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Exploring Public Sentiment on Green Economy Policy: A Natural Language Processing-Based Analysis

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ABSTRACT

This study employs a natural language processing (NLP) methodology to examine public sentiment toward green economy policies in Indonesia, utilizing data collected via direct surveys. Green economic policies, including carbon taxes and investments in renewable energy, are gaining significance in addressing environmental and economic concerns. Sentiment analysis and topic modeling are employed to discern trends in public opinion, encompassing positive, negative, and neutral sentiments regarding diverse policy elements. The research findings indicate that 79.34% of public answers endorse green economic initiatives, notably those associated with renewable energy investments and carbon emission reductions, whereas 20.66% exhibit a negative stance, primarily due to apprehensions regarding short-term economic effects. This study offers critical insights for policymakers to improve communication and execution tactics to bolster public support for green economy initiatives in Indonesia.

Keywords: Green Economy, Public Sentiment, Natural Language Processing, Bidirectional Encoder Representations from Transformers

JEL Classifications: M20, N95, O20, O38, P1.

1. INTRODUCTION

A worldwide reaction to the ever more pressing environmental situation is green economic initiatives. Aiming at sustainable economic development while minimizing negative effects on the environment (UNEP, 2022) international organisations such the United Nations Environment Programme (UNEP) have pushed the use of a green economy. Emphasizing sustainable resource management, energy efficiency, and carbon emissions reduction, the green economy The government of Indonesia's dedication to lower greenhouse gas emissions by 29% by 2030, as reported in the nationally determined contribution (NDC) sent to the United Nations Ministry of Environment and Forestry, 2023, reflects the paths towards a green economy there. Though this strategy is strategically significant, its adoption by the general public is yet unknown.

Indonesia has lately adopted several green economy policies, including the carbon tax starting to be applied in 2022 under the Harmonization of Tax Regulations Law (UU HPP) (Ministry of Finance, 2022). This fee seeks to persuade businesses to lower emissions and increase energy efficiency. With the government's aim to produce 23% of energy from renewable sources by 2025 (Ministry of Energy and Mineral Resources, 2023) investment in renewable energy, especially solar and hydro power, has fast grown. Still, various issues have surfaced over the execution of this strategy, particularly with relation to public acceptance, infrastructural readiness, and the scarcity of qualified field-based human resources in the field of renewable energy.

Given the vital part society plays in either supporting or opposing green economic measures, public opinion analysis on such policies becomes even more important. Previous research indicates that effective application of environmental policies (Smith and Turner, 2021) depends much on public support. Although public awareness of environmental problems has grown in Indonesia, policies including carbon taxes—which are perceived as an extra burden on the community—are still opposed even in industries that mostly depend on fossil fuels (Halim, 2022). Thus, strengthening communication methods and guaranteeing more acceptability of green economic policies depend on a better knowledge of public view.

The gathering and examination of vast volumes of data have lately grown simpler as digital technology develops. Natural language processing (NLP) is now a quick approach for gaining understanding from many text data sources, including social media and online news (Li, 2023). Public sentiment analysis conducted more broadly and in real-time using NLP offers a picture of how different society groups evaluate environmentally friendly economic initiatives. In Indonesia, data from direct polls and social media can reveal significant popular opinions on policies such carbon taxes and renewable energy investments as well as highlight major themes in public debates on these subjects.

This study is to investigate public opinion on green economic policies in Indonesia via an NLP technique. This study aims to reveal the opinions of society about several facets of green economic policies by means of data from social media, news items, and direct polls. The results of this study will give legislators important new perspectives on enhancing policy communication and raising public acceptance, therefore supporting the effective application of green economic policies in Indonesia.

2. REVIEW OF THE LITERATURE

Rapidly developing as a technique for analysing vast amounts of text data—including public opinions spoken via social media, news stories, and online polls—NLP has become NLP is frequently used in the field of public policy to find trends in public opinion and extract ideas from unorganised material (Li et al., 2020). Sentiment analysis—which seeks to classify text into positive, negative, or neutral attitudes—is a common method in natural language processing.

For tasks including text categorisation and sentiment analysis, traditional models in NLP include Bag of Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF) have long been employed. These models, which solely take word frequency into account without regard to word order or links between words, thereby have restrictions in precisely interpreting the context of sentences (Mikolov et al., 2013).

2.1. BERT Applied in Natural Language Processing

Bidirectional Encoder Representations from Transformers (BERT) are one of the most recent NLP developments that have greatly raised text understanding accuracy. Originally developed by Google, BERT has grown to be among the most often used models in NLP applications including topic modelling and sentiment analysis. Devlin et al. 2019. BERT's capacity to grasp bidirectional context in sentences allows the model to capture the meanings of words in more complicated relationships than in unidirectional approaches, therefore providing its main advantage.

By means of a transformer design, BERT enables the model to take into account the interactions among words in the whole sentence, therefore transcending the simple order of adjacent words. BERT can be customised for different NLP tasks with very exact outcomes by means of a pre-training and fine-tuning technique. Training this model on Masked Language Modelling (MLM) and Next Sentence Prediction (NSP improves its grasp of more general situations inside the text (Devlin et al., 2019).

2.2. BERT for Green Economic Policy Sentiment Analysis and Topic Modelling

In the framework of public policy, including green economic policy, the use of BERT can help to solve the difficulties of comprehending complicated public emotion. Policies like carbon pricing help the public to voice more varied and multi-layered views. More conventional NLP models cannot help to capture those subtleties than models like BERT.

Recent studies reveal that public opinion towards different policies and social concerns has been effectively examined using BERT. For instance, Zhang et al. (2020) examined sentiment towards climate change policies on social media using BERT and showed that, particularly in regard to contextual or ambiguous language, this model gave better accuracy than past methods. Given the complexity of public opinions on matters like carbon taxes and renewable energy, BERT can be employed in this study to more precisely ascertain popular sentiment in Indonesia about green economic policies.

Apart from mood analysis, BERT can also be applied in topic modelling to find the core topics arising in public debates on green economic policies. This will offer closer understanding of the most talked about problems and their connection to the current policy. Sun and Zhang 2021.

3. STATISTICAL AND METHODS

3.1. Self-Attention Mechanism

BERT is constructed on the Transformer architecture, employing a self-attention mechanism to bidirectionally capture relationships among words in a sentence. The fundamental equation of scaled dot-product attention, which underpins self-attention, is as follows:

$$\text{Attention}(\mathrm{Q},\mathrm{K},\mathrm{V})=\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{1}$$

Where:

- Q (Query), K (Key), and V (Value) are vector representations of the input. (In the case of BERT, this is the token used in the text).
- dk denotes the dimension of the key vector.
- $Q\mathrm{K}^T$ computes the dot product between Query and Key, indicating how relevant each word in a sentence is to the others.

The softmax function assigns probability weights to each word based on the attention received from other words.

3.2. Positional Encoding

Because transformers lack an intrinsic sequential structure, unlike recurrent neural networks (RNNs), BERT relies on positional encoding to keep track of the sequence of words in sentences. This positional encoding uses the sine and cosine functions as follows:

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{\frac{2i}{d_{\text{model}}}}}\right)$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{\frac{2i}{d_{\text{model}}}}}\right) \tag{2}$$

Where:

- pos indicates the word's position in the sequence.
- i is the index of the embedding dimension.
- d_{model} denotes the dimension of the BERT embedding.

3.3. Masked Language Modeling (MLM)

BERT is trained with the Masked Language Modeling (MLM) technique, wherein certain words in a phrase are concealed, and the model is instructed to anticipate these obscured words. This task involves classification, wherein the model generates probabilities for each word in the lexicon and identifies the most probable option. The prevalent loss function utilized in this training is Cross-Entropy Loss, represented as:

$$\text{Loss} = -\sum_{i=1}^{N} yi \log(\hat{y}i) \tag{3}$$

Where:

- Y_i is the actual value (0 or 1) of the word to be predicted.
- Y_i is the probability predicted by the model for the i-th word.

4. RESULTS

4.1. Pre-Processing Data

The preprocessing of data is a critical stage in guaranteeing that the text collected can be effectively processed by Natural Language Processing (NLP) models, particularly BERT. The data utilised in this study is comprised of public opinions and remarks concerning Indonesia's renewable energy and green economic policies. In order to facilitate subsequent analysis, this data must undergo numerous preprocessing stages.

4.1.1. Tokenisation

The initial stage of preprocessing is tokenisation, which involves the breaking down of text into tokens, which are units of words. In order to facilitate analysis, each comment in the dataset is delineated by words. For instance, one of the comments in the dataset is as follows:

> "*Renewable energy development, such as solar power, will be a key driver of economic growth in Indonesia*."

This sentence will be deconstructed into the following tokens following tokenisation:

> *"Renewable", "energy", "development", "such", "as", "solar", "power", "will", "be", "a", "key", "driver", "of", "economic", "growth", "in", "Indonesia"*

In the dataset, which comprises hundreds of entries, this procedure is implemented for each comment.

4.1.2. Normalization and lemmatization

The text is then normalized, which involves converting all letters to lowercase and deleting any unnecessary punctuation. The lemmatization procedure is also used to reduce words to their base forms; for example, the verb "*moving*" becomes "*move.*"

4.1.3. Stop word removal

Stop words (common words like "and," "in," and "to") are deleted to ensure that the analysis focuses on relevant terms. This seeks to reduce interference from words with no substantial significance in sentiment analysis.

4.2. Sentiment Analysis using BERT

Following the pre-processing step, the BERT model was trained to analyze sentiment toward green economic initiatives. This methodology may classify public opinion into three categories: positive, negative, and neutral.

4.2.1. Sentiment distribution

According to the analysis results, public opinion on carbon tax policies and renewable energy expenditure differs substantially depending on area and industrial sector. The following table displays the sentiment distribution of the dataset used:

Approximately 79.34% of replies indicated support for green measures, especially regarding investments in renewable energy and reductions in carbon emissions. Merely 20.66% of the responses conveyed a negative attitude, predominantly concerning apprehensions of short-term economic repercussions, particularly within the industrial sector. Alongside sentiment dispersion, the average length of response text was determined to be 14.91 words per response. The analysis indicates that the majority of responses are succinct and concise, a characteristic typical of social media and internet surveys.

Next, we may reinforce the results in the Table 1 and Figure 1. shows the emotion distribution graph, which:

- Peak at neutral score (0): The distribution indicates that many texts have neutral emotion or are close to zero. This shows that the majority of the assessed opinions are neutral, with no positive or negative feeling.
- Positive score (0.25-1.0): Most opinions are positive, with a significant peak between 0.5 and 0.75. This suggests that

Table 1: Sentiment distribution

Sentiment	Opinion	(%)
Positive (LABEL_1)	603	79.34
Negative (LABEL_0)	157	20.66
Total	760	100

in discussions about certain themes (such as green economy policies or environmental issues), many people express positive sentiment. A high sentiment number may indicate support or an enthusiastic attitude toward the issues under discussion.

- Negative score (−0.75-0): Although a tiny quantity of negative sentiment has been discovered, it is less intense than positive sentiment. Negative comments have a lesser distribution, which could imply that there are some concerns, but they are not the majority in this conversation.

Overall, this distribution is tilted to the positive, indicating that many opinions are more supportive or hopeful about the investigated topic. This is consistent with prior analysis results, which reveal a high frequency of words such as "agree," "good," and "renewable," indicating a positive tone in the conversation.

4.2.2. Word frequency analysis

Alongside sentiment analysis, the word cloud representation in Figure 2. facilitates the comprehension of the most frequently occurring words in the examined text. The picture below illustrates the distribution of keywords in public discourse around green economy policies and carbon taxation in Indonesia. Terms such as "green economy," "environment," "renewable energy," and "Indonesia" are frequently mentioned, signifying that public discourse predominantly centers on matters concerning sustainable economic development and renewable energy.

To gain a better understanding of the themes most commonly discussed by the public, we examine the frequency of word occurrences in the text. Figure 3. shows the twenty most commonly occurring words:

Figure 1: Distribution of sentiment intensity

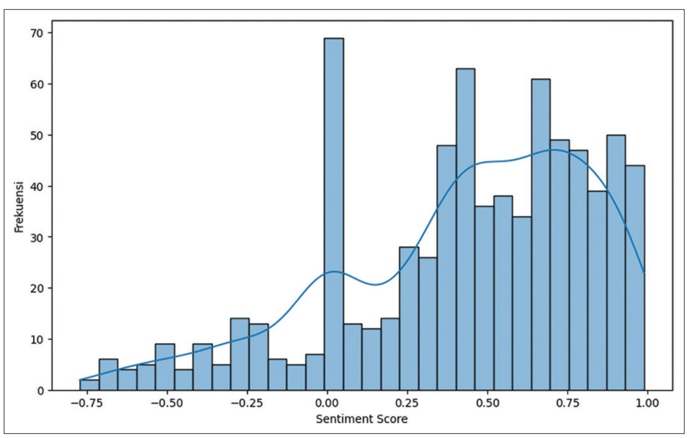
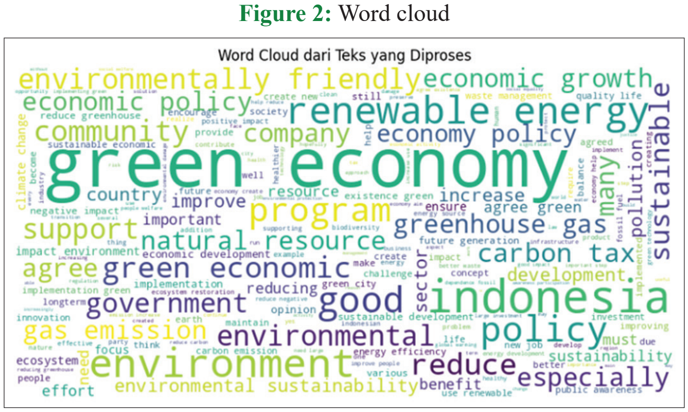


Figure 2: Word cloud



The phrases "green" and "economy" are most frequently used, followed by "policy," "economic," and "environment." This suggests that public conversations are heavily focused on parts of green economy policies, particularly the implementation of renewable energy and environmental legislation. The phrase "Indonesia" appears frequently, indicating that these topics are highly relevant to the national context, notably in the implementation of green economy and environmental policies in Indonesia.

4.2.3. Correlation of words in public text

The heatmap below depicts the relationship between the most commonly used words in the processed text. Correlation is calculated by the frequency with which two words appear together in a text or sentence. The red hue on the heatmap shows a strong connection (close to one), whereas the blue color indicates a weaker correlation (approach 0).

The interpretation of vivid red hue implies words that frequently appear together in similar settings. Figure 4. demonstrates that the word "green" has a strong association with "economy," implying that discussions about "green" are almost always related to "economy," indicating that the majority of conversations about "green" are oriented toward the green economy. Furthermore, the correlation between "Policy" and "Economic" shows a pretty strong relationship with the phrases "economic," "renewable," and "environment." This shows that policy discussions frequently connect with economic and environmental issues, implying that society is concerned about regulatory aspects of renewable energy and environmental laws. The correlation between "renewable" and "carbon" is also significant, demonstrating that many talks about renewable energy are always tied to plans to reduce carbon emissions, which is consistent with the global narrative on climate change and sustainable habitats.

The relationship between these words indicates the interdependence of significant issues of public concern, particularly in the context of green economy and environmental policies. This research allows us to uncover prominent debate patterns in which green economy policies are not only discussed separately but also in relation to concerns such as climate change, renewable energy, and carbon emissions.

Figure 3: Most frequently occuring words

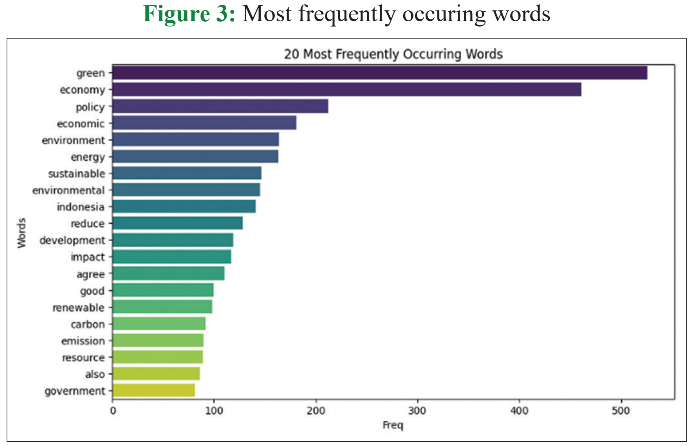
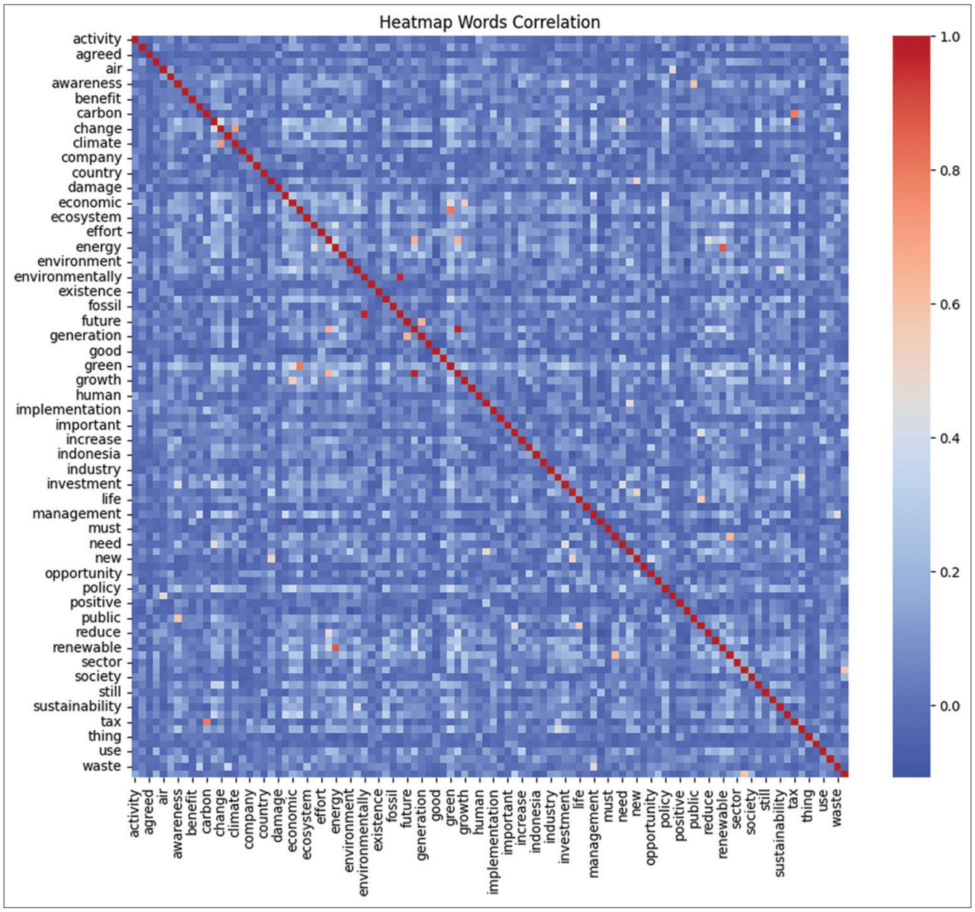


Figure 4: Heatmap words correlation



4.3. In-depth Analysis

Main topic convergence: Discussions frequently center on major topics such as the "green economy" and "renewable energy." This combination of terms shows that public discourse frequently emphasizes the significance of shifting to a more environmentally friendly economy and renewable energy.

Environmental policy: The strong link between the phrases "policy," "carbon," and "reduce" demonstrates widespread concern about the role of government policies in reducing carbon emissions and protecting the environment. This also demonstrates the public's expectation that the government take decisive action on environmental challenges.

Global issues and the Indonesian context: The use of the word "Indonesia" in the discussion suggests that green economy policies in Indonesia are a key focus of this conversation. The debate over the green economy and environmental policy in this country is regarded in a global framework, with climate change and environmental sustainability being critical topics.

5. DISCUSSION

The results of this study indicate that the majority of the Indonesian population has a positive sentiment towards green economy policies, especially in the context of renewable energy investments. This is consistent with the study by Huang et al. (2021), which shows that in developing countries, people tend to support renewable energy policies more because of the perceived long-term environmental and economic benefits. Nevertheless, there are still challenges faced, especially from the industrial sector that feels burdened by the carbon tax policy. This feeling arises from concerns about the additional costs imposed by the new regulations, as explained in the study by Pahle et al. (2018) regarding the economic impact of environmental policies in countries with strong industrial sectors.

This research also reveals variations in sentiment based on geographical regions, with areas that are more advanced in infrastructure showing greater support for green economic policies compared to areas where energy infrastructure is still lagging. These findings underscore the importance of infrastructure readiness in influencing public perception of environmental policies, which is also supported by the research of Li et al. (2020). Regions with better renewable energy infrastructure tend to respond more positively to this policy, as the community can more directly experience the benefits of the energy transition. Meanwhile, in areas where the energy infrastructure is not yet ready, there is greater resistance, especially concerning concerns about the availability of labor and appropriate training.

Therefore, policy strategies must consider local factors and provide more inclusive solutions for all layers of society. As suggested by Aklin and Urpelainen (2018), the success of green energy policies in developing countries greatly depends on how the government communicates and engages with the broader community. Improving policy transparency and providing incentives for the affected industrial sectors, as well as strengthening training programs for the workforce in the renewable energy sector, will enhance public support and facilitate the implementation of green economy policies in Indonesia.

6. CONCLUSION

This study effectively examined public attitude toward green economy policies in Indonesia using Natural Language Processing (NLP) techniques, specifically the BERT model. According to an examination of social media data and direct surveys, the majority of public opinion (79.34%) supports measures such as renewable energy investments, while 20.66% is concerned about the short-term economic repercussions, notably in the industrial sector. This study also discovered that public conversations frequently center on themes such as renewable energy, carbon emission reduction, and resource efficiency, demonstrating public concern for environmental sustainability. Sentiment varies by geographic location and economic sector, indicating the necessity for policy adaptations based on regional and industrial factors. Policymakers should consider strengthening more inclusive and open communication tactics, as well as improving infrastructure and personnel preparation in the renewable energy sector. This study adds to our understanding of public perception and can be used as a resource for future research and policy-making.

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REFERENCES

Aklin, M., Urpelainen, J. (2018), Renewables: The Politics of a Global Energy Transition. United States: MIT Press.

Devlin, J., Chang, M.W., Lee, K., Toutanova, K. (2019), BERT: Pre-training of deep bidirectional transformers for language understanding. NAACL-HLT, 1(19), 4171-4186.

Halim, R. (2022), The societal impact of carbon taxes on fossil fuel industries in Indonesia. Journal of Energy Economics, 14(2), 123-139.

Huang, W., Wei, Y., Ma, F. (2021), Public acceptance of renewable energy in developing countries: A comparative study of China and India. Energy Policy, 151, 112152.

Li, J., Wang, J., Wu, G. (2020), Public perception and acceptance of renewable energy in China: A case study from Fujian province. Renewable and Sustainable Energy Reviews, 132, 110107.

Li, Y. (2023), Natural Language Processing for policy analysis: Advances and future directions. Journal of Policy Analytics, 15(2), 98-115.

Mikolov, T., Chen, K., Corrado, G., Dean, J. (2013), Efficient Estimation of Word Representations in Vector Space. ArXiv, Available from: https://arxiv:1301.3781

Ministry of Energy and Mineral Resources. (2023), Renewable Energy Development in Indonesia: A Policy Framework. Available from: https://www.esdm.go.id

Ministry of Environment and Forestry. (2023), Nationally Determined Contribution (NDC) Indonesia. Available from: https://www.menlhk.go.id

Ministry of Finance. (2022), Harmonisation of Tax Regulations Law (UU HPP). Available from: https://www.kemenkeu.go.id

Pahle, M., Burtraw, D., Kelsey, N. (2018), Pricing carbon as an insurance policy: Emissions pricing strategies in industrial countries. Nature Climate Change, 8(8), 648-653.

Smith, J., Turner, P. (2021), Public support for environmental policies: A comparative analysis. Environmental Policy Review, 9(3), 245-261.

Sun, L., Zhang, F. (2021), Topic modeling for green economic policy debates: Insights from social media data. Journal of Environmental Economics, 12(4), 299-315.

United Nations Environment Programme (UNEP). (2022), Green Economy: Measuring Progress Towards Sustainability. UNEP. Available from: https://www.unep.org/green-economy

Zhang, W., Zhang, H., Li, C., Wang, Y. (2020), Sentiment analysis of climate change policies on social media using BERT. Journal of Environmental Science and Policy, 110, 54-62.