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Sentiment Unleashed: Electric Vehicle Incentives Under the Lens of Support Vector Machine and TF-IDF Analysis

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Abstract

This research examines public sentiment regarding electric vehicle incentives through sentiment analysis of online comments. These incentives include tax deductions and other financial rewards offered to promote the adoption of electric vehicles. In this study, the researchers collected and analyzed over 1,000 comments from various online platforms to understand the public's perspective on these incentives. The study employs Support Vector Machine (SVM), a powerful machine learning algorithm, as the main method and utilizes Term Frequency-Inverse Document Frequency (TF-IDF) to analyze comment texts. The research findings depict significant variation in public sentiment regarding electric vehicle incentives, with approximately 57.3% of comments expressing negative sentiment, 33.2% positive, and the rest neutral. This study makes a unique contribution to the existing literature by shedding light on the nuanced perspectives of the public, revealing strong support for incentives from a financial standpoint, coupled with notable concerns about electric vehicle prices and charging infrastructure availability. External factors such as government policies and vehicle prices significantly influence public sentiment, and easy access to charging infrastructure plays a crucial role in shaping positive sentiment. Furthermore, the study emphasizes the positive influence of environmental concerns on public support for electric vehicle incentives. The results provide valuable insights into public sentiment, contributing to a better understanding of the factors influencing it, and offer practical policy recommendations for the design and implementation of effective electric vehicle incentives to foster sustainable and environmentally friendly transportation.

Keywords: Electric vehicle incentives, Sentiment analysis, Support Vector Machine (SVM), Term Frequency-Inverse Document Frequency (TF-IDF)

1. Introduction

The electric vehicle has emerged as a key solution to reduce carbon emissions and air pollution, yet its adoption faces various challenges. Despite clear environmental benefits, high prices and uncertainties related to charging infrastructure remain significant obstacles. This is why government incentives play a crucial role in accelerating the transition to electric vehicles. In the past decade, issues related to climate change and the adverse impacts of fossil fuel-powered vehicles have gained global attention. Reducing carbon emissions has become a crucial goal to maintain the balance of the global ecosystem. Electric vehicles have emerged as an attractive solution to mitigate greenhouse gas emissions, but challenges such as high costs and charging infrastructure uncertainties have hindered mass adoption. The urgency of carbon emissions and their impact on the global climate has intensified over time, prompting efforts to explore more environmentally friendly alternatives in the transportation sector [1][2]. In this context, electric vehicles have emerged as a promising solution.

This research aims to explore public sentiment and perspectives regarding electric vehicle incentives. The primary focus is to identify factors influencing positive or negative sentiment towards these incentives and how such sentiment may affect the decision-making process for electric vehicle purchases [3][4]. Why are some individuals motivated to adopt electric vehicle technology, while others may be skeptical? Are there specific factors influencing public opinions? Through a comprehensive understanding of this sentiment, the research aims to provide insights that can help formulate more effective strategies to promote electric vehicle adoption.

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In this context, the research aims to understand public sentiment regarding electric vehicle incentives, identify influencing factors, and evaluate the impact of this sentiment on electric vehicle adoption. Additionally, the research will formulate policy recommendations based on these findings to encourage the adoption of electric vehicles. As part of this objective, the research will also involve the development of a predictive model that can project adoption trends based on public sentiment. It is essential to note that this research will limit its analysis to reviews, opinions, and public comments related to electric vehicle incentives, excluding technical aspects such as tax considerations or technical regulations. The research will use text-based sentiment analysis methods and TF-IDF feature extraction techniques to understand public sentiment [5][6][7]. Data sources for this study will be limited to online platforms that capture public opinions regarding electric vehicles.

To achieve the research objectives, data will be collected from various open sources such as social media, review platforms, and discussion forums. This data will be processed using trained sentiment analysis algorithms [8][9] and TF-IDF feature extraction techniques [7]. The research will also utilize Natural Language Processing (NLP) frameworks to identify sentiment patterns. Additionally, the study will develop a predictive model leveraging machine learning methods to project electric vehicle adoption trends based on public sentiment.

This research will provide valuable insights to policymakers, electric vehicle manufacturers, and the general public regarding public sentiment on electric vehicle incentives. The research findings can be used to design more effective policies to encourage electric vehicle adoption. Furthermore, the study will contribute to the literature on the acceptance of new technology and factors influencing consumer purchasing decisions. With increasing global attention on climate change issues, this research holds growing significance in guiding the transformation of the transportation sector.

2. Literature Review

2.1. The Importance of Incentives in Driving Electric Vehicle Adoption

The introduction of electric vehicles has become a crucial step in the global effort to reduce greenhouse gas emissions and minimize the adverse impacts of climate change. Electric vehicles are considered a potential solution to reduce urban air pollution, dependence on fossil fuels, and provide a more sustainable alternative in mobility [10]. However, despite the clear benefits of electric vehicles, their adoption has not reached its full potential.

To boost electric vehicle adoption, incentives have become a key component of government strategies worldwide. These incentives take various forms, such as tax deductions, purchase incentives, cheap charging, and access to special lanes [11]. The primary goal of these incentives is to reduce financial barriers and enhance the appeal of electric vehicles for consumers.

Understanding why these incentives are crucial in driving electric vehicle adoption is paramount. Firstly, electric vehicles often come with higher prices compared to traditional fuel-powered vehicles [12]. Therefore, financial incentives such as tax deductions or purchase subsidies can make electric vehicles more affordable for consumers, offsetting the initial price difference. In other words, these incentives help overcome the financial barriers that often deter many consumers.

Furthermore, these incentives also consider the practical aspects of electric vehicle ownership. For instance, access to special lanes and affordable or free charging makes using electric vehicles more convenient and efficient, especially in densely populated urban areas [13]. This provides an additional incentive for consumers to switch to electric vehicles, offering a better driving experience.

The importance of incentives in driving electric vehicle adoption is also reflected in achieving carbon emission targets and energy sustainability. Many countries have set ambitious targets to reduce their carbon emissions, and electric vehicles play a key role in achieving these targets [14]. Incentives supporting the adoption of electric vehicles help expedite the transition from environmentally harmful fossil fuel vehicles to cleaner and more environmentally friendly alternatives.

Moreover, these incentives also create new economic opportunities. They stimulate the growth of the electric vehicle industry, the development of advanced technologies, and the creation of jobs in related sectors. By fostering innovation in battery technology, charging systems, and other electric vehicle components, these incentives can help create a stronger ecosystem for sustainable mobility.

2.2. Sentiment Analysis and Its Influence on Decision-Making

Sentiment analysis, a valuable tool in contemporary research, plays a pivotal role in discerning the prevailing public sentiments surrounding electric vehicle incentives [14]. The assessment of whether these sentiments lean towards positivity, negativity, or neutrality is crucial, particularly in the realm of consumer decision-making, with a specific focus on vehicle purchases. Notably, empirical studies have illuminated the profound impact that public sentiment can wield over individuals' choices in the automotive market. A positive outlook towards incentives for electric vehicles tends to foster heightened interest among consumers, potentially translating into increased adoption of electric vehicles.

Understanding the factors that influence public sentiment towards electric vehicle incentives holds significant implications for designing effective policy strategies. Policymakers can leverage this knowledge to tailor incentives in ways that resonate positively with the public, thereby creating a more favorable environment for the adoption of electric vehicles. Whether through financial incentives, infrastructure development, or public awareness campaigns, aligning policies with the sentiments of the target audience is crucial for the success of sustainable transportation initiatives. Moreover, recognizing and addressing the sources of negative sentiment can help policymakers mitigate potential barriers and objections, fostering a more positive reception of electric vehicle incentives.

In conclusion, the intricate interplay between public sentiment and electric vehicle incentives underscores the importance of a nuanced approach in policymaking. Sentiment analysis not only serves as a diagnostic tool for gauging the current landscape but also as a proactive guide for shaping future policies. By incorporating a deep understanding of public sentiment, policymakers can foster a more supportive ecosystem for electric vehicles, contributing to the broader goals of sustainable and environmentally friendly transportation.

2.3. TF-IDF Technology in Text Analysis

Sentiment analysis, a pivotal component of this research, harnesses the potency of the Term Frequency-Inverse Document Frequency (TF-IDF) feature extraction technique. TF-IDF serves as a robust methodology for extracting and evaluating the significance of keywords within a given text [6][7]. Operating on the principle of assigning weights to words based on their frequency in a specific document relative to their occurrence across a broader corpus, TF-IDF provides researchers with a powerful tool to discern words or phrases that recurrently surface in reviews and comments pertaining to electric vehicle incentives.

By incorporating TF-IDF in sentiment analysis, researchers gain a nuanced understanding of public opinion, allowing them to pinpoint key elements that play a pivotal role in shaping sentiments. This analytical approach goes beyond mere sentiment polarity and delves into the intricate details of the textual data, shedding light on the specific factors that hold substantial influence in discussions related to electric vehicle incentives. Through this method, the research aims to unravel the complexities of public perception, offering valuable insights into the factors that dominate discussions and contribute significantly to the overall sentiment surrounding electric vehicle incentives.

In essence, the TF-IDF feature extraction technique empowers the research to go beyond surface-level sentiment analysis, providing a more comprehensive and detailed exploration of the textual landscape. The significance of this approach lies in its ability to uncover subtle nuances and specific aspects within the discourse surrounding electric vehicle incentives, ultimately contributing to a more profound understanding of the dynamics influencing public sentiment in this particular domain.

As the research progresses, the utilization of TF-IDF not only enhances the depth and precision of sentiment analysis but also facilitates a holistic examination of the intricate factors at play. By unveiling the most influential aspects within reviews and comments, the research endeavors to offer a nuanced and well-rounded perspective on the various dimensions of public sentiment concerning electric vehicle incentives, thus contributing substantively to the broader discourse in this field.

2.4. The Impact of Electric Vehicle Adoption on the Environment

Furthermore, delving into the multifaceted realm of environmental sustainability, the embrace of electric vehicles unfolds a spectrum of far-reaching implications. Beyond merely influencing sentiments, the pivotal role those electric vehicles play in fostering a cleaner, greener environment cannot be overstated. A salient advantage lies in the discernible reduction of carbon emissions, a paramount factor in the global pursuit of mitigating climate change. As electric vehicles seamlessly replace conventional fuel-powered counterparts, the tangible decrease in air pollution and greenhouse gas emissions becomes a linchpin in fortifying environmental protection efforts. This shift not only aligns with the imperatives of responsible resource utilization but also underscores a conscientious commitment to the overall well-being of society [15].

In essence, this research endeavors to comprehensively illuminate the manifold positive impacts that unfold concomitantly with the widespread adoption of electric vehicles. Beyond the apparent reduction in carbon footprints, the ripple effects extend to realms such as improved air quality, diminished reliance on finite fossil fuel resources, and the cultivation of a sustainable ecosystem. Through an intricate exploration of these facets, we aim to underscore the pivotal role those electric vehicles can play in steering societies towards a more ecologically balanced and resilient future.

2.5. The Importance of Evidence-Based Policy

This research holds paramount significance within the realm of evidence-based policy-making, particularly in the dynamic landscape of sustainable transportation. The comprehension of public sentiment surrounding electric vehicle incentives, coupled with a nuanced analysis of influencing factors, equips governments and policy institutions with invaluable insights. Armed with this knowledge, policymakers can strategically craft and implement more targeted and resonant policies that harmonize with the evolving preferences of the public [16][17]. This tailored approach not only ensures greater acceptance and compliance but also accelerates the pace of electric vehicle adoption.

The implications of such well-informed policies extend far beyond immediate public reception. They form a pivotal catalyst in attaining ambitious carbon emission reduction goals, contributing significantly to the broader agenda of environmental sustainability. As nations strive to transition towards sustainable mobility, the efficacy of policies shaped by insights from this research becomes apparent. These findings do not merely exist in the theoretical realm; they hold tangible and pragmatic implications for steering societies towards cleaner and greener transportation alternatives.

In essence, this research transcends the conventional boundaries of academic inquiry by directly addressing the practical needs of policymakers and institutions. It serves as a guide for the formulation of strategic and responsive measures that foster not only the widespread acceptance of electric vehicles but also contribute meaningfully to global efforts in mitigating climate change. The collaborative synergy between public sentiment, policy design, and sustainable mobility underscores the pivotal role of this research in shaping a more environmentally conscious and resilient future.

3. Method

In employing a sentiment analysis approach, this research seeks to delve into the intricate landscape of public sentiment surrounding incentives for electric vehicles. The methodology adopted is comprehensive, encompassing the extraction of textual data from an array of sources, such as online reviews, social media comments, and discussions within forums dedicated to the discourse on these incentives. By leveraging these diverse channels, the study aims to capture a multifaceted spectrum of opinions and perspectives emanating from the public sphere concerning electric vehicle incentives.

The textual data gathered in this research serves as a rich tapestry, woven with the varied threads of public discourse. From enthusiastic endorsements to critical appraisals, the opinions expressed span a wide spectrum, providing a nuanced understanding of the prevailing sentiments. The inclusion of online reviews offers insights into individual experiences, while social media comments contribute real-time reactions, and discussion forums facilitate in-depth conversations. This multi-sourced approach not only enhances the depth of analysis but also ensures a holistic representation of the public sentiment landscape surrounding electric vehicle incentives.

Figure 1. below serves as a visual representation, illustrating the meticulous methodology employed throughout the course of this study. The diagram delineates the interconnected processes of data collection, highlighting the synergy between online reviews, social media comments, and discussion forums. Through this methodological framework, the research endeavors to unravel the intricate layers of public sentiment, shedding light on the various factors that shape perceptions and attitudes towards electric vehicle incentives. In doing so, the study aims to contribute valuable insights that may inform policy decisions and further the discourse on sustainable transportation solutions.

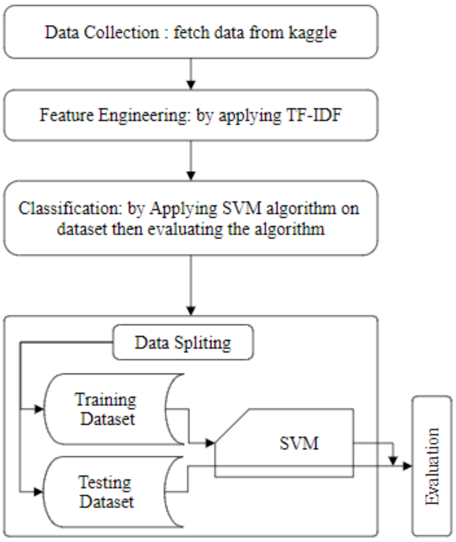

Figure 1. Research Step

3.1. Dataset

The dataset for this research was selected from Kaggle based on specific criteria that prioritize reliability, diversity, and relevance to the study's focus on electric vehicle incentives. Kaggle is chosen as the source due to its reputation as a trusted platform that offers a wide range of validated datasets [18][19][20]. The criteria for selecting datasets from Kaggle include their alignment with the research topic, the credibility of the sources from which they are compiled, and their applicability to sentiment analysis related to electric vehicle incentives.

It is important to acknowledge that, like any data source, Kaggle may have inherent biases. For instance, the datasets available on Kaggle may be contributed by individuals or organizations with their own perspectives and potential biases. Additionally, the user base of Kaggle itself may have certain demographic and geographic biases.

To address potential biases, our study employs a careful curation process, ensuring that selected datasets are thoroughly vetted for credibility and relevance. Despite these precautions, it is crucial to recognize the limitations associated with any external dataset and interpret the findings with consideration for potential biases inherent in the chosen platform.

3.2. Feature Engineering

This research employs the Term Frequency-Inverse Document Frequency (TF-IDF) technique to measure the occurrence rate of keywords in each text document [6][7][21]. TF-IDF assigns weights to words that appear uniquely in specific documents and can identify the most relevant words in sentiment analysis.

The TF-IDF (Term Frequency-Inverse Document Frequency) formula is used to calculate the weight of words in a document within the context of text representation. The formula for calculating the TF-IDF value for a word in a document is as follows:

Term Frequency (TF) formula (1) measures how often a word appears in a document:

$$TF(t,d) = \frac{number\ of\ words\ t\ in\ the\ document\ d}{total\ words\ t\ in\ the\ document\ d} \quad (1)$$

Here t is the word for which we want to calculate its TF-IDF weight in the document d.

Inverse Document Frequency (IDF) formula (2) measures how important a word is across the entire document collection. IDF is the logarithm of the inverse of the document frequency containing that word:

$$IDF(t,D) = \log\left(\frac{total\ documents\ in\ collection\ D}{number\ of\ documents\ in\ collection\ D\ containing\ the\ word\ t}\right) \quad (2)$$

Here, D is a larger collection of documents.

The TF-IDF Score formulas (3) is the result of the multiplication between TF and IDF:

$$TFIDF(t,d,D) = TF(t,d) \times IDF(t,D) \quad (3)$$

This is the TF-IDF score for the word t in the document d within the context of the document collection D. By using the formulas above, the TF-IDF score for each word in each document in the collection will be obtained. The results will serve as a numerical representation of these documents, which can then be used for various text processing tasks such as classification, clustering, or information retrieval.

3.3. Classification

Support Vector Machine (SVM) is an effective machine learning algorithm for classification tasks, especially when dealing with complex and unstructured data [22][23]. SVM aims to find an optimal hyperplane that separates two classes in a high-dimensional space by maximizing the margin and relying on support vectors as critical points. Formulas (4) is the basic formulation of SVM can be expressed as:

$$f(x) = sign(w.x + b) \quad (4)$$

Where:

$f(x)$ is the decision function,

w is the weight vector,

x is the feature vector of the data,

b is the bias.

The main goal of SVM is to find w and b that maximize the margin, which is the distance between the hyperplane and support vectors. The margin p formula (5) can be expressed as:

$$p = \frac{1}{||w||} \quad (5)$$

The objective function of SVM is to minimize $||w||^2$ (L2 norm of w) by considering class discrepancies (hinge loss). Formula (6) is the optimization problem of SVM can be formulated as:

$$min_{w,b} \frac{1}{2} ||w||^2 + C \sum_{i=1}^{N} \max\left(0, 1 - y_i(w.x_i + b\right) \quad (6)$$

In this study, Support Vector Machines (SVM) are chosen as the classification algorithm due to their efficacy in handling complex and non-linear relationships within data. SVMs excel in scenarios where the decision boundary between classes is intricate and requires a high-dimensional space. This makes them particularly well-suited for sentiment analysis tasks, including the classification of electric vehicle incentive sentiments.

The choice of SVM is grounded in its ability to handle high-dimensional feature spaces, making it suitable for processing textual data with a multitude of features. Moreover, SVMs are known for their versatility in adapting to different data characteristics, and they perform well even in cases where the relationship between input features and output classes is not explicitly known.

The parameters, such as the regularization parameter (C) and the choice of an appropriate kernel, are crucial in fine-tuning the SVM for the specific characteristics of our sentiment analysis task. The flexibility offered by SVMs allows us to optimize these parameters to achieve the most accurate classification results.

In summary, SVM is selected for its ability to handle non-linear relationships, adaptability to high-dimensional feature spaces, and versatility in classifying sentiments in text data. These attributes make SVM a robust choice for our specific research task of sentiment analysis related to electric vehicle incentives.

3.4. Evaluation

To ensure the robustness and reliability of the sentiment analysis outcomes, the validation process incorporates a meticulously curated and distinct set of processed data samples, pre-segregated for rigorous evaluation. Established evaluation metrics, including accuracy, precision, and recall, are employed to quantitatively measure the alignment between automated analytical findings and subjective assessments by human evaluators [24].

Accuracy, as a metric, indicates the overall correctness of the sentiment predictions. Precision measures the proportion of correctly identified positive or negative sentiments among all predicted positive or negative sentiments. Recall, on the other hand, assesses the ability to capture all actual positive or negative sentiments among all instances.

In our study, these metrics play a crucial role in quantifying the performance of the sentiment analysis model. High accuracy suggests a reliable overall predictive capability, while precision and recall offer insights into the model's ability to correctly identify specific sentiment categories.

To deepen the understanding of analytical outcomes, the study incorporates rigorous statistical analysis techniques. These methods not only determine the confidence level associated with the results but also unveil key factors significantly influencing sentiment patterns. Through a multifaceted analysis, the research emphasizes not only accuracy but also delves into the intricacies of precision and recall, offering a more nuanced and comprehensive assessment of sentiment analysis.

In summary, accuracy, precision, and recall serve as pivotal metrics in evaluating the sentiment analysis model's performance. A detailed exploration of these metrics enhances the interpretability of evaluation results, providing readers with a more comprehensive understanding of the model's predictive capabilities.

4. Result and Discussion

4.1. Sentiment Analysis Results

In the sentiment analysis regarding electric vehicle incentives, this research presents the performance evaluation results of the SVM model on the utilized dataset. The SVM model achieved an accuracy of 78.1%, reflecting its ability to classify sentiments correctly. Furthermore, the model's precision for negative, neutral, and positive sentiments was 55.6%, 80.0%, and 80.0%, respectively. These results indicate that the model tends to provide more accurate results in classifying neutral and positive sentiments compared to negative sentiments.

Meanwhile, the recall or sensitivity level of the model indicates its ability to recognize different sentiments. The recall for negative sentiments was only 10.6%, while for neutral sentiments, it reached 71.1%, and for positive sentiments, it reached 94.6%. These results suggest that the model has a good ability to identify positive sentiments, but there is still room for improvement in recognizing negative and neutral sentiments. Thus, this sentiment analysis provides a holistic overview of the SVM model's performance in the context of electric vehicle incentives, focusing on accuracy, precision, and recall in classifying various sentiments. Figure 2 below is the Sentiment Result Chart that was successfully created in this research.

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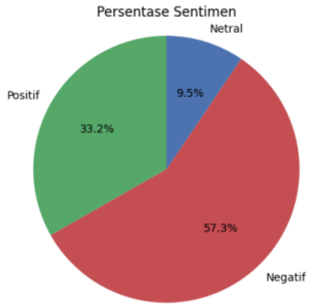

Figure 2. Sentiment Result Chart

The figure above represents the results of sentiment analysis reflecting the public's views on electric vehicle incentives. The analysis results provide a comprehensive overview of the public's responses to these incentives. From the data collected and analyzed by the researcher, the majority of identified sentiments are negative, reaching 57.3%. On the other hand, positive sentiments account for 33.2%, while neutral sentiments make up 9.5%. These findings hold significant importance as they indicate strong disagreement within the community regarding electric vehicle incentives. Despite the dominance of negative sentiments, these results also reflect positive views from a portion of the community that sees these incentives as a positive step toward more sustainable mobility.

4.2. Sentiment Components

To gain a deeper understanding of what drives positive and negative sentiments in the community, the researcher conducted further analysis. Positive sentiments regarding electric vehicle incentives in the public's view are driven by several key factors. One of the main factors is financial incentives, such as tax deductions and other financial incentives, which reduce the ownership costs of electric vehicles. Additionally, the increasingly affordable prices of electric vehicles are also a crucial factor contributing to this positive sentiment. Advances in electric vehicle technology, producing more efficient and environmentally friendly vehicles, also contribute to this positive view. Figure 3 below show the wordcloud result produced from this research.

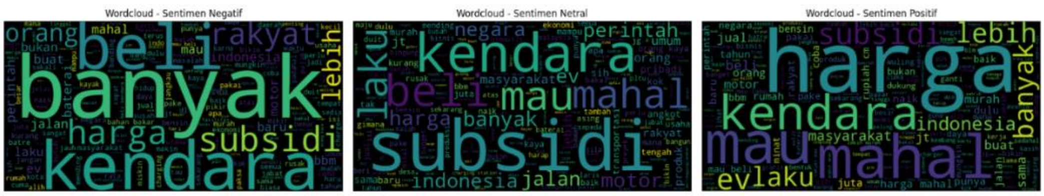

Figure 3. Wordcloud Sentiment Result

On the other hand, negative sentiments in society are often associated with various constraints and concerns. One of the main constraints is the inadequate charging infrastructure. Many respondents expressed their concerns about the difficulty of finding suitable charging stations. Additionally, uncertainty about future government policy changes also creates negative sentiments. Some respondents may feel uncertain about whether existing incentives will remain in place, which can impact their decision to switch to electric vehicles.

The findings of this research have significant implications for formulating policies that support the growth of electric vehicle adoption. In this context, a holistic approach is needed to ensure that existing incentives cover various aspects influencing consumer decisions. This includes, among other things, tax deductions, financial incentives, investment in charging infrastructure, and public awareness campaigns. Effective policies should be able to address the constraints faced by potential electric vehicle buyers, such as concerns about inadequate charging infrastructure.

This research has some limitations that need to be considered. First, it is limited to online text data, which may not capture all public opinions. This data may also reflect the views of those more inclined to speak online and may not encompass the same views from a more heterogeneous group. Second, sentiment analysis can vary depending on the method used, and researchers have attempted to maintain consistency in the methodology of this study. Although this research has tried to detail the sentiment analysis process, there may still be subjective elements in sentiment assessment.

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5. Conclusion

This research has yielded valuable insights into public sentiment regarding electric vehicle incentives through comprehensive sentiment analysis. Key findings include:

- Diverse Opinions: The study unveiled a spectrum of opinions on electric vehicle incentives, ranging from strong support to dissatisfaction.
- Influential Factors: External factors, such as tax deductions and vehicle prices, were found to significantly impact public sentiment. Positive sentiment tended to increase when incentives were perceived as financially beneficial.
- Role of Charging Infrastructure: The availability of easily accessible charging facilities emerged as a crucial factor shaping sentiment and enhancing the acceptance of electric vehicles.
- Environmental Impact: Environmental considerations played a significant role, with environmentally conscious individuals exhibiting more positive sentiment towards electric cars.

Policy recommendations derived from this research highlight the importance of considering these factors when designing and implementing electric vehicle incentives. Improving pricing, infrastructure, and environmental education is crucial for fostering electric vehicle adoption in society.

Moreover, this study suggests opportunities for further in-depth research on public sentiment regarding electric vehicle incentives, exploring more specific and complex variables.

In conclusion, this research contributes to a better understanding of public perspectives on electric vehicle incentives and the influencing factors. The hope is that these findings can serve as a foundation for informed decision-making, supporting the development of sustainable and environmentally friendly electric vehicles.

6. Declarations

6.1. Author Contributions

Conceptualization: J.R.B. and T.H.; Methodology: T.H.; Software: J.R.B.; Validation: J.R.B. and T.H.; Formal Analysis: J.R.B. and T.H.; Investigation: J.R.B.; Resources: T.H.; Data Curation: T.H.; Writing Original Draft Preparation: J.R.B. and J.R.B.; Writing Review and Editing: T.H. and J.R.B.; Visualization: J.R.B.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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