reputation among environmentally conscious stakeholders.

In contrast, 'Risk'-related texts accounted for around 15–20% of the total disclosures. As Rezaee et al. [19] observed, firms may deliberately downplay climate risks in public disclosures to avoid alarming investors or damaging their market position. By focusing more on

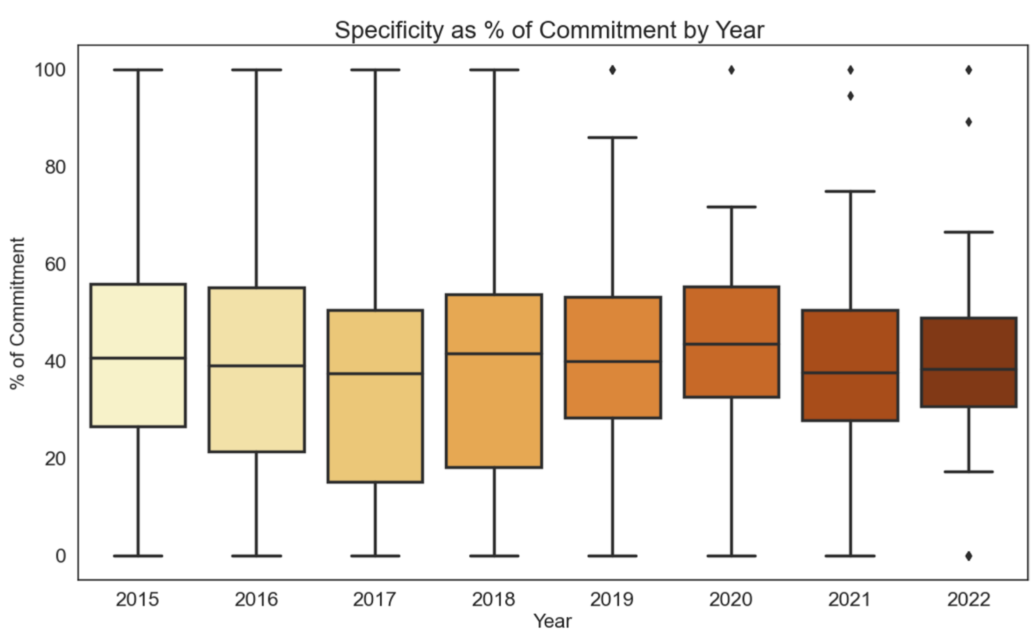


Fig. 8 Percentual evolution in the variance of specificity level of the committed-classified companies' climate disclosure. Source: Authors' own creation

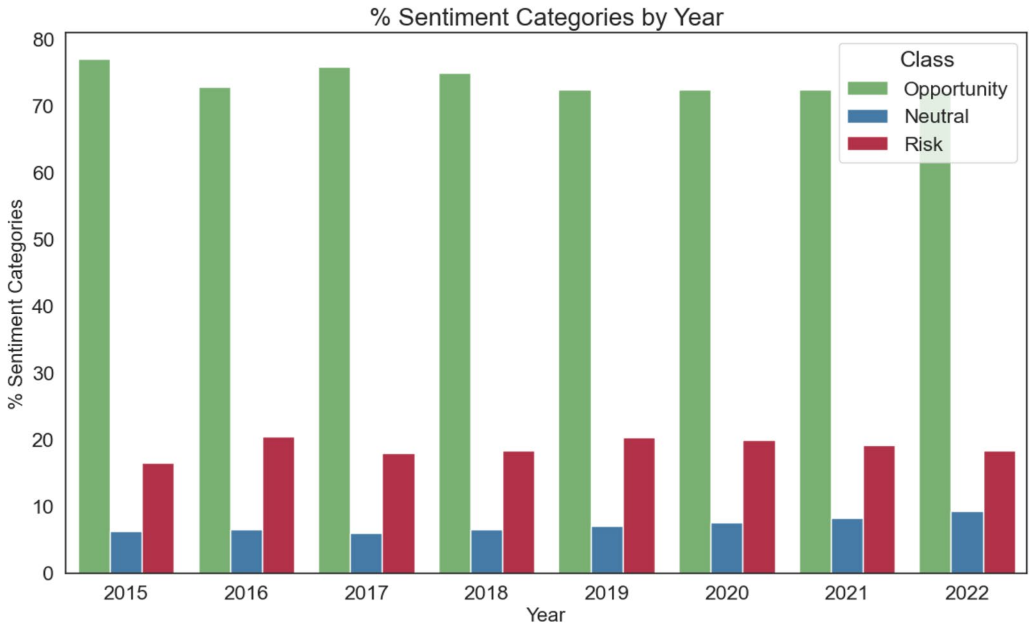


Fig. 9 Percentual evolution in the sentiment representation of the companies' aggregated climate disclosure. Source: Authors' own creation

opportunities and less on risks, companies project an optimistic outlook, likely seeking to attract sustainability-minded investors without highlighting potential threats. 'Neutral' texts, representing only a small portion of disclosures, further reinforce the notion that companies prioritize framing their climate actions positively rather than presenting impartial narratives.

Figures 14 and 15 (in Appendix 4) provide an in-depth analysis of commitment and specificity within opportunity-detected climate texts. Figure 14 illustrates that the percentage of opportunity-related texts indicating commitment ranged between 20 and 28% of the total climate disclosures, showing a slight upward trend from 2015 to 2019 before stabilizing at approximately 26%. In contrast, Figure 15 demonstrates that the proportion of committed texts exhibiting specificity varied considerably, fluctuating between 42 and 60% over the analyzed period. This variability highlights inconsistencies in the level of actionable detail provided within committed disclosures.

When compared to the global analysis of all climate-related texts (where commitment ranged from 16 to 20% and specificity from 44 to 51%), opportunity-related texts displayed higher levels of commitment but greater variability in specificity. While the increased commitment may reflect stronger alignment with external pressures such as regulatory demands and stakeholder expectations, the inconsistent specificity underscores challenges in translating these commitments into detailed, actionable plans. The divergence between commitment and specificity, particularly after 2018, as shown in Figures 14 and 15, suggests that companies often struggle to articulate detailed strategies for implementing their climate pledges. This pattern indicates that while firms are increasingly inclined to signal their intent to address climate risks, variability in specificity may reflect differences in their capacity to operationalize these commitments. Consequently, improving the consistency and precision of disclosed action plans remains a critical area for enhancing the credibility and effectiveness of corporate climate reporting.

Further analysis, as depicted in Figure 16 (in Appendix 4), reveals that risk-related texts—despite being fewer in number—contained a higher proportion of commitment-related content and displayed more specificity than opportunity-related texts by around 6%. These findings indicate that while companies often frame climate initiatives as opportunities, they tend to provide more concrete and detailed disclosures when addressing climate risks, likely due to the heightened scrutiny and accountability associated with risk reporting. This trend echoes the observations of O'Dwyer and Unerman [72], who emphasize that companies under greater regulatory or societal pressure are more likely to produce specific and actionable risk-related disclosures.

The findings also align with Helfaya and Moussa [74], who emphasize the role of board-level CSR strategy in shaping the quality of environmental sustainability disclosures. Firms with strong CSR committees and sustainability-oriented leadership are more likely to provide detailed, high-quality disclosures, particularly in environmentally sensitive sectors. This may explain why risk-related disclosures are often more specific; companies operating in high-risk sectors are under greater pressure to demonstrate accountability and legitimacy through precise climate risk management plans.

However, the year 2020 presented an anomaly in these patterns. During this period, commitment and specificity within risk-related texts dropped by 7%, whereas opportunity-related texts maintained similar levels. This deviation can be attributed to the COVID-19 pandemic, which created unprecedented challenges for businesses worldwide. The pandemic forced companies to prioritize immediate operational risks and short-term contingencies over long-term strategic planning, leading to a temporary decline in the quality of risk-related climate disclosures. Abhayawansa and Adams [80] support this explanation, noting that the pandemic shifted corporate ESG reporting priorities toward survival-oriented measures at the expense of detailed sustainability disclosures.

The disruption in stakeholder engagement processes during the pandemic likely contributed to this decline. As Herremans et al. [76] observe, companies may have temporarily shifted from transformational engagement, which emphasizes long-term strategies and relationship-building, to transactional engagement, focusing on immediate needs and short-term market pressures. This shift helps explain the reduced specificity in risk-related disclosures during 2020. Additionally, Michelon [75] highlights the role of media scrutiny and reputational concerns in shaping disclosure practices, suggesting that companies under significant public attention during the pandemic may have minimized their risk-related disclosures to avoid potential backlash or negative stakeholder perceptions.

In contrast, opportunity-related disclosures remained stable, likely because companies continued to see strategic advantages in sustainability initiatives even during the crisis. As businesses navigated the uncertainty of 2020, many recognized the potential for sustainability-driven innovation and reputation-building, seeing climate action as a way to differentiate themselves in a challenging market environment. This observation aligns with Rezaee et al. [19], who argue that companies often leverage sustainability reporting to enhance their corporate image, particularly in times of crisis. By maintaining consistency in their opportunity-related disclosures, firms could continue to project a proactive stance on climate issues, appealing to stakeholders such as investors and consumers who increasingly value sustainability.

In 2021, the data suggest a return to the previous trend, with commitment and specificity in risk-related disclosures regaining similar levels as before, while the percentages in opportunity-related texts decreased by 4%. This reversion suggests that the deviation in 2020 was an outlier, likely driven by external factors such as the pandemic, rather than a long-term shift in disclosure practices. The recovery of risk-related specificity aligns with Herremans et al.'s view [76] that companies can recalibrate their stakeholder engagement processes once operational stability returns, moving back toward more transformational engagement that includes long-term commitments. Additionally, Michelon's work supports this reversion, as media exposure and stakeholder demands likely pushed companies to return to more detailed climate risk disclosures as the immediate pressures of the pandemic eased.

Having scrutinized the commitment and specificity within sentiment-classified texts, the final stage of this global analysis seeks to align the examined climate-related texts with the TCFD categories. The aim is to identify noteworthy patterns and potential insights within this classification. Additionally, an analysis will be conducted to ascertain which themes the 'Opportunity'-detected texts principally correspond to.

Mirroring our previous observations with sentiment analysis, there was an evident growth in the volume of texts associated with each TCFD category over the years. This increase is consistent with the surge in overall climate-related disclosures that we have previously noted.

Nonetheless, while the volume of text in each category expanded, their proportional representation within climate-related disclosures exhibited relative stability. As shown in Fig. 10, most of climate-related disclosures, 59–65%, fell under the 'Risk Management' category. The prevalence of 'Risk Management' might reflect corporations' increasing focus on identifying, assessing, and managing climate-related risks, likely in response to rising stakeholder expectations and stricter regulatory demands. This finding aligns with the observations of O'Dwyer and Unerman [72], who emphasize the critical role of integrating climate risks into corporate risk management and highlight the transformative potential of TCFD reporting in shifting sustainability accounting toward a focus on risks and dependencies.

On the contrary, the 'Metrics and Targets' category accounted for about 20–25% of the total climate-related disclosures. The remaining texts were relatively evenly distributed between the 'Strategy' and 'Governance' categories, with a minor inclination toward the latter. Over the years, however, there appears to be a mild growth in the 'Strategy' category and a slight decline in 'Governance'. This shift may be indicative of companies gradually prioritizing strategic responses to climate change over governance-related disclosures. Andersson and Arvidsson [21] observe a similar trend among Swedish firms,

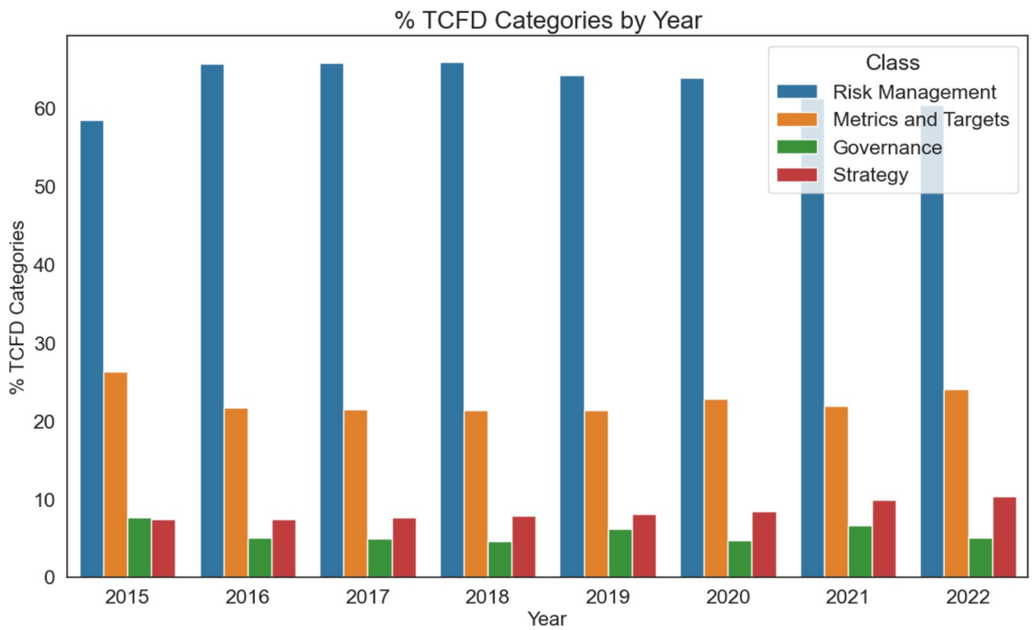


Fig. 10 Percentual evolution in the TCFD category representation in the companies' aggregated climate disclosure. Source: Authors' own creation

noting an increased focus on strategic planning and implementation of climate-related initiatives.

Upon delving into the 'Opportunity'-detected texts, we found that the TCFD category distribution mirrored the global distribution. This congruence is understandable given the preponderance of 'Opportunity' texts within climate disclosures. However, the category distribution within the 'Risk'-related texts diverged from this pattern. Here, a remarkable 80% fell under 'Risk Management', with the rest largely attributed to 'Metrics and Targets'. For 'Neutral' texts, the category distribution was quite similar to that of the 'Risk' texts, albeit with a slight uptick in the 'Strategy' category over the years.

Sector-based analysis

The global analysis provided a valuable foundation for understanding overarching trends in corporate climate disclosures, including the evolution of disclosure volume, commitment, specificity, sentiment, and TCFD categorization patterns. It also highlighted temporal variations, such as the influence of regulatory changes and the disruptions caused by the COVID-19 pandemic. However, while the global analysis reveals broad patterns, it inherently averages out sector-specific nuances and fails to account for the distinct climate risks, opportunities, and disclosure behaviors unique to each industry.

To complement this macro-level perspective and delve deeper into sectoral dynamics, we conducted a sector-based analysis. By examining individual sectors, we aim to uncover richer insights into how distinct industries respond to climate-related challenges and opportunities. A detailed explanation of the methodology applied in this analysis can be found in Appendix 2, including adjustments for sample bias by normalizing disclosure volumes across sectors.

Comparative analysis with fine-tuned model

In this final section, we pivot to a comparative analysis using a refined version of the *ClimateBERT* model, fine-tuned with the ClimaText dataset [14]. This dataset, a rich amalgamation of text from diverse sources like Wikipedia, SEC's 10-K filings, and web-based climate change claims, provides a unique lens through which to scrutinize climate risk disclosures. This section aims to juxtapose the findings from the original and fine-tuned models, shedding light on the nuances and variations in climate risk disclosure and sentiment analysis outcomes.

The fine-tuning of *ClimateBERT* employed the "AL-Wiki" dataset for training and the "10 Ks (2018, test)" dataset for testing. With a substantial focus on climate change relevance, the fine-tuning process was designed to enhance the model's proficiency in discerning climate-related text. Importantly, the datasets used for fine-tuning encompass a broad spectrum of climate-related topics, with stringent criteria for determining relevance. This methodology underpins the comparative analysis, providing a foundation for understanding discrepancies between the original and fine-tuned model outcomes.

Commencing our comparison with the assessment of the evolution of the volume of climate text submitted by the various companies, the fine-tuned model reveals a notably lower overall volume of climate-related disclosures (Figure 18 in Appendix 4). However, an intriguing observation is the steeper growth trajectory of climate disclosure volume from 2015 to 2022 when analyzed through the fine-tuned model (Figure 19 in Appendix 4). This disparity in volume and growth patterns between the models highlights the fine-tuned model's enhanced sensitivity to climate-specific content, possibly capturing more nuanced or indirect references to climate change.

The next aspect of our analysis is the comparison of commitment and specificity in climate-related texts identified by both models. The fine-tuned model demonstrates a higher proportion of both commitment and specificity, with a notably steeper growth in these metrics (Figure 20 in Appendix 4, and Fig. 11). This suggests that the fine-tuned model is more adept at identifying texts that exhibit a clear commitment to climate change mitigation and adaptation, as well as those that provide detailed, specific information about such initiatives.

Contrasting the sentiment analysis results, the fine-tuned model predominantly identifies texts with a neutral sentiment (approximately 80%), a stark deviation from the original model's findings (Figure 22 in Appendix 4). This suggests that the fine-tuned model may have a propensity for detecting texts that are factual or descriptive in nature, as opposed to those expressing explicit opportunities or risks. This observation underlines the fine-tuned model's inclination toward neutrality, potentially stemming from its training on a dataset with a substantial focus on objective, factual information about climate change.

When it comes to the TCFD category analysis, both models exhibit similar proportional distributions, with 'Risk Management' dominating (60–65%), followed by 'Metrics and Targets' (around 25%), and 'Strategy' and 'Governance' sharing the remainder (Figure 23 in Appendix 4). This consistency across models underscores the prevalent focus on risk management in corporate climate disclosures, irrespective of the model used for analysis.

The comparative analysis between the standard *ClimateBERT* model and the fine-tuned version reveals significant insights into the effectiveness of specialized training for analyzing climate risk disclosures. The fine-tuned model, trained on the *ClimaText* dataset—a large corpus of climate-specific texts—demonstrates a superior ability to detect and classify climate-related content. This specialized training enables the model to apply stricter criteria when identifying climate-relevant text, leading to more accurate and focused classifications.

One of the most notable outcomes of this enhanced precision is the substantial increase in the detection of commitment and specificity within corporate disclosures. The standard model, lacking specialized climate training, tends to adopt a broader approach, capturing a wide range of text that may only be loosely related to climate issues. In contrast, the fine-tuned model effectively filters out irrelevant content, zeroing in on disclosures

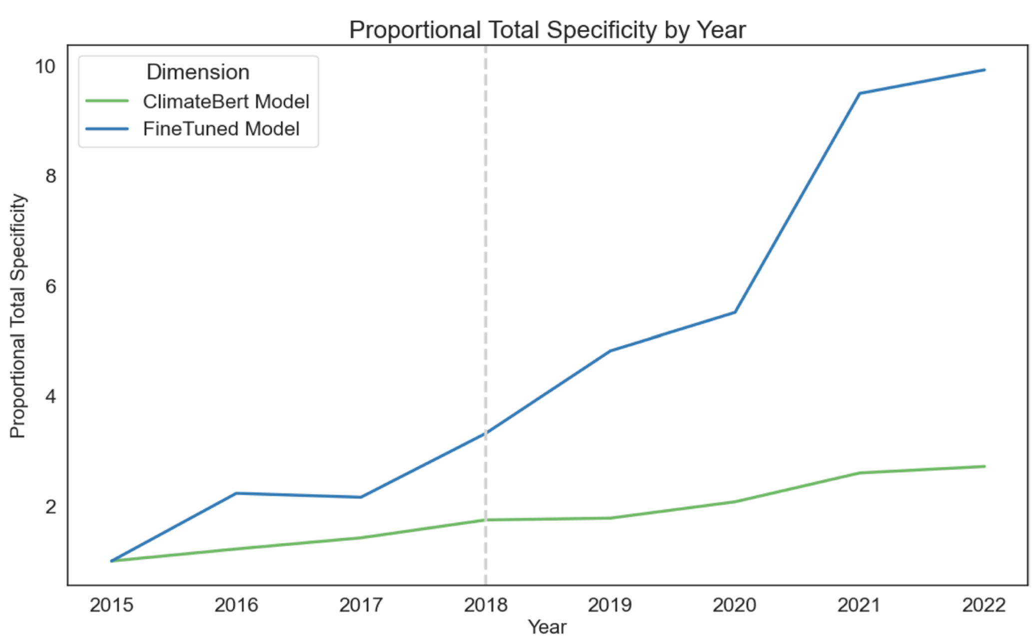


Fig. 11 Comparison in proportional variation of aggregated specificity for studied companies between ClimateBERT and fine-tuned models. Source: Authors' own creation

Table 4 Comparison between ClimateBERT standard and fine-tuned model

Metric	ClimateBERT (standard)	Fine-tuned model
Average disclosure volume	**35,027**	2,997
Disclosure volume growth	2.61	**7.82**
Average proportional commitment	2.1	**4.26**
Proportional commitment growth	2.23	**7.00**
Average proportional specificity	1.82	**4.81**
Proportional specificity growth	1.71	**8.93**

Source: Authors' own creation

that specifically pertain to climate commitments and detailed action plans. This targeted focus is evident in the significantly higher average proportional commitment and specificity scores achieved by the fine-tuned model compared to the standard model (Table 4).

For example, in a paragraph from Naturgy's 2017 Corporate Responsibility Report,[8] the following text was analyzed:

> *"During 2017 we have performed several initiatives in all businesses and countries, targeted at improving water management. This is the case, for example, of a study carried out for the recirculation/reuse of purge water from boilers to the desalination water tank at the Aceca combined-cycle power station, or optimisation of the regeneration cycles of the mixed beds at the water treatment plant of the combined-cycle power station of Barcelona Port to reduce water consumption for washing at the plant. [...]"*

The standard ClimateBERT model classified this paragraph as climate-related with a probability of 0.81, largely due to the presence of terms such as "water management," "reuse," and "optimisation." However, the paragraph offers limited details about specific climate action or explicit commitments to climate-related goals, resulting in a lower specificity and commitment score.

The fine-tuned model, with its stricter focus, assigned a probability of 0.52, below the 0.7 threshold for climate-related classification. This reflects its emphasis on specificity (detailed actions tied to climate change, such as emissions reductions) and commitment (clear pledges or goals addressing climate change). The absence of explicit references to decarbonization or greenhouse gas reductions led to lower scores for both metrics.

This example underscores the fine-tuned model's ability to prioritize texts with greater specificity and commitment, contributing to its higher proportional scores in these metrics. By filtering out content that, although environmentally relevant, lacks clear ties to climate change, the fine-tuned model provides a more focused and actionable analysis of corporate climate disclosures.

- Average disclosure volume: This metric represents the average number of paragraphs identified as climate-related by each model across all analyzed reports. The standard model identified a significantly higher volume (35,027 paragraphs) compared to the fine-tuned model (2,997 paragraphs). This discrepancy indicates that the standard model captures a broader range of content, including text that may not be directly pertinent to climate issues. In contrast, the fine-tuned model's lower volume reflects its ability to precisely isolate genuinely climate-relevant content, avoiding extraneous information.
- Disclosure volume growth: Measuring the growth rate in the number of climate-related disclosures from 2015 to 2022, the fine-tuned model exhibits a higher growth rate (7.82) compared to the standard model (2.61). This suggests that the fine-tuned model is more sensitive to the increasing emphasis on climate disclosures in recent years, effectively capturing the trend of companies expanding their climate-related reporting.
- Average proportional commitment: This metric quantifies the average proportion of climate-related paragraphs that express a commitment to climate action. The fine-tuned model achieves a higher score (4.26) versus the standard model (2.10), indicating its enhanced ability to detect disclosures where companies articulate specific commitments to addressing climate change.
- Proportional commitment growth: Reflecting the increase in the proportion of committed climate-related disclosures over time, the fine-tuned model shows a significant rise from 2.23 to 7.00. This demonstrates that as companies have strengthened their climate strategies and commitments over the years, the fine-tuned model more effectively identifies and tracks these developments.
- Average proportional specificity: This metric measures the average proportion of climate-related paragraphs that provide specific details or actions. With the fine-tuned model scoring higher (4.81) compared to the standard model (1.82), it underscores the model's superior capability in discerning detailed and specific climate disclosures, as opposed to general or vague statements.

[8] **Gas Natural Fenosa.** (2017). *2017 Corporate Responsibility Report* (p. 195).

- Proportional specificity growth: Indicating the growth in the specificity of climate disclosures over the studied period, the fine-tuned model exhibits a substantial increase from 1.71 to 8.93. This suggests that companies are providing more detailed and specific information in their climate disclosures over time, and the fine-tuned model is adept at capturing this enhanced specificity.

The lower overall disclosure volume identified by the fine-tuned model, despite the higher precision in detecting commitment and specificity, highlights its effectiveness in filtering out irrelevant content. By focusing on disclosures with direct relevance to climate risk, the fine-tuned model provides a more concentrated analysis of corporate actions related to climate change. This is particularly valuable for stakeholders who require accurate and pertinent information to assess a company's climate strategy and performance.

Moreover, the steeper growth trends observed in the fine-tuned model's metrics over the 2015–2022 period indicate its heightened sensitivity to changes in corporate disclosure practices. As companies have increasingly incorporated detailed climate strategies and specific actions into their reports—likely in response to regulatory pressures and stakeholder expectations—the fine-tuned model effectively captures this progression. This reinforces the importance of utilizing specialized NLP models when analyzing complex and evolving domains like climate risk disclosures.

The significant increases in both commitment and specificity detected by the fine-tuned model suggest that companies are not only disclosing more about climate-related issues but are also providing more substantive and detailed information. This aligns with the global trend toward greater transparency and accountability in sustainability reporting, driven by both regulatory changes and heightened stakeholder awareness.

Discussion of the objectives

Objective 1 achieved: The first objective aimed to compare the disclosure quality and comprehensiveness of Spanish firms' non-financial reports under voluntary and mandatory reporting regimes (2015–2022 period) as stated in RQ1. This goal was pursued through quantitative analysis of pre- and post-regulatory climate disclosures. Concretely, the sentiment scores, specificity indices, and commitment levels within the disclosure text were quantitatively assessed pre- and post-regulation. Our results indicate interesting patterns and strong trends of enhancement in these parameters spanning the period 2015–2022 (not causally related to the NFRD, but potentially confounding its effects). This aligns with prior literature that points to pronounced anticipation effects related to the NFRD, introducing uncertainty about the timing of the treatment effect after the enforcement of the mandatory disclosure requirements [52]. Thus, we document a rise in specificity and commitment, particularly in risk-related texts, having an explorative appeal and providing descriptive evidence that underscores the regulations' influence, among many other factors also identified by prior literature, in fostering a higher quality and more comprehensive approach to climate risk reporting. We acknowledge that the introduction and implementation of the NFRD is one of many factors that may underlie the time trends documented in our study; not only the enforcement of mandatory versus voluntary, but also other stakeholders' requirements and expectations from companies (clients, investors, financial institutions, etc.), aside from the regulatory stakeholders, may influence reporting quality, as previous research shows.

Objective 2 achieved: The second objective aimed to analyze the content of climate-related disclosures in NFIRs to comprehend the topics addressed and the communication methods employed by corporations. The text mining and analysis unveiled a variety of climate-related topics, including a focus on risk management in accordance with the TCFD categories. Variations among different sectors, such as a high level of commitment toward climate-related issues in the Retail sector and distinct patterns in climate disclosures for Energy and Construction sectors, were also identified. These findings add further insights to answering RQ2: Companies actually depict their climate-related strategies, commitments, and actions in their NFIRs as shown by the transformer processing of the texts.

Objective 3 achieved: The third objective aimed to provide empirical evidence that supports the claim that our fine-tuned *ClimateBERT* model generally outperforms the *ClimateBERT* model in diverse climate text classification tasks, as stated in RQ3. A key advancement in our research is the integration of a comparative analysis using a fine-tuned version of the *ClimateBERT* model, utilizing the *ClimaText* dataset. This strategic enhancement revealed subtle yet insightful differences in how climate disclosures are interpreted. Notably, the fine-tuned model exhibited an increased sensitivity to elements of commitment, specificity, and neutrality in climate texts. This nuanced approach not only reinforced our initial findings but also illuminated the potential for refining NLP techniques to achieve a more precise and exhaustive analysis of environmental disclosures. Our findings, in general, and this fact, particularly, have important implications for practitioners. In effect, using a fine-tuned version of Transformers (as our proposed fine-tuned methodology) is cheap in computational terms, thus allowing any organization to perform it. It is affordable to all companies, investors, regulators, policymakers, and other stakeholders. The insights gained from this research are valuable for these stakeholders, improving their informed decision-making processes in the context of climate change and sustainability. The approach used in this study can enable stakeholders to conduct preliminary descriptive or exploratory evaluations of firms' actual quality disclosure that supports a subsequent decision of these stakeholders. For example, certain stakeholders (investors, companies, etc.) can build a statistic based on the information obtained through our proposed methodology. This quantitative measure or indicator needs to be additionally reviewed by a regulation expert, serving as an indicator but not as a definitive definition of quality or transparency. However, it is a hint that can save a lot of time for the practitioner.

Conclusion

This research, characterized by its technical and deductive approach, embarked on an in-depth exploration of climate risk disclosures by Spanish companies. Leveraging state-of-the-art NLP techniques, particularly the *ClimateBERT* model and our proposed fine-tuned *ClimateBERT* model, the study scrutinized non-financial information corporate reports to assess the role of mandatory disclosure regulations such as NFRD and Spanish *Law 11/2018* on the quality and comprehensiveness of environmental disclosures. In the academic field, our study contributes to the research community in three distinct associated research areas related to environmental disclosure: We make a methodological contribution to the environmental disclosure literature regarding the enormous advances in NLP and LLMs. Our paper highlights the potential of cutting-edge NLP techniques, like fine-tuned transformers, in the assessment of the evolution and quality measurement of environmental disclosures, either mandatory or voluntary, thus, also contributing to the literature on the quality measurement of climate-related reporting. Our proposed methodology will also allow future analysis and comparison of the European Corporate Sustainability Due Diligence Directive (CSDDD), with the first submissions in 2029, once the new companies' sustainability reports still required by CSDDD become available. We finally contribute to the debate and to the strand of the literature on the recent trend toward mandatory rather than voluntary reporting worldwide. Thus, we extend our paper's target audience to all these strands of the literature related to environmental disclosure.

We acknowledge the limitations inherent in the chosen research methodology, which in turn underscore future directions for further research. One primary limitation is tied to the use of NLP techniques, particularly the *ClimateBERT* model. Despite being a cutting-edge tool, the subtleties and nuances that characterize human language may pose challenges that are beyond its analytical capability. Consequently, the model might not capture the entire spectrum of language variability present in corporate reports. However, utilizing the fine-tuned *ClimateBERT* model with the *ClimaText* dataset has already shown promise, suggesting potential for further advancements in NLP applications within the ESG domain. Future research could focus on enhancing these models to capture a more diverse array of environmental-related discourse, thereby enriching the analytical landscape of ESG disclosure to identify and mitigate environmental challenges. We also propose to use our cutting-edge NLP approach to compare the first integrated reports on 2025 from the imminent application of the new European CSRD Directive with the NFIRs from the current NFRD Directive, to obtain a first assessment of the effectiveness of the CSRD in identifying and mitigating environmental challenges.

Another caveat is that the geographical and sectoral focus of this study, centered on Spanish financial and non-financial companies, yields results that may not be extrapolated to companies operating in different regulatory environments or corporate cultures. Consequently, the scope for sector-specific analyses and international comparison of disclosure practices emerges as a significant area for future research (for example, Müller et al. [20], to explore if their results (based on EU companies) generalize to U.S. firms, benchmark EU firms' climate disclosure inside and outside financial statements to those of S&P 500 firms). Detailed scrutiny of individual sectors could illuminate industry-specific climate risks, opportunities, and reporting tendencies. It could also identify unique challenges and innovative practices within sectors, paving the way for more targeted policymaking and regulation. Additionally, extending the scope of research to encompass companies operating in different countries or regions could enrich our understanding of climate risk management from a more global perspective. Comparative analyses could unveil how regulatory environments, cultural differences, and other factors shape climate risk disclosure practices. Such research could identify and share best practices across borders, thereby contributing to more effective global climate risk management.

Finally, for consistency and depth of analysis, we focused on comprehensive reports such as annual reports, corporate sustainability reports, and ESG reports, and excluded "non-traditional" publications like ESG factsheets or brief summaries. This allowed us to ensure that the reports used in the study provided detailed and standardized information suitable for the

NLP-based analysis. However, we acknowledge that ESG factsheets are an essential part of ESG communication and reporting for companies. They provide investors and other stakeholders with a quick overview of the company's ESG performance and can help to transparently showcase the sustainability strategy and performance. Thus, future studies can assess if the results hold for these other forms of disclosure documents and also find the most appropriate methodology to treat them.

Abbreviations

AI	Artificial intelligence
BERT	Bidirectional encoder representations from transformers
CDP	Carbon disclosure project
CNN	Convolutional neural network
CRD	Climate-related disclosure
CSDDD	Corporate sustainability due diligence directive
CSR	Corporate social responsibility
CSRD	Corporate sustainability reporting directive
DL	Deep learning
EFRAG	European Financial Reporting Advisory Group
ED	Environmental disclosure
ER	Environmental reporting
ESG	Environmental, Social, Governance
ESRS	European Sustainability Reporting Standards
EU	European Union
ESAP	European Single Access Point
FSB	Financial Stability Board
IFRS	International Financial Reporting Standards
GRI	Global Reporting Initiative
GPT	Generative pre-trained transformer
GRU	Gated recurrent unit
HMM	Hidden Markov models
IIRC	International Integrated Reporting Council
ISSB	International Sustainability Standards Board
IOSCO	International Organization of Securities Commissions
KPI	Key performance indicator
LLM	Large language model
LDA	Latent Dirichlet allocation
LSTM	Long short-term memory
ML	Machine learning
NLP	Natural language processing
NFRD	Non-financial reporting directive
NFIR	Report of Non-financial information
OCR	Optical character recognition
RNN	Recurrent neural network
SASB	Sustainability accounting standards board
SEC	Securities and Exchange Commission
SFDR	Sustainable Finance Disclosure Regulation
SVM	Support vector machines
TCFD	Task force on climate-related financial disclosures
TF-IDF	Term frequency-inverse document frequency
UNGC	United Nations Global Compact
US	United States
WDI	Workforce Disclosure Initiative

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12302-025-01067-z.

Supplementary material 1.

Supplementary material 2.

Supplementary material 3.

Supplementary material 4.

Acknowledgements

Research partially funded by the project "The impact of artificial intelligence on the normative system. Special consideration of its effect on legal liability" ("Noria" Project, Universidad Pontificia Comillas. Reference: PP2023_1).

Author contributions

All authors contributed equally to this study.

Funding

Research was partially funded by the project "The impact of artificial intelligence on the normative system. Special consideration of its effect on legal liability" ("Noria" Project, Universidad Pontificia Comillas. Reference: PP2023_1).

Availability of data and materials

The data that support the findings of this study (corporates' reports) are available from Bloomberg and Factset, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. These reports are instead publicly available from each corporate's website. Data are, however, available from the authors upon reasonable request. More details on data can be found in Supplementary Material Appendix 1. Data.

Code availability

To ensure the reproducibility of the research, all Data and Code of the paper are freely and fully available at GitHub: https://github.com/villacampaporta/climateBERT-analysis. More details on software and code can be found in the Supplementary Material Appendix 3. Software & Code.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Author details

[1]Faculty of Economics and Business (ICADE), Universidad Pontificia Comillas, Alberto Aguilera 23, 28015 Madrid, Spain. [2]School of Engineering (ICAI), Universidad Pontificia Comillas, Alberto Aguilera 25, 28015 Madrid, Spain. [3]Institute for Research in Technology (IIT), Universidad Pontificia Comillas, Rey Francisco 4, 28008 Madrid, Spain.

Received: 6 July 2024 Accepted: 2 February 2025
Published online: 21 February 2025

References

1. World Economic Forum (2023) The Global Risks Report 2023. https://www.weforum.org/publications/global-risks-report-2023/. Accessed 8 Jan 2024.
2. Carney M (2015) Breaking the tragedy of the horizon–climate change and financial stability. Speech given at Lloyd's of London 29, 220–230. https://www.bankofengland.co.uk/speech/2015/breaking-the-tragedy-of-the-horizon-climate-change-and-financial-stability. Accessed 3 Nov 2023.
3. Ilhan E, Krueger P, Sautner Z, Starks LT (2023) Climate risk disclosure and institutional investors. Rev Financ Stud 36(7):2617–2650. https://doi.org/10.1093/rfs/hhad002
4. Zhang N (2011) Greening academia: Developing sustainable waste management at UK higher educational institutions (Doctoral dissertation, University of Southampton)
5. Hummel K, Jobst D (2024) An overview of corporate sustainability reporting legislation in the European Union. Account Eur. https://doi.org/10.1080/17449480.2024.2312145

6. European NFRD, The Non-Financial Reporting Directive (2014), Regulation DIRECTIVE 2014/95/EU of the European Parliament and of the Council of 22 October 2014 amending Directive 2013/34/EU as regards disclosure of non-financial and diversity information by certain large undertakings and groups. Directive 2014/95/EU. Official Journal of the European Union. European Union. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32014L0095. Accessed 10 Nov 2023.
7. Spanish Law 11/2018, of 28 December 2018, which modifies the Commercial Code, the consolidated text of the Capital Companies Law approved by Royal Legislative Decree 1/2010, of July 2, and Law 22 /2015, of July 20, on Audit of Accounts, on non-financial information and diversity. https://www.boe.es/eli/es/l/2018/12/28/11. Accessed 10 Nov 2023.
8. European CSRD (2022), *Corporate Sustainability Reporting Directive*. Directive (EU) 2022/2464 of the European Parliament and of the Council of 14 December 2022 amending Regulation (EU) No 537/2014, Directive 2004/109/EC, Directive 2006/43/EC and Directive 2013/34/EU, as regards corporate sustainability reporting. https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32022L2464. Accessed 10 Nov 2023.
9. EFRAG, European Financial Reporting Advisory Group (2021), First set of draft European sustainability reporting standards. https://www.efrag.org/lab6. Accessed 10 Nov 2023.
10. European Sustainability Reporting Standards (ESRS) (2023) Commission Delegated Regulation (EU) 2023/2772 of 31 July 2023 supplementing Directive 2013/34/EU of the European Parliament and of the Council as regards sustainability reporting standards, DOUE-L-2023-81893. https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=OJ:L_202302772. Accessed 28 Sept 2024.
11. Patten DM (1992) Intra-industry environmental disclosures in response to the Alaskan oil spill: a note on legitimacy theory. Account Organ Soc 17(5):471–475. https://doi.org/10.1016/0361-3682(92)90042-Q
12. Deegan C, Gordon B (1996) A study of the environmental disclosure practices of Australian corporations. Account Bus Res 26(3):187–199. https://doi.org/10.1080/00014788.1996.9729510
13. Neu D, Warsame H, Pedwell K (1998) Managing public impressions: environmental disclosures in annual reports. Account Organ Soc 23(3):265–282. https://doi.org/10.1016/S0361-3682(97)00008-1
14. Cormier D, Gordon IM, Magnan M (2004) Corporate environmental disclosure: contrasting management's perceptions with reality. J Bus Ethics 49:143–165. https://doi.org/10.1023/B:BUSI.0000015844.86206.b9
15. Cho CH, Patten DM (2007) The role of environmental disclosures as tools of legitimacy: a research note. Account Organ Soc 32(7–8):639–647. https://doi.org/10.1016/j.aos.2006.09.009
16. Mahoney LS, Thorne L, Cecil L, LaGore W (2013) A research note on standalone corporate social responsibility reports: signaling or greenwashing? Crit Perspect Account 24(4–5):350–359. https://doi.org/10.1016/j.cpa.2012.09.008
17. Hahn R, Kühnen M (2013) Determinants of sustainability reporting: a review of results, trends, theory, and opportunities in an expanding field of research. J Clean Prod 59:5–21. https://doi.org/10.1016/j.jclepro.2013.07.005
18. Korca B, Costa E, Farneti F (2021) From voluntary to mandatory non-financial disclosure following Directive 2014/95/EU: an Italian case study. Account Eur 18(3):353–377. https://doi.org/10.1080/17449480.2021.1933113
19. Rezaee Z, Homayoun S, Poursoleyman E, Rezaee NJ (2023) Comparative analysis of environmental, social, and governance disclosures. Glob Financ J 55:100804. https://doi.org/10.1016/j.gfj.2022.100804
20. Müller M A, Ormazabal G, Sellhorn T, Wagner V (2024) Climate Disclosure in Financial Statements, TRR 266 Accounting for Transparency Working Paper Series No. 144, https://doi.org/10.2139/ssrn.4763140.
21. Andersson FN, Arvidsson S (2023) Understanding, mapping and reporting of climate-related risks among listed firms in Sweden. Clim Policy 23(8):945–958. https://doi.org/10.1080/14693062.2022.2116383
22. Ottenstein P, Erben S, Jost S, Weuster CW, Zülch H (2022) From voluntarism to regulation: effects of Directive 2014/95/EU on sustainability reporting in the EU. J Appl Account Res 23(1):55–98. https://doi.org/10.1108/JAAR-03-2021-0075
23. Fatima AH, Abdullah N, Sulaiman M (2015) Environmental disclosure quality: examining the impact of the stock exchange of Malaysia's listing requirements. Soc Responsib J 11(4):904–922. https://doi.org/10.1108/SRJ-03-2014-0041
24. Ioannis I, Serafeim G (2018) The consequences of mandatory corporate sustainability reporting. In: McWilliams A et al (eds) The Oxford handbook of corporate social responsibility psychological and organizational perspectives. Oxford Academic, Oxford
25. Criado-Jiménez I, Fernández-Chulián M, Husillos-Carqués FJ, Larrinaga-González C (2008) Compliance with mandatory environmental reporting in financial statements: the case of Spain (2001–2003). J Bus Ethics 79:245–262. https://doi.org/10.1007/s10551-007-9375-7
26. Hahn R, Lülfs R (2014) Legitimizing negative aspects in GRI-oriented sustainability reporting: a qualitative analysis of corporate disclosure strategies. J Bus Ethics 123:401–420. https://doi.org/10.1007/s10551-013-1801-4
27. Hsiao P-CK, De Villiers C, Horner C, Oosthuizen H (2022) A review and synthesis of contemporary sustainability accounting research and the development of a research agenda. Account Financ 62(4):4453–4483. https://doi.org/10.1111/acfi.12936
28. Afeltra G, Korca B, Costa E, Tettamanzi P (2024) The quality of voluntary and mandatory disclosures in company reports: a systematic literature network analysis. Account Forum 48(1):1–34. https://doi.org/10.1080/01559982.2023.2176731
29. Paananen M, Runesson E, Samani N (2021) Time to clean up environmental liabilities reporting: disclosures, media exposure and market implications. Account Forum 45(1):85–116. https://doi.org/10.1080/01559982.2021.1872909
30. Moreno AI, Caminero T (2022) Application of text mining to the analysis of climate-related disclosures. Int Rev Financ Anal 83:102307. https://doi.org/10.1016/J.IRFA.2022.102307
31. Sautner Z, Van Lent L, Vilkov G, Zhang R (2023) Firm-level climate change exposure. J Financ 78(3):1449–1498. https://doi.org/10.1111/jofi.13219
32. Düsterhöft M, Schiemann F, Walther T (2023) Let's talk about risk! Stock market effects of risk disclosure for European energy utilities. Energy Econ 125:106794. https://doi.org/10.1016/j.eneco.2023.106794
33. Hsu A, Rauber R (2021) Diverse climate actors show limited coordination in a large-scale text analysis of strategy documents. Commun Earth Environ 2(1):1–12. https://doi.org/10.1038/s43247-021-00098-7
34. Mohamad Sham N, Mohamed A (2022) Climate change sentiment analysis using lexicon, machine learning and hybrid approaches. Sustainability 14:4723. https://doi.org/10.3390/su14084723
35. Papoutsi A, Sodhi MS (2020) Does disclosure in sustainability reports indicate actual sustainability performance? J Clean Prod 260:121049. https://doi.org/10.1016/j.jclepro.2020.121049
36. Lys T, Naughton J, Wang C (2015) Signaling through corporate accountability reporting. J Account Econ 60(1):56–72. https://doi.org/10.1016/j.jacceco.2015.03.001
37. Rezaee Z, Tuo L (2017) Voluntary disclosure of non-financial information and its association with sustainability performance. Adv Account 39:47–59. https://doi.org/10.1016/j.adiac.2017.08.001
38. Luo L, Tang Q (2014) Does voluntary carbon disclosure reflect underlying carbon performance? J Contemp Account Econ 10(3):191–205. https://doi.org/10.1016/j.jcae.2014.08.003
39. Dainelli F, Bini L, Giunta F (2013) Signaling strategies in annual reports: evidence from the disclosure of performance indicators. Adv Account 29(2):267–277. https://doi.org/10.1016/j.adiac.2013.09.003
40. Nazari JA, Hrazdil K, Mahmoudian F (2017) Assessing social and environmental performance through narrative complexity in CSR reports. J Contemp Account Econ 13(2):166–178. https://doi.org/10.1016/j.jcae.2017.05.002
41. Webersinke N, Kraus M, Bingler J A, Leippold M (2021) ClimateBert: A Pretrained Language Model for Climate-Related Text, arXiv:2110.12010
42. Garrido-Merchán EC, González-Barthe C, Coronado-Vaca M (2023) Fine-tuning ClimateBert transformer with ClimaText for the disclosure analysis of climate-related financial risks, March 2023. https://arxiv.org/abs/2303.13373v1. Accessed 30 Oct 2023
43. Al-Tuwaijri SA, Christensen TE, Hughes K II (2004) The relations among environmental disclosure, environmental performance, and economic

performance: a simultaneous equations approach. Account Organ Soc 29(5–6):447–471. https://doi.org/10.1016/S0361-3682(03)00032-1
44. Herbohn K, Walker J, Loo HYM (2014) Corporate social responsibility: the link between sustainability disclosure and sustainability performance. Abacus 50(4):422–459. https://doi.org/10.1111/abac.12036
45. Tate WL, Ellram LM, Kirchoff JF (2010) Corporate social responsibility reports: a thematic analysis related to supply chain management. J Supply Chain Manag 46(1):19–44. https://doi.org/10.1111/j.1745-493X.2009.03184.x
46. Spence AM (1974) Market signaling: informational transfer in hiring and related screening processes. Harvard University Press, Boston
47. Connelly BL, Certo ST, Ireland RD, Reutzel CR (2011) Signaling theory: a review and assessment. J Manag 37(1):39–67. https://doi.org/10.1177/0149206310388419
48. Suchman MC (1995) Managing legitimacy: strategic and institutional approaches. Acad Manag J 20(3):571–610. https://doi.org/10.2307/258788
49. Seow RYC (2024) Determinants of environmental, social, and governance disclosure: a systematic literature review. Bus Strat Env 33(3):2314–2330. https://doi.org/10.1002/bse.3604
50. Pedersen ERG, Neergaard P, Pedersen JT, Gwozdz W (2013) Conformance and deviance: company responses to institutional pressures for corporate social responsibility reporting. Bus Strat Env 22(6):357–373. https://doi.org/10.1002/bse.1743
51. Vormedal I, Ruud A (2009) Sustainability reporting in Norway–an assessment of performance in the context of legal demands and socio-political drivers. Bus Strat Env 18(4):207–222. https://doi.org/10.1002/bse.560
52. Fiechter P, Hitz J, Lehmann N (2022) Real effects of a widespread CSR reporting mandate: evidence from the European Union's CSR Directive. J Account Res 60(4):1499–1549. https://doi.org/10.1111/1475-679X.12424
53. Lock I, Seele P (2016) The credibility of CSR (corporate social responsibility) reports in Europe. Evidence from a quantitative content analysis in 11 countries. J Clean Prod 12:186–200. https://doi.org/10.1016/j.jclepro.2016.02.060
54. Carungu J, Di Pietra R, Molinari M (2020) Mandatory vs voluntary exercise on non-financial reporting: does a normative/coercive isomorphism facilitate an increase in quality? Meditari Account Res 29(3):449–476. https://doi.org/10.1108/MEDAR-08-2019-0540
55. Cordazzo M, Bini L, Marzo G (2020) Does the EU Directive on non-financial information influence the value relevance of ESG disclosure? Italian evidence. Bus Strat Environ 29(8):3470–3483. https://doi.org/10.1002/bse.2589
56. MacGregor Pelikánová R (2019) Corporate social responsibility information in annual reports in the EU. A Czech case study. Sustainability 11(1):237. https://doi.org/10.3390/su11010237
57. Dumitru M, Dyduch J, Gușe RG, Krasodomska J (2017) Corporate reporting practices in Poland and Romania–an ex-ante study to the new non-financial reporting European directive. Account Eur 14(3):279–304. https://doi.org/10.1080/17449480.2017.1378427
58. Larrinaga C, Carrasco F, Correa C, Llena F, Moneva JM (2002) Accountability and accounting regulation: the case of the Spanish environmental disclosure standard. Eur Account Rev 11(4):723–740. https://doi.org/10.1080/0963818022000001000
59. Llena FJ, Moneva M, Hernandez B (2007) Environmental disclosures and compulsory accounting standards: the case of Spanish annual reports. Bus Strat Env 16(1):50–63. https://doi.org/10.1002/bse.466
60. TCFD, Task Force on Climate-Related Financial Disclosures (2017) Recommendations of the Task Force on Climate-related Financial Disclosures: Final report (June). https://assets.bbhub.io/company/sites/60/2021/10/FINAL-2017-TCFD-Report.pdf. Accessed 3 Nov 2023.
61. TCFD, Task Force on Climate-Related Financial Disclosures (2023), Task Force on Climate-related Financial Disclosures: 2023 status report. https://www.fsb.org/wp-content/uploads/P121023-2.pdf. Accessed 9 Jan 2024.
62. IFRS, International Financial Reporting Standard (2023), IFRS S2 Climate related Disclosures. IFRS Foundation. https://www.ifrs.org/issued-standards/ifrs-sustainability-standards-navigator/ifrs-s2-climate-related-disclosures/. Accessed 3 Nov 2023.
63. IFRS, International Financial Reporting Standard (2024), IFRS Sustainability Disclosure Taxonomy. IFRS Foundation. https://www.ifrs.org/issued-standards/ifrs-sustainability-taxonomy/ifrs-sustainability-disclosure-taxonomy-2024/. Accessed 10 June 2024.
64. EFRAG and IFRS Foundation (2024) ESRS–ISSB Standards. Interoperability Guidance. https://www.efrag.org/Assets/Download?assetUrl=/sites/webpublishing/SiteAssets/ESRS-ISSB+Standards+Interoperability+Guidance.pdf. Accessed 10 June 2024.
65. Global Sustainability Standards Board (GSSB) (2024) Consolidated set of the GRI Standards 2024. https://www.globalreporting.org/how-to-use-the-gri-standards/gri-standards-english-language/. Accessed 10 June 2024.
66. Matisoff DC, Noonan DS, O'Brien JJ (2013) Convergence in environmental reporting: assessing the Carbon Disclosure Project. Bus Strategy Environ 22(5):285–305. https://doi.org/10.1002/bse.1741
67. Orzes G, Moretto AM, Moro M, Rossi M, Sartor M, Caniato F, Nassimbeni G (2020) The impact of the United Nations global compact on firm performance: a longitudinal analysis. Int J Prod Econ 227:107664. https://doi.org/10.1016/j.ijpe.2020.107664
68. Workforce Disclosure Initiative (WDI) (2023) Workforce Disclosure in 2022. Trends and Insights, April. https://cdn2.assets-servd.host/shareaction-api/production/resources/reports/WDI-2022-Trends-and-Insights.pdf. Accessed 3 Nov 2023.
69. Rodriguez A, Cotran H, Stewart LS (2017) Evaluating the effectiveness of sustainability disclosure: findings from a recent SASB Study. J Appl Corporate Financ 29(2):100–108. https://doi.org/10.1111/jacf.12237
70. Hales J (2021) Sustainability Accounting Standards Board (SASB). In: Dash JW (ed) World scientific encyclopedia of climate change. Case studies of climate risk, action, and opportunity. World Scientific, Singapore, pp 37–41
71. O'Dwyer B, Unerman J (2020) Shifting the focus of sustainability accounting from impacts to risks and dependencies: researching the transformative potential of TCFD reporting. Account Auditing Account J 33(5):1113–1141. https://doi.org/10.1108/AAAJ-02-2020-4445
72. Chua WF, James R, King A, Lee E, Soderstrom N (2022) Task Force on Climate-related Financial Disclosures (TCFD) implementation: an overview and insights from the Australian Accounting Standards Board dialogue series. Aust Account Rev 32(3):396–405. https://doi.org/10.1111/auar.12388
73. Unerman J, Bebbington J, O'Dwyer B (2018) Corporate reporting and accounting for externalities. Account Bus Res 48(5):497–522. https://doi.org/10.1080/00014788.2018.1470155
74. Helfaya A, Moussa T (2017) Do board's corporate social responsibility strategy and orientation influence environmental sustainability disclosure? UK evidence. Bus Strateg Environ 26(8):1061–1077. https://doi.org/10.1002/bse.1960
75. Michelon G (2011) Sustainability disclosure and reputation: a comparative study. Corp Reputation Rev 14:79–96. https://doi.org/10.1057/crr.2011.10
76. Herremans IM, Nazari JA, Mahmoudian F (2016) Stakeholder relationships, engagement, and sustainability reporting. J Bus Ethics 138:417–435. https://doi.org/10.1007/s10551-015-2634-0
77. Fernandez-Feijoo B, Romero S, Ruiz S (2014) Effect of stakeholders' pressure on transparency of sustainability reports within the GRI framework. J Bus Ethics 122:53–63. https://doi.org/10.1007/s10551-013-1748-5
78. Arvidsson S, Dumay J (2022) Corporate ESG reporting quantity, quality and performance: where to now for environmental policy and practice? Bus Strat Env 31(3):1091–1110. https://doi.org/10.1002/bse.2937
79. Al Amosh H, Khatib SFA (2023) ESG performance in the time of COVID-19 pandemic: cross-country evidence. Environ Sci Pollut R 30:39978–39993. https://doi.org/10.1007/s11356-022-25050-w
80. Abhayawansa S, Adams C (2021) Towards a conceptual framework for non-financial reporting inclusive of pandemic and climate risk reporting. Meditari Account Res 30(3):710–738. https://doi.org/10.1108/MEDAR-11-2020-1097
81. Reverte C (2020) Do investors value the voluntary assurance of sustainability information? Evidence from the Spanish stock market. Sustain Dev 29(5):793–809. https://doi.org/10.1002/sd.2157
82. Dando N, Swift T (2003) Transparency and assurance minding the credibility gap. J Bus Ethics 44:195–200. https://doi.org/10.1023/A:1023351816790

83. Ball A, Owen DL, Gray R (2000) External transparency or internal capture? The role of third-party statements in adding value to corporate environmental reports. Bus Strat Env 9(1):1–23. https://doi.org/10.1002/(SICI)1099-0836(200001/02)9:1%3c1::AID-BSE227%3e3.0.CO;2-H
84. Fernandez-Feijoo B, Romero S, Ruiz S (2016) The assurance market of sustainability reports: What do accounting firms do? J Clean Prod 139:1128–1137. https://doi.org/10.1016/j.jclepro.2016.08.157
85. Ballou B, Chen PC, Grenier JH, Heitger DL (2018) Corporate social responsibility assurance and reporting quality: evidence from restatements. J Account Public Policy 37(2):167–188. https://doi.org/10.1016/j.jaccpubpol.2018.02.001
86. Tsang A, Frost T, Cao H (2023) Environmental, social, and governance (ESG) disclosure: a literature review. Br Account Rev 55(1):101149. https://doi.org/10.1016/j.bar.2022.101149
87. Fernandez-Feijoo B, Romero S, Ruiz-Blanco S (2012) Measuring quality of sustainability reports and assurance statements: characteristics of the high-quality reporting companies. Int J Soc Syst Sci 4(1):5–27. https://doi.org/10.1504/IJSSS.2012.045371
88. Herz B, Rogers J (2016) Measuring what matters: Industry specificity helps companies and investors gain traction on sustainability. J Appl Corp Financ 28(2):34–38
89. Samani N, Overland C, Sabelfeld S (2023) The role of the EU non-financial reporting directive and employee representation in employee-related disclosures. Account Forum 47(2):278–306. https://doi.org/10.1080/01559982.2022.2158773
90. Gao F, Dong Y, Ni C, Fu R (2016) Determinants and economic consequences of non-financial disclosure quality. Eur Account Rev 25(2):287–317. https://doi.org/10.1080/09638180.2015.1013049
91. Runesson E, Samani N (2024) Reporting for sustainability—a presentation of challenges. In: Bruncevic C et al (eds) Towards a sustainable world academic insights and perspectives. University of Gothenburg, Gothenburg. https://www.gu.se/sites/default/files/2024-02/Towards%20a%20Sustainable%20World.pdf
92. Khurana D, Koli A, Khatter K, Singh S (2022) Natural language processing: state of the art, current trends and challenges. Multimed Tools Appl 82(3):3713–3744. https://doi.org/10.1007/s11042-022-13428-4
93. Kraus M, Feuerriegel S (2017) Decision support from financial disclosures with deep neural networks and transfer learning. Decis Support Syst 104:38–48. https://doi.org/10.1016/j.dss.2017.10.001
94. Huang AH, Wang H, Yang Y (2023) FinBERT: A large language model for extracting information from financial text. Contemp Account Res 40(2):806–841. https://doi.org/10.1111/1911-3846.12832
95. Vestrelli R, Colladon AF, Pisello AL (2024) When attention to climate change matters: the impact of climate risk disclosure on firm market value. Energ Policy 185:113938. https://doi.org/10.1016/j.enpol.2023.113938
96. Miller GA (1995) WordNet: a lexical database for English. Commun ACM 38(11):39–41. https://doi.org/10.1145/219717.219748
97. Johri P, Khatri SK, Al-Taani AT, Sabharwal M, Suvanov S, Kumar A (2021) Natural Language Processing: history, evolution, application, and future work. In: Abraham A, Castillo O, Virmani D. (eds) Proceedings of 3rd International Conference on Computing Informatics and Networks. Lecture Notes in Networks and Systems, vol 167, Springer, Singapore. 365–375. https://doi.org/10.1007/978-981-15-9712-1_31.
98. Garrido-Merchán EC, Gozalo-Brizuela R, González-Carvajal (2023) Comparing BERT against traditional machine learning text classification. J Comput Cogn Eng 2(4):352–356. https://doi.org/10.47852/bonviewJCCE3202838
99. Kölbel JF, Leippold M, Rillaerts J, Wang Q (2024) Ask BERT: How regulatory disclosure of transition and physical climate risks affects the CDS term structure. J Financ Econom 22(1):30–69. https://doi.org/10.1093/jjfinec/nbac027
100. Corringham T, Spokoyny D, Xiao E, Cha C, Lemarchand C, Syal M, Gershunov A (2021) Bert classification of Paris agreement climate action plans. In ICML 2021 Workshop on Tackling Climate Change with Machine Learning (Vol. 45). https://www.climatechange.ai/papers/icml2021/45. Accessed 24 June 2024.
101. Sanh V, Debut L, Chaumond J, Wolf T (2019) DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108.
102. Bishop CM, Bishop H (2023) Deep learning: foundations and concepts. Springer Nature, Cham
103. Lin T, Wang Y, Liu X, Qiu X (2022) A survey of transformers. AI open 3:111–132. https://doi.org/10.1016/j.aiopen.2022.10.001
104. Varini FS, Boyd-Graber J, Ciaramita M, Leippold (2020) ClimaText: A dataset for climate change topic detection (2020). In: Tackling Climate Change with Machine Learning workshop at NeurIPS 2020, Online, 11 December https://www.sustainablefinance.uzh.ch/en/research/climate-fever/climatext.html. Accessed 3 Nov 2023.
105. Kim JB, Wang C, Wu F (2023) The real effects of risk disclosures: evidence from climate change reporting in 10-Ks. Rev Account Stud 28(4):2271–2318. https://doi.org/10.1007/s11142-022-09687-z
106. Halkos G, Nomikos S (2021) Corporate social responsibility: trends in global reporting initiative standards. Econ Anal Policy 69:106–117. https://doi.org/10.1016/j.eap.2020.11.008
107. Dyer T, Lang M, Stice-Lawrence L (2017) The evolution of 10-K textual disclosure: evidence from Latent Dirichlet Allocation. J Account Econ 64(2–3):221–245. https://doi.org/10.1016/j.jacceco.2017.07.002
108. Ertugrul M, Lei J, Qiu J, Wan C (2017) Annual report readability, tone ambiguity, and the cost of borrowing. J Financ Quant Anal 52(2):811–836. https://doi.org/10.1017/S0022109017000187
109. Ehrmann M, Gaballo G, Hoffmann P, Strasser G (2019) Can more public information raise uncertainty? The international evidence on forward guidance. J Monetary Econ 108:93–112. https://doi.org/10.1016/j.jmoneco.2019.08.012
110. Debener J, Fenner A, Klein P, Ongena S (2023) Textual Disclosure in Prospectuses and Investors' Security Pricing. Swiss Finance Institute Research Paper 23–93. Available at SSRN: https://doi.org/10.2139/ssrn.4603229
111. United Nations Environment Programme (2021) 2021 Global status report for buildings and construction. Towards a zero-emissions, efficient and resilient buildings and construction sector. Nairobi. www.globalabc.org. Accessed 21 Nov 2023
112. Friedrich R, Hoffmann S, Lampe T, Ullrich S (2021) Putting sustainability at the top of the telco agenda. BCG (Boston Consulting Group) Report. https://www.bcg.com/publications/2021/building-sustainable-telecommunications-companies
113. IEA (International Energy Association) (2021) Global energy review: CO2 emissions in 2020. IEA Report, March 2021. https://www.iea.org/articles/global-energy-review-co2-emissions-in-2020
114. United Nations (UN) (2015) Paris Agreement of the United Nations Framework Convention on Climate Change (UNFCCC), December 12, 2015. https://unfccc.int/sites/default/files/english_paris_agreement.pdf. Accessed 27 Sept 2024.
115. European Climate Law (2021) REGULATION (EU) 2021/1119 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 30 June 2021 establishing the framework for achieving climate neutrality and amending Regulations (EC) No 401/2009 and (EU) 2018/1999 ('European Climate Law'). https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32021R1119. Accessed 27 Sept 2024.
116. Spanish Law 7/2021 of Climate Change and Energy Transition, of 20 May 2021. https://www.boe.es/boe/dias/2021/05/21/pdfs/BOE-A-2021-8447.pdf. Accessed 27 Sept 2024.
117. Bhargava A, Hoffman S, Jakic N (2022) Climate sustainability in retail: who will pay? McKinsey & Company, May 2022. https://www.mckinsey.com/industries/retail/our-insights/climate-sustainability-in-retail-who-will-pay

Publisher's Note