GLITTER OR GOLD? DERIVING STRUCTURED INSIGHTS FROM SUSTAINABILITY REPORTS VIA LARGE LANGUAGE MODELS

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ABSTRACT

Over the last decade, several regulatory bodies have started requiring the disclosure of non-financial information from publicly listed companies, in light of the investors' increasing attention to Environmental, Social, and Governance (ESG) issues. Such information is publicly released in a variety of non-structured and multi-modal documentation. Hence, it is not straightforward to aggregate and consolidate such data in a cohesive framework to further derive insights about sustainability practices across companies and markets.

Given these premises, it is natural to resort to Information Extraction (IE) techniques to provide concise, informative, and actionable data to the stakeholders. Moving beyond traditional text processing techniques, in this work we leverage Large Language Models (LLMs), along with the prominent in-context learning technique and the Retrieved Augmented Generation (RAG) paradigm, to extract semantically structured ESG-related information from companies' sustainability reports.

We then adopt graph-based representations to conduct meaningful statistical, similarity and correlation analyses concerning the ESG-related actions disclosed by companies in their sustainability reports. These analyses unveiled that companies address ESG-related issues through several actions encompassing recognition, compliance, and partnerships; highlighting the complexity and joint efforts needed to address them. Moreover, disclosure similarities emerged among companies from the same region or sector.

Lastly, we investigate which factual aspects impact the most on companies' ESG scores using our findings and other company information. This analysis unveiled that companies' disclosures affect ESG scores more than other financial or company characteristics.

Keywords ESG Dimensions · Non-financial Disclosures · Information Extraction · Large Language Models · In-context Learning · Knowledge Graphs · Bipartite Graph Analyses · Interpretability

1 Introduction

Public health, climate change, social inequalities, diversity, and inclusiveness are challenges that need global attention as well as innovative and collaborative solutions. However, building a sustainable society requires defining a common set of sustainable-related issues to disclose, measure and comply with. ESG, which stands for Environmental, Social, and Governance, is an established set of principles used to monitor the sustainability and ethical practices of businesses within society. These three E/S/G aspects are further broken down into quantitative and qualitative indicators, such as waste management, emissions, labour rights, and diversity, that define and evaluate the extent to which a corporation contributes to achieving societal goals. Assessing these ESG aspects can also help monitor the progress of the seventeen Sustainable Development Goals (SDGs) included in the United Nations' 2030 Agenda for Sustainable Development [1] which sets ambitious goals for building a sustainable society such as gender equality, responsible consumption and production, and climate action.

In the last decade, there has been a growing demand for disclosing companies' non-financial information. This demand comes from legislation such as the European Union's Non-Financial Reporting Directive (NFRD, [2]), enforced since 2014, which requires all public-interest companies with more than 500 employees to disclose non-financial information periodically. Furthermore, starting in 2024, large companies must comply with new demanding rules in the European Union's Corporate Sustainability Reporting Directive (CSRD, [3]), enforced in January 2023. This directive also enlarged the pool of companies concerned by a factor of 4, from roughly 12 thousand to 50 thousand companies [4].

These non-financial disclosures are typically reported in sustainability reports, web pages, social media posts, news, press releases or earning calls transcripts. To manage this variety of sources, stakeholders generally rely on a third-party assessment of corporations' ESG performance to inform their decisions: ESG ratings provided by agencies such as *Sustainalytics*, *MSCI*, *S&P Global*, *Moody's* and *Refinitiv* [5]. Currently, these rating agencies rely on proprietary assessment methodologies, with different perspectives on the measurement, scope and weight of ESG aspects, resulting in divergences in companies' evaluations across agencies and thus unsatisfactory degrees of explainability, transparency or fairness [6, 7, 8, 9]. Stakeholders might overcome this issue by directly accessing non-financial information and imposing their own scope and weight to assess corporates' ESG performance [5, 10]. However, it can be challenging and laborious to extract meaningful insights from ESG-related data sources which often include lengthy documents.

In this scenario, data-driven approaches, and specifically Natural Language Processing (NLP) techniques, can automatically extract insights from textual data, providing stakeholders with a good trade-off between relying on opaque assessments and reading verbose textual content. These extracted insights can provide them with a means for comparing companies' ESG-related assertions.

In this work, we propose a methodology based on Large Language Models (LLMs, [11, 12, 13]) to extract insights from non-financial disclosures. LLMs have consistently been shown to hold semantic understanding and store factual knowledge [14, 15, 16, 17]. The instruction-tuning approach (that is, providing task descriptions via natural language instructions) can further enhance their generalization capabilities to successfully tackle downstream NLP tasks like information extraction [11, 18, 19, 20, 21]. Generating model instructions, a task known as prompt engineering, can consequently make LLMs even more powerful and flexible tools. Furthermore, these models have also demonstrated a remarkable ability as few-shot learners using in-context learning [22], a technique that relies on providing a few input-output samples within the textual prompt itself.

Our approach relies on an instruction-finetuned generative LLM, alongside the technique of in-context learning and the paradigm of Retrieval Augmented Generation (RAG, [14]), to extract structured information related to ESG aspects from companies' non-financial disclosures. Specifically, we adopted the LLaMA-based "WizardLM" model [20] which empowers the LLaMA foundational model [23] to follow complex instructions. The authors [20] enhanced the foundational model through fine-tuning, employing open-domain instruction data of different complexities, which were generated automatically using language models instead of manually crafted instructions.

We used this generative language model to extract structured information as triples in the form of node-edge-node, and accordingly generate a knowledge graph. Graph representation offers a versatile method for storing structured information [24] since concepts and their relationships can be represented using nodes and edges [25, 26]. Knowledge graphs can be constructed using several approaches ranging from manually crafted knowledge bases to advanced NLP-based pipelines [27]. Here, we propose an NLP pipeline relying on a generative LLM to automatically generate triples and populate a knowledge graph from sustainability reports. This approach for knowledge graph generation has also been explored by other recent research works [28, 29, 30, 31] based on OpenAI's commercial LLMs. We followed the same research direction but relied instead on an open-sourced LLM [20] and introduced some semantic constraints to extract ESG-focused triples.

Starting from the generated knowledge graph, we created three distinct bipartite graphs [32, 33] to extrapolate meaningful insights. Our findings include descriptive, similarity and correlation analyses concerning ESG-related actions disclosed by companies in their sustainability reports. These analyses unveiled that companies addressed ESG-related issues from several perspectives ranging from recognition to partnerships, highlighting the complexity and joint efforts needed to address ESG-related matters. Nevertheless, many companies adopt a shared approach to address certain ESG concerns, such as reducing energy and air emissions. In addition, common strategies emerged among companies from the same geographical region or the same sector. Lastly, our work investigated which factual aspects impact the most on companies' ESG scores using features based on our findings (actions disclosed) and other company information. This interpretability analysis highlighted that the company's disclosures impact more than other company or financial aspects on ESG scores. In addition, it unveiled that transparency rewards since disclosing a lot of non-financial information affects ESG scores positively, whereas reporting fewer ESG-related issues hurts scores.

2 Related work

In this section, we first discuss the state-of-the-art approaches for creating Knowledge Graphs (KGs, Section 2.1), encompassing a spectrum ranging from conventional NLP pipelines to the exploitation of Large Language Models (LLMs). In Section 2.2, we then summarise the main studies focused on ESG-related textual information.

2.1 Knowledge Graphs generation

Knowledge Graphs (KGs, [25, 26]) offer a versatile method of representing knowledge that can be leveraged in various use cases and domains [34, 35]. They can be applied to question-answering [36], recommendation systems [37], and information retrieval [24]. The task of KG generation, also known as knowledge acquisition, aims to create KGs by extracting information from unstructured, semi-structured or structured sources as well as augmenting existing graphs [35, 38, 39]. Traditional approaches for knowledge acquisition involve several NLP tasks which are generally disjointly learned, a process that is prone to error accumulation. To overcome this problem, new one-stage NLP pipelines have been proposed to jointly extract both entities and relations [40, 41].

In this context, Open Information Extraction (OIE, [42]) emerged as the task of extracting structured information, typically in the form of subject-predicate-object (SPO) triples, without relying on a predefined template or a specific domain. This approach can mitigate the impact of depending on external knowledge, such as patterns and domain-specific heuristic rules present in the training data. Recently, OIE models (e.g., Multi^{2}OIE [43] and DeepEx [44]) have employed transformer-based LLMs (e.g., BERT [45]) to extract both syntactic and semantic information [46].

LLMs trained on large-scale corpora have demonstrated significant potential across diverse NLP tasks thanks to the technique of prompt engineering [47]. Many researchers [28, 29, 30, 31] have demonstrated the ability of LLMs (i.e., OpenAI's GPT models) to extract structured data from texts, accomplishing the KG generation task. Furthermore, LLMs can enhance KGs through several other perspectives: (1) enrich entity and relation representations using embeddings, (2) generate new facts (i.e., KG completion [48]), (3)

produce natural-language descriptions of KG facts (i.e., KG-to-text [49]) and (4) answer natural-language questions (i.e., question-answering [47]).

We follow this promising research direction by exploiting the semantic understanding, generative abilities and flexibility of LLMs to extract ESG-related structured information. Our methodology adopts LLMs, alongside cutting-edge approaches such as the Retrieval Augmented Generation (RAG) paradigm [14] and in-context learning, to address the main constraint of conventional OIE methods in achieving our goal. These methods yield structured information based only on the syntactical structure of a sentence, posing important limitations in the type of information extracted. An LLM-based information extraction approach allows us to generate semantically-aware and ESG-focused triples rather than traditional SPO triples, thus producing a full-fledged ESG-oriented KG.

2.2 Text Analytics on ESG-related information

A number of works have explored the use of NLP technology to process companies' non-financial textual information and extract meaningful insights concerning statements, facts and actions disclosed by companies. For example, Chou *et al.* [50] applied distributional semantics on 10-K filings (i.e., annual financial reports required by the U.S. Securities and Exchange Commission) for extracting topics related to climate change that are disclosed by companies, aiming to monitor environmental policy compliance. Raghupathi *et al.* [51] applied traditional approaches ranging from trigram co-occurrences to clustering and classification to gain insights into the shareholders' perspectives and objectives regarding sustainability and climate change. LLMs have also been leveraged for Text Analytics in the ESG domain. Jacouton *et al.* [52, 53] introduced *SDG Prospector*, a tool exploiting LLMs to identify paragraphs in Public Development Banks' sustainability reports that address SDGs. Similarly, Webersinke *et al.* [54] introduced *ClimateBert*, a transformer-based language model finetuned for climate-related classification tasks. Vaghefi *et al.* [55] adopted the paradigm of RAG [14] to enrich GPT-4 with the ability to reliably answer climate-related questions, by augmenting the posed questions with contextual information retrieved from the Sixth Assessment Report, released by the United Nations Intergovernmental Panel on Climate Change (IPCC). The authors also released a conversational agent [56] based on their proposed approach. Ni *et al.* [57], developed *ChatReport*, an LLM-based tool that evaluates companies' sustainability reports according to the eleven recommendations [58] provided by the Task Force for Climate-Related Financial Disclosures (TCFD). The tool combines semantic search to identify text chunks that are pertinent to each recommendation and LLM prompting to summarize them.

Our work differs from existing approaches by jointly (1) leveraging generative LLMs for Knowledge Graph (KG) generation, (2) enhancing in-context learning, (3) adopting an open-sourced generative LLM and (4) relying directly on companies' sustainability reports. This methodology, alongside the exploitation of bipartite graph representation, allows us to conduct non-trivial analyses concerning ESG-related issues and actions disclosed by companies.

3 Materials and Methods

This section discusses the data, the approaches, and the methods used in this work. First, we describe the data sources (Section 3.1); second, we provide a detailed overview of our approach, from data preparation (Section 3.2) to triple generation (Section 3.3) and KG generation (Section 3.4). Finally, we discuss the methods and approaches used to analyse, compare and evaluate the findings concerning the generated triples (Section 3.5).

3.1 Data sources

Here, we describe the three main data sources used in our work, which include (i) sustainability reports (Section 3.1.1), (ii) an ESG taxonomy (Section 3.1.2), and (iii) ESG rating scores and other companies' information (Section 3.1.3).

3.1.1 Sustainability reports

Sustainability reports are non-financial documents published by companies to disclose information concerning the impact of their activities on the environment and people. Therein are described the actions the company took or expects to take regarding ESG matters – such as respect for human rights, fair treatment of employees, anti-corruption and bribery as well as board diversity [4]. However, ESG reporting can be subjective and opaque due to the complexity of reporting qualitative aspects, particularly those related to social and governance issues [59]. Furthermore, the lack of a standardised framework for ESG reporting makes quantitative/comparative analyses difficult [60, 61].

We initially collected 6,456 sustainability reports from 4,222 different companies using the report URLs available on two public websites [62, 63]. Although these sustainability reports are mainly written in English (94% of all the available documents), the nationality of the companies is fairly diversified, covering 74 different countries. However, the majority of the available reports (56%) come from North American companies. For our study, we consider only the reports written in English because of its broad coverage and the wide range of pre-trained language models available for this language (many thousands of language models on the Hugging Face platform [64]).

Concerning the period covered, we gather reports up to fiscal year 2022 (9.6% of the available documents), even though the majority of the documents (54%) refer to the fiscal year 2021 (i.e. a fiscal year is a twelve-month period that is generally equal to a calendar year). This temporal distribution displays an expected coverage since we gathered these sustainability reports in February 2023 with the majority of the reports published throughout 2022 disclosing information concerning the previous fiscal year (2021).

Nevertheless, processing over six thousand sustainability reports from four thousand diverse companies poses a significant computational workload. Hence, we endeavour to choose a representative subset of companies striking a balance between sector representation and company prominence. This subset comprises approximately one hundred and twenty-four companies spanning eleven sectors (Table 1). Additionally, we ensure fairness in our analysis by considering only the most recent sustainability report available for each selected company, avoiding any skewness effect caused by varying report quantities per company.

Further details concerning the original dataset, the full list of the selected companies and the fiscal years of the considered reports can be found in the Supplementary Material (SM) document (see Sections SM20, SM21 and SM22).

Sector	Number	Companies
Industrial	20	Airbus, 3M Corporation, Adecco, Daikin Industries, ...
Technology	16	Apple, STMicroelectronics, Intel, NVIDIA, LG Display, ...
Financial Services	13	Bank of America, Deutsche Bank, Visa, Mastercard, ...
Consumer Defensive	11	Coca-Cola, British American Tobacco, Walmart, ...
Consumer Cyclical	11	Amazon, Adidas, Toyota Motor, Alibaba, Tesla, ...
Communication Services	10	Fox, Netflix, Walt Disney, Activision Blizzard, Meta, ...
Healthcare	10	Amplifon, AstraZeneca, Bayer, Johnson&Johnson, ...
Basic Materials	9	United States Steel, ArcelorMittal, DuPont, Croda, ...
Energy	9	Saudi Aramco, TotalEnergies, Paramount Resources, ...
Real Estate	8	China Evergrande, Park Hotels Resorts, British Land, ...
Utilities	7	American Electric Power, Edison, Enel, Uniper, ...
	124	

Table 1: *Selected companies by sector. Each sector showcases the number of companies represented. The "Companies" column shows a glimpse of the representative companies within each sector, offering a snapshot of the prominent companies chosen.*

3.1.2 ESG taxonomy

We adopt the ESG classification taxonomy proposed by Berg *et al.* in [9]. The authors grouped, using a bottom-up methodology, nearly seven hundred ESG-related indicators from six distinct ESG data providers (Sustainalytics, S&P Global, Refinitiv, Moody's ESG, Morgan Stanley Capital International-MSCI, and MSCI-KLD) into a unified taxonomy comprising sixty-four ESG categories. These categories encom-

pass environmental, social and corporate governance issues such as employee development, supply chain, climate risk management, energy, financial inclusion, biodiversity, customer relationship, access to basic services, board diversity, etc. A complete list of all the ESG categories can be found in the Supplementary Material file (see Section SM19).

3.1.3 ESG ratings and other company information

Rating agencies such as Refinitiv, MSCI, and Sustainalytics utilise non-financial reports and ESG-related information to systematically assess the impact of companies' activities on the environment and society. This assessment, typically done through numerical scores, offers stakeholders valuable measures for evaluating and comparing companies in terms of their performance related to ESG issues.

Regarding Refinitiv, the data provider used in this work, individual scores represent percentages [65], where lower values (0-25) indicate poor relative ESG performance and a lack of transparency in publicly reporting material on ESG data (i.e., laggard companies). Conversely, higher values (75-100) indicate excellent relative ESG performance and a high level of transparency in publicly reporting material on ESG data (i.e., leader companies). In addition, it is worth mentioning that a zero score is assigned in the rare case that a company does not disclose any metrics or information relevant to its industry [10, 66].

The company's ESG performance is assessed relative to industry peers due to industry-specific ESG concerns. For instance, packaging might be more relevant for companies operating in the consumer-defensive sector (e.g., Pepsi), while basic material companies (e.g., DuPont) should stress issues related to employee safety. The combined ESG score is a cumulative measure of E/S/G pillars' weights, which differ by industry for the first two pillars (E and S), while the weight of the third pillar (G) remains consistent across all industries [65].

For each company, we collect twelve company features encompassing ESG scores, unchanging company details and annual financial data (regarding the same fiscal year of the considered sustainability reports). Specifically, we gather the combined ESG scores, individual scores for the E/S/G pillars, company sector, industry, country, region and continent as well as the number of employees, market capitalization, EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization), and total liabilities.

3.2 Data preparation

Our NLP pipeline consists of several components (Figure 1), including some pre-processing methods, to extract structured insights from sustainability reports.

In this section, we describe the NLP methods adopted to prepare the data for our subsequent analyses. These pre-processing methods include extracting text from PDF files and segmenting sentences (Section 3.2.1) as well as using semantic search to select only sentences related to ESG topics (Section 3.2.2). The latter relies on the ESG taxonomy introduced in Section 3.1.2.
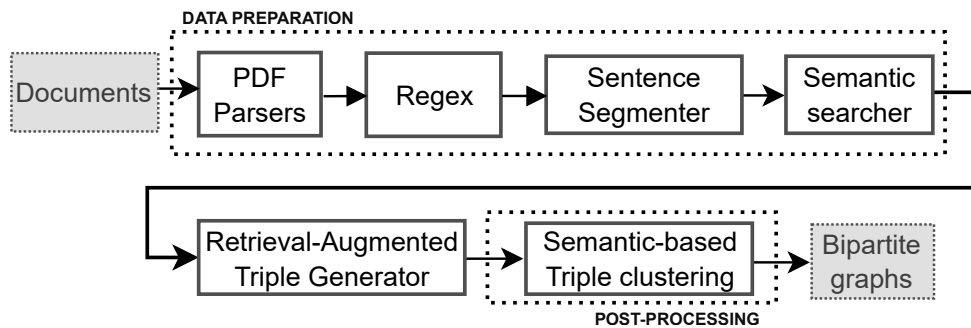

Figure 1: *Our proposed approach and its components.* *Given a collection of textual documents as inputs and preprocessed using different NLP methods, semantically structured insights are extracted by the retrieval-augmented triple generator. Bipartite graphs are created after performing a semantic-based triple clustering.*

3.2.1 NLP pipeline

Sustainability reports are lengthy and visually rich PDF files that generally span more than one hundred pages [67]: our reports' collection has a median page value of 61 pages. Unfortunately, the incentive of companies to present visually appealing infographics and tables, results in degraded quality of standard text extraction tools.

Hence, for the textual part, we rely on a PDF parser (PyMuPDF, [68]) and apply standard preprocessing steps to improve the quality of the extracted text and reduce the artefacts generated by the parser. Specifically, regular expressions are used to add a full stop between two sentences when missing, remove new lines in the middle of sentences and remove duplicate white spaces and lines.

Processing textual data also requires defining the granularity of the input data according to purpose, needs and limitations. A text corpus contains textual items representing singular tokens, words, sentences, paragraphs, or entire documents. We adopt sentence-level textual inputs as a good trade-off between the semantic meaning conveyed by a sentence and technical limitations (e.g., the maximum prompt length of the language model). Consequently, after extracting textual data from the sustainability reports, we decompose each report into sentences with PySBD [69, 70], a tool widely considered the state of the art in Sentence Boundary Disambiguation (SBD).

3.2.2 Asymmetric semantic search

Sustainability reports include generic and vague statements, for example, phrases such as "Air is something that surrounds us 24 hours a day"[1]. Accordingly, a filtering process is required to consider only ESG-related sentences for downstream tasks. The two most well-known filtering methods for information retrieval are keyword-based and vector-based search [71]. We adopt the approach of neural semantic search [72, 73, 74, 75], a vector-based search method, that exploits text embeddings to represent both documents and queries in the same vector space. This representation allows one to measure the semantic similarity between a document and a query by simply computing the distance, and contrarily the similarity, between their corresponding embedded vectors [72].

Our retrieval task involves discovering sentences related to each of the ESG taxonomy categories (Section 3.1.2) within each sentence-segmented sustainability report. This implies working in a setting of asymmetric semantic search in which queries (ESG categories) and corpus documents (sentences) are not interchangeable as they represent different semantic object types and have different lengths; similarly to the question answering framework [73, 74]. In contrast, symmetric semantic search is adopted when queries and corpus documents are interchangeable such as in similar document retrieval systems [76, 77, 78]. After extensive testing, we determine that "INSTRUCTOR-xl" [79], an instruction-tuned embedding model [80], is the most suitable choice for our specific tasks. The authors of the model [80] offer a universal instruction template ("Represent the [domain] [text type] for [task objective]:") along with a list of examples. Since we deal with asymmetric semantic search, the instructions provided to the model vary depending on the type of input. For embedding the ESG categories (queries), we use the instruction "`Represent the title for retrieving relevant statements`". To embed the sentences (corpus documents), the instruction employed is "`Represent the statement for retrieval`".

After generating the text embeddings for a sentence-segmented sustainability report, we retrieve the most semantically relevant sentences for each ESG category (semantic search, Table 2). We set the similarity cut-off threshold t_{sim} equal to 0.6 to retrieve relevant sentences to a given ESG category. Empirical experiments show an acceptable sentence relevance with a similarity threshold equal to or above 0.4. Thus, we adopt a cut-off point of 0.6 as a good trade-off between sentence coverage and computational workload. In addition, we consider the top k sentences (with $k = 30$) to limit the number of retrieved sentences following the aforementioned trade-off.

This filtering layer also helps us reduce the computational time of the follow-up steps (e.g., the inference of the generative language model) and prune the resulting KG.

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[1]Extrapolated from page 2 of Daikin's 2022 sustainability report

ESG category	Sim score	Company sentence
Labor Practices	0.73	It also guarantees *the implementation of legislation on workers' rights* defining appropriate application standards ...
	0.73	All Group workers, both in Italy and in Brazil, are covered by *Collective Labour Agreements* reached with trade union organizations and ...
	0.72	In addition to the protections and rights provided by law and *the national collective labour agreement* for the sector ...
Waste	0.68	*Total amount of waste by type* and disposal method 306-2 KPI A1.3 & KPI A1.4 Environmental Management
	0.64	At the same time, to *avoid unnecessary material loss and waste*, the Group has formulated loss rate standards for materials ...
	0.68	Through continuous publicity and education on *garbage classification*, the project wastes were gradually reduced, recycled and harmless ...

Table 2: *Example of the top three sentences selected for two ESG categories. The approach is capable of retrieving sentences that pertain to the two topics. However, it may also pick some meaningless sentences, such as the first one for the* `Waste` *category, which comes from an infographic or a tabular layout.*

3.3 Retrieval-Augmented Triple Generation

Our work aims to create a KG connecting companies, ESG categories, and actions taken by companies to address issues related to those categories. To achieve this goal, we need to represent ESG-related sentences as triples in a predefined semantic template: category-predicate-object (`cat-pred-obj`). Precisely, each triple should consist of an ESG category (`cat`) taken from the ESG taxonomy (Section 3.1.2), a predicate affecting that category (`pred`), and an entity (`obj`) related to the ESG category undergoing the predicate.

Consequently, our goal requires knowing the semantic meaning of words as well as defining a semantic template to generate ESG-focused triples. The latest OIE techniques (Section 2.1) incorporate semantic information for extracting structured information, yet they rely only on the syntactical structure of the sentence. For example, given the sentence: "*Microsoft has invested 125 million in cutting-edge recycling technologies*"[2], conventional OIE techniques [81] would identify and generate a traditional SPO triple as the following: (`Microsoft, Invested, 125 million`). Although the above triple can well represent the semantic meaning conveyed, it would not be suitable for our goal. Indeed, the ideal triple would have been: (`Waste, Investment in, Cutting-edge recycling technologies`). Generating the latter requires defining a semantically-aware triple template. Firstly, the entity `Waste`, representing an ESG category, is not explicitly mentioned, although it could be inferred from the term `recycling technologies`. This type of inference involves both information extraction and semantic classification tasks. Secondly, our goal requires extracting ESG-related actions rather than generic statements. Hence, triples should envelop predicates and objects related to an ESG category.

LLMs have already demonstrated abilities in semantic understanding and handling a broad range of NLP-related tasks [11, 18]. Accordingly, in this work, we employ instruction-tuned LLMs, the in-context learning technique and the prominent RAG paradigm [14] to address this challenge. Our work exploits these techniques to provide an LLM with an input (ESG-related sentence) and an external context (examples and a semantic schema) to extract structured information from the sentence.

We choose the `Kor` library [82] to create in-context instructions for LLMs. `Kor` allows to programmatically construct prompts by specifying the semantic data schema for the ideal triples (`cat-pred-obj`) as well as including labelled examples. Each element of the triple has a unique name and a description conveying the semantic meaning of the associated entity. It then uses this information to generate a textual instruction that is used to prompt an LLM using a predefined template. Its precise content is shown in Figure 2. The full model instruction is reported in the Supplementary Material file (Section SM2).

We tested different instruction-tuned LLMs such as Google's Flan-T5 [83] and LLaMA-based models [23]. We empirically found that LLaMA-based models (e.g., Alpaca [84]) generate better results when prompted to extract structured information, with `WizardLM-7B` [20, 85] producing the highest-quality results.

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[2]This sentence is created for explanatory purposes and does not represent a real fact.

```
Your goal is to extract structured information from the user's input that matches the form described below.
When extracting information please make sure it matches the type of information exactly.  Do not add any
attributes that do not appear in the schema shown below.
$DATASCHEMA
Please output the extracted information in JSON format.  Do not output anything except for the extracted
information.  Do not add any clarifying information.  Do not add any fields that are not in the schema.
If the text contains attributes that do not appear in the schema, please ignore them.  All output must be
in JSON format and follow the schema specified above.  Wrap the JSON in <json> tags.
$EXAMPLES
input:  $INPUT
output:
```

Figure 2: *The instruction template used.* It is created and compiled by the `Kor` library to prompt an LLM to extract structured data using in-context learning. `DATASCHEMA` *is a placeholder for the output data schema.* `EXAMPLES` *is a placeholder for the labelled examples in the format of input-output pairs. While* `INPUT` *represents an ESG-related sentence from which structured data needs to be retrieved.*

3.4 Knowledge Graph generation

Before constructing a KG using the generated triples `cat-pred-obj`, we apply a data-cleaning process to reduce data redundancy. The redundancy in the KG comes from nodes and edges representing similar concepts and their relationships multiple times.

To achieve this goal, we perform semantic clustering on all the ESG categories (`cat`) and predicates (`pred`) included in the generated triples. Firstly, we generate text embeddings using the "INSTRUCTOR-xl" embedding model [80] with the model instruction "`Represent the title`". Secondly, semantic clusters are discovered as high-density regions in the embedded vector space using cosine similarity as a metric. We conduct several empirical experiments to evaluate the cluster goodness using different similarity cut-off thresholds, ranging from 0.5 to 0.9. Eventually, we adopt a similarity cut-off point of 0.8, as it strikes a good balance between the semantic coherence of the cluster elements (cluster quality) and the cluster sizes.

Finally, we label each cluster with its centroid and use cluster labels to replace the original ESG categories and predicates of the original triples. For instance, the predicate cluster labelled `Partnership with` groups 103 different predicates encompassing `Working together with`, `Partnering with others to` and `Collaborating of`. Other cluster examples and replacing examples are reported in the Supplementary Material file (Section SM1).

3.5 Approaches for statistical analyses

In the Results Section (Section 4), we mostly deal with undirected bipartite graphs obtained from the original KG. A bipartite graph is a graph whose vertices can be divided into two distinct and independent sets or partitions [32, 86, 87]. It can be described through its binary *bi-adjacency* matrix $\mathbf{B}$, a $\{0,1\}^{n \times m}$ matrix where n and m are the numbers of nodes in the two partitions.

Specifically, we create three distinct bipartite graphs for our analyses which are obtained through node and edge filtering of the comprehensive KG. In our setting, the graph edges are context-dependent and thus change based on the perspective used to generate the bipartite graph. From this point forward, they are referred to as (1) the category-predicate graph $\mathbb{B}_{\text{catpred}}$, (2) the company-category graph $\mathbb{B}_{\text{cocat}}$, and (3) the company-action graph $\mathbb{B}_{\text{coact}}$.

We define an action `act` as the concatenation between the category `cat` and the predicate `pred` of a `cat-pred-obj` triple. For instance, given the ideal triple mentioned in Section 3.3, the action is defined as the category `Waste` concatenated with the predicate `Investment in`, resulting in the action "`Waste:Investment in`". A table encompassing the number of partition nodes, the number of edges and the density for each bipartite graph is provided in the Supplementary Material (see Section SM4).

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3.5.1 Bipartite graph statistics

Most of the unipartite graph metrics can be extended to the bipartite case [32, 87]. Specifically, here we compute the bipartite variants of network statistics such as degree centrality, closeness centrality and betweenness centrality [87, 88].

The degree centrality of a partition node is the fraction of the nodes of the other partition connected to it [89]. The closeness centrality of a node [86, 87] is determined by calculating its average shortest path distance to all other nodes and represents the efficiency of a node to be connected directly to nodes from the other partition and indirectly to nodes from the same partition [90]. For instance given $\mathbb{B}_{\text{cocat}}$, a company node with a high closeness score indicates the company is connected, and thus it is close, to many category nodes which in turn are connected to several other company nodes. Lastly, betweenness centrality [86, 91] assesses the level of influence a node holds over information flow within a graph. In the context of bipartite graphs, it identifies nodes serving as critical mediators in enabling interactions between the two separate node partitions [32].

3.5.2 ESG-related actions' variability

We leverage information theory to assess the entropy of ESG topics based on their associated predicates yielded from companies' sustainability reports. Specifically, we adopt Shannon's entropy (Equation 1, [92]) to measure the information, and thus the variability, present in a set of events $\mathcal{X}$ through their respective occurrence probabilities $p(x)$:

$$H(\mathcal{X}) := - \sum_{x \in \mathcal{X}} p(x) \ln p(x) \tag{1}$$

In our context, the events $\mathcal{X}$ are the predicates disclosed by all companies for a given ESG topic, while $p(x)$ represents their relative occurrences. High entropy denotes high variability in the predicate occurrences, indicating an ESG topic addressed through many actions (predicates) with an almost uniform probability of predicate occurrence. On the other hand, low entropy indicates the predominance of a limited set of predicates for an ESG topic.

3.5.3 Similarity analysis

We estimate company similarities based on jointly disclosed ESG-related actions through the Jaccard similarity coefficient [93], which measures the similarity between two sets as the cardinality of their intersection over the cardinality of their union:

$$J(\mathcal{A}_{c_1}, \mathcal{A}_{c_2}) = \frac{|\mathcal{A}_{c_1} \cap \mathcal{A}_{c_2}|}{|\mathcal{A}_{c_1} \cup \mathcal{A}_{c_2}|} \tag{2}$$

where $\mathcal{A}_{c_i}$ is the set of ESG-related actions disclosed by company c_i. To mitigate the influence of stochastic fluctuations on the similarity score, we generated a null model [94] with a bootstrapping technique by computing company similarities on the randomised action sets through 1,000 simulations, and substracted this null model from the observed company similarities.

3.5.4 Correlation analysis

We evaluate whether company similarities in terms of jointly disclosed ESG-related actions (Section 3.5.3) are correlated to similarities in ESG scores or other company characteristics such as market capitalization or geographical location. We first measure feature similarities through different strategies, ensuring the same numerical range and monotonicity. The similarities in numerical features, such as ESG scores, are measured by computing the absolute numerical difference normalised using max-min scaling [95]. While, similarities in textual features, such as company sectors, are first embedded using the "INSTRUCTOR-xl" embedding model [80], and then their semantic similarities are assessed through the cosine similarity normalised in [0,1] using min-max scaling [95]. A complete list of all the features and measures used can be found in the Supplementary Material (see Section SM9).

Afterwards, we perform a bivariate analysis through a correlation analysis to measure the monotonic association between action similarities and similarities of other company features.

We rely on Kendall's τ correlation coefficient (Equation 3, [96]), a non-parametric and rank-based statistic computed as:

$$\tau = \frac{n_c - n_d}{n_c + n_d} \tag{3}$$

where n_c and n_d are the numbers of concordant and discordant pairs respectively. Rank-based correlation methods overcome some limitations of traditional correlation methods such as the well-known Pearson correlation coefficient [97]: they can measure nonlinear monotonic relationships, are more robust against outliers and normality assumption is not required [98]. High positive coefficients express a high level of order consistency in the company similarities sorted according to actions' and other similarities, while high negative coefficients occur when these two similarities are sorted reversely [96].

3.5.5 Interpretability of ESG scores

Lastly, we investigate the interpretability of ESG scores through a linear regression and the SHAP (SHapley Additive exPlanations) framework [99]. Here, we investigate the most impacting factors on the ESG scores of companies by exploiting the interpretability of a first-order linear regression model.

The model predictors are based on our findings and other company information (Section 3.1.3). We first compute the category and action entropy for each company, indirectly representing the cardinality of the ESG categories and actions disclosed in its sustainability report (Section 3.5.2). For each company, we also consider the percentage of the top ten most disclosed ESG categories and the proportion of the three E/S/G pillars based on the disclosed categories. In addition, we consider nine company-related features encompassing company characteristics and annual financial data. Categorical variables are turned into binary indicator variables (i.e., dummy variables [100]), whereas standardisation is applied to those numerical. A complete list of features is exhibited in Section SM12 of the Supplementary Material (SM) document.

Then, we perform an Ordinary Least Squares (OLS, [101]) regression with Elastic Net Regularization [102] to perform inference on companies' ESG scores available. We adopt Elastic Net Regularization, a generalisation of the LASSO method [103], to perform both feature selection and training regularisation. We choose this regularisation method as it improves performance when the number of predictors ($|features| = 97$) is higher than the observations ($|companies| = 89$) as well as in the presence of strong pairwise correlations [102]. We train the OLS model using the Elastic Net cost function and an eight-fold cross-validation approach [104] (see Section SM14). The performance of the OLS model is discussed in Appendix C.

Subsequently, we employ the SHAP framework [99] to investigate which predictors impact the inference of ESG scores most. SHAP is a model-agnostic and additive feature importance measure which is based on cooperative game theory. It provides local interpretations of model predictions as additive sums of the directed effects of each predictor using a conditional expectation function. SHAP values quantify the magnitude and direction of the observed effects of each predictor. Predictors with positive SHAP values affect the expected model output with additive increments, conversely, those with negative values have additive decrement impacts.

4 Results

In this section, we first report the network statistics computed at the node level from the three bipartite graphs in Section 4.1. Next, a diversity analysis examines how ESG-related issues are disclosed across companies and different sectors. (Section 4.2). Section 4.3 reports company similarities according to jointly disclosed ESG actions. The follow-up section (4.4) addresses whether these company similarities are associated with similarities in other company information. Finally, we evaluate the interpretability of ESG scores by investigating the most impacting factual aspects (Section 4.5). A qualitative analysis of the generated triples and an ablation study on the model instruction are exhibited in Appendix A and Appendix B.

4.1 Bipartite graphs' analysis

We here present some network statistics concerning the three bipartite graphs $\mathbb{B}_{cocat}$, $\mathbb{B}_{catpred}$, and $\mathbb{B}_{coact}$. Further statistics and extensive tables for all three bipartite graphs are shown in the Supplementary Material document in Sections SM4, SM5 and SM6.

The ESG movement encompasses many socially responsible issues. The 124 companies disclosed 542 distinct ESG-related issues in their sustainability reports. The company-category bipartite graph $\mathbb{B}_{cocat}$ has an average degree distribution equal to almost 11%, making this graph relatively connected. There are however some mainstream ESG categories: `Climate Risk Management`, `Supply Chain`, `Energy` and `Corporate Governance` are connected to, and thus disclosed by, almost all the considered companies (degree $> 92\%$, Table 3). Conversely, the list of the least disclosed issues is rather surprising: `Market Responsibility`, `Anti-Discrimination` and `LGBTQ+ Inclusion` are disclosed by less than 5% of all the considered companies (Table 3).

Category node (cat)	**Degree** (%)	**Closeness** (%)	**Betweenness** (%)
Supply Chain	95.3	98.9	2.3
Climate Risk Management	94.5	98.5	2.3
Corporate Governance	93.0	98.1	2.1
Community and Society	91.4	98.1	2.1
Philanthropy	88.3	96.8	2.0
Packaging	50.0	77.7	0.6
Human Resources	39.8	74.2	0.4
LGBTQ+ Inclusion	4.7	55.4	0.0
Anti-Discrimination	2.3	52.1	0.0
Marketing Responsibly	0.8	47.8	0.0

Table 3: *Graph metrics of a sample of all the 542 category nodes of the bipartite graph* $\mathbb{B}_{cocat}$.

ESG topics are addressed from several perspectives, with some frequent ones. The average degree centrality of the category-predicate bipartite graph $\mathbb{B}_{catpred}$ is less than 1%. There are however some predominant predicate nodes (see Section SM6) that are associated with more than ninety ESG categories (degree $\geq 16.6\%$) such as `Commitment and involvement with` (113 categories), `Advisor support for` (102), `Partnership with` (97), and `Establishment of` (94). These prominent nodes interestingly exhibit high closeness centrality ($> 88\%$) in contrast to their relatively low degree centrality values. This indicates that common category nodes indirectly connect them.

Common actions are the exception. The company-action bipartite graph $\mathbb{B}_{coact}$ connects the company nodes to almost twenty thousand different ESG-related actions (19,574) disclosed in companies' sustainability reports. However, there are a few prominent actions, such as `Air Emission:Reduction of` (degree of 70%) and `Energy:Reduction of` (60%), that are disclosed by the majority of the considered companies.

4.2 Diversity analysis on disclosing ESG categories

In this section, we analyse the differences in disclosing and addressing ESG-related issues in companies' sustainability reports.

Companies approach ESG-related issues from plenty of perspectives, especially those generic and vague. The predicates associated with each ESG category vary significantly with an average Shannon's entropy of 1.5 nats. This broad action variety is predominant in generic and umbrella ESG topics such as `Corporate Governance`, `Human Rights`, and `Supply Chain` (Table 4). For example, when addressing `Product Safety`, companies approach it from different perspectives, ranging from developments (2.3%) to regulatory compliance (2.3%) and assessments (4.4%, Table 4). However, a notable correlation (*corr* $= 0.84$) exists between the entropy of categories and the number of companies disclosing information about a particular ESG category. This suggests differences in how each company approaches these ESG-related issues.

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ESG category (`cat`)	Entropy (nats)	Companies (%)	Category predicates (`pred`)
Supply Chain	5.72	95	Partnership with (3.7%), Assessment of (2.4%), Engagement in (2.2%)
Corporate Governance	5.62	94	Establishment of (4.3%), Commitment and involvement with (3.7%), Overseeing (2.9%)
Human Rights	5.62	90	Commitment and involvement with (5.1%), Respect for (2.6%), Assessment of (2.4%)
Product Safety	5.27	69	Assessment of (4.4%), Compliance with (2.3%), Development and implementation of (2.3%)
Food Waste	2.44	6	Commitment and involvement with (14.3%), Reduction of (14.3%), Development of (7.1%)
Anti-Slavery Practices	1.61	4	Undertaking of (20%), Integration of (20%), Required training (20%)

Table 4: *A sample of the ESG categories with their entropy values computed. The three most frequent category predicates are reported alongside the percentage of companies disclosing that category.*

There are cross-sector and sector-focused issues. A proportion of almost 12% among all the 542 ESG categories is disclosed across all company sectors, encompassing various umbrella aspects such as `Climate Risk Management`, `Supply Chain` and `Business Ethics`. However, it is noteworthy that certain sectors emphasise specific issues more than others (Table 5). For example, `Packaging` is more emphasised in Consumer Defensive companies, such as PepsiCo (18% of all the company triples), Coca-Cola (9%), Monster Beverage (6%), and Tesco (5%). This category accounts for 4.9% of all generated company triples within this sector as exhibited in Table 5. Another example is `Water` which is more stressed by companies operating in water-intensive sectors such as Consumer Defensive (6.6%, Table 5, e.g., Coca-Cola) and Basic Materials (4.9%, e.g., DuPont) rather than Financial Services companies (0.5%, e.g., Goldman Sachs).

ESG category (`cat`)	Triples (%)	Companies (%)	Sectors (%)	Triples per company sector (%)
Corporate Governance	6.7	94	100	Industrials (7.8%), Financial Services (7.5%), Healthcare (7.4%)
Air Emissions	3.7	92	100	Energy (6.9%), Basic Materials (4%), Industrials (3.8%)
Water	3.1	85	100	Consumer Defensive (6.6%), Basic Materials (4.9%), Energy (4.4%)
Green Buildings	1.5	88	100	Real Estate (3.5%), Consumer Cyclical (1.8%), Technology (1.6%)
Packaging	0.9	49	100	Consumer Defensive (4.9%), Consumer Cyclical (1.5%), Technology (0.9%)
Business Ethics	0.3	61	100	Healthcare (0.7%), Utilities (0.5%), Industrials (0.4%),

Table 5: *Sample of all the ESG categories disclosed by companies in their sustainability reports. This table exhibits the category coverage through different percentages concerning: (i) the company triples including a category, (ii) the companies reporting a category (iii) also aggregated by sector, and (iv) the company triples aggregated by sector.*

Different sectors employ tailored actions to address ESG-related issues. Although there are a few widely disclosed actions (Section 4.1), the same action is disclosed, on average, by less than 2% of the considered companies. Whereas, only 15% of the company sectors are, on average, engaged in the same action. This unveils different priorities and a variety of approaches among companies and sectors. For example, the `Assessment of` aspects concerning `Climate Risk Management` are more emphasised by Real Estate companies which manage assets vulnerable to climate risks, such as Park Hotels Resorts (2% of all the company triples) and Sun Communities (1%). Conversely, Basic Materials companies such as United States Steel (1%), Yamana Gold (1%) and Aluminum Corporation of China (1%), emphasise instead the `Commitment and involvement` concerning `Employee Safety`, a worker-related issue.

Further extensive tables can be found in the Supplementary Material document (see Section SM3).

4.3 Company similarities based on disclosed ESG-related actions

Here, we discuss company similarities according to jointly disclosed actions using the Jaccard similarity coefficient (see Section 3.5).

Companies from the same sectors tend to perform similar actions. For example, as depicted in Figure 3 and outlined in Table 6, five companies among the top ten similar companies of `Deutsche Bank` are banks too: `Royal Bank of Canada` (action similarity equal to 7%), `Banco Santander` (6%) and `UniCredit` (6%). Notably, `Visa` and `Mastercard`, both operating in the Credit Services industry, form a distinct group (Figure 3). Comparably, action similarities emerge in companies operating in the healthcare sector: Moderna, Vertex Pharmaceuticals and AstraZeneca (Table 6). Further details are visible in Section SM8 of the Supplementary Material document.

Companies from the same geographical region tend to perform similar actions. For example, as can be visually noted in Figure 3, 80% of the ten most similar companies of `Sony` (Japan, Eastern Asia) are companies from the same geographical region: 40% from Japan and 40% from South Korea. Similarly, `Geely Automobile` (China, Eastern Asia) has 70% of its ten most similar companies from the same region too: 40% from China and 30% from South Korea. On the west side, there are six European companies in the ten most similar companies of `Enel` (Italy, Southern Europe) with Italian companies representing 40% of the total.
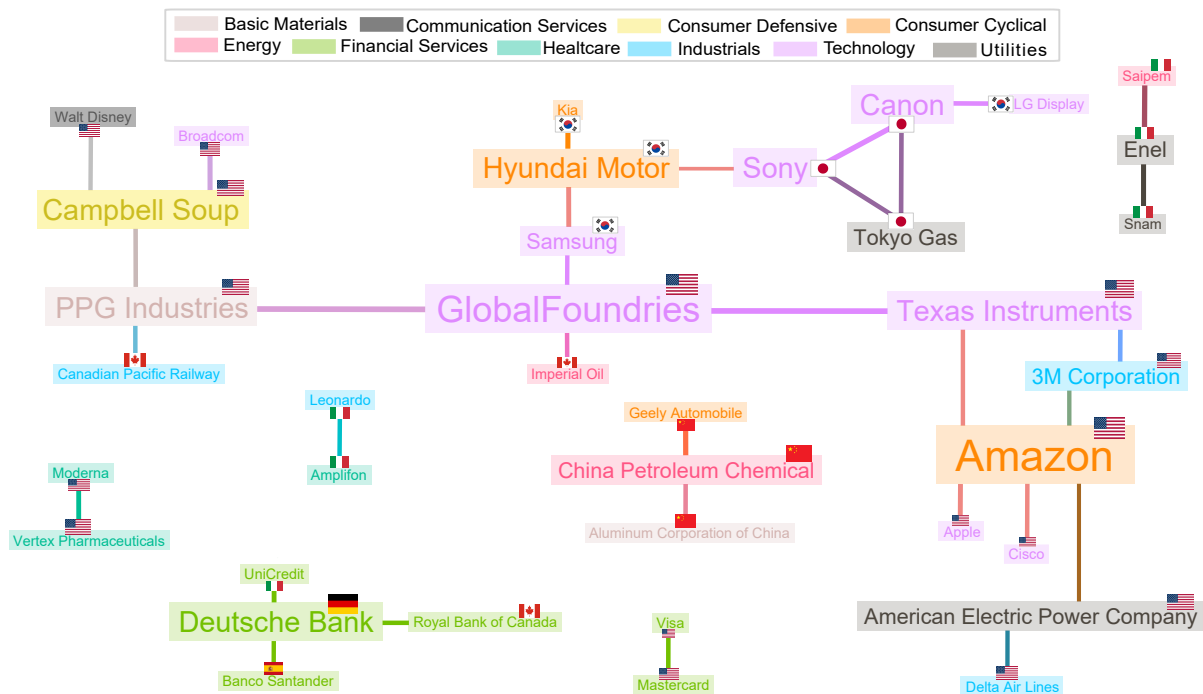

Figure 3: *A network diagram linking companies that report similar actions, determined by the Jaccard similarity coefficient.* It exhibits only connections between companies with a similarity equal to or greater than 6%. Node colour corresponds to distinct sectors, and node size is proportional to their connectivity. Some connections are noteworthy for linking companies within the same sectors or geographical regions.

Company	Most reported actions	Most similar companies
Sony	PACKAGING: Reduction of (x7) PHILANTHROPY: Advisory support for (x6) CORPORATE GOVERNANCE: Establishment of (x6)	Canon (7%), Tokyo Gas (6%), Hyundai Motor (6%), Toshiba (6%), Kia (6%)
Deutsche Bank	ENERGY: Reduction of (x4) BIODIVERSITY: Promotion of (x4) CORPORATE GOVERNANCE: Establishment of (x4)	Royal Bank of Canada (7%), Banco Santander (6%), UniCredit (6%)
Global-Foundries	WATER: Use of (x6) AIR EMISSIONS: Reduction of (x7) PHILANTHROPY: Donation by (x7)	Texas Instruments (7%), PPG Industries (7%), Samsung (6%), Visa (6%)
Geely Automobile	PHILANTHROPY: Participation in (x5) SUPPLY CHAIN: Establishment of (x5) CORPORATE GOVERNANCE: Development and implementation of (x5)	China Petroleum Chemical (7%), Baidu (6%), LG Display (6%), Alibaba (5%), Korean Air Lines (6%)
Saudi Aramco	AIR EMISSIONS: Reduction of (x4) BIODIVERSITY: Protection of (x4) ENERGY: Investment in (x4)	Tokyo Gas (5%), Royal Dutch Shell (5%), Yamana Gold (5%), Visa (5%)
Philip Morris	WASTE: Continuous efforts to reduce, reuse, or recycle (x5) BIODIVERSITY: Continuing to set goals and work towards (x4) PHILANTHROPY: Investment in (x3)	Croda (4%), 3M (4%), Coca-Cola (4%), GlobalFoundries (4%) Samsung (4%), United States Steel (4%)

Table 6: *A company sample with the top three most reported actions and the most similar companies for each. Company similarities are assessed by computing the Jaccard similarity on the companies' disclosed action set.*

4.4 Correlation analysis among company similarities

This section answers the research question concerning whether company similarities in terms of jointly disclosed actions (Section 4.3) are associated with similarities in other company information (Section 3.1.3). We perform a bivariate correlation analysis using Kendall's correlation coefficient (Section 3.5) for each company with all information available: 81% of the considered companies. Aggregated results are exhibited in Figure 4 through box plots.
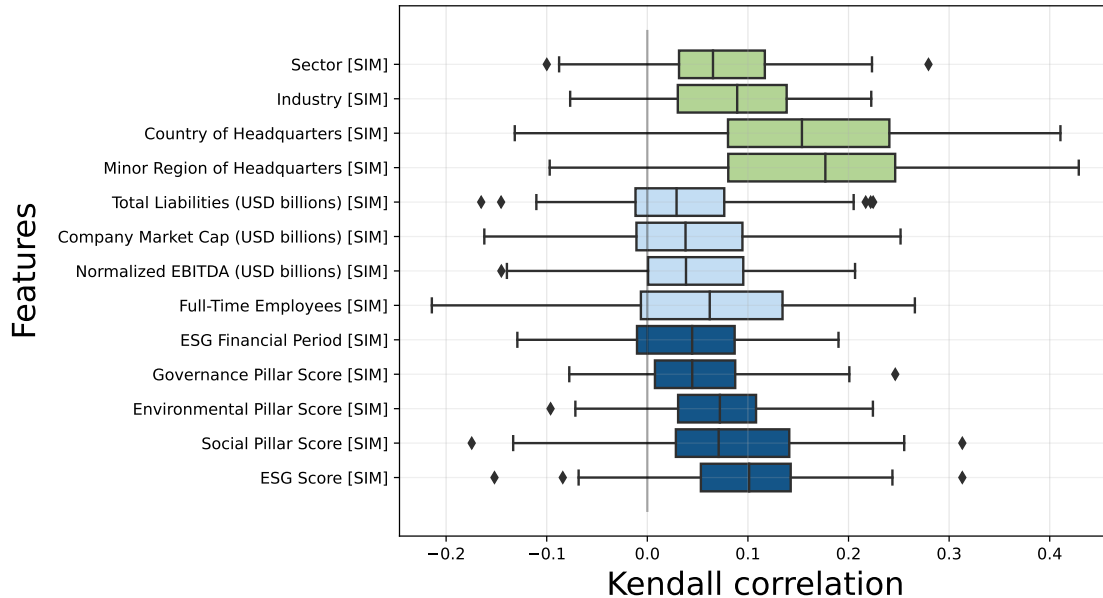

Figure 4: *Distributions of pairwise correlations between companies' action similarities and similarities in other company features (rows). Features are color-grouped according to their type of information. Light-green features categorical company characteristics, while azure and dark blue features represent numerical features concerning companies' financial and ESG information.*

Similarities in companies' disclosed actions are correlated with companies' geographical regions.   Action similarities have the highest, yet weak, correlation with the `Region` and `Country` of the company headquarters, with a median correlation coefficient of 0.18 and 0.15. This confirms the empirical findings discussed in the previous section (4.3). Moreover, only these two features demonstrate median p-values, resulting from the null hypothesis test of zero monotonic correlation, below the established accepting threshold of 5%, respectively 1% and 2%. The p-value distributions for all the features are shown in Section SM10 of the Supplementary Material (SM) document. Taking the previous example companies, `Sony` and `Enel` exhibit a relatively high monotonic correlation between their company similarities in terms of disclosed actions and geographical locations. `Sony` has an action-country similarity correlation equal to 0.22 and an action-region correlation equal to 0.20, while `Enel` exhibits a lower action-country correlation (0.14) and a higher action-region correlation (0.25).

No other statistically significant similarity correlations emerge.   Company similarities in `ESG scores` and `Industries` have a median pairwise correlation with companies' disclosed actions equal to 0.1 and 0.09. Their statistical significance appears however relatively weak due to high median p-values (13% and 15%), which suggest accepting the null hypothesis of zero monotonic correlation.

ESG scores are only correlated with their underlying components.   After analysing company similarities from the disclosed action perspective, we perform a pairwise correlation analysis to unveil monotonic associations among company similarities in all these features. Strong monotonic correlations appear between similarities in companies' `Region` and `Country` (median correlation equal to 0.7) as well as between companies' `ESG score` and their `Social` (0.5) and `Environmental Pillar scores` (0.4). No other relevant correlations emerge for ESG scores or other company information. A graphical representation of all the pairwise correlations is exhibited in Section SM11 of the Supplementary Material (SM) document.

4.5   Interpretability of ESG scores

Lastly, we investigate the interpretability of ESG scores by employing a first-order linear regression and the SHAP framework (Section 3.5.5). We specifically evaluate how various factual and corporate aspects impact these scores.
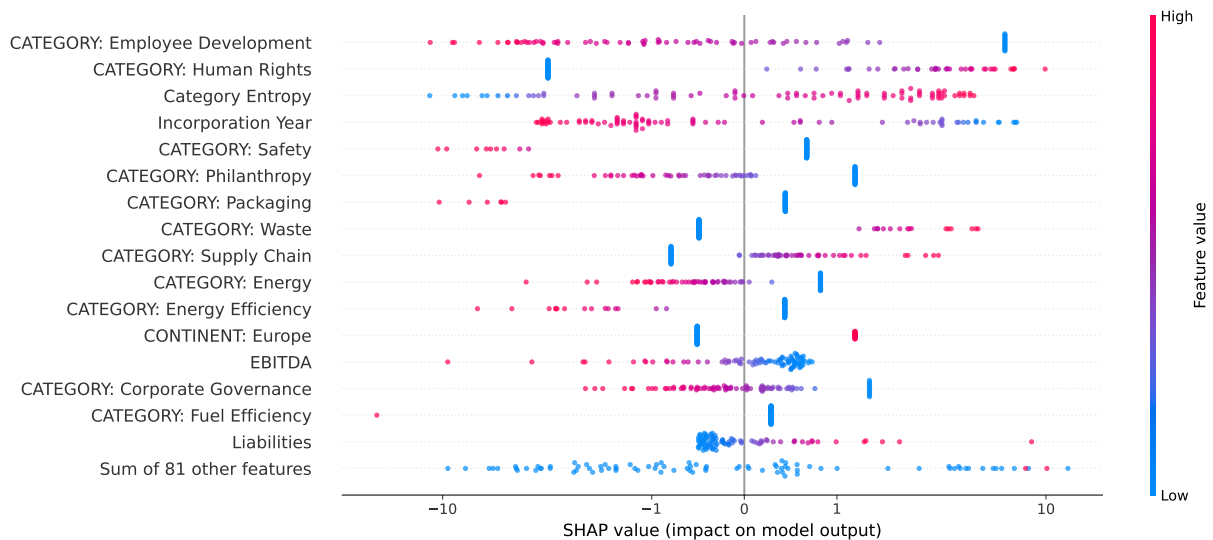

Figure 5: *Summary of the top sixteen features impacting the most the inference of ESG score. The features are ordered according to their median shape value. The x-axis represents the degree of a positive and negative impact on model output. Each dot represents a company instance and colours represent the company values of the standardised feature.*

Social-related actions, company transparency and incorporation dates have a significant impact on ESG scores. On average, the most impacting aspects affecting ESG scores are the percentages of disclosed actions related to `Human Rights` and `Employee Development`, with a mean SHAP value of 2.6 and 2.7. High percentages of the former (colour scale in Figure 5) positively impact ESG scores, while the latter has the effect of hurting them. High disclosing percentages in actions related to `Philanthropy` (mean SHAP value of 1.1) and `Energy` (0.7) also hurt companies' scores. Similar average magnitude, but an opposite effect, disclosing several actions related to `Waste` (0.8) or `Supply Chain` (0.7) has a positive impact. Furthermore, high variety in the disclosed ESG topics (`Category Entropy`) positively affects ESG scores with a mean SHAP value of 2.1 (Figure 5). Sharing a similar average magnitude (1.9), being founded earlier, represented by an older `Incorporation Year`, positively impacts a company's score. Further noteworthy factors positively impacting ESG scores are being a European company (`CONTINENT:Europe`, mean SHAP value of 0.7) and exhibiting a high level of `Liabilities` (0.5). In contrast, high annual earnings (`EBITDA`, 0.6) have a slight negative impact on ESG scores.

Local interpretability analysis reveals company-specific impacting factors. Moving from global to local interpretability, we choose `Sony` as an example company and investigate the most impacting factors for its ESG score (Figure 6). The `Incorporation Year` and `Category Entropy` features, respectively far below (standardised value of -1.03, representing the year 1946) and above (0.87, 3.6 nats) the average of company values, positively affect its score. In addition, disclosing several actions related to `Human Rights` (0.57, 4.4% of all its extracted actions) and `Waste` (1.31, 3.4%) has a positive impact. In contrast, disclosing fewer `Energy`-related actions than the average (-0.98, not among the top ten disclosed topics) positively affects its scores. Furthermore, being an Asian company (`CONTINENT:Asia` and `CONTINENT:Europe`) slightly hurts its score.
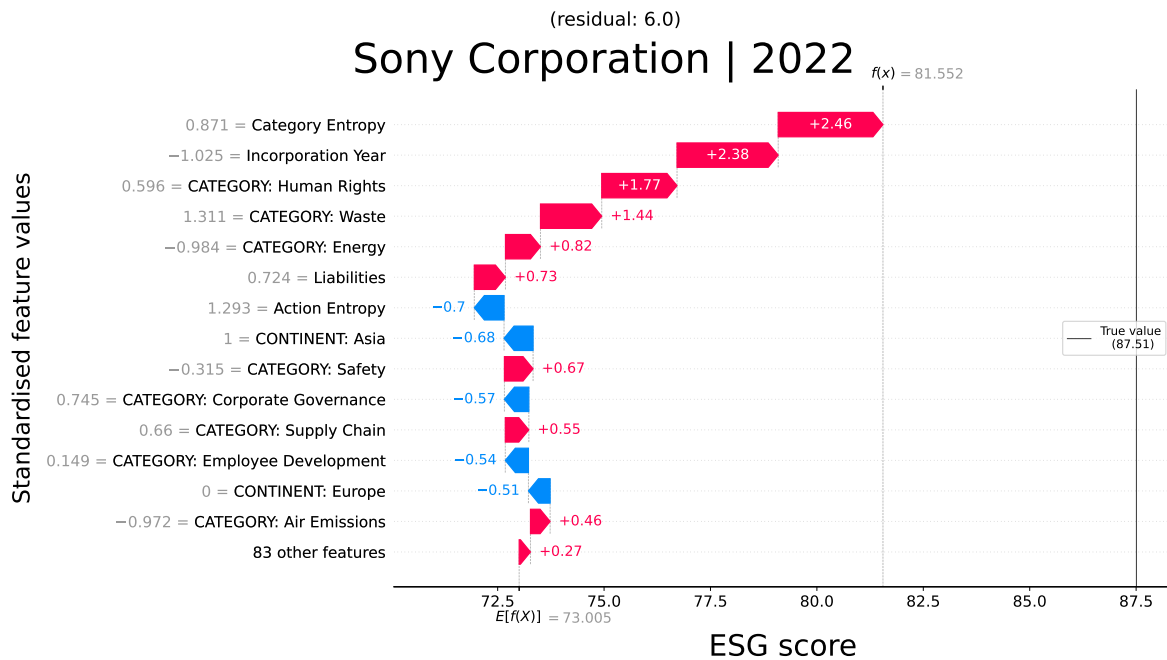

Figure 6: *Example of explanations for individual predictors for the ESG score of a company. The category-based features are extracted from the 2022 sustainability report of the Japanese company `Sony` and other company information from the same fiscal year is considered. In addition, the actual ESG score and the model error (residual) are shown.*

Region-based interpretability analysis reveals common patterns. Lastly, we conduct a more granular analysis by exploring the ESG score interpretability of a company cluster. Coherently with the example company, we select Asian companies encompassing five Chinese companies (e.g., Alibaba), five Japanese companies (e.g., Sony), Aramco (Saudi Arabia) and Greely Automobile (Hong Kong). The `Incorporation`

`Year` strongly affects their ESG scores, with an average SHAP value of 2.7, in line with the global interpretation. All companies established in the 20th century, such as Toshiba (1904, score of 93.6), Toyota (1937, score of 84.5) and Geely (1946, score of 75.4), exhibit ESG scores above 66. Whereas those established in this century have all lower scores such as Baidu (2000, score of 53.5), China Evergrande (2006, score of 52.8) and Aramco (2018, score of 42.9). From the geographical point of view, being a Chinese company (`COUNTRY:China`) hurts ESG scores with an average SHAP value of 0.6. This is further emphasised by the observation that all the Chinese companies consistently have ESG scores below 62.5, whereas both Hong Kong-based and Japanese companies consistently display higher scores. Furthermore, this analysis confirms that disclosing several actions related to `Human Rights` (e.g., Toshiba and Tokyo Gas) and `Waste` (e.g., Toyota and Sony) positively impact ESG scores, whereas their lack hurts (e.g., Baidu and Daikin Industries). The ESG scores group by region, a details list of the considered Asian companies and the bee-swarm graph of the latter analysis are reported in the Supplementary Material (see Sections SM16, SM17 and SM18).

5 Discussion

Now, we address the practical implications of our findings (Section 5.1) as well as the methodological implications of our proposed approach (Section 5.2). Lastly, we discuss some potential limitations of our work in Section 5.3.

5.1 Practical implications

As highlighted in Section 4.1 and 4.2, companies address ESG-related issues from many perspectives, ranging from recognition and commitments to developments, partnerships and compliance. This foregrounds the complexity and joint efforts needed to address ESG-related aspects and the involved external subjects such as regulatory agencies. Our analysis unveils that, the same action is disclosed, on average, by only 2% of the companies, and by only 15% of all the company sectors, confirming a lack of a common approach across companies and different sectors. However, some ESG aspects are addressed through a common strategy by the majority of the companies such as reducing air emissions and energy as well as donating and advisory support concerning philanthropic aspects.

Concerning the topics disclosed, our methodology extracts more than five hundred ESG-related issues from companies' sustainability reports, representing an eight-times greater set of issues originally included in the ESG taxonomy used in this work (section 3.1.2). Firstly, this unveils the broad scope of the ESG phenomenon involving socially responsible issues ranging from waste management and supply chain to employee safety and tax compliance. Secondly, this highlights the presence of widely disclosed issues, such as supply chain, and sector-focused issues such as packaging and water for the consumer defensive sector. The diversity analysis reported in Section 4.2 confirms this sector-based importance for certain topics. For instance, water-related issues are more stressed by water-intensive companies, while the packaging-related aspects are more emphasised by companies producing consumer staples. These analyses confirm the difficulty of defining, framing, and standardising ESG reporting [61] and comparing companies' ESG-related disclosures.

The findings reported in Section 4.3 emphasise company similarities based on their sectors, confirming indirectly a relatively high presence of common strategies among companies from the same sector. However, the most impacting factor in grouping companies based on their disclosures is their geographical region as shown in Section 4.3 and Section 4.4. This represents an interesting finding of our work emphasising the external pressures on companies to operate in a free market economy considering also their social responsibility, and thus, to be accountable for non-financial aspects too. This spotlights the influence of the company's origins in terms of regulatory compliance and cultural factors, although businesses nowadays operate in a global market. European, American and Asian companies might prioritise socially responsible efforts, investments and disclosures based on the demands coming from their own region. For instance, European companies' climate-related efforts could be driven by more stringent and pioneering climate regulations in Europe, such as the European Union's Emissions Trading System [105] or the ambitious "Fit for 55" plan [106] recently proposed by the European Union to make this region climate-neutral by 2050. This may also be confirmed by averaging the environmental pillar scores by region: European companies have

an average score of 81.8, Asian companies have an average score of 69 and American companies exhibit the lowest average score of 65.6 (see Section SM16 in the Supplementary Material document).

The bivariate correlation analysis reported in Section 4.4 shows that similarities in ESG scores are neither associated with similarities in disclosed actions nor other financial or company characteristics, representing a noteworthy finding of our work. It however unveils strong monotonic correlations between similarities in the company region and country (median correlation of 0.7) as well as between the ESG score and the social (0.5) and environmental pillar score (0.4). These two appear fairly trivial associations: first, the ESG score is a weighted score combining the scores of the three E/S/G pillars (Section 3.1.3); second, the region and country have a natural geographical relation. However, the monotonic associations of ESG scores could be exploited to roughly infer the average influence, and thus the importance, of the E/S/G pillar scores towards the combined score. For instance, a weak or zero monotonic correlation suggests that (dis)similarities among scores of one specific pillar are not associated with (dis)similarities in the combined score. This could imply a particular pillar holds relatively less importance, or weight, in determining the combined ESG scores. Conversely, when a significant pillar is present, its (dis)similarities reflect the (dis)similarities of the combined ESG scores. Hence, based on the monotonic associations of ESG scores, it could be inferred that, on average, the social pillar (0.5) holds slightly greater importance compared to the environmental pillar (0.4). In contrast, corporate governance bears minimal importance in ESG scores (0.2).

The interpretability analysis of ESG scores reported in Section 4.5 highlights that the company's disclosures impact ESG scores more than other financial aspects or company characteristics. Disclosing plenty of non-financial information (category entropy) positively affects ESG scores, whereas fewer disclosures hurt scores. Thus, transparency rewards. This analysis also confirms the negligible impact of governance-related issues towards ESG scores in comparison to social- and environmental-related issues such as human rights, energy and waste. Other noteworthy findings of this analysis are that being a European company and being established earlier as well as having high liabilities have a slight, yet positive, impact on ESG scores, while high annual earnings (EBITDA) slightly hurt scores. The positive influence of being European can also be confirmed by grouping ESG scores by company region: the twenty-six companies from Europe exhibit the highest average ESG score equal to 82, the forty-nine American companies have an average ESG score of 69.7, whereas the average ESG score of the twelve Asian companies is equal to 67 (see Section SM16 in the Supplementary Material document). Moreover, the region-based interpretability analysis of ESG scores (Section 4.5) spotlights that being a Chinese company hurts ESG scores. This effect might be explained by low Chinese standards concerning ESG-related issues as well as the fact that all the considered Chinese companies were established between 1999 and 2006, likely due to its remarkable economic development starting in the 2000s, and thus associated with the negative impact of being relatively young companies (Incorporation Year). The negative impact of disclosing more actions related to employee development or energy is still unknown and further analyses might better investigate it. One hypothesis is that their high presence might unveil a lack of other important ESG-related issues. For instance, in the example of the local interpretation of Sony's ESG score, a low disclosing percentage of energy-related actions and a high disclosing percentage of waste-related actions positively impact its score.

5.2   Methodological implications

As mentioned in Section 3.3, generative LLMs provide us with the semantic understanding and flexibility needed to overcome the limitation of traditional OIE approaches which rely only on the syntactical sentence structure. This allows us to generate semantically-aware and ESG-focused triples instead of traditional SPO ones. This is pivotal in generating all the meaningful insights of our work.

In addition, the flexibility and generative abilities of these language models allow us to highlight, and overcome some limitations in the data sources such as those of the ESG taxonomy. This taxonomy extrapolates a concise set of ESG topics by categorising several ESG-related indicators shared among ESG rating providers (Section 3.1.2). However, defining the scope of the ESG phenomenon from the perspective of rating agencies might result in a biased or incomplete set of ESG-related issues. Indeed, our LLM-based methodology extracts, as mentioned earlier, an eight-times greater set of ESG categories than those included in this taxonomy. For instance, our methodology unveils Education as a pivotal ESG-related issue disclosed by more

than two-thirds of the selected companies. Education is not explicitly included in the taxonomy, although it could be framed within three taxonomy categories: Access to Basic Services, Human rights (Art. 26) or Philanthropy. Additional examples include Circular Economy which might fall under the taxonomy categories of Waste or Resource Efficiency as well as Air Quality which could be framed within Green Buildings or Health and Safety.

Accordingly, the aforementioned ESG taxonomy encompasses critical issues hidden within vague categories or potentially overlooks them altogether, resulting in a reduction of substantial significance in subsequent analyses. This drawback is overcome by our methodology that exploits generative language models and in-context learning to jointly emulate the output of a supervised text classifier, whose labels are the ESG categories, and generalise those labels semantically. This helps us to extract more suitable topics while keeping the domain and semantics of the original ESG taxonomy. This generative-based and semantically-aware classification can also be leveraged in several NLP-related scenarios to enhance, using a bottom-up approach, the limited set of known labels. Nevertheless, this could also lead to the undesirable phenomenon of over-specialization which was tackled using semantic clustering (Section 3.4).

Lastly, our methodology differs from other recent ESG-focused and LLM-based tools (Section 2) such as ChatClimate [55] and ChatReport [57] by employing the paradigm of Retrieval-Augmented Generation (RAG), alongside in-context learning, for Knowledge Graph generation. This methodology, in combination with bipartite graph representation, allows us to report meaningful insights concerning the actions disclosed in companies' sustainability reports. In comparison, ChatClimate adopts the RAG paradigm to augment ESG-related questions for question-answering, whereas ChatReport leverages this paradigm to operationalise the compliance assessment of sustainability reports towards the recommendation guidelines of the Task Force on Climate-related Financial Disclosures (TFCFD).

5.3 Limitations

Our data preparation NLP pipeline relies on a PDF parser [68] to extract texts from sustainability reports. This parser extracts all texts including those from infographics and tables. This might yield some sentences without a proper syntactic structure, making extracting semantic meaning from them difficult or even impossible. Table 2 in Section 3.2.2 exhibits an example of this issue in the first sentence retrieved for the waste category. The sentence contains some details about the ESG-related issue, but it lacks a coherent message.

However, the semantic understanding of LLMs in combination with the in-context learning technique and the paradigm of RAG could implicitly address this issue. Indeed, the sentence coverage of our retrieval-augmented triple generation (Section 3.3) is equal to 68.1 %, meaning that the language model acts as an implicit filtering layer and avoids generating triples for just about 30% of all the processed input sentences. The aforementioned example is within this set of ignored sentences. Although an end-to-end approach might be desired, discarding such meaningless sentences beforehand could help avoid an unnecessary computational workload. For instance, future works could tackle this issue by enhancing document parsing (e.g., by preserving the original layout) or adding a further, yet lightweight, filtering component. The latter might filter sentences according to their syntactical correctness or meaningfulness.

Another potential limitation concerns the interpretability of ESG scores using SHAP values. The SHAP framework is used to roughly interpret the impact of predictors on individual predictions. Global interpretability is derived using simple aggregating statistics such as mean/median SHAP values. Nevertheless, this aggregating approach for global interpretability might result in a mixed global interpretation in the presence of high diversity in the observations as can be a set of companies from worldwide nations covering eleven distinct sectors. The global impact of some predictors could still be accurate, yet some might be a mix of sector-dependent relationships or caused by the diversity of cause-effect connections. Indeed, the region-based interpretability analysis (Section 4.5) unveils more impacting factors or relationships for a specific company cluster in comparison to the global interpretability (Section 5.1). However, future works might conduct a further subset-based interpretability analysis by adopting a bottom-up approach and letting company groups emerge by themselves.

Lastly, the data provider for ESG scores used for our work might be a limitation worth highlighting. We rely on the ESG scores from the Refinitiv platform (Section 3.1.3), but, as highlighted in the Introduction Section,

rating agencies have their assessment methodologies which could result in divergences in companies' ESG scores. Consequently, the findings relying on ESG scores (Section 4.4 and 4.5) might vary using ESG scores from other rating agencies such as Sustainalytics which adopts a risk-based assessment [107]. In addition, future works could integrate further ESG-related attributes from these rating agencies such as quantifying companies' water withdrawal, hazardous waste, gender pay gap and employee turnover.

6 Conclusions

LLMs can be versatile tools to accomplish diverse NLP-related tasks such as extracting structured information from textual data. We further explored this promising research direction by adopting in-context learning and RAG to extract ESG-related information as semantically structured triples. We then adopted a graph representation to extract non-trivial statistics and conduct meaningful analyses concerning companies' disclosed actions. We employed a pre-trained language model from the open-source community, distinguishing us from other recent publications as far as we know. Furthermore, our LLM-based methodology overcomes important limitations related to traditional OIE techniques and the ESG taxonomy, allowing us to generate both semantically-aware and ESG-focused triples instead of traditional subject-predicate-object triples. This helped us to yield meaningful findings such as statistical, similarity and correlation analyses on the ESG-related topics and actions extrapolated from companies' sustainability reports as well as conduct an interpretability analysis of ESG scores. Future works might integrate further data sources, such as ESG-related news, to analyse possible inconsistencies in companies' claims and actions. Another interesting research direction might be to integrate Semantic Role Labelling (SRL) to enhance the extracted structured information with semantic roles, such as the agent, manner, and purpose of an action, as well as other contextual information, such as time and location.

List of Abbreviations

EBITDA: Earnings Before Interest, Taxes, Depreciation, and Amortization
ESG: Environmental, Social, and Corporate Governance
KG: Knowledge Graph
LASSO: Least Absolute Shrinkage and Selection Operator
LLM(s): Large Language Model(s)
NLP: Natural Language Processing
OIE: Open Information Extraction
OLS: Ordinary Least Squares
RAG: Retrieved Augmented Generation
SDG(s): Sustainable Development Goal(s)
SHAP: SHapley Additive exPlanations
SM: Supplementary Material
SPO: Subject-Predicate-Object

Declarations

Supplementary Material

Further tabular and graphical views are exhibited in the Supplementary Material (SM) document.

Availability of data and materials

The sustainability reports used, processed and analysed during the current study can be publicly retrieved from the following websites: sasb.org [62] and responsibilityreports.com [63]. The complete list of the companies we considered can be found in Section SM21 of the supplementary material document. The ESG taxonomy adopted during the current study was extrapolated from Table IV (4) of the work [9] by Berg *et al.*.

It is also exhibited in Section SM19 of the supplementary material document. The ESG scores and other financial information used in this study are available from the Refinitiv platform, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. All the datasets used, processed and analysed and the extracted companies triples can be found at: github.com/saturnMars/derivingStructuredInsightsFromSustainabilityReportsViaLargeLanguageModels. Further data and findings are available from the corresponding author upon reasonable request.

Author's contributions

MB collected, prepared and processed the data, implemented the proposed approach, wrote the paper and interpreted the findings. MB, CN and JS conceptualised and designed the proposed approach. CN, JS, BL and AP supervised the research direction of this study. CN, JS and BL supervised the writing process. All authors read and approved the final manuscript.

References

[1] United Nations. The Sustainable Development Agenda. `https://www.un.org/sustainabledevelopment/development-agenda`. [Accessed 22-09-2023].

[2] European Union. Non-financial reporting directive (nfrd).

[3] European Union. Corporate sustainability reporting directive (csrd).

[4] European Union. Corporate sustainability reporting.

[5] Christina Wong and Erika Petroy. Rate the Raters 2020: Investor survey and interview results. Survey report, SustainAbility Institute by ERM, 2020.

[6] Aaron K Chatterji, Rodolphe Durand, David I Levine, and Samuel Touboul. Do ratings of firms converge? implications for managers, investors and strategy researchers. *Strategic Management Journal*, 37(8):1597–1614, 2016.

[7] Subhash Abhayawansa and Shailesh Tyagi. Sustainable investing: The black box of environmental, social, and governance (esg) ratings. *The Journal of Wealth Management*, 2021.

[8] Monica Billio, Michele Costola, Iva Hristova, Carmelo Latino, and Loriana Pelizzon. Inside the esg ratings:(dis) agreement and performance. *Corporate Social Responsibility and Environmental Management*, 28(5):1426–1445, 2021.

[9] Florian Berg, Julian F Koelbel, and Roberto Rigobon. Aggregate confusion: The divergence of esg ratings. *Review of Finance*, 26(6):1315–1344, 2022.

[10] Torsten Ehlers, Ulrike Elsenhuber, Kumar Jegarasasingam, and Eric Jondeau. Deconstructing esg scores: How to invest with your own criteria? *IMF Working Papers*, 2023(057):A001, 2023.

[11] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.

[12] Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. Finetuned language models are zero-shot learners. *arXiv preprint arXiv:2109.01652*, 2021.

[13] Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, Ed H. Chi, Tatsunori Hashimoto, Oriol Vinyals, Percy Liang, Jeff Dean, and William Fedus. Emergent abilities of large language models, 2022.

[14] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems*, 33:9459–9474, 2020.

[15] Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. Large language models are zero-shot reasoners. *Advances in neural information processing systems*, 35:22199–22213, 2022.

[16] Sean Trott, Cameron Jones, Tyler Chang, James Michaelov, and Benjamin Bergen. Do large language models know what humans know? *Cognitive Science*, 47(7):e13309, 2023.

[17] Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. A survey of large language models. *arXiv preprint arXiv:2303.18223*, 2023.

[18] Laria Reynolds and Kyle McDonell. Prompt programming for large language models: Beyond the few-shot paradigm. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*, pages 1–7, 2021.

[19] Yufei Wang, Wanjun Zhong, Liangyou Li, Fei Mi, Xingshan Zeng, Wenyong Huang, Lifeng Shang, Xin Jiang, and Qun Liu. Aligning large language models with human: A survey, 2023.

[20] Can Xu, Qingfeng Sun, Kai Zheng, Xiubo Geng, Pu Zhao, Jiazhan Feng, Chongyang Tao, and Daxin Jiang. Wizardlm: Empowering large language models to follow complex instructions, 2023.

[21] Shengyu Zhang, Linfeng Dong, Xiaoya Li, Sen Zhang, Xiaofei Sun, Shuhe Wang, Jiwei Li, Runyi Hu, Tianwei Zhang, Fei Wu, et al. Instruction tuning for large language models: A survey. *arXiv preprint arXiv:2308.10792*, 2023.

[22] Qingxiu Dong, Lei Li, Damai Dai, Ce Zheng, Zhiyong Wu, Baobao Chang, Xu Sun, Jingjing Xu, Lei Li, and Zhifang Sui. A survey on in-context learning, 2023.

[23] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models, 2023.

[24] Ridho Reinanda, Edgar Meij, Maarten de Rijke, et al. Knowledge graphs: An information retrieval perspective. *Foundations and Trends® in Information Retrieval*, 14(4):289–444, 2020.

[25] Dieter Fensel, Umutcan Şimşek, Kevin Angele, Elwin Huaman, Elias Kärle, Oleksandra Panasiuk, Ioan Toma, Jürgen Umbrich, Alexander Wahler, Dieter Fensel, et al. Introduction: what is a knowledge graph? *Knowledge graphs: Methodology, tools and selected use cases*, pages 1–10, 2020.

[26] Aidan Hogan, Eva Blomqvist, Michael Cochez, Claudia d'Amato, Gerard De Melo, Claudio Gutierrez, Sabrina Kirrane, José Emilio Labra Gayo, Roberto Navigli, Sebastian Neumaier, et al. Knowledge graphs. *ACM Computing Surveys (Csur)*, 54(4):1–37, 2021.

[27] Michael Färber, Frederic Bartscherer, Carsten Menne, and Achim Rettinger. Linked data quality of dbpedia, freebase, opencyc, wikidata, and yago. *Semantic Web*, 9(1):77–129, 2018.

[28] Salvatore Carta, Alessandro Giuliani, Leonardo Piano, Alessandro Sebastian Podda, Livio Pompianu, and Sandro Gabriele Tiddia. Iterative zero-shot llm prompting for knowledge graph construction, 2023.

[29] Lars-Peter Meyer, Claus Stadler, Johannes Frey, Norman Radtke, Kurt Junghanns, Roy Meissner, Gordian Dziwis, Kirill Bulert, and Michael Martin. Llm-assisted knowledge graph engineering: Experiments with chatgpt. *arXiv preprint arXiv:2307.06917*, 2023.

[30] Milena Trajanoska, Riste Stojanov, and Dimitar Trajanov. Enhancing knowledge graph construction using large language models, 2023.

[31] Yuqi Zhu, Xiaohan Wang, Jing Chen, Shuofei Qiao, Yixin Ou, Yunzhi Yao, Shumin Deng, Huajun Chen, and Ningyu Zhang. Llms for knowledge graph construction and reasoning: Recent capabilities and future opportunities, 2023.

[32] Armen S Asratian, Tristan MJ Denley, and Roland Häggkvist. *Bipartite graphs and their applications*, volume 131. Cambridge university press, 1998.

[33] Jean-Loup Guillaume and Matthieu Latapy. Bipartite graphs as models of complex networks. *Physica A: Statistical Mechanics and its Applications*, 371(2):795–813, 2006.

[34] Xiaohan Zou. A survey on application of knowledge graph. In *Journal of Physics: Conference Series*, volume 1487, page 012016. IOP Publishing, 2020.

[35] Shaoxiong Ji, Shirui Pan, Erik Cambria, Pekka Marttinen, and S Yu Philip. A survey on knowledge graphs: Representation, acquisition, and applications. *IEEE transactions on neural networks and learning systems*, 33(2):494–514, 2021.

[36] Zhen Jia, Soumajit Pramanik, Rishiraj Saha Roy, and Gerhard Weikum. Complex temporal question answering on knowledge graphs. In *Proceedings of the 30th ACM international conference on information & knowledge management*, pages 792–802, 2021.

[37] Bilin Shao, Xiaojun Li, and Genqing Bian. A survey of research hotspots and frontier trends of recommendation systems from the perspective of knowledge graph. *Expert Systems with Applications*, 165:113764, 2021.

[38] Dieter Fensel, U Simsek, Kevin Angele, Elwin Huaman, Elias Kärle, Oleksandra Panasiuk, Ioan Toma, Jürgen Umbrich, and Alexander Wahler. *Knowledge graphs*. Springer, 2020.

[39] Jihong Yan, Chengyu Wang, Wenliang Cheng, Ming Gao, and Aoying Zhou. A retrospective of knowledge graphs. *Frontiers of Computer Science*, 12:55–74, 2018.

[40] Arzoo Katiyar and Claire Cardie. Going out on a limb: Joint extraction of entity mentions and relations without dependency trees. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 917–928, 2017.

[41] Yucheng Wang, Bowen Yu, Yueyang Zhang, Tingwen Liu, Hongsong Zhu, and Limin Sun. Tplinker: Single-stage joint extraction of entities and relations through token pair linking. *arXiv preprint arXiv:2010.13415*, 2020.

[42] Christina Niklaus, Matthias Cetto, André Freitas, and Siegfried Handschuh. A survey on open information extraction. *arXiv preprint arXiv:1806.05599*, 2018.

[43] Youngbin Ro, Yukyung Lee, and Pilsung Kang. Multi^2OIE: Multilingual open information extraction based on multi-head attention with BERT. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1107–1117, Online, November 2020. Association for Computational Linguistics.

[44] Chenguang Wang, Xiao Liu, Zui Chen, Haoyun Hong, Jie Tang, and Dawn Song. Zero-shot information extraction as a unified text-to-triple translation. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 1225–1238, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics.

[45] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

[46] Pai Liu, Wenyang Gao, Wenjie Dong, Songfang Huang, and Yue Zhang. Open information extraction from 2007 to 2022 – a survey, 2022.

[47] Shirui Pan, Linhao Luo, Yufei Wang, Chen Chen, Jiapu Wang, and Xindong Wu. Unifying large language models and knowledge graphs: A roadmap. *arXiv preprint arXiv:2306.08302*, 2023.

[48] Jiao Chen, Luyi Ma, Xiaohan Li, Nikhil Thakurdesai, Jianpeng Xu, Jason H. D. Cho, Kaushiki Nag, Evren Korpeoglu, Sushant Kumar, and Kannan Achan. Knowledge graph completion models are few-shot learners: An empirical study of relation labeling in e-commerce with llms, 2023.

[49] Agnes Axelsson and Gabriel Skantze. Using large language models for zero-shot natural language generation from knowledge graphs, 2023.

[50] Christine Chou, Robin Clark, and Steven O Kimbrough. What do firms say in reporting on impacts of climate change? an approach to monitoring esg actions and environmental policy. *Corporate Social Responsibility and Environmental Management*, 2023.

[51] Viju Raghupathi, Jie Ren, and Wullianallur Raghupathi. Identifying corporate sustainability issues by analyzing shareholder resolutions: A machine-learning text analytics approach. *Sustainability*, 12(11):4753, 2020.

[52] Régis MARODON, Jean-Baptiste Jacouton, and Adeline LAULANIE. The Proof is in the Pudding. Revealing the SDGs with Artificial Intelligence. Working Paper 85f81dba-c8e2-4255-878a-0, Agence française de développement, October 2022.

[53] SDG Prospector - artificial intelligence serving the sdgs. `https://www.sdgprospector.org`. [Accessed 22-09-2023].

[54] Nicolas Webersinke, Mathias Kraus, Julia Anna Bingler, and Markus Leippold. Climatebert: A pre-trained language model for climate-related text. *arXiv preprint arXiv:2110.12010*, 2021.

[55] Saeid Ashraf Vaghefi, Qian Wang, Veruska Muccione, Jingwei Ni, Mathias Kraus, Julia Bingler, Tobias Schimanski, Chiara Colesanti-Senni, Dominik Stammbach, Nicolas Webersinke, et al. Chatclimate: Grounding conversational ai in climate science. 2023.

[56] ChatClimate grounded on the latest ipcc report. `https://www.chatclimate.ai`. [Accessed 22-09-2023].

[57] Jingwei Ni, Julia Bingler, Chiara Colesanti-Senni, Mathias Kraus, Glen Gostlow, Tobias Schimanski, Dominik Stammbach, Saeid Ashraf Vaghefi, Qian Wang, Nicolas Webersinke, et al. Paradigm shift in sustainability disclosure analysis: Empowering stakeholders with chatreport, a language model-based tool. *arXiv preprint arXiv:2306.15518*, 2023.

[58] TCFD. Recommendations of the task force on climate-related financial disclosures, 2017.

[59] Timothy M Doyle. Ratings that don't rate: the subjective world of esg ratings agencies. *American Council for Capital Formation*, pages 65–71, 2018.

[60] OECD. *OECD Business and Finance Outlook 2020: Sustainable and Resilient Finance*. Number 6th (2020) in OECD Business and Finance Outlook. OECD, Paris, 2020.

[61] Elmira Aliakbari and Steven Globerman. The impracticality of standardizing esg reporting (esg: Myths and realities). 2023.

[62] SSAB. Sasb reporters.

[63] IR Solutions. Responsibilityreports.

[64] Hugging Face. Statistics on the number of monolingual models by language hosted on the hugging face platform.

[65] Refinitiv. Environmental, social and governance (esg) scores from refinitiv - may 2022.

[66] Özge Sahin, Karoline Bax, Claudia Czado, and Sandra Paterlini. Environmental, social, governance scores and the missing pillar—why does missing information matter? *Corporate Social Responsibility and Environmental Management*, 29(5):1782–1798, 2022.

[67] Eco-Business. Sustainability reporting: 4 things companies get wrong.

[68] Artifex. PyMuPDF — pypi.org. `https://pypi.org/project/PyMuPDF`. [Accessed 22-09-2023].

[69] Nipun Sadvilkar and Mark Neumann. PySBD: Pragmatic sentence boundary disambiguation. In *Proceedings of Second Workshop for NLP Open Source Software (NLP-OSS)*, pages 110–114, Online, 11 2020. Association for Computational Linguistics.

[70] Nipun Sadvilkar. PySBD — pypi.org. `pypi.org/project/pysbd`. [Accessed 22-09-2023].

[71] W Bruce Croft, Donald Metzler, and Trevor Strohman. *Search engines: Information retrieval in practice*, volume 520. Addison-Wesley Reading, 2010.

[72] Hannah Bast, Björn Buchhold, and Elmar Haussmann. Semantic search on text and knowledge bases. *Foundations and Trends® in Information Retrieval*, 10(2-3):119–271, 2016.

[73] Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084*, 2019.

[74] Niklas Muennighoff. Sgpt: Gpt sentence embeddings for semantic search, 2022.

[75] Jiafeng Guo, Yinqiong Cai, Yixing Fan, Fei Sun, Ruqing Zhang, and Xueqi Cheng. Semantic models for the first-stage retrieval: A comprehensive review. *ACM Transactions on Information Systems (TOIS)*, 40(4):1–42, 2022.

[76] Stefan Buttcher, Charles LA Clarke, and Gordon V Cormack. *Information retrieval: Implementing and evaluating search engines*. Mit Press, 2016.

[77] Hamid Palangi, Li Deng, Yelong Shen, Jianfeng Gao, Xiaodong He, Jianshu Chen, Xinying Song, and Rabab Ward. Deep sentence embedding using long short-term memory networks: Analysis and application to information retrieval. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 24(4):694–707, 2016.

[78] Wei Yang, Haotian Zhang, and Jimmy Lin. Simple applications of bert for ad hoc document retrieval. *arXiv preprint arXiv:1903.10972*, 2019.

[79] NLP Group of The University of Hong Kong. Instructor-xl · Hugging Face — huggingface.co. `https://huggingface.co/hkunlp/instructor-xl`. [Accessed 25-09-2023].

[80] Hongjin Su, Jungo Kasai, Yizhong Wang, Yushi Hu, Mari Ostendorf, Wen-tau Yih, Noah A Smith, Luke Zettlemoyer, Tao Yu, et al. One embedder, any task: Instruction-finetuned text embeddings. *arXiv preprint arXiv:2212.09741*, 2022.

[81] Allen Institute for AI. Open information extraction - demo.

[82] Eugene Yurtsev. Kor— pypi.org. `https://pypi.org/project/kor`. [Accessed 25-09-2023].

[83] Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416*, 2022.

[84] Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B Hashimoto. Stanford alpaca: An instruction-following llama model, 2023.

[85] Tom Jobbins. TheBloke/wizardLM-7B-HF · Hugging Face. `https://huggingface.co/TheBloke/wizardLM-7B-HF`. [Accessed 25-09-2023].

[86] Ernesto Estrada. *The Structure of Complex Networks: Theory and Applications*. Oxford University Press, 10 2011.

[87] Mark Newman. *Networks: An Introduction*. Oxford University Press, Inc., USA, 2010.

[88] Ulrik Brandes. *Network analysis: methodological foundations*, volume 3418. Springer Science & Business Media, 2005.

[89] Junlong Zhang and Yu Luo. Degree centrality, betweenness centrality, and closeness centrality in social network. In *2017 2nd international conference on modelling, simulation and applied mathematics (MSAM2017)*, pages 300–303. Atlantis press, 2017.

[90] Katherine Faust. Centrality in affiliation networks. *Social networks*, 19(2):157–191, 1997.

[91] Marc Barthelemy. Betweenness centrality in large complex networks. *The European physical journal B*, 38(2):163–168, 2004.

[92] Thomas M Cover. *Elements of information theory*. John Wiley & Sons, 1999.

[93] Luciano da F Costa. Further generalizations of the jaccard index. *arXiv preprint arXiv:2110.09619*, 2021.

[94] Gotelli, Nicholas J, and Werner Ulrich. Statistical challenges in null model analysis. *Oikos*, 121(2):171–180, 2012.

[95] Alice Zheng and Amanda Casari. *Feature engineering for machine learning: principles and techniques for data scientists*. ″ O'Reilly Media, Inc.″, 2018.

[96] Hervé Abdi. The kendall rank correlation coefficient. *Encyclopedia of Measurement and Statistics. Sage, Thousand Oaks, CA*, pages 508–510, 2007.

[97] Israel Cohen, Yiteng Huang, Jingdong Chen, Jacob Benesty, Jacob Benesty, Jingdong Chen, Yiteng Huang, and Israel Cohen. Pearson correlation coefficient. *Noise reduction in speech processing*, pages 1–4, 2009.

[98] R Lyman Ott and Micheal T Longnecker. *An introduction to statistical methods and data analysis*. Cengage Learning, 2015.

[99] Scott M Lundberg and Su-In Lee. A unified approach to interpreting model predictions. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems 30*, pages 4765–4774. Curran Associates, Inc., 2017.

[100] Norman R Draper and Harry Smith. *Applied regression analysis*, volume 326. John Wiley & Sons, 1998.

[101] Clara Dismuke and Richard Lindrooth. Ordinary least squares. *Methods and designs for outcomes research*, 93(1):93–104, 2006.

[102] Hui Zou and Trevor Hastie. Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 67(2):301–320, 2005.

[103] Trevor Hastie, Robert Tibshirani, Jerome H Friedman, and Jerome H Friedman. *The elements of statistical learning: data mining, inference, and prediction*, volume 2. Springer, 2009.

[104] Daniel Berrar. Cross-validation, 01 2018.

[105] European Union. Eu emissions trading system (eu ets).

[106] European Union. Fit for 55.

[107] Sustainalytics. Esg risk ratings – methodology abstract, version 2.1.

[108] Zihao Zhao, Eric Wallace, Shi Feng, Dan Klein, and Sameer Singh. Calibrate before use: Improving few-shot performance of language models. In *International Conference on Machine Learning*, pages 12697–12706. PMLR, 2021.

[109] Dabao Zhang. A coefficient of determination for generalized linear models. *The American Statistician*, 71(4):310–316, 2017.

[110] Cort J Willmott and Kenji Matsuura. Advantages of the mean absolute error (mae) over the root mean square error (rmse) in assessing average model performance. *Climate research*, 30(1):79–82, 2005.

[111] Sungil Kim and Heeyoung Kim. A new metric of absolute percentage error for intermittent demand forecasts. *International Journal of Forecasting*, 32(3):669–679, 2016.

[112] Lloyd S Nelson. The anderson-darling test for normality. *Journal of Quality Technology*, 30(3):298, 1998.

A   Qualitative analysis of the generated triples

Overall, the triples generated exhibit high-quality semantically structured information, for instance, triples B, C, D and F in Table 7 represent meaningful ESG-related actions.

However, there are also some unsatisfactory triples mainly due to information incompleteness. For instance, in row A the lack of a meaningful object (`obj`) in the triple results in the omission of important information related to the two mentioned categories. Similarly, the triple in row E has a partial satisfaction level since it does not entirely encompass the meaning conveyed in the original sentence, which involves the conversion of these emissions into CO_2.

	ESG category (`cat`)	**Predicate** (`pred`)	**Object** (`obj`)
A	Remuneration	Compensation	This compensation falls into two categories
B	Employee Development	Providing access to	Career development programs, ongoing inclusion and diversity education, and support throughout their career journey
C	Data Privacy	Establishment of	A corporate network security evaluation system
D	Green Buildings	Equipped with	Dematerialised management methods
E	Air Emissions	Conversion to	Emissions of PFCs and other greenhouse gases
F	Environmental	Alignment with	The SASB 2018 Real Estate Standards and the TCFD

Table 7: *Examples of the triples cat-pred-obj generated through our approach. The six triples were picked randomly from all the nearly 50 thousand generated triples.*

B Ablation study on the model instruction

Furthermore, since the model instruction has a great impact on the quality of the generated text [108], we conduct an ablation study to compare qualitatively the triples generated through different prompt templates: with(out) in-context learning (`EXAMPLES` in Figure 2) and with(out) the semantic output schema (`DATASCHEMA`).

	ESG category (`cat`)	**Predicate** (`pred`)	**Object** (`obj`)
`EXAMPLES`	Work-Life Balance	Provision of	A policy providing clarity around flexible work options
without `EXAMPLES`	Family Friendly Policies	Provides	Flexible work option
`EXAMPLES`	Health and Safety	Creation of	COVID-19 safety tips for ridesharing
without `EXAMPLES`	Public Health	Created	COVID-19 safety tips
`EXAMPLES`	Climate Risk Management	Partnership with	CoGo to provide personalised carbon footprints
without `EXAMPLES`	Climate Risk Management	Announced	Partnership

Table 8: *Three comparing examples of the triples generated with/without using in-context learning in the model instruction.*

We find that including `examples` in the prompt, and thus exploiting the in-context learning capabilities of the model, generates better triples in terms of both information completeness and semantic representation, observable respectively in the first two comparisons and the third one in Table 8. Furthermore, that helps the model compose its response by adhering to a specific output format. Indeed, although the model was already prompted to generate text as a valid JSON object, it outputs texts in a valid format only after adding in-context learning.

	ESG category (`cat`)	**Predicate** (`pred`)	**Object** (`obj`)
`DATASCHEMA`	Work-Life Balance	Provision of	A policy providing clarity around flexible work options
without `DATASCHEMA`	Work-Life Balance	Providing clarity around	Flexible work options available to parents and caregivers
`DATASCHEMA`	Philanthropy	Partnership with	The Bill and Melinda Gates Foundation and the Western Cape Department of Health
without `DATASCHEMA`	Healthcare	Delivery of	Over 1.4 million prescriptions
`DATASCHEMA`	Climate Risk Management	Partnership with	CoGo to provide personalised carbon footprints
without `DATASCHEMA`	Carbon Footprint	Partnership with	To provide personalised carbon footprints

Table 9: *Three comparing examples of triples generated with/without the semantic output data schema in the model instruction.*

Moreover, adding a semantic output schema in the prompt (`DATASCHEMA`) helps the generative language model to better focus on ESG-related information as exhibited in Table 9. The semantic schema provides the language model with detailed semantic descriptions concerning the types of information to extract: an issue related to an ESG aspect (`cat`), a nominalised verb affecting that aspect (`pred`), and an entity undergoing the predicate (`obj`). This could drastically change the extracted information, especially in sentences with multiple prepositions, such as in the second comparison shown in Table 9. Furthermore, defining a semantic schema allows us to incorporate the ESG taxonomy (Section 3.1.2) into the semantic description of the item `cat`. This enhanced the model's ability to extract an ESG-related issue from a sentence (`cat`) by emulating a supervised text classifier using the ESG taxonomy categories as semantic labels while leveraging its generative capabilities. An example of this enhancement can be observed in the third comparison in Table 9, while the complete semantic schema can be seen in the Supplementary Material document within the full model instruction (see Section SM2).

C Performance of the OLS model

We here report the performance of the OLS regression through different metrics (see also Section SM13 in the Supplementary Material document). Firstly, the Coefficient of Determination (R^2, [109]) measures the proportion of variation in the dependent variable explained by the model predictors, representing the goodness of the inference ability of the model. Low coefficients express a little variation proportion explained by the model predictors, resulting in poor performance on the inference of the dependent variable (ESG scores). In contrast, in the presence of a high variation proportion explained, the model predicts the dependent variable with small errors. Our OLS model achieves a R^2 of 0.71 using the optimal alpha, demonstrating a broad variation explained by our features to infer ESG scores. On the other hand, the Root Mean Square Error (RMSE, [110]) is a quadratic score, in the same units of the dependent variable, in which the average error in the model predictions is computed by averaging the squared individual errors. Our regression model achieves an RMSE equal to 7.76, representing the average difference between the actual ESG score and the inferred one. Lastly, we report the model performance (7.9 %) using the Weighted Mean Absolute Percentage Error (wMAPE, [111, 103]), a scale-independent score that measures the average of absolute percentage errors.

To conclude the review of the regression model performance, we conduct a residual analysis to check the linear assumptions required to properly shape the problem as a linear model. The assumption of normal distribution of the residuals ($E_i \sim N(0, \sigma^2)$) is confirmed by the Anderson-Darling test [112] with a p-value equal to 6.6 % as well as through the QQ plot of residuals versus Normal distribution showing points lie on a line. Concerning homoscedasticity, a condition in which the residual variance is constant across all the model predictions, there are no visible patterns in the scatter plot of residuals versus predicted ESG scores. The same condition is confirmed by the scatter plot of the predicted ESG scores versus the actual scores. However, a slight overestimation trend might be spotted for ESG scores below 50, showing a limit of our predictors for interpreting these low scores. A graphical panel with all the graphical residual analyses is shown in the Supplementary Material document (see Section SM15).