Root Cause Analysis of Social Media Public Sentiment Toward Carbon Tax Policy Using Support Vector Machine

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Abstract. Indonesia has set a Nationally Determined Contribution (NDC) target to reduce greenhouse gas emissions by 32% or approximately 834 million tons of CO_2e by 2030. To achieve this, the government has implemented a carbon tax policy using a cap-and-tax approach to limit emissions and encourage a transition to clean energy. This study aims to classify public sentiment toward the policy and identify the root causes of negative responses using data from the social media platform X. A total of 721 tweets were collected through web scraping, labeled using a sentiment lexicon, and validated by experts. Sentiment classification was performed using the Support Vector Machine (SVM) algorithm, with the best model using a linear kernel and a 90:10 train-test split, achieving an accuracy of 87%, precision of 80%, recall of 66.67%, and an F1-score of 72%. Further analysis of negative sentiments using Latent Dirichlet Allocation (LDA) revealed four dominant topics such as regulatory uncertainty, economic burden, lack of public trust, and skepticism about environmental impact. The model with four topics was selected based on a coherence score of 33.47% and a diversity score of 92.5%. The study recommends industrial incentives, strengthening the MRV system, and clearer emission caps and roadmaps.

Keywords: Carbon Tax, Root Cause Analysis, Sentiment Analysis, Support Vector Machine, Topic Modelling, Latent Dirichlet Allocation.

1 Introduction

Climate change poses a major environmental and economic challenge for Indonesia, an archipelagic nation highly vulnerable to rising temperatures, sea-level rise, and extreme weather events. In 2023, Indonesia ranked as the world's sixth-largest carbon emitter, producing approximately 1,200 million tons of CO_2 equivalent (2.27% of global emissions) [1]. Without effective mitigation, these emissions threaten food security, marine ecosystems, and are projected to reduce Indonesia's GDP by up to 3.45% by 2030 [2]. To address these challenges, the government introduced a carbon tax under Law No. 7 of 2021 on the Harmonization of Tax Regulations as part of its commitment to the Paris Agreement, supporting its Nationally Determined Contribution (NDC) target of reducing greenhouse gas emissions by 32% by 2030 and achieving net-zero emissions by 2060.

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The effectiveness of carbon taxation, however, depends on public acceptance. Opposition or misunderstanding can reduce policy compliance, making it essential to understand citizens' perceptions during the early stages of implementation. In Indonesia, social media has become a major platform for policy discussions, with Platform X reaching approximately 27 million users in 2024, the fourth-largest user base globally [3]. This large volume of user-generated content provides valuable real-time public opinion that can be analyzed using sentiment analysis to support evidence-based policy evaluation and identify emerging public concerns.

Previous studies have demonstrated the effectiveness of Support Vector Machine (SVM) for sentiment analysis in Indonesian public policy, achieving accuracies of 99% for social welfare programs [6], 95.94% for pandemic restriction policies [7], and 93% for regional taxation policies [8]. Meanwhile, Latent Dirichlet Allocation (LDA) has been used to identify policy themes [9], and Root Cause Analysis (RCA) to investigate the drivers of public resistance [10]. However, these approaches are typically applied separately, limiting their ability to provide a comprehensive understanding of public opinion.

This study proposes an integrated framework that combines SVM for sentiment classification, LDA for topic discovery, and RCA to identify the underlying causes of negative public sentiment toward Indonesia's carbon tax policy. By linking sentiment classification with thematic and causal analysis, the proposed framework provides more interpretable and actionable insights for policymakers. Accordingly, this study addresses two research questions: (1) How can SVM be effectively applied to classify public sentiment toward Indonesia's carbon tax policy based on discussions on Platform X? (2) How can RCA, informed by LDA-derived topics, systematically identify and explain the underlying factors driving negative public sentiment toward the policy.

2 Methodology

2.1 Data Collection

The empirical dataset comprises 721 public posts harvested from Platform X using Tweet-Harvest between November 2021 and April 2025. By targeting the keywords "carbon tax" and "emission tax," this temporal window spans from the policy's legislative introduction to its active implementation debates. Platform X was selected because its open, real-time architecture offers an authentic digital environment for tracking spontaneous civic reactions and evolving public sentiment trends regarding state regulatory actions [13, 14]. The data is available on this link

2.2 Text Preprocessing

Raw social media data is inherently noisy and unstructured, requiring a multi-stage text preprocessing pipeline to prepare the corpus for computational analysis [15]. The process initiated with case folding to convert all characters to lowercase, followed by comprehensive noise removal to eliminate punctuation, numbers, emojis, and web hyperlinks before

tokenizing the text into discrete lexical units. To address the informal nature of online communication, slang, colloquialisms, and abbreviations were normalized according to the official Indonesian dictionary (KBBI). Finally, stopword removal discarded high-frequency words lacking semantic value, and algorithmic stemming reduced inflected terms to their base morphological forms, standardizing variations and minimizing feature space complexity.

2.3 Data Labeling

Initial data labeling was conducted using the InSet Lexicon to assign polar categories based on pre-weighted Indonesian sentiment terms. Because the InSet Lexicon cannot capture sarcasm and cultural idioms, outputs were audited by three expert judges with two lecturers and one teacher specializing in Indonesian Language and Literature Education and with final ground-truth labels determined via a majority-voting protocol. This approach ensured that the sentiment classification was contextually accurate and linguistically reliable, resulting in a verified dataset of 554 negative and 167 positive tweets.

2.4 Term Weighting

This study employs two task-specific vectorization strategies. For the supervised sentiment classification model, the Term Frequency-Inverse Document Frequency (TF-IDF) framework weights terms by balancing local frequency against global distribution to highlight highly discriminative words [16, 17]. Conversely, the unsupervised topic modeling pipeline utilizes the Bag-of-Words (BoW) framework, which represents documents as aggregated token frequency counts within a fixed vector space while omitting syntax [18]. This frequency-driven approach provides a computationally efficient foundation for identifying the statistical token distributions necessary to map thematic clusters.

2.5 Sentiment Classification using Support vector machine (SVM)

The core sentiment classification task was executed using a Support Vector Machine (SVM), a supervised learning algorithm well-suited for high-dimensional text feature spaces [19]. SVM operates by constructing an optimal separating hyperplane that maximizes the geometric margin between distinct classes within the vector space, relying on specialized boundary instances called support vectors to establish this line [20]. The structural boundary of this hyperplane is formulated mathematically as:

$$h(x) = w \cdot x + b \tag{1}$$

where h(x) is the decision boundary, w the weight vector, and b the bias.

2.6 Sentiment classification evaluation

To evaluate classification performance, a confusion matrix was constructed to record True Positive, True Negative, False Positive, and False Negative outcomes [20]. The classification framework was systematically evaluated across multiple train-test split ratios and

alternative kernel variants, including linear, polynomial, radial basis function, and sigmoid [21]. To address the class imbalance problem, the Synthetic Minority Oversampling Technique (SMOTE) was applied exclusively to the training data to generate synthetic samples for the minority class, thereby improving class representation while preventing information leakage into the test set. Additionally, a k-fold cross-validation framework was integrated to confirm model generalization and maintain predictive consistency across varying data partitions [22].

2.7 Topic modeling with latent Dirichlet allocation (LDA)

To move past simple classification and understand the specific issues driving public opposition, the negative sentiment subset was analyzed using Latent Dirichlet Allocation (LDA) [23]. LDA models documents as mixtures of latent topics, each defined by a probability distribution over vocabulary, clustering co-occurring terms into interpretable semantic themes [24, 25].

To ensure statistical reliability and interpretive clarity, the optimal number of topics was determined by calculating coherence and diversity metrics. Coherence scores measure the semantic similarity of top-ranking words within an individual topic to ensure they represent a unified concept [26]. In parallel, diversity metrics evaluate the uniqueness of these words across different topics to minimize overlapping definitions and ensure distinct themes [27]. In this study, the LDA model was implemented using Gensim's LdaModel with its default hyperparameter settings, including alpha='symmetric', eta=None, passes=1, iterations=50, and chunksize=2000, while only the number of topics was varied to identify the optimal model based on coherence and diversity metrics.

2.8 Root cause analysis

Once the distinct topic clusters were extracted via LDA, the themes were fed into a Root Cause Analysis (RCA) framework to uncover the structural reasons for public resistance to the carbon tax [28]. A fishbone diagram was used to visually map and systematically categorize these issues into four core dimensions: economic impacts, social issues, environmental concerns, and policy design flaws [29].

3 Result and Discussion

3.1 Sentiment classification evaluation

To ensure its reliability as a forecasting tool for future public opinion, the SVM model's capability to categorize carbon tax sentiment was evaluated using various train-test splits, kernel comparisons, and k-fold cross-validation. Performance was quantified using accuracy, precision, recall, and F1-score to guarantee robust and effective predictive capabilities.

Model performance testing

Performance testing was conducted across five scenarios, with training-to-test data ratios ranging from 50:50 to 90:10. The results showed that model performance improved as the proportion of training data increased. The best results were achieved with a 90:10 split, reaching 87.67% accuracy and a 72.7% F1-score. This suggests that the model performs more effectively when trained on larger datasets.

Table 1. Training data scenarios

Data Ratio	Accuracy	Precision	Recall	F1-Score
50%:50%	82.27%	60%	56.96%	58.4%
60%:40%	83.39%	65.08%	61.19%	63%
70%:30%	84.79%	69.39%	65.38%	67.3%
80%:20%	86.21%	75.68%	71.79%	73.6%
90%:10%	87.67%	80%	66.67%	72.7%

SVM kernel testing

Evaluation of the SVM kernels (Table 2) demonstrated that the linear variant outperformed the RBF, polynomial, and sigmoid models, achieving 88% accuracy, 80% precision, and a 73% F1-score. This success is driven by the linear separability common to high-dimensional TF-IDF vectors derived from short social media text. Conversely, the RBF and polynomial kernels overfit the sparse dataset, reducing recall, while the sigmoid variant produced inconsistent decision boundaries. The linear kernel was therefore selected for its superior generalization and predictive reliability within this corpus.

Table 2. SVM kernel testing scenario

Kernel	Accuracy	Precision	Recall	F1-Score
Linear	88%	80%	67%	73%
RBF	81%	83%	38%	53%
Polynomial	79%	100%	21%	34%
Sigmoid	83%	67%	72%	69%

Oversampling using SMOTE

SMOTE was applied to address class imbalance and the relatively low recall observed in earlier experiments, which indicated limited detection of minority-class instances. However, as shown in the table, SMOTE did not improve model performance. Accuracy, precision, recall, and F1-score all decreased after oversampling, indicating that the non-oversampling approach remained more effective for the given dataset and kernel configuration.

Table 3. SMOTE testing scenario

Scenario	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Without SMOTE	88%	80%	67%	73%
With SMOTE	86%	78%	61%	68%

K-fold cross-validation

The K-Fold Cross-Validation results show that accuracy, precision, recall, and F1-score varied across different folds, with the first fold achieving the highest performance at 88% and the eighth fold the lowest at 67%. On average, however, the metrics were fairly stable,

hovering around 80% across all folds as seen in Fig. 1. This indicates that the model performs consistently and can generalize well to different parts of the dataset, even though some variation was seen in specific folds.

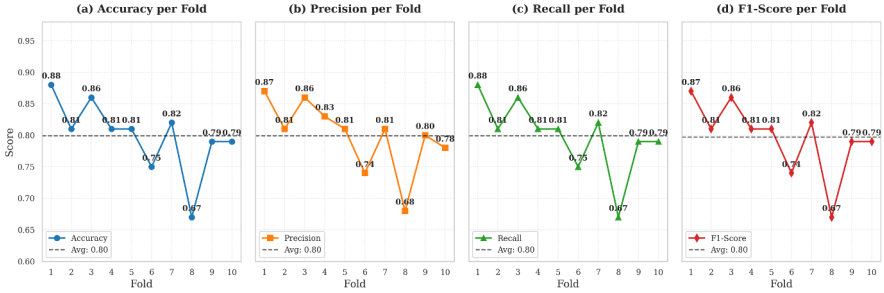


Fig 1. K-fold cross-validation testing scenario

3.2 Topic modeling evaluation

To identify the primary themes shaping carbon tax sentiment, Latent Dirichlet Allocation (LDA) topic modeling was applied. The optimal topic count was determined by evaluating coherence scores for internal semantic similarity and diversity scores for word uniqueness across different themes.

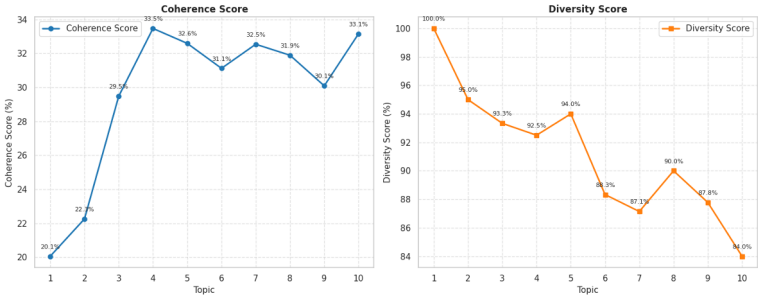


Fig. 2. Topic modeling using LDA

As detailed in Fig. 2 the coherence score peaked at 33.47% for the four-topic configuration, rising steadily from 20% for a single topic. Beyond four topics, coherence declined or fluctuated, indicating topic fragmentation. Simultaneously, the diversity score decreased from 100% to 92.5% at four topics, continuing to drop as more topics were introduced due to increasing keyword overlap. This trade-off demonstrates that a four-topic model provides the optimal balance between semantic interpretability and distinct thematic separation.

3.3 Root cause analysis

After using LDA for topic modeling and determining that four topics provided the best fit, the next step was to interpret and categorize each topic based on its most representative keywords (see Table 3). This process helped assign meaningful themes to each topic, laying the groundwork for the subsequent root cause analysis.

Table 4. Interpretation of topic modeling

Topic	Keywords	Category
1	"uu" (law), "perintah" (order), "atur" (regulate), "terap" (implement), "jalan" (way), "salah" (wrong), "laku" (act), "bijak" (wise), "iklim" (climate), "hpp" (cost price)	Policy and Regulation
2	"kena" (affected), "biaya" (cost), "industri" (industry), "naik" (increase), "tarif" (tariff), "barang" (goods), "masyarakat" (society), "hasil" (result), "iklim" (climate)	Economy and Industry
3	"orang" (person), "negara" (country), "pabrik" (factory), "gede" (big), "rakyat" (people), "kaya" (rich), "usaha" (business), "bayar" (pay), "coba" (try), "banget" (very)	Public Perception
4	"polusi" (pollution), "lingkung" (environment), "uang" (money), "bayar" (pay), "energi" (energy), "udara" (air), "usaha" (business), "pakai" (use), "bakar" (burn), "hasil" (result)	Environmental Impact

The fishbone diagram (Fig. 3) maps the four LDA-derived themes into structural root causes. Regulatory uncertainty stems from vague implementation thresholds and weak inter-ministerial coordination. Economic resistance is driven by rising production costs and the absence of protective instruments like CBAM. Public skepticism reflects opaque revenue recycling and limited outreach. Environmental concerns center on inadequate MRV infrastructure and the absence of quantitative emission targets. Across all four dimensions, the diagram reveals a compounding pattern: governance gaps in regulation and monitoring directly erode public trust, while the absence of visible environmental outcomes reinforces the perception that the carbon tax functions primarily as a revenue instrument rather than a climate solution. This interconnection suggests that technical fixes applied to any single dimension in isolation are unlikely to shift public sentiment unless accompanied by parallel improvements in institutional transparency and emissions accountability.

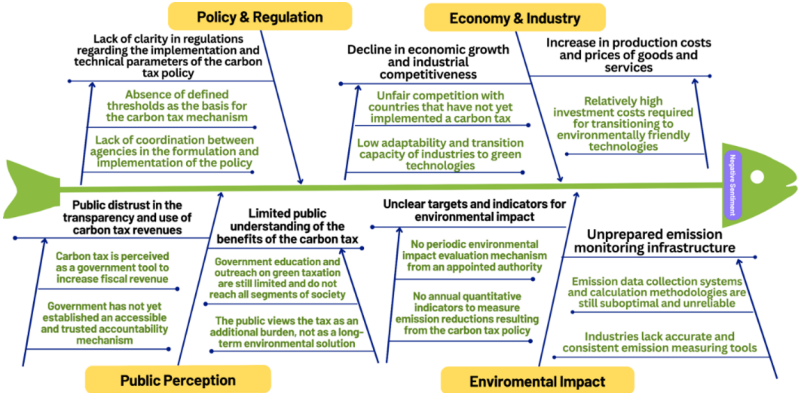


Fig. 3. Root cause analysis of carbon tax policy using fishbone diagram

3.4 Policy recommendation

Once the root causes and contributing factors in each category have been identified, the next step is to develop policy recommendations that are practical and solution focused. These recommendations consider how the issues are interconnected and ensure that the proposed policy responses are relevant and effective.

Table 5. Policy Recommendation

Topic	Recommendation
Policy and Regulation	• Conduct sector-specific impact assessments and international benchmarking to establish realistic emission thresholds. • Establish a permanent inter-ministerial coordinating body with the legal authority to unify regulations and prevent administrative overlaps.
Economy and Industry	• Launch a phased domestic Carbon Border Adjustment Mechanism (CBAM) using sector-specific pilots. • Provide targeted subsidies, tax incentives, and green financing to accelerate low-carbon technology adoption. • Allocate a specific portion of carbon tax revenues directly to social safety nets for small businesses and low-income households.
Public Perception	• Legally earmark carbon tax revenues for visible public goods, such as clean energy infrastructure and sustainable transportation, to improve public trust and fairness perceptions. • Strengthen transparency through open-data portals and multi-stakeholder oversight committees to ensure accountability in revenue management. • Implement community-led outreach programs showcasing local success stories to increase public support for carbon taxation policies.
Environmental Impact	• Standardize environmental impact assessments by clearly defining the regulatory roles of independent external evaluators. • Integrate mandatory, sector-specific annual CO_2 reduction targets directly into the national climate strategy. • Deploy a unified Monitoring, Reporting, and Verification (MRV) system to standardize reliable data collection.

4 Conclusion

This study demonstrates that integrating computational sentiment classification with diagnostic topic modeling and root cause analysis can move public opinion research beyond passive measurement into actionable policy intelligence. The SVM-LDA-RCA pipeline developed here offers environmental authorities a replicable diagnostic tool that does not merely report that public sentiment is negative, but identifies the underlying causes and maps them to specific governance failures. This distinction matters: policy communication strategies built on sentiment labels alone risk addressing symptoms rather than causes.

The four root causes identified, namely regulatory fragmentation, financial inaccessibility, institutional distrust, and monitoring deficits, are not unique to the carbon tax. They

reflect structural weaknesses in Indonesia's broader environmental governance architecture. This suggests that any future climate fiscal instrument introduced without first resolving these systemic conditions is likely to encounter the same patterns of public resistance, regardless of its technical design.

Future research should extend this framework in two directions. First, expanding data collection across multiple platforms and regions would test whether the four themes identified here are nationally representative or concentrated within particular demographic and geographic segments of Platform X users. Second, pairing computational findings with structured interviews or focus groups involving policymakers and industry stakeholders would validate whether the grievances surfaced through LDA align with those recognized inside the institutions responsible for implementation. The gap between public perception and institutional awareness in this regard itself constitutes a governance problem worth investigating.

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