ESGSenticNet: A Neurosymbolic Knowledge Base for Corporate Sustainability Analysis

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Abstract

Evaluating corporate sustainability performance is essential to drive sustainable business practices, amid the need for a more sustainable economy. However, this is hindered by the complexity and volume of corporate sustainability data (i.e. sustainability disclosures), not least by the effectiveness of the NLP tools used to analyse them. To this end, we identify three primary challenges – *immateriality, complexity,* and *subjectivity*, that exacerbate the difficulty of extracting insights from sustainability disclosures. To address these issues, we introduce ESGSenticNet, a publicly available knowledge base for sustainability analysis. ESGSenticNet is constructed from a neurosymbolic framework that integrates specialised concept parsing, GPT-4o inference, and semi-supervised label propagation, together with a hierarchical taxonomy. This approach culminates in a structured knowledge base of 44k knowledge triplets – *('halve carbon emission', supports, 'emissions control')*, for effective sustainability analysis. Experiments indicate

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that ESGSenticNet, when deployed as a lexical method, more effectively captures relevant and actionable sustainability information from sustainability disclosures compared to state of the art baselines. Besides capturing a high number of unique ESG topic terms, ESGSenticNet outperforms baselines on the ESG relatedness and ESG action orientation of these terms by 26% and 31% respectively. These metrics describe the extent to which topic terms are related to ESG, and depict an action toward ESG. Moreover, when deployed as a lexical method, ESGSenticNet does not require any training, possessing a key advantage in its simplicity for non-technical stakeholders.

Keywords: Generative AI, Large Language Models, Knowledge Base, Lexicons, Corporate Sustainability Analysis

1. Introduction

With growing concerns over social inequality and global warming, it is imperative to ensure the sustainability of public companies [13]. To this end, accurate insights into the sustainability efforts of corporations are crucial to drive responsible business practices [40]. However, the complexity and volume of corporate sustainability data [38], often disclosed through sustainability reports (i.e. sustainability disclosures), can make these insights inaccessible without specialised tools.

While NLP tools can unlock insights from this vast array of corporate sustainability data, their deployment remains nascent within this field, often lacking the specialised design needed for corporate sustainability analysis. Specifically, they do not address the challenges of *immateriality, complexity* and *subjectivity*, which are frequently associated with sustainability data [41].

- **Immateriality**: Sustainability disclosures are lengthy, containing significant amounts of irrelevant content for sustainability analysis [51, 28]. Key or *material* information for stakeholders can often be obfuscated [49], making their extraction via NLP tools challenging.

- **Complexity**: Sustainability ideas are sophisticated, and are typically expressed by complex syntactic constructions [50]. The distinctiveness in sustainability language necessitates that NLP tools must encompass more than just general language understanding capabilities.

- **Subjectivity**: Stakeholders are interested in diverse sustainability areas, and utilise different frameworks and methods for sustainability analysis [39, 46].

Therefore, designing an NLP tool that comprehensively meets the needs of different stakeholders is challenging.

As a result, NLP algorithms, including the state of the art, are largely ineffective at extracting useful corporate sustainability insights. In our experiments later in this paper (section 6.3), we validate this ineffectiveness by benchmarking these algorithms in the sustainability topic analysis task.

In response to these limitations, we develop ESGSenticNet, a publicly available knowledge base that comprises 44k sustainability knowledge triplets from 23k unique concepts, specifically designed to mine insights from sustainability disclosures. To address the aforementioned issues of *complexity, immateriality* and *subjectivity*, ESGSenticNet is constructed from a neurosymbolic framework that blends symbolic linguistics rules with sub-symbolic reasoning through deep learning. The symbolic component of this framework involves specialised concept parsing that leverages predefined linguistic patterns and rules within the sustainability domain to identify meaningful concepts within sustainability text, addressing the *complexity* of sustainability language. Additionally, these rules focus on the most pertinent linguistic structures in sustainability, enabling the identification of key sustainability information such as sustainability efforts and actions to reduce *immateriality* [7]. Building on the structured outputs of the symbolic component, the subsymbolic component integrates GPT-4o inference with semi-supervised label propagation to classify the relation between the parsed concepts and their respective sustainability categories. By interpreting nuanced language variations and contextual subtleties that symbolic rules cannot fully capture, this component ensures that concepts are organised according to key sustainability categories, further enhancing their *materiality*. Additionally, these categories within ESGSenticNet are arranged according to a hierarchical and comprehensive taxonomy, addressing *subjectivity* by allowing concepts to be leveraged at different levels of granularity, tailored to the specific interest of stakeholders. The result is an extensive knowledge base, ESGSenticNet, that comprises actionable information in the form of knowledge triplets. These triplets highlight concepts and their relation toward sustainability themes, such as ('minimise paper waste' *(concept)*, supports *(relation)*, 'waste management' *(category)*).

We evaluate ESGSenticNet's ability to extract meaningful insights from sustainability disclosures, by deploying the knowledge base as a structured lexicon method for sustainability topic analysis. In this task, the concepts within ESGSenticNet's knowledge triplets are matched from a large sustainability corpora. ESGSenticNet improves on established baselines significantly, more extensively capturing sustainability related information, including material content that highlight sustainability efforts. ESGSenticNet yields a significant number of ESG topic terms, outperforming existing state of the art baselines by at least 26% and 31% respectively on the *ESG relatedness* and *ESG action orientation* of these terms. This highlights demonstrates ESGSenticNet's potential to contribute meaningfully to sustainability analysis. Moreover, as a lexical method, ESGSenticNet is able to extract ESG topic terms without any training or significant technical expertise. This significantly allows it to be leveraged by stakeholders of different backgrounds.

The rest of our paper is arranged as follows. We first develop a comprehensive and hierarchical sustainability taxonomy for organising our concepts (section 4). Secondly, we delve into the extraction of concepts via ESG Concept Parser (section 5.2), processing the concepts to ensure coherence (section 5.3), as well as our methodology for classifying these concepts via GPT-4o and semi-supervised label propagation (sections 5.4, 5.5, 5.6, 5.7). Finally, we evaluate the accuracy of ESGSenticNet labels (section 5.9), before running extensive experiments to assess the effectiveness of ESGSenticNet for sustainability analysis against established baselines (section 6). The development process for ESGSenticNet is summarised by figure 1, showcasing the key steps for concept parsing and taxonomy derivation, and how they are intertwined with the labelling process (1-4).

2. Literature Review

NLP-driven Sustainability Analysis. To enhance sustainability analysis, NLP can be deployed for different tasks, such as analysing sustainability topics [65], sustainability sentiment classification [43], extracting textual patterns [8], among other tasks. The insights extracted from NLP can powerfully reduce time costs and increase the consistency of evaluation [2, 15], making NLP a useful tool for sustainability analysis. Yet, despite NLP's potential applications, it has only been explored within sustainability analysis to a limited degree, often lacking specialised design [41]. This motivates the development of specially designed NLP tools for corporate sustainability analysis.

Lexicons for Sustainability Analysis. For corporate sustainability analysis, lexical approaches have been widely leveraged for textual analysis [22], due to their simplicity and relevance to financial text analysis [53, 55]. To facilitate lexical analysis, sustainablity-specific lexicons have been developed. Approaches such as Baier's dictionary [6], have focused on developing single-word lexicons according to ESG pillars. However, while Baier's dictionary has been a popular choice for sustainability analysis works [25], single word lexicons cannot adequately capture the semantics of the sustainability field. In contrast, dictionaries that have collected sustainability related text spans (of multiple-grams) [17, 29], are limited, not publicly available, and not comprehensively labelled beyond ESG pillars. Additionally, due to their reliance on manual human-annotation, these dictionaries have an exceedingly small number of lexicons (less than 800), raising questions on their comprehensiveness, and consequently their effectiveness for capturing textual patterns. This motivates the development of an extensive knowledge base that can function as a structured dictionary of concepts, and the exploration of automated methods such as NLP for constructing and organising sustainability lexicons.

Knowledge Base Construction. Methods for constructing knowledge bases can vary according to the domain and application [26]. Notable knowledge bases, such as ConceptNet [31] involved concept parsing and human annotation, SenticNet 5 [11] leveraged deep learning and lexical substitution, question answering via advanced graphical neural networks (GNNs) [63]. Newer avenues for knowledge construction involve generative-LLMs, which have shown strong performance in related tasks such as reasoning, construction, and generalisation [67]. Unlike all the previous methods which heavily rely on semantic similarities for labelling, generative LLMs possess powerful emergent capabilities that extend beyond textual similarities [58]. These include reasoning, knowledge relationship construction, and generalisation to different domains [67]. Moreover, unlike GNNs that rely on heavily structed text data [32], generative-LLMs can flexibly adapt to unstructured text. This, coupled with added domain flexibility and inferencing capabilities on limited textual cues, motivates our use of generative-LLMs for knowledge derivation within sustainability.

3. Data

1680 sustainability disclosures from a wide range of Singapore Exchange (SGX) based companies, in the period of 2017 to 2022 inclusive, are utilised for taxonomy and knowledge base construction. These reports can be found online via respective company websites, and on request, we can provide a list of the reports utilised (i.e. the companies and year of reporting).

4. Sustainability Taxonomy

Firms may not report in accordance with existing sustainability taxonomies (i.e. GRI [33]), given that their operations are complex and may not be adequately

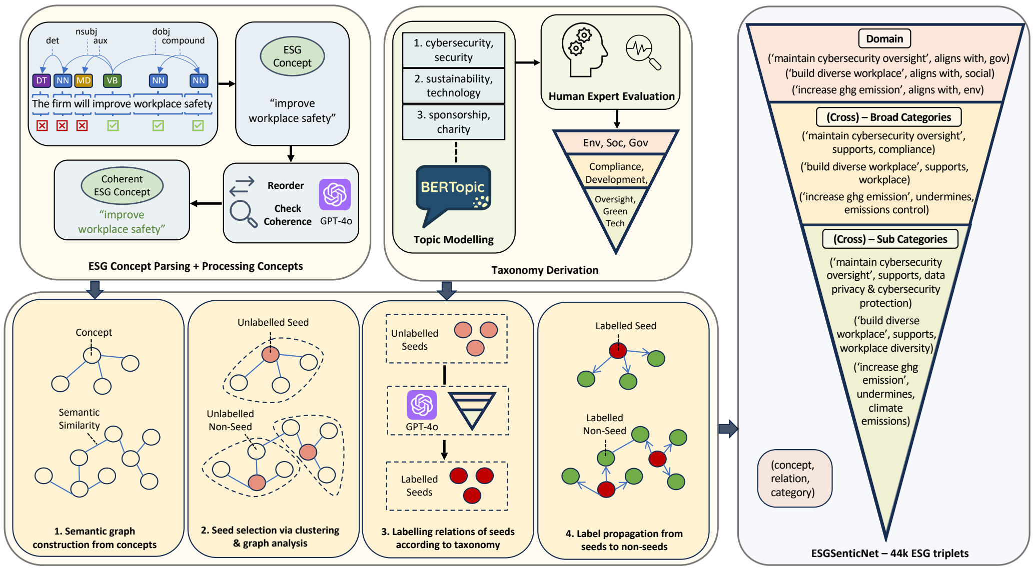

Figure 1: Overview of ESGSenticNet Development

captured by these taxonomies [41]. To further align taxonomies with sustainability report content, data-driven approaches can be utilised for taxonomy derivation [5]. Yet, empirical approaches in the literature are limited, and these methods do not involve human-in-the-loop inference to ensure the meaningfulness of constructed sustainability topics. These challenges motivate our taxonomy construction, that, while empirically driven, involves human-in-the-loop inference to ensure the relevance and meaningfulness of categories.

4.1. Methodology

Sustainability disclosures are tokenised into separate sentences, with each sentence transformed into embeddings by Sentence-BERT (S-BERT) [45]. BERTopic is then run on these embeddings, with the configuration of KeyBERT [20]. The topic words are then provided to sustainability experts (Appendix A) to facilitate their development of the taxonomy for ESGSenticNet (table 1). Examples of topic words and their inferred topics can be found in table 1. The result is a taxonomy (table 2) with the following features.

- **Realistic**: Given that taxonomy development leverages empirical insights from the sustainability reports themselves, categories can capture content within sustainability reports that might otherwise be overlooked by standard frameworks. For instance, 'Green Technology' is derived as a taxonomy category, while not being explicitly emphasised in standard reporting frameworks (i.e. GRI [33]).

- **Activities Cross-Theme**: To capture the interconnectedness of sustainability dimensions [38], categories include areas of a firm's activities ('operations', 'development' etc.), on top of sustainability impacts ('emissions control', 'waste management' etc.). In contrast with existing frameworks, this offers insight into the sustainability of specific business activities.

- **Granularity**: The taxonomy has a hierarchical nature to enable analysis at different levels of granularity.

Topic keywords	**Category**
strengths, staff, training, opportunities, employees	Workplace Development
cybersecurity, security, cybersecure, authentication	Data Privacy & Cybersecurity Protection
sustainability, technology, technological, digitalisation	Green Technology
sponsorship, sponsor, charity, scholarship	Community Empowerment

Table 1: Examples of Categories Inferred from Topic Keywords

4.2. Resultant Taxonomy

Table 2 shows the hierarchical taxonomy derived for ESGSenticNet. It contains the definitions of the pillars (Environmental, Social, Governance) and topics used in ESGSenticNet. Along with the pillars, the broad topics, and cross-broad topics are bolded, with their constituent sub-topics highlighted in bullet points. Beside the broad and cross-broad topics, a letter denotes which pillar the topic falls under – (E) Environmental, (S) Social, (G) Governance.

Category	Description
Environmental	Focuses on impact on the environment. This includes, but is not limited to, green innovation, green infrastructure, resource stewardship, energy consumption, waste management, pollution reduction, natural resource conservation, and animal welfare.
Social	Focuses on managing relationships with its employees, suppliers, customers, and the communities. This includes, but is not limited to, employee diversity, equity, working conditions, customer relations, partnerships and social engagement.
Governance	Focuses on the system of rules, practices, and processes by which a company is directed and controlled. This includes, but is not limited to, corporate oversight, corporate transparency, executive compensation, ethical behavior, and shareholder rights.

Development (E)	Drives innovation and growth in sustainability by creating new technologies or infrastructure for sustainability, or supporting these efforts through green financing.
• Green Technologies	Technological systems, products, and processes that assist in reducing environmental impact.
• Green Infrastructure	Environmentally sustainable buildings, infrastructure, energy solutions and urban systems.
• Green Financing	Financial services that support efforts aimed at environmental sustainability.
Operations (E)	Focuses on optimizing existing business activities for the sole purpose of minimizing environmental impact. This includes minimising environmental impact by enhancing current practices in corporate operations, supply chains, production processes, or land management, distinct from the development of innovative solutions and technologies.
• Sustainable Corporate Operations	Environmentally responsible practices within corporate offices. Examples include but are not limited to promoting sustainability amongst employees, eco-friendly office lighting.
• Sustainable Supply Chain	Logistics and distribution methods or practices that are environmentally responsible, ensuring sustainability in the movement and handling of goods.
• Sustainable Production Processes	Manufacturing processes or practices that are environmentally responsible.
• Sustainable Land Management	Using and managing land in a way that is environmentally responsible, conserves natural resources and protects biodiversity.
Ecological Conservation (E)	Manages the company's interaction with natural ecosystems, focusing on minimizing harmful impacts and promoting biodiversity and habitat conservation.

Emissions Control (E)	Targets the reduction of various emissions from company operations, with an emphasis on mitigating climate change impacts or protecting air quality.
• Climate Emissions	Manages greenhouse gas emissions that contribute to global warming, such as CO2 and methane. The phrase must explicitly relate to greenhouse gases or related terms such as 'carbon', 'methane'.
• Air Quality Emissions	Manages emissions of non-greenhouse gases, like toxic gas, particulates and sulfur dioxide, which are critical for local air quality and public health.
Waste Management (E)	Concentrates on managing waste after it has been produced, including the reduction, handling, disposal, and treatment of solid waste and wastewater. It involves but is not limited to recycling, reusing materials, and employing wastewater treatment processes to mitigate environmental degradation and facilitate resource recovery.
• Wastewater Management	Focuses on the treatment, reuse and recycling of wastewater or liquid waste to prevent pollution or conserve water resources.
• Solid Waste Management	Addresses the management of solid wastes, promoting reduction, recycling treatment, and responsible disposal to minimize environmental impact and encourage circular economy principles.
Resource Optimisation (E)	Prioritizes the proactive, efficient, and sustainable selection and use of energy, water, and materials. This approach focuses on minimizing environmental impact through the strategic choice and utilization of resources. Distinct from waste management as it does not primarily deal with waste but rather prevents waste generation by optimizing resource use from the start.

• Renewable and Efficient Energy	Focuses on using energy efficiently, reducing energy consumption and increasing the use of renewable energy sources such as solar, wind, and hydroelectric power to minimize environmental impact.
• Material Sustainability	Prioritizes the use of sustainable and renewable materials, focusing on maximizing their efficiency from the outset. Distinct from recycling and reuse, which are part of waste management, this approach aims to reduce environmental impact before materials enter the waste stream.
• Water Conservation	Focuses on using water efficienctly, reducing water usage and enhancing sustainable water management practices to minimize initial consumption. Distinct from water recycling and reusing, which address management of wastewater.
Workplace (S)	Focuses on the social aspects of sustainability within the company to promote equity, inclusivity, or quality of life, emphasizing employee well-being, inclusivity, or professional growth.
• Workplace Wellness	Efforts that focus on the satisfaction, emotional and physical well-being of employees.
• Workplace Diversity	Efforts that emphasise gender and racial diversity and fairness in the workplace, such as anti-discrimination measures, fair hiring practices etc.
• Workplace Development	Efforts that focus on the skill training and professional development of staff.
Communications (E/S/G)	Focuses on how a company transparently and honestly communicates and discloses its activities.

Outreach (S)	Enhances social sustainability by contributing to community well-being, fostering customer satisfaction, building customer relationships, or collaborating with strategic partners to promote equity, inclusivity, and quality of life.
• Community Empowerment	Contributions to the welfare of local communities through various forms of support and engagement.
• Strategic Partnerships	Collaborations with stakeholders like NGOs, businesses, and charities to achieve shared sustainability goals.
• Customer Engagement	Fostering customer satisfaction, strong relationships and reputation with customers.
Management (G)	Ensures strategic, ethical, or effective governance through rigorous oversight, diverse board composition, active stakeholder engagement, or high ethical standards within company leadership.
• Management Composition	Structures the board or management with diverse expertise and backgrounds to strengthen decision-making and governance effectiveness.
• Management Ethics	Enforces strict ethical standards within company leadership, ensuring management actions uphold corporate integrity.
• Management Compensation	Aligns management, executive and board remuneration with company performance, sustainability or ethical objectives.
• Stakeholder Engagement	Engages key stakeholders to align board or management decisions with broader interests and feedback.
• Oversight	Involves the systematic review and evaluation of management actions to ensure they align with the company's performance goals, sustainability goals and ethical standards.

Compliance (G)	Ensures adherence to laws, regulations, or standards across environmental protection, labor rights, consumer safety, ethical conduct, financial practices, or data protection, distinguishing itself from voluntary sustainability initiatives by focusing on mandatory requirements.
• Environmental Compliance	Adherence to environmental laws such as for emissions, water pollution, protection of biodiversity etc.
• Worker & Consumer Safety	Adherence to laws that guarantee the safety of products and services to consumer health, as well as fair labor practices and the protection of workers' rights.
• Business Compliance	Adherence to anti-corruption, anti-competitive practices, financial regulations, or financial reporting.
• Data Privacy & Cybersecurity Protection	Protection and confidentiality of data, which includes measures against cyber threats and compliance with data security regulations.

Table 2: ESGSenticNet Sustainability Taxonomy

5. ESGSenticNet

ESGSenticNet comprises knowledge triplets with the format of (*concept, relation, category*), following from [27]. To form the knowledge triplets, concepts within our knowledge base are labelled according to their relations (table 3) with the categories in our taxonomy (table 2). The relations, *'supports'* and *'undermines'*, clarify how concepts advance or impede crucial aspects of corporate sustainability. In contrast, the relation *'aligns with'* does not consider a concept's impact, highlighting a concept's general connection with broader pillars of environmental, social or governance. Additionally, categories are divided according to their different category types–*pillar, broad, cross-broad, sub, cross-sub*, as shown in table 4, with relations assigned according to rules (section 5.1).

ESGSenticNet is constructed through a pipeline that involves three main phases: parsing concepts from the text corpus (section 5.2), processing parsed concepts to ensure coherence (section 5.3), labelling processed concepts according to their relation with respect to our developed taxonomy (sections 5.5, 5.6, 5.4, 5.7). Concept parsing involves extracting candidate concepts from sustainability disclosures through dependency parsing and part-of-speech tagging. From these candidates, coherent concepts are filtered through text parsing followed by leveraging GPT-4 [3] (section 5.2). The filtered concepts undergo a labelling methodology that we have developed to minimise computational cost while enhancing the diversity of labelled concepts. Accordingly, this labelling methodology (figure 1 1 through 4) entails leveraging semantic graphs, clustering techniques, seed selection algorithms, and label propagation. This methodology allows us to label a large amount of diverse concepts despite performing inference on a subset of the concept samples. As a result, the extensiveness and diversity of our knowledge base is significantly increased, which is imperative to its application for corporate sustainability analysis.

5.1. ESGSenticNet Relations & Rules

Relation	**Description**
aligns with	The concept is positively or negatively related to a specific Environmental, Social, or Governance (ESG) pillar.
supports	The concept directly advances the sustainability topic with a clear and immediate positive impact.
undermines	The concept directly impedes the sustainability topic with a clear and immediate negative impact.

Table 3: Relations Types

ESGSenticNet is defined with the following relations (table 3), category types (table 4), as well as the following rules.

- **Pillar Assignment:** Each concept 'aligns with' a specific pillar, mapping the concepts to the broader sustainability context. **Single Label within Category Types:** Each concept can hold only one relation with one category within each category type.
- **Cross-Labels between Parent & Children:** Each concept can hold relations with higher-level categories ('broad' and 'cross-broad'), as well as with more detailed categories ('sub' and 'cross-sub').

Category Type	Categories
Pillar	‘Environmental’, ‘Social’, ‘Governance’.
Broad	‘Development’, ‘Operations’, ‘Workplace’, ‘Outreach’, ‘Management’, ‘Communications’, ‘Compliance’
Sub	Children categories of broad categories
Cross-Broad	‘Resource Optimisation’, ‘Waste Management’, ‘Emissions Control’, ‘Ecological Conservation’
Cross-Sub	Children categories of cross-broad categories

Table 4: Categories and category types

- **Cross-Labels between Cross & Non-Cross:** Concepts that ‘align with’ the ‘environmental’ pillar can hold relations with ‘cross-broad’ and ‘cross-sub’ categories, in addition to ‘broad’ and ‘sub’ categories. This reflects the multi-faceted nature of environmental concepts, which can simultaneously impact environmental stewardship (represented by ‘cross-broad’, ‘cross-sub’ categories) and strategic business activities (represented by ‘broad’ and ‘sub’ categories).

5.2. ESG Concept Parser

Multiword expressions are linguistic phenomena that refer to common linguistic constructions such as idioms, collocations and sayings [16]. In the context of sustainability analysis, multiword expressions frequently communicate key sustainability ideas [51]. We refer to these multiword expressions as sustainability ”concepts”. Extracting these concepts or ”concept extraction” has been explored for metaphors [36], finance [18] and sentiment analysis [10]. Yet, to the best of our knowledge, concept extraction within the sustainability domain has not been studied. Therefore, to capture these sustainability concepts, a new concept parser is required, with an explicit focus on the distinct elements of sustainability discourse. These include the following designs:

- **Complex Nominals, Modifiers, Nouns & Adjectives**: Sustainability discourse is complex, containing a high concentration of adjectives and nouns which commonly function as modifiers within nominal phrases [50]. Phrases such as ‘renewable energy’, ‘carbon emissions’, demonstrate constructions that efficiently convey complex sustainability ideas.

- **Descriptive & Prescriptive Elements**: Sustainability discourse often involves descriptive and prescriptive language. The former (i.e. stative verbs like 'invested', 'reduced') is utilised when a company reports its current sustainability activities [42], while the latter (i.e. verbs of volition like 'plan', 'commit') is observed when a company pledges future sustainability activities [48].

To effectively extract these unique aspects of sustainability language, we formalise sustainability concepts, or ESG concepts, through the following syntactic structure–verbs acting on complex noun phrases, where the words involved function as modifiers, descriptive and prescriptive elements. Specifically, the concepts are two or three word phrases, typically beginning with a $verb$, followed by $noun + noun$, or $adjective + noun$ combinations with specific grammatical dependencies. These dependencies include: $verb - noun$ connection via *(nsubj, obj, obl)*, $adjective - noun$ or $noun - noun$ connection via *(compound, amod, nn, appos, flat, nmod)*. This framework underpins the ESG Concept Parser algorithm (1), designed to capture key ideas within sustainability disclosures, particularly sustainability efforts. For instance, *'improve (VB) workplace (NN) safety (NN)'*, where *'workplace'* is the $compound$ of *'safety'* and *'safety'* is the $dobj$ of *'improve'*.

Algorithm 1 ESG Concept Parser

```
Input: Sentence from sustainability disclosure
Output: ESG Concepts
POS tag the sentence
Dependency parse the sentence
for dependency, head, dependent in sentence do
    if dependency ∈ {nsubj, obj, obl} then
        if head is noun & dependent is verb then
            add to Phrases: dependent+head as verb+noun combination
        end if
    end if
end for
for word_1, word_2 in Phrases do
    for dependency, head, dependent in sentence do
        if head is noun & dependency ∈ {compound, amod, nn, appos, flat, nmod} then
            if dependent is noun then
                add to Phrases: word_1+dependent+word_2 as verb+noun+noun combination
            end if
            if dependent is adj then
                add to Phrases: word_1+dependent+word_2 as verb+adj+noun combination
            end if
        end if
    end for
end for
```

5.3. Processing concepts for coherence

To minimise computational cost, parsed ESG concepts from algorithm (1) are filtered to retain the top 110k most frequently occurring ones. Of these, we eventually annotate 23k concepts based on our estimated computational resources, which dictates the number of seeds we select within our semantic graph. Prior to the annotation process, these concepts must undergo processing to ensure their coherence. This involves utilising GPT-4o in few-shot setting (Brown, 2020) to ensure their coherence. GPT-4o is leveraged due to the capacity of large generative LLMs to infer [58], as well as their powerful natural language understanding capabilities [62]. Using GPT-4o to process concepts for coherence involves conducting the following inference tasks in order: (1) reorder words, if required, to improve the coherence of the ESG concept, (2) determine if the subsequent ESG concept is intelligible. We provide the prompt for (1) and (2) through figures 3 and 4 respectively.

[Task Description]
As a language expert, your task is to rearrange words in phrases to enhance their coherence and intelligibility if necessary.

[Response Instructions]
Please list all your outputs for all the phrases given. Follow these steps for each given phrase: Assess whether reordering the words in the phrase can improve its coherence and intelligibility. If needed, reorder the words to achieve the best clarity and coherence, but do not add new words and do not change the words. If no reordering is needed, retain the original order. Record the output accordingly.

[Response Format]
Fill in your response in the triple backticks below using the following format:

```
Input: <original phrase>
Output: <reordered or original phrase>
```

Figure 2: Prompt for reordering an ESG concept for coherence

[Task Description]
As a language expert, you are tasked with determining if a phrase is intelligible.

[Response Instructions]
Please list all your outputs for all the phrases given. Follow these steps for each given phrase: Assess if a given phrase is intelligible. If the phrase is intelligible, output a 'True' for the phrase. If the phrase is not intelligible, output a 'False' for the phrase.

[Response Format]
Fill in your response in the triple backticks below using the following format:
```
Input: <phrase>
Output: <True/False>
```

Figure 3: Prompt for evaluating an ESG concept's coherence

5.4. Semantic Graph Construction

$$G = (V, E) \tag{1}$$

$$V = \{\mathbf{e}_i \mid \mathbf{e}_i = \text{S-BERT}(cp_i)\} \tag{2}$$

$$\text{sim}(\mathbf{e}_i, \mathbf{e}_j) = \frac{\mathbf{e}_i \cdot \mathbf{e}_j}{\|\mathbf{e}_i\|\|\mathbf{e}_j\|} \tag{3}$$

$$E = \{(\mathbf{e}_i, \mathbf{e}_j) \mid \text{sim}(\mathbf{e}_i, \mathbf{e}_j) > 0.80\} \tag{4}$$

Processed ESG concepts undergo labelling to derive their relationships with different sustainability topics. Given the exceedingly large number of ESG concepts, annotating all concepts would be prohibitively expensive. To overcome this, we devise a semi-supervised framework that enables a large volume of diverse ESG concepts to be labelled from annotating only a subset of all ESG concepts. Via a semantic graph, we leverage the semantic similarities between ESG concepts to propagate labels from annotated concepts (seeds) to unlabelled concepts (non-seeds). This graph is constructed by transforming each concept cp_i into embeddings e_i through S-BERT [45], with edges constructed by leveraging a cosine similarity threshold of 0.80 between each node e_i.

5.5. Seed Selection

Within our semantic graph, seeds are selected for annotation through data clustering and graph analysis. Given the semi-supervised label propagation from seeds to non-seeds, we formulate the following objectives for seed selection: **(I)** Seeds must be semantically diverse to ensure that diverse labelled samples are yielded post label propagation. This enhances the variety and comprehensiveness of labelled ESG concepts in our knowledge base. **(II)** Seeds must propagate their labels to as many non-seeds as possible. This maximises the number of labelled samples we can attain while minimising annotation costs.

5.5.1. Data Clustering

$$CQI = \frac{|\{e \in V \mid \alpha_e > 0.60\}|}{|V|} \tag{5}$$

To accomplish (I), the embeddings of ESG concepts e_i are clustered to enable seed selection from diverse semantic spaces. This clustering involves projecting the embeddings to a lower dimensional space via UMAP [37], before running HDBSCAN [12] on these projected embeddings. While HDBSCAN is flexible to the shape and number of clusters, and robust to noise [12], reducing the dimensionality of embeddings ensures good clustering performance. This is because HDBSCAN relies on distance-based metrics which lack meaningfulness in the high dimensional spaces of textual embeddings [4]. The embeddings are projected to lower dimensions for the sole purpose of clustering. In our later section, label propagation leverages the default dimensions of S-BERT embeddings.

Clusters are evaluated via a Confidence Quality Index (CQI), which denotes the proportion of embeddings, e, out of all embeddings, V, with a clustering confidence level α_e beyond 0.60. For our use of HDBSCAN, this simple metric is more appropriate than others like Slihouette Score [47], which assumes that all embeddings belong to a cluster. Hyperparameter tuning is done via random search, with the best run having a CQI of 0.66, UMAP parameters $n\_neighbours$=32, $n\_components$=2, and the HDBSCAN parameter $min\_cluster\_size$=2.

5.5.2. Graph Analysis

$$\begin{aligned} Q(\mathbf{e}_i) = |\, \{(\mathbf{e}_i, \mathbf{e}_j) \in E \mid (\mathbf{e}_i \in \mathbf{c_k}) \\ \wedge (\forall \mathbf{e}_s \in S_{c_k}, (\mathbf{e}_s, \mathbf{e}_j) \notin E)\} \,| \end{aligned} \tag{6}$$

To accomplish (II), graph analysis is utilised to select seeds that are the most consequential nodes. Given that edges facilitate label propagation, a node is considered more consequential if it possesses a greater number of unique edges. Unique edges are defined as connections to nodes that do not share an edge with the already selected seed nodes within the same cluster. We formulate the local consequential score $Q(e_i)$, where S_{c_k} is the set of nodes already selected as seeds within the same cluster, c_k, as the node e_i.

5.5.3. *Seed Selection Algorithm*

Capitalising on *Data Clustering* and *Graph Analysis*, an algorithm (2) is developed for seed selection to achieve objectives (I) & (II). Given a target number of seeds to label, T, and the embeddings of all ESG concepts, V, seeds, S_{total}, are selected from clusters, C. Each cluster, c_k, within C, is a set of embeddings of concepts, e_i. Within each c_k, seeds of a cluster, S_{c_k}, are selected by taking the embedding with the maximum local consequential score $Q(e_i)$ at each selection step. This maximises the selection of seeds with unique edges to increase label propagation to non-seeds. Additionally, each cluster should ideally possess an equivalent proportion, P, of seeds, and at least one seed each. We accomplish this by iteratively adjusting P according to parameter β (ESGSenticNet uses $\beta = 0.01$), to ensure that our estimated number of seeds N_s is as close to our target number as possible T (the difference between N_s and T denoted by Δ). From P, the specific number of seeds for each cluster, n_{c_k} can be computed. This ensures that seeds are fairly represented across different clusters to enable the semantic diversity of seeds.

Algorithm 2 Seed Selection

Input: V, T, C
Output: S_{total}
$N \leftarrow |V|$
$P \leftarrow \frac{T}{N}$
$\Delta_{prev} \leftarrow \infty$
while True **do**
    $N_s \leftarrow \sum_{c \in C} \max(1, \lfloor P \cdot |c| \rfloor)$
    $\Delta_{curr} \leftarrow |N_s - T|$
    if $\Delta_{curr} \geq \Delta_{prev}$ **then**
        break
    else
        $\Delta_{prev} \leftarrow \Delta_{curr}$
    end if
    if $N_s < T$ **then**
        $P \leftarrow P + \beta$
    else
        $P \leftarrow P - \beta$
    end if
end while
for $c_k \in C$ **do**
    $n_{c_k} \leftarrow \max(1, \lfloor P \cdot |c_k| \rfloor)$
    $S_{c_k} \leftarrow \emptyset$
    while $|S_{c_k}| < n_{c_i}$ **do**
        $e_{\max} \leftarrow \arg\max_{e \in c_k} Q(e)$
        $c_k \leftarrow c_k \setminus \{e_{\max}\}$
        $S_{c_k} \leftarrow S_{c_k} \cup \{e_{\max}\}$
    end while
    $S_{total} \leftarrow S_{total} \cup S_{c_k}$
end for
return S_{total}

5.5.4. Effectiveness of ESGSenticNet Seed Selection Algorithm

In this baseline study, we assess the extent of label propagation through ESGSenticNet's seed selection algorithm, against naive methods like selecting seeds randomly or based on highest degree centrality scores. Each method is run on the constructed semantic graph (section 5.4), to select different batches of 10k seeds. Aligning with majority of the classification tasks in the main study, three different psuedo-labels are used, and randomly assigned to the selected seeds. Label

Seed Selection Method	Propagated Labels
Highest Degree Centrality	4686
Random Selection	7456
ESGSenticNet	**9617**

Table 5: Effectiveness of Label Propagation, based on the number of newly propagated labels

propagation is run to observe the number of newly propagated labels. Although propagation would be more accurate with real labels, random pseudo-labelling provides an unbiased estimate of propagation extensiveness irrespective of label content, and reduces the cost of extensive testing. Moreover, the entire process is repeated over 100 trials, showing that across each method, the number of newly propagated labels remain consistent despite the randomness of seed labelling. Compared to naive methods, we observe that ESGSenticNet's seed selection algorithm results in a greater number of newly propagated labels.

5.6. *Seed Annotation*

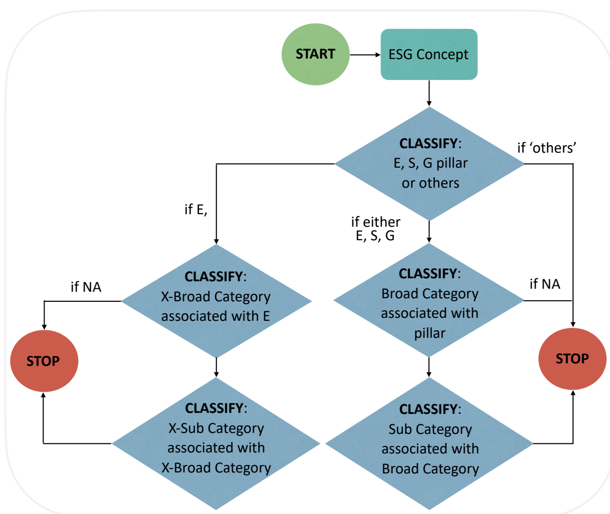

Figure 4: Flowchart depicting inference process

Through GPT-4o few-shot prompting, selected seeds are annotated with their relations ('aligns with', 'supports', 'undermines') with respect to a pillar or category, before their labels are propagated within the semantic graph. Similar to popular sustainability lexicons [6, 54], ESGSenticNet's approach focuses on seed annotation before leveraging textual similarities to expand the initial seed corpus. Yet, while approaches in the literature annotate a small number of seeds, ESGSenticNet annotates an extensive number of seeds ($> 16k$) through GPT-4o. Consequently, ESGSenticNet retains a significant proportion of seed concepts directly labelled through GPT-4o, while non-seeds that rely on textual similarity for labelling are less prevalent. This enriches the diversity of ESGSenticNet, given that the reasoning capabilities of GPT-4o [24] allows it to infer relations for concepts outside of similar semantic spaces. For example, consider the concepts 'use led light', 'achieve energy efficiency' categorised under 'Resource Optimisation'. Textual similarity methods leveraging these for comparison might not categorise 'emphasise water importance' similarly, despite its relevance. However, using GPT-4o, 'emphasise water importance' is appropriately labelled, due to the LLM's capacity to infer semantic relationships beyond mere textual similarities. Moreover, GPT4o as an automated technique allows for a large number of concepts to be labelled, overcoming prohibitive human labelling costs. This allows us to derive an extensive knowledge base.

To improve GPT-4o classification accuracy, inference tasks are divided into smaller, more manageable sub-tasks [14]. These tasks align with the taxonomy's hierarchy levels, following the flowchart in figure 4. Subsequent categorisations of seeds are contingent upon their initial classification into broader categories, and it aligns with the predefined associations between the ESG pillars and broad categories, as well as the connections between the broad and sub categories. Prompts for these tasks are highlighted in figure 5 (pillar labelling), figure 6 (relation-topic labelling).

[Task Description]
As a sustainability expert, your task is to classify phrases into the categories of Environmental, Social, Governance, or Others based on their explicit relevance to the Environmental, Social, Governance topics.

[Definitions of Categories]
Definitions of ESG according to taxonomy, with the inclusion of 'Others'
Others: Reserved for phrases that do not meet the explicitness and specificity requirements for Environmental, Social, or Governance. This includes phrases that are vague, ambiguous, or cover multiple Environmental, Social, Governance topics without clear categorization.

[Response Instructions]
Evaluate each phrase's explicit content to determine its most appropriate category. Assign each phrase to only one category: Environmental, Social, Governance, or Others. Only phrases that are clear and explicit can be categorized under Environmental, Social, or Governance. Phrases that are vague or not clearly related to these topics should be categorized as Others. Ensure all responses strictly adhere to the definitions and format provided.

[Response Format]
Fill in your response in the triple backticks below using the following format:

```
Input: <phrase>
Response: <Environmental, Social, Governance, or Others>
```

Figure 5: Prompt for labelling an ESG concept's pillar

[Task Description]
As a sustainability expert, you are tasked with evaluating the relationship between phrases and sustainability-related topics.

[Definitions of Relationships]
supports: The phrase, specific and explicit to the topic, directly advances it with a clear and immediate positive impact.
undermines: The phrase, specific and explicit to the topic, directly impedes its goals with a clear and immediate negative impact.

[Definitions of Topics]
Definitions of topics according to taxonomy

[Response Instructions]
Evaluate the explicit content of each phrase to determine the most appropriate and accurate relationship and topic. Identify the single most relevant and appropriate relationship and topic. If no specific and explicit relationship can be determined between the phrase and any topic, or if the phrase does not fit any topic due to vagueness or irrelevance, classify the phrase as 'not applicable'.

[Response Format]
For each phrase, provide your analysis using the format below. Output only one tuple if applicable, otherwise state 'not applicable'.

```
Input: <phrase>
Response: <(relationship, topic)> or 'not applicable'
```

Figure 6: Prompt for labeling an ESG concept's relation with a topic

5.7. Label Propagation Algorithm

$$L^{(k+1)} = D^{-1/2} A D^{-1/2} L^{(k)}, \tag{7}$$

$$l_i^{(k+1)} = l_i^{(0)} \quad \forall i \leq m \tag{8}$$

Annotated seeds have their labels propagated to non-seeds via the label propagation algorithm [56]. This increases the labelled data within our knowledge base without incurring additional labelling costs. Specifically, the following algorithm is iterated until convergence, where A is an adjacency matrix containing $a_{i,j}$ that denotes the edge weight between connected nodes e_i and e_j. Each node represents an embedding of a concept, while the edge weight denotes cosine similarity between concepts. L is a matrix that represents the relations labels of each node with respect to a topic (i.e. *supports* within the ('reduce water consumption', *supports*, 'resource optimisation'). m is the number of nodes possessing labels and D is a diagonal matrix containing $d_{i,i}$, which equals the sum of elements in row i of A. We use parameters n_layers=50, α=0.5.

5.8. ESGSenticNet Statistics

Categories	**Total Triplets**	**Number of triplets with the relations**		
		supports	**undermines**	**aligns with**
Environmental	5904	-	-	5904
Social	6897	-	-	6897
Governance	10444	-	-	10444
Development (E)	314	298	16	
• Green Technologies	58	49	9	-
• Green Infrastructure	105	104	1	-
• Green Financing	16	16	-	-
Operations (E)	1470	1209	261	-
• Sustainable Corporate Operations	215	186	29	-
• Sustainable Supply Chain	48	46	2	-
• Sustainable Production Processes	265	148	117	-
• Sustainable Land Management	174	141	33	-
Resource Optimisation (E)	935	855	80	-
• Renewable and Efficient Energy	348	321	27	-
• Material Sustainability	58	50	8	-
• Water Conservation	107	100	7	-
Waste Management (E)	578	493	83	-
• Wastewater Management	82	67	15	-
• Solid Waste Management	166	156	10	-
Emissions Control (E)	533	407	146	-
• Climate Emissions	173	152	21	-
• Air Quality Emissions	36	19	17	
Ecological Conservation (E)	238	205	33	-
Workplace (S)	2077	2006	71	-
• Workplace Wellness	463	432	31	-
• Workplace Diversity	237	222	15	-
• Workplace Development	705	704	1	-

Outreach (S)	1212	1211	1	-
• Community Empowerment	498	498	0	-
• Strategic Partnerships	137	137	0	-
• Customer Engagement	77	77	0	-
Management (G)	2332	2305	27	-
• Management Composition	30	30	-	-
• Management Ethics	124	118	6	-
• Management Compensation	19	17	2	-
• Stakeholder Engagement	105	105	-	-
• Oversight	532	532	-	-
Communications (E/S/G)	1196	1192	4	-
Compliance (G)	3405	3093	312	-
• Environmental Compliance	436	403	33	-
• Worker & Consumer Safety	1154	1040	114	-
• Business Compliance	208	170	38	-
• Data Privacy & Cybersecurity Protection	103	100	3	-

Table 6: ESGSenticNet Statistics

Concept	**Relation**	**Category**
build diverse workplace	supports	workplace diversity
halve carbon emission	supports	emissions control
involve workplace injury	undermines	worker & consumer safety compliance
minimise resource consumption	supports	resource optimisation
organise charity event	supports	outreach
produce chemical waste	undermines	operations

Table 7: Samples of knowledge triplets from ESGSenticNet

Samples of knowledge triplets within ESGSenticNet is provided in table 7. Additionally, a full statistical breakdown of ESGSenticNet's 44k knowledge triplets is outlined in table 6.

5.9. ESGSenticNet Human Evaluation

ESGSenticNet comprises 44232 triplets containing 23245 unique concepts. Of the 23245 concepts, 16011 are seeds and 7234 are non-seeds. We provide a meta statistic of ESGSenticNet (table 8), a full statistical breakdown (table 6), and samples (table 7). To evaluate our knowledge base, human annotators determine the

Sustainability Corpora	Total Terms
ESGSenticNet	**23245**
Baier	491
Naiara	167
Kang*	792

Table 8: Total number of terms of different sustainability corpora, Baier [6], Naiara [44], Kang [29], *indicates not publicly available.

Relation Type	Accuracy
Pillar	95.0%
Broad	89.3%
Cross-Broad	86.1%
Sub	87.8%
Cross-Sub	90.1%

Table 9: Accuracy of ESGSenticNet

accuracy of relations between concept and categories. 500 concepts are randomly selected from our knowledge base. A concept may be found in multiple knowledge triplets, possessing multiple relations with different categories. The accuracy of the labels are human evaluated at every GPT-4o decision point as shown in figure 4. Specifically, we evaluate the accuracy of relation labels separately for each category type–*pillar, broad, cross-broad, sub, cross-sub*, with each of them including only select categories (table 4). Appendix A provides more details on our annotators and annotation scheme.

For evaluating ESGSenticNet accuracy in section 5.9, the following instructions were given:

> The table below presents various concepts along with their polarities and respective relations toward sustainability categories. Each concept may be associated with multiple relations across different sustainability categories. These categories are classified into five category types: pillar, broad, sub, cross-broad, and cross-sub. If a concept has no relevant association with a category, it is marked as 'not applicable'. Your task is to evaluate whether each concept is correctly related to its corresponding categories. For each category, determine if the relation is the most appropriate compared to the other categories within the same category type. Mark 'TRUE' if the relation and category are correct, and 'FALSE' if they are incorrect. Additionally, assess the accuracy of the polarity of each concept, and mark 'TRUE' if it is correct and 'FALSE' if it is incorrect.

6. Topical Analysis of Sustainability Disclosures through ESGSenticNet

Topic analysis of sustainability disclosures provide stakeholders significant insights about a corporation's sustainability performance [41]. Distinct from discovering topics without any inclination of what the topics should be, topic analysis within sustainability analysis frequently seeks to derive topics within established sustainability themes and frameworks [41]. To elaborate on this, sustainability stakeholders often have specific themes they are monitoring, such as alignment with UN Sustainability Development Goals [57], future orientation of reporting within ESG pillars [23], performance with respect to economic, environmental, social dimensions [54]. Therefore, the demands of the topic analysis within sustainability requires capturing content related to sustainability and its associated frameworks. ESGSenticNet aims to address the shortcomings with respect to unstructured topic terms, unstructured topics, the limited structured methods, as well as the materiality of information extracted. To elaborate, the hierarchical structure of ESGSenticNet ensures that the topics extracted are directly related to a sustainability taxonomy, while the specialised concept parsing and GPT-4o inference increases the materiality and ESG-relevance of extracted topic terms.

6.1. Critique of current methods

Different methods can be leveraged for sustainability topic analysis, including rule-based methods that leverage existing dictionaries [25], and unsupervised topic modelling that can be adapted to explore specific areas within sustainability frameworks [66, 35]. Yet, while having advantages, these methods may not be tailored for sustainability topic analysis, given the specialised nature of sustainability content and the demands of sustainability stakeholders. We elaborate on this in the following.

- **Unrelated topic terms**: Existing topic modelling methods, while excellent at producing topic terms without supervision [1], cannot be tuned to capture specialised word constructions that typically describe sustainability ideas (i.e. nominals, modifiers as described in 5.2) [50]. Moreover, sustainability content is multifaceted and complex, often varying across different sectors and contexts [39]. Therefore, captured topic terms may not be relevant to sustainability, leading to topics irrelevant for sustainability analysis.

- **Unstructured topics**: Unsupervised topic modelling may not yield topics that are structured according to sustainability themes, even if sustainability-related topics can be derived from topic words. Therefore, the derived topics may not be meaningful for sustainability stakeholders, who typically rely on structured frameworks with predefined sustainability themes and topics to analyse sustainability content [34, 19].

- **Limited Structured Methods**: Although publicly available ESG dictionaries such as Baier [6] introduce a structured method for topic analysis [22], they contain lexicons, which we will demonstrate, that are not predominantly related to sustainability. This makes the alignment between the lexicons and their supposed sustainability categories unclear. Other dictionaries (i.e Naira [44]) are limited (< 200 terms).

- **Material Information**: Although topic terms may highlight the presence of sustainability issues, stakeholders often prioritise content that explicitly convey the sustainability efforts or actions undertaken by corporations [7]. Therefore, greater specificity of topic terms is required to enrich the materiality of topical information in alignment with stakeholder interests. Nevertheless, current methods may fall short in generating specialised topic terms that articulate sustainability action, a limitation that we will explore further.

6.2. Topic Analysis Evaluation

In line with the aforementioned critiques and requirements with respect to sustainability topic analysis, ESGSenticNet is tested against baselines. These include, topic models that are algebraic – NMF [30], probabilistic – LDA [9], neural – ProdLDA [52], TSCTM [60], BERTopic [21], ECRTM [59], and other publicly available sustainability dictionaries – Baier [6] Naiara [44]. We aim to answer the following research questions to assess whether the tested methods provide meaningful topic analysis for sustainability stakeholders:

- **RQ1**: To what extent are the topic terms yielded by a method related to ESG, and by extension, sustainability analysis?

- **RQ2**: To what extent are the ESG topic terms yielded by a method diverse, allowing analysts to view a variety of sustainability topics?

- **RQ3**: To what extent do the topic terms yielded by a method express an action toward ESG, or a sustainability effort, thereby providing more material insights?

To address these research questions, topic analysis methods are evaluated according to the following.

- **ESG relatedness**: The proportion of all topic terms that are ESG-related, highlighting the extent to which yielded topics are relevant to sustainability and therefore sustainability analysis.
- **Unique ESG terms**: The number of unique ESG topic terms, indicating the comprehensiveness and diversity of ESG content captured.
- **ESG action orientation**: The proportion of all topic terms that express an action taken toward ESG, or in other words, a sustainability effort. This indicates whether the terms are able to express information *material*, and of interest to stakeholders.

For the above metrics, GPT-4 is leveraged to classify all topic terms yielded from the models. GPT-4 distinguishes the following – 1) whether each topic term is ESG-related, 2) whether each topic term constitutes an action toward improving ESG. Thereafter, we aggregate the GPT-4 classification results to produce scores for *ESG relation, unique ESG terms, ESG action*. We validate using GPT-4 in our evaluation through an GPT4-human agreement study (section 6.6). Full experimental details for topic analysis evaluation are described in section 6.3, with the prompts provided in figure 7 (ESG relatedness), and figure 8 (ESG action orientation).

[Task Description]
As a sustainability expert, your task is to classify terms based on their relevance to Environmental, Social, and Governance (ESG) factors.

[Response Instructions]
Evaluate each term based on its content to determine its most appropriate category. If a term is explicitly related to ESG, assign the label 'ESG'. If a term is not related to ESG or the relationship is vague, assign the label 'non-ESG'. Ensure all responses strictly adhere to the definitions and format provided.

[Response Format]
Fill in your response in the triple backticks below using the following format:

```
Input: <term>
Response: <ESG or non-ESG>
```

Figure 7: Prompt for evaluating ESG relatedness

[Task Description]
As a sustainability expert, your task is to classify terms based on whether they express an action taken toward ESG.

[Response Instructions]
Evaluate each term based on its content to determine whether it describes an action taken to advance Environmental, Social, and Governance (ESG) goals. If a term describes an action taken to enhance ESG objectives, assign the label 'True'. If a term does not describe an action taken toward ESG objectives, assign the label 'False'. Ensure all responses strictly adhere to the definitions and format provided.

[Response Format]
Fill in your response in the triple backticks below using the following format:
```
Input: <term>
Response: <True or False>
```

Figure 8: Prompt for evaluating ESG action orientation

6.3. Experimental Settings

Topic analysis is performed on 319 sustainability disclosures from 75 large Singaporean Companies from 2015 to 2023, obtained from the respective company websites. These reports were unused during the development of ESGSenticNet. *Algebraic, Probabilistic & Neural* methods such as NMF [30], LDA [9], ProdLDA [52], BERTopic [21], TSCTM [60], ECRTM [59], are unsupervised, and we run them across a wide range of hyperparameters, to obtain the best results for each method. These parameters include every combination for vocab size= $\{2500, 5000, 7500, 10000, 12500\}$, number of topics= $\{10, 20, 30, 40, 50, 60, 70\}$, number of topic words= $\{5, 10, 15, 20, 25, 30\}$. Additionally, these models were deployed through the TopMost package [61]. *Dictionary* methods comprise terms that are categorised according to specific sustainability topics. A topic's occurrence is computed from the frequency of occurrence of its associated terms. In our experiment, the topic terms of the dictionaries correspond to dictionary terms that appear within the corpora of sustainability disclosures. To the best of our knowledge, dictionary methods in the published literature are limited, with only a few works that make their full dictionaries publicly available. These include Baier [6] and Naiara [44].

ESGSenticNet comprises knowledge triplets in the format *(concept, relation, category)*, delineating how specific concepts related with sustainability categories or topics. To enhance semantic specificity and context, we employ three word concepts, exclusively using those that possess the ‘supports’ relation toward a sustainability topic. Similar to *dictionary* methods, a topic’s occurrence is determined by the frequency of appearance of concepts that support the topic (we explore this further in a case study in section (6.5)). The topic terms of ESGSenticNet correspond to these concepts that appear within the sustainability disclosures corpora. Additionally, we experiment with two configurations for ESGSenticNet: *Exact* involves exact string matches of each concept, *Flexible* involves taking advantage of the (verb, noun phrase) arrangement of concepts for matching. To elaborate on this, the verb (1st word) is matched separately from the corresponding noun-phrase (2nd & 3rd words) within each sentence. Given the example “We reduce our water consumption”, ‘reduce’ is matched as the verb, and ‘water consumption’ is matched as the noun-phrase, with ‘reduce water consumption’ returned as the matched concept without requiring its exact string match. *Flexible* enables greater detection of ESG concepts by allowing for semantic variability (see study in section 6.7), while *Exact* is useful for detecting precise ESG impacts.

6.4. Results & Discussion

Baseline	**Best ESG-unique**			**Best ESG-rel**			**Best ESG-act**		
	ESG-unique	ESG-rel	ESG-act	ESG-unique	ESG-rel	ESG-act	ESG-unique	ESG-rel	ESG-act
NMF	332*	0.28*	0.08*	3	0.42	0.00	332*	0.28*	0.08*
LDA	23*	0.31*	0.01*	3	0.36	0.00	23*	0.31*	0.01*
ProdLDA	334*	0.26*	0.07*	17	0.38	0.10	13	0.38	0.16
BERTopic	76	0.33	0.05	13	0.40	0.04	13	0.35	0.05
TSCTM	359	0.15	0.06	11	0.32	0.06	23	0.31	0.15
ECRTM	440	0.18	0.09	23	0.46	0.08	182	0.31	0.15
Baier	212*	0.49*	0.29*	212*	0.49*	0.29*	212*	0.49*	0.29*
Naiara	1*	0.50*	0.50*	1*	0.50*	0.50*	1*	0.50*	0.50*
ESGSenticNet (exact)	359*	0.76*	**0.84***	359*	0.76*	**0.84***	359*	0.76*	**0.84***
ESGSenticNet (flexible)	**2555***	**0.79***	0.81*	**2555***	**0.79***	0.81*	**2555***	**0.79***	0.81*

Table 10: Evaluation of Topic Analysis Methods, through the metrics of unique ESG terms (ESG-unique), ESG relatedness (ESG-rel), and ESG action orientation (ESG-act). Best results are marked in bold and the best baseline results are underlined. (*) indicates the results from the same run (i.e. same parameters). Best ESG-unique, Best ESG-rel, and Best ESG-act represent the top-performing results from the respective runs of the tested methods.

Our experimental results (table 10) indicate that ESGSenticNet scores higher than the other topic analysis methods on *ESG relatedness* and *ESG action orien-*

tation by at least 26% and 31% respectively. Additionally, both ESGSenticNet (exact) and ESGSenticNet (flexible) extract a high number of unique ESG terms, with ESGSenticNet (flexible) scoring the highest amongst all methods tested. Although requiring limited computational resources as a lexical method, ESGSenticNet produces significantly higher performance compared to the more expensive unsupervised topic modelling methods. This is despite how the topic models were exhaustively ran on numerous permutations of parameters (section 6.3) that required extensive computational costs.

Unsupervised topic models such as TSCTM, ECRTM, ProdLDA, NMF can extract a high number of unique ESG terms (> 300). Yet, for the same runs, the concentration or prevalence of ESG terms within each topic is modest, as highlighted by their limited scores in *ESG relatedness* (< 0.30). Therefore, despite capturing diverse ESG topic terms, these methods fall short in generating topics that are richly centered on ESG themes. From table 11, we highlight examples of the topics generated by these methods in comparison to ESGSenticNet, highlighting how most of the topics generated by these topic models are not ESG-centric. This limitation is critical in sustainability topic analysis, given that the primary goal is to derive insights from topics that are not only inclusive of ESG terms but are also substantially focused on ESG issues.

Moreover, topic model runs that yield the highest *ESG relatedness* are only able to yield few unique ESG-terms (< 25). Furthermore, for these topic model configurations, as well as for other dictionaries such as Baier and Naiara, *ESG relatedness* is still ≤ 0.50. This suggests that yielded topics are still not predominantly centred around ESG themes.

Finally, most of the tested baseline methods score modestly for *ESG action orientation*, Naiara noticeably higher. Yet, Naiara is only able to derive 1 unique ESG-term, which limits the significance of its analysis. These results suggest that the baseline methods may not fully capture information that is *material* to stakeholders, particularly in terms of conveying sustainability actions and efforts.

Method	Topic	Example Topic Words
TSCTM	Topic 1	offshore, baker, vessels, oil, cho, vessel, chartering, ship, sea charter
	Topic 2	rsp, venture, johor, black, sites
	Topic 3	controlling, provision, shall, period, accounting, mainly, listing, media, entity, time
ECRTM	Topic 1	minerals, healthcare, disa, teh, bhd holdings, agm, sdn, heatec, sri
	Topic 2	banks, grand employees, duty, palm
	Topic 3	disa, shares, theft share, anniversary, lau, purchase, options, june cancellation
ProdLDA	Topic 1	financial, value, non assets, december
	Topic 2	loss, company, board, statements, directors
	Topic 3	greenhouse, mountain, aspires, gresb, honeyness, feel, strategy, board, candid, phenomenon, conforms, performance, cubic, cabling, unoccupied
NMF	Topic 1	duly, assets, transparency, value, priority
	Topic 2	property, fair, rate, million, new
	Topic 3	esg, administration, confirmed, quarter, save, present, businesses, employees, workplace, flow, focusing, ceo, default, meetings, termination
ESGSenticNet	Topic 1	abide local law, achieve regulatory compliance, fulfill regulatory requirement, follow international law, comply environmental rule
	Topic 2	increase employee satisfaction, improve staff engagement, invest career development, maintain employee safety
	Topic 3	minimise carbon footprint, monitor ghg emission, reduce environmental pollution, lower air emission

Table 11: Examples of topic words for topic models with the highest numbers of unique ESG terms, in comparison with ESGSenticNet for qualitative analysis

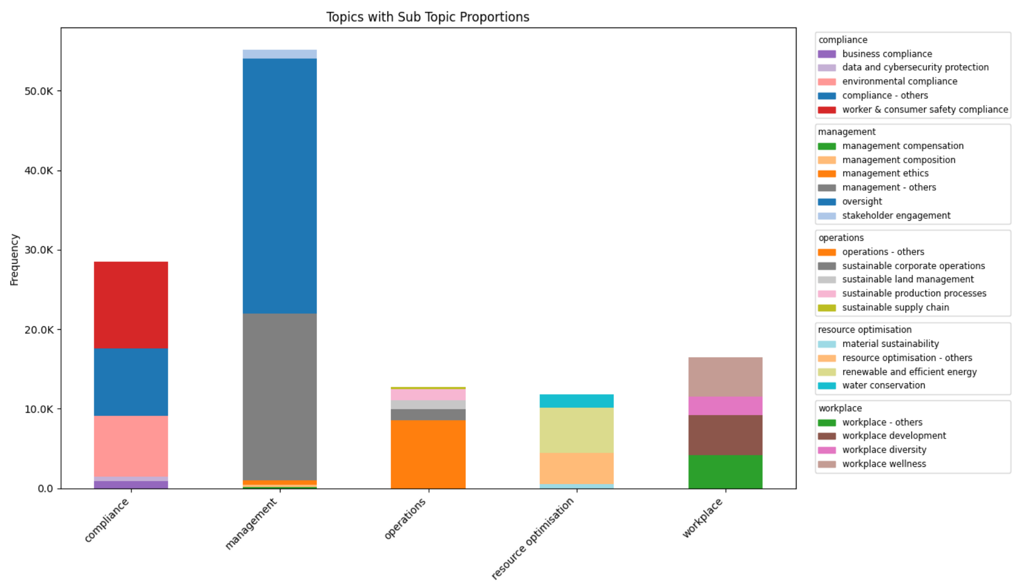

Figure 9: Frequency of ESGSenticNet topics from the *flexible* run

Workplace

Workplace Development	Workplace Wellness	Workplace Diversity
provide training development	provide workplace health	create inclusive environment
support career development	ensure staff health	promote inclusive workplace
provide staff development	support mental health	provide equal employment

Compliance

Worker & consumer Safety	Environmental Compliance	Business Compliance
ensure safe environment	ensure environmental compliance	conduct legal compliance
conduct safety assessment	have sustainability certification	align business reporting
have safety training	maintain environmental compliance	assess business compliance

Resource Optimisation

Material Sustainability	Renewable and Efficient Energy	Water Conservation
use sustainable material	use renewable energy	reduce water consumption
minimise paper usage	manage energy consumption	improve water efficiency
use environmental packaging	reduce fuel use	achieve water savings

Management

Oversight	Management Composition	Management Compensation	Management Ethics	Stakeholder Engagement
report sustainability approach	promote board diversity	review remuneration structure	have ethics code	identify sustainability stakeholder
ensure management performance	appoint independent director	approve remuneration committee	guide ethical management	collaborate supply stakeholder
sustainability management review	have female director	link management remuneration	implement ethical code	maintain stakeholder engagement

Operations

Sustainable Corporate Operations	Sustainable Land Management	Sustainable Production Processes	Sustainable Supply Chain
reduce food waste	support palm conservation	improve production efficiency	reducing packaging waste
use smart building	improve fertiliser use	reuse production waste	use sustainable packaging
promote building conservation	protect local biodiversity	reduce production approach	reduce daily travel

Figure 10: Top ESGSenticNet concepts from the *flexible* run, in *support* of the sub topics (dark blue), and their corresponding broad topic (light blue)

The topic analysis conducted by ESGSenticNet in section 6 is visualised with the figures 9 & 10, which represent different ways to analyse the text corpus. Figure 9 provides a higher level breakdown of the topics present in the corpus. It highlights the top 5 frequently occurring broad sustainability topics present in the corpus, as well as the proportion of their constituent sub topics, in accordance with ESGSenticNet's hierarchical taxonomy. The topic frequencies are denoted by the occurrence of matched concepts that *'support'* a topic, leveraging ESGSenticNet's predefined relations. Separately, figure 10 provides a more granular analysis of the corpus, highlighting matched concepts that explicitly convey sustainability actions, thereby communicating important sustainability information. Figure 10 displays the top occurring concepts that *support* the topics shown in figure 9. Put together, figures 9 and 10 highlight different methods to analyse a sustainability corpus, which can be utilised depending on a stakeholder's interest and preference.

6.6. GPT-4 Human Expert Agreement on Topic Analysis Evaluation Metrics

GPT-4 evaluations have shown significant reliability in the literature [64]. A study is conducted to assess GPT-4's ability for the following tasks– i) classifying topic terms as ESG-related, ii) classifying topic terms as actions taken toward ESG. A random sample of 510 topic terms were gathered for each task. GPT-4 annotations for each set of topic terms are compared with annotations from 2 different groups of 3 human experts each, with each group handling a different task. An average agreement score of 83.7% observed for task i) and 91.8% for task ii).

For evaluating GPT-4 human agreement, the following instructions were given for classifying topic terms as ESG-related.

The table below presents various terms. Determine if each term is ESG-related. Mark 'TRUE' if the term is ESG-related and 'FALSE' otherwise.

For evaluating GPT-4 human agreement, the following instructions were given for classifying topic terms as an action taken toward ESG.

The table below presents various terms. Determine if each term expresses an action toward improving a company's ESG performance. Mark 'TRUE' if the term express an action toward improving ESG performance and 'FALSE' otherwise.

6.7. Effectiveness of ESGSenticNet Flexible Matching Method

A study is conducted to assess the precision of matching ESGSenticNet concepts through the 'flexible' method. A random sample of 200 sentences matched through this method was collected, excluding sentences matched via the 'precise' method. Human annotators were tasked with evaluating whether each sentence clearly conveys the idea expressed represented by its matched concept. From our results, 75.0% of sentences comprised the idea expressed by its corresponding matched concepts. This suggests that the 'flexible' method retains a moderately high level of precision, despite allowing for greater semantic variability. For evaluating the ESGSenticNet flexible matching method, the following instructions were given to evaluate if each sentence clearly conveys the idea expressed by its matched concept.

> The table below presents different sentences and a corresponding concept. Determine if each sentence clearly conveys the idea expressed by its matched concept. Mark 'TRUE' if the sentence clearly conveys the concept's idea, and 'FALSE' otherwise.

7. Conclusion & Future Work

This paper suggests that by focusing on the identified challenges of *immateriality, complexity* and *subjectivity*, NLP methods can be enhanced for sustainability analysis. As our findings indicate, ESGSenticNet, developed with these challenges in mind, provides more relevant and actionable insights for sustainability stakeholders, presentiing a significant improvement over existing sustainability lexicons, let alone state-of-the-art NLP methods for corporate sustainability analysis. This is despite how ESGSenticNet's deployment does not entail computational training or technical expertise. Ultimately, ESGSenticNet aims to be a tool that can be readily used by stakeholders regardless of their technical background, to democratise access to crucial corporate sustainability insights.

Appendix A. Additional details on Human Validation

For evaluating ESGSenticNet accuracy (section 5.9), ESGSenticNet's flexible matching method (section 6.7), GPT-4 human agreement (section 6.6), there are a total of 9 volunteer human annotators. These annotators are based in Singapore, comprising researchers from the Asian Institute of Digital Finance, Sustainable and Green Finance Institute, who are pursuing doctoral-level and post-doctoral research within the corporate sustainability field. All human validation studies follow the same annotation scheme. When there are disagreements, discussions are held to achieve a resolution. Where there is no clear resolution, majority voting is taken to determine the ground truth label. For the derivation of the taxonomy for ESGSenticNet, we enlisted the help of two tenured researchers from the Singapore Sustainable and Green Finance Institute (SGFIN), whom we deem as experts within the sustainable finance field.

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