Analyzing Social Media Sentiment Towards Electric Vehicles

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Abstract

This study investigates social media sentiment towards electric vehicles (EVs) through text mining techniques, aiming to analyze user-generated content on platforms such as Reddit. As the adoption of EVs accelerates, understanding public perceptions is essential for stakeholders, including automotive manufacturers and policy makers. The research focuses on key influencing factors, including environmental concerns, technological advancements, economic considerations, and user experiences. By employing keyword frequency analysis, sentiment analysis, and topic modeling, the study seeks to uncover patterns in discourse and variations across user groups. Additionally, it examines temporal changes in sentiment in relation to industry events. The findings aim to provide actionable insights to enhance communication strategies and foster EV adoption, contributing to a sustainable future in transportation.

Keywords: *ev, car, electric, vehicles, battery*

1. Introduction

The transportation industry is experiencing a paradigm shift towards eco-friendly solutions, with electric vehicles (EVs) at the forefront of efforts to decrease carbon output and address climate concerns. The EV market has seen significant expansion in recent times, driven by innovations in technology, supportive government policies, and heightened ecological consciousness. As car manufacturers hasten their shift from conventional internal combustion engines to electric systems, the public's embrace of EVs is becoming increasingly pivotal in shaping the speed and extent of this transition.

Although EVs offer clear advantages for the environment and economy, public opinion regarding these vehicles remains mixed. Issues such as the availability of charging stations, concerns about travel range, financial considerations, and doubts about the dependability of EV technology continue to shape consumer choices and uptake rates. As the automotive sector navigates this major shift, gaining insight into public views and feelings towards EVs has become vital for car makers, government officials, and environmental campaigners.

Conventional methods of assessing public opinion on this scale have been limited, typically relying on restricted surveys or small discussion groups. The advent of social networking platforms, however, has opened new avenues for a more thorough evaluation of public sentiment. These digital spaces, where individuals freely voice their thoughts, relay their experiences, and participate in dialogues about new technologies, offer a wealth of information for comprehending public attitudes towards electric vehicles.

Despite the growth in the EV market, there remains a significant gap in our understanding of how the broader population perceives this move towards electric transportation. This knowledge deficit poses a significant challenge: key players in the industry need to grasp not just what drives positive opinions, but also what fuels doubt or opposition. Without such insights, initiatives to encourage EV adoption and tackle public concerns risk being poorly targeted or ineffective.

2. Purpose Statement

The purpose of this study is to uncover patterns of public perceptions through analyzing social media content related to electric vehicles, aiming to identify key discussion topics, and track changes in perception over time. By delving into the extensive pool of user-created content on social media platforms, this research seeks to offer a more detailed and comprehensive view of public perceptions, worries, and attitudes towards EVs.

This analysis will provide valuable insights for stakeholders in the EV industry to better understand consumer attitudes, address concerns, and tailor their communication strategies.

3. Literature Review

The growing emphasis on reducing carbon emissions has led to a significant shift in the transportation sector towards electric vehicles (EVs). Understanding public sentiment regarding EVs is crucial for stakeholders, including manufacturers and policymakers, as it directly impacts adoption rates. Existing literature provides insights into various factors influencing public perceptions and the methodologies employed to analyze sentiment in social media contexts.

3.1 Public Sentiment Towards Electric Vehicles

Numerous studies have investigated the factors influencing public attitudes towards EVs. Sovacool and Hirsh (2009) highlight that consumer acceptance is hindered by barriers related to technology, economic considerations, and the availability of charging infrastructure. Chen and Zhang (2017) further emphasize the importance of perceived reliability and range anxiety, indicating that these factors significantly shape public opinion and acceptance of electric vehicles.

3.2 Sentiment Analysis Techniques

Sentiment analysis has emerged as a powerful tool to gauge public opinion, particularly in the realm of social media. Pang et al. (2002) established foundational machine learning techniques for classifying sentiment in text, which Liu (2012) expanded upon by providing a comprehensive overview of methodologies relevant to opinion mining. These techniques are essential for analyzing user-generated content to uncover public attitudes and feelings towards EVs.

3.3 The Role of Social Media

The proliferation of social media platforms offers researchers a wealth of real-time data for sentiment analysis. Lazer et al. (2014) stress the transformative potential of computational methods in social science research, allowing for the analysis of large-scale social media data to capture nuanced public sentiment. Tufekci (2014) discusses how social media shapes public discourse and consumer attitudes, while Lyu and Kim (2019) illustrate the application of text mining techniques in assessing public sentiment towards renewable energy sources, showcasing the relevance of social media data in understanding emerging technologies.

4. Conceptual Framework

A. Central Concept
The core focus of the study which is "Social Media Sentiment Towards Electric Vehicles"
B. Influencing Factors
The social media discourse surrounding EVs is influenced by several key factors as shown below:
1.Environmental concerns: Reflected through user discussions and sentiment towards EVs.
2.Technological advancements: Captured in user comments and posts discussing EV performance and innovations.
3.Economic considerations: Insights drawn from the score of posts/comments related to financial aspects of EVs.
4.Infrastructure development: Comments discussing charging stations, availability and user experiences.
5.User experiences and reviews: Personal anecdotes from comments reflecting user satisfaction and dissatisfaction
C. Text Mining Analysis Methods
This indicates the primary analysis methods and how they will be used to analyze the sentiment.
1.Keyword/Phrase Frequency: Analyzing common words and phrases in discussions using both Term Frequency and TF*IDF.
2.N-Gram Analysis: Identifying common phrases and key n-grams associated with sentiment towards EVs.
3.Sentiment Analysis: Evaluating sentiment expressed in posts and comments.
4.Subgroup Comparisons: Comparing sentiments across different user groups based on comments.
5. Categorization Models: Developing models to classify discussions into themes based on keywords and sentiment. Figure 1. below illustrates the key elements of the study on social media sentiment

towards electric vehicles.

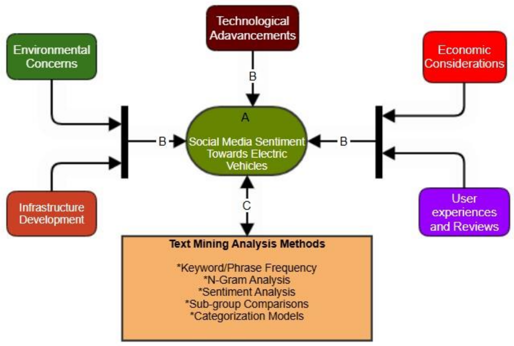

Figure 1.Conceptual framework

I hypothesize that sentiment towards EVs is shaped by the interplay of these factors, and that analyzing social media content can reveal the relative importance of each in driving public opinion.

5. Research Questions

Based on the project requirements and my conceptual framework, I propose the following research questions:

1. What are the most frequently occurring keywords and phrases in social media discussions about electric vehicles?
2. What are the key phrases and n-grams associated with positive and negative sentiment towards electric vehicles?
3. How does sentiment towards electric vehicles vary across different user subgroups for example environmentally conscious users vs. skeptics) based on their comments?
4. Can we categorize social media posts about EVs into distinct topics or themes using a developed dictionary or predefined categories?
5. What are the key variables influencing sentiment, for example post score, upvotes, and comments in the discussion surrounding electric vehicles?

6. Methodology

6.1 Data Availability

For this study, I will collect publicly available social media data from Reddit, focusing on discussions related to electric vehicles (EVs). The dataset will include text content from posts and comments, timestamps, and basic user information, all while respecting privacy constraints. The primary focus will be on English-language posts from the past two years to ensure relevance and maintain a manageable data volume. The use of recent data is critical to capturing the latest trends and sentiments in the rapidly evolving EV market.

6.2 Data Collection and Preparation

To gather the relevant data, I employed the RedditExtractoR package in R, which provides seamless access to Reddit’s API that utilizes functions to extract discussions from various subreddits associated with electric vehicles. Specifically, I identified several key subreddits, including r/ElectricVehicles a subreddit dedicated to EV discussions ranging from technological advances to market trends, r/TodayILearned that contains occasional posts related to surprising insights and statistics about EVs, r/UsedCars that discusses trends in the used car market, with particular focus on EV resale value and depreciation, and r/UnpopularOpinion that hosts candid, often controversial views on EVs and their viability. The data collection process involved several steps. First, I found relevant subreddits using the package's search functions. Next, I extracted content from specific threads that discuss electric vehicles with much focus on attributes such as title, text, author, timestamp, score and voting data. Finally, the individual datasets were combined into a single data frame for comprehensive analysis.

6.3 Data Cleaning and Enrichment

Data preparation is a crucial step in facilitating analysis. To ensure the dataset was clean and usable, I undertook several steps to wrangle the data. The process began with text cleaning, where data underwent American Standard Code for Information Interchange (ASCII) conversion and was standardized to lowercase a step that included removing punctuation, numbers, and non-printable characters. Common contractions were expanded, and symbols were replaced with relevant words for consistency. Following this, comments were tokenized into individual words and phrases classified as unigrams and bigrams respectively, with common stop words removed to ensure the analysis focused on meaningful keywords and linguistic patterns. Comments were then enriched by appending relevant key words based on context to enhance the understanding of EV discussions. For example, descriptions such as “charging speed” or “battery life” were added when specific terms appeared. After that, I checked for missing values in the dataset to assess its completeness. Depending on the results, I would implement necessary measures to handle any identified missing values, such as imputation or removal. Additionally, I assessed the dataset for duplicate entries to ensure data integrity, which is essential for accurate analysis. Parallelly, in Python, the dataset underwent additional cleaning, focusing on removing non-printable ASCII characters and validating data integrity. Finally, the cleaned and enriched dataset was saved in CSV format for efficient access and retrieval in subsequent analysis stages. This structured approach to data collection and preparation ensures that the analysis will be based on high-quality, relevant data.

6.4 Modeling and Analytical Approach

This study employs a comprehensive combination of sentiment analysis, keyword extraction, and topic modeling to address the research questions regarding public sentiment toward electric vehicles (EVs). Both R and Python were utilized for data preprocessing, exploratory data analysis (EDA), and advanced analytics, enabling a multi-faceted approach to understanding the data. The Python analysis began with data cleaning and preprocessing. The dataset, extracted from Reddit threads, was imported using the pandas library. Non-printable ASCII characters in the text data were removed using regular expressions, ensuring clean and readable comments for analysis. Missing values were checked across all columns, revealing that the majority of data was complete, with missing values only present in specific textual fields. Additionally, duplicate rows were identified and eliminated, confirming the uniqueness of entries in the dataset. The cleaned dataset was then explored to understand its structure and distribution, leveraging the .info() and .describe() functions in pandas to extract summary statistics for key engagement metrics, such as comments.score and comments.upvotes.

To analyze sentiment, the TextBlob library was employed to compute polarity scores for each comment. These scores ranged from -1 (very negative) to +1 (very positive), enabling a detailed understanding of public sentiment. The results were further categorized into positive, negative, and neutral sentiment classes. This categorization allowed the creation of sentiment distribution summaries, which were visualized using matplotlib and seaborn. A histogram of sentiment polarity provided insights into the overall mood of the comments, while further segmentations were used to explore how sentiment varied across different user groups.

A significant portion of the analysis focused on identifying trends in user engagement over time. By converting comment timestamps into datetime objects, a temporal analysis of comment frequency was performed. Line plots and bar charts illustrated the fluctuation in user engagement over different periods, revealing patterns and peaks in discussions around EV-related topics.

The study also delved into keyword and n-gram analysis. The text data was tokenized to extract individual words and phrases, removing stop words to focus on meaningful content. The most frequently occurring keywords, such as "electric," "battery," and "charging," were identified using token frequency calculations. Additionally, bigram (two-word phrase) analysis was performed to uncover common phrases like "battery degradation" and "tax incentives," which were often associated with specific sentiments. Sentiment-related n-grams provided deeper insights into how users expressed their opinions, with positive sentiments tied to terms like "incentives" and negative sentiments linked to concerns about "maintenance costs."

Topic modeling was conducted using a Latent Dirichlet Allocation (LDA) model to classify the comments into thematic clusters. The DocumentTermMatrix was created to preprocess textual data, removing punctuation, numbers, and stop words, while ensuring case consistency. The LDA model identified distinct topics such as performance, battery life, charging infrastructure, and environmental benefits. These topics were visualized to highlight their distribution over time, illustrating the evolution of public discourse around EVs. Furthermore, the hierarchical relationships between topics were examined through similarity measures and dendrograms, providing a structured understanding of the thematic landscape.

To explore the correlation between sentiment and key engagement metrics, regression analysis was performed. Variables such as comment scores, upvotes, and thread engagement levels were analyzed to identify their influence on sentiment. Results indicated which factors most strongly influenced public perception, shedding light on how engagement metrics shaped the discourse on EVs.

Lastly, machine learning techniques were employed for classification tasks. A Naive Bayes classifier was trained using a document-term matrix (DTM) to categorize comments based on their associated thread titles. The classifier's performance was evaluated using confusion matrices, providing insights into the accuracy and reliability of the model. Despite the challenges in classifying diverse comment themes, the results highlighted recurring patterns and provided a basis for further refinement.

Below is a detailed explanation of specific techniques and packages utilized to analyze the data and derive insights:

1. Sentiment Analysis: Using the "syuzhet" and "sentiment" packages, sentiment scores will be calculated for each comment, which provides polarity scores to determine whether each comment leans positive, negative, or neutral. To gain deeper insights, common bigrams and n-grams associated with each sentiment category (positive or negative) will be identified. This approach uncovers prevalent expressions tied to users' emotions towards EVs, such as "battery degradation" for negative sentiments or "tax incentives" for positive sentiments.

2. Keyword Frequency and N-Gram Analysis: The "tidytext" package is employed to tokenize the text and analyze term frequency across the dataset. Word frequencies was calculated to determine the most commonly used keywords and phrases. A Term Frequency-Inverse Document Frequency (TF*IDF) analysis will also be conducted to highlight unique, contextually significant terms in different posts, such as those related to charging infrastructure, EV pricing, or environmental impact. (Figure 2 and Figure 3). Figure 2. Below illustrates the Top 20 keywords in EV discussions on Reddit.

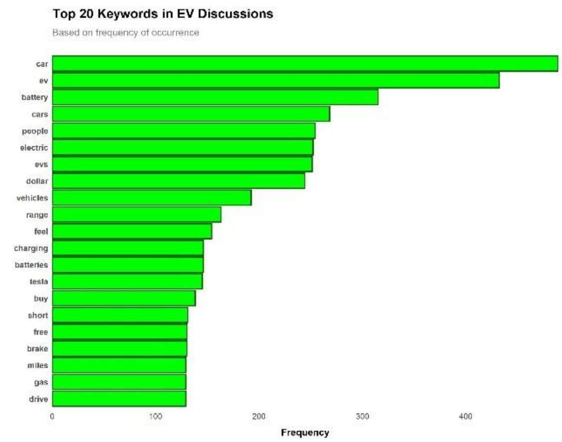

Figure 2. Top 20 keywords.

3. Topic Modeling: A Latent Dirichlet Allocation (LDA) model, implemented with 'topicmodels' package, was used to classify posts into distinct topics. This step identifies clusters of themes, such as performance, battery life, or EV infrastructure, enabling a structured analysis of recurring topics in EV discussions. By visualizing the distribution of topics overtime, the LDA model will help reveal shifts in public discourse, providing a temporal dimension to the analysis.

4. Sentiment Analysis Across User Groups: The comments were segmented into user groups, such as environmentalists, tech enthusiasts and skeptics, based on keywords and language patterns. Sentiment scores across these subgroups will be analyzed to assess how perspectives vary among different demographics. This segmentation aims to reveal nuanced opinions, such as whether environmentally focused users exhibit more positive sentiments about EV adoption compared to cost- conscious or performance -focused users.

Correlation and Regression Analysis: Key variables influencing sentiment like post score, upvotes and comment volume will be examined using correlation and regression analysis. This step aims to determine which factors most strongly influence sentiment, providing insight into how engagement metrics affect public perception of EVs. Figure 7. Below illustrates the Correlation analysis for sentiment variables in EV discussions on Reddit.

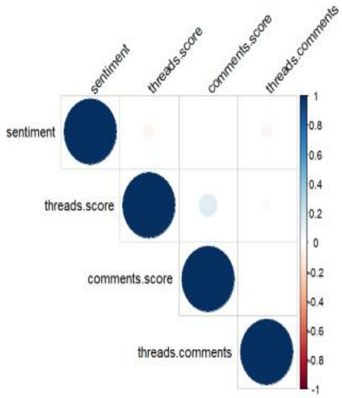

Figure 7. Correlation of variables

7. Findings

The analysis of social media sentiment towards electric vehicles (EVs) reveals a complex landscape of public opinion. A significant proportion of positive sentiment is linked to the environmental benefits of EVs and the financial incentives provided by governments, such as tax breaks and subsidies. These factors are frequently celebrated by users who value eco-conscious living and long-term cost savings. However, negative sentiments persist, driven by concerns about battery life, charging infrastructure, and the upfront cost of EVs (Figure 8). Comments often mention "battery degradation," "charging speed," and "range anxiety" as barriers to adoption, illustrating that while technological advancements have addressed some issues, public skepticism remains a challenge. Figure 9. Below illustrates a basic word cloud of terms in EV discussions on Reddit

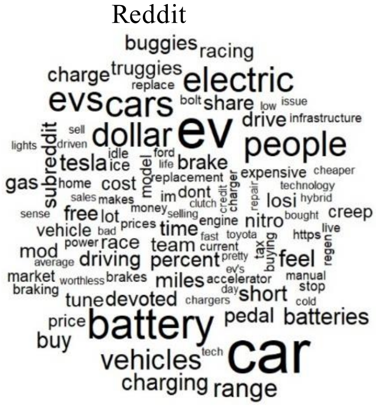

Figure 9. Word cloud

Keyword analysis and n-gram extractions provide deeper insights into public discourse. Terms like "battery," "charging," "range," and "cost" dominate the discussions, underscoring the central themes shaping sentiment. These findings are further supported by topic modeling using Latent Dirichlet Allocation (LDA), which groups discussions into coherent themes (Figure 4). Key topics discussed around performance and reliability of EVs, their affordability, and their role in reducing environmental impact. These clusters highlight a strong awareness of the technological and financial aspects of EV adoption, as well as a growing interest in the broader ecological implications. The topic modeling analysis provides an in-depth understanding of the thematic structure of electric vehicle (EV) discussions, offering a rich narrative of user concerns, interests, and evolving perspectives. Using the Latent Dirichlet Allocation (LDA) model, five distinct topics were identified, each defined by its top 10 terms ranked by their beta values. These terms reveal the dominant themes within EV conversations and provide a basis for thematic categorization.

The first topic, EV Ownership and Range, focuses on general discussions about owning an EV, with key terms such as "ev," "car," "battery," "range," "people," and "price." This topic underscores widespread concerns regarding battery performance, cost implications, and user experiences. For instance, terms like "creep" point to specific driving features that users either appreciate or find problematic. The discourse highlights a blend of practical considerations and personal experiences, reflecting the everyday challenges and benefits of EV ownership.

The second topic, EV Infrastructure, emphasizes discussions surrounding the development and scalability of EV charging networks and power requirements. Key terms include "power," "battery," "charge," "infrastructure," and "cars," which collectively highlight the infrastructural challenges faced by the EV industry. These discussions likely focus on the need for reliable and widespread charging stations to support increasing EV adoption. This topic reflects the crucial role infrastructure plays in enabling the transition to electric mobility, as well as the barriers it poses to broader acceptance.

The third topic, Cost and Performance, revolves around financial and performance-related aspects of EVs. Terms such as "thousand," "car," "dollar," "battery," "range," and "charging" indicate that users are particularly concerned with the cost of batteries, overall vehicle pricing, and the trade-offs between range and charging times. This theme suggests that financial considerations, coupled with performance metrics, are central to the decision-making process for potential EV buyers. It further highlights the impact of economic factors on public sentiment and EV market trends.

The fourth topic, Braking and Pedal Experience, delves into technical discussions about EV driving mechanics. Key terms such as "brake," "car," "battery," "pedal," and "braking" suggest that users are keenly interested in regenerative braking systems and pedal behavior. These conversations indicate specific preferences or concerns, with users likely comparing these features to those of traditional internal combustion engine vehicles. This topic reflects a growing awareness of EV-specific driving characteristics and their influence on user satisfaction.

The fifth topic, Environmental and Learning Discussions, captures a more reflective and forward-looking narrative. Key terms such as "electric," "learn," "vehicles," "vehicle," and "day" highlight discussions about the environmental benefits of EVs and the learning curve associated with adopting new technologies. This theme includes both technical and personal dimensions, with users exploring the environmental impact of EVs and sharing their journeys of understanding and adopting this technology.

The findings from topic modeling reveal three critical insights. First, there is a notable interconnectedness of themes, as evidenced by the overlapping focus of topics like cost and performance (Topic 3) and braking systems (Topic 4). While some topics share thematic elements, others, such as infrastructure (Topic 2) and environmental narratives (Topic 5), are distinct and highlight specific aspects of EV discourse. Second, the analysis underscores a strong focus on practical concerns, with terms like "battery," "range," "charging," and "price" recurring across multiple topics. These terms reveal that users are primarily concerned with tangible factors that directly affect their EV ownership experience. Finally, the analysis brings to light emerging narratives that may not dominate public discourse but are of significant interest to specific subgroups. Discussions on braking systems and environmental impacts illustrate how nuanced issues are gaining traction among audiences.

Subgroup analysis reveals notable variations in sentiment among different user groups. Environmentally conscious individuals tend to exhibit predominantly positive sentiments, emphasizing the ecological advantages of EVs and their alignment with sustainability goals. In contrast, cost-sensitive skeptics express significant reservations, particularly about the financial burden associated with purchasing and maintaining EVs. This divergence highlights the importance of tailoring communication strategies to address the specific concerns and motivations of different demographics. Figure 7. Below illustrates the sentiment variation across use subgroups in EV discussions on Reddit.

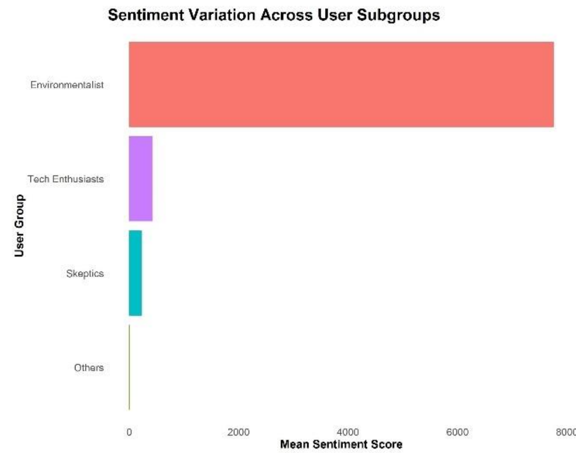

Figure 3. Sentiment variation across subgroups.

8. Discussion and Recommendations

The findings underscore critical challenges that must be addressed to facilitate the widespread adoption of electric vehicles. Infrastructure limitations, such as the uneven distribution of charging stations, remain a persistent concern among users. Similarly, the high upfront cost of EVs continues to deter potential buyers, despite long-term savings in fuel and maintenance. These barriers are compounded by perceptions of inadequate technological reliability, such as fears of battery degradation over time.

To overcome these challenges, a multifaceted approach is necessary. Automotive manufacturers should focus on addressing battery efficiency and longevity concerns through transparent communication and tangible advancements. Highlighting innovations that improve charging speed and extend range can alleviate consumer anxiety and bolster confidence in EV technology. Additionally, showcasing the long-term cost benefits of EV ownership, including reduced fuel expenses and maintenance costs, can counteract apprehensions about the initial investment.

Policymakers play a pivotal role in shaping the EV landscape. Increasing investments in charging infrastructure can directly address concerns about accessibility and convenience, particularly in underserved areas. Expanding financial incentives, such as tax rebates and grants, can further reduce the cost barrier and attract a broader audience of potential EV buyers. Furthermore, public awareness campaigns emphasizing the environmental and economic advantages of EVs can shift perceptions and drive adoption.

9. Future Research

While this study provides valuable insights into public sentiment, several areas warrant further exploration. One promising avenue is the cross-platform analysis of sentiment, comparing user discussions on platforms like Twitter, YouTube, and Facebook to capture a more comprehensive picture of public opinion. Each platform has distinct user demographics and communication styles, which can enrich our understanding of how different groups perceive EVs.

Longitudinal studies can also provide crucial insights into how sentiment evolves over time. Analyzing changes in public discourse in response to technological advancements, policy shifts, and market trends can help stakeholders anticipate future challenges and opportunities. For example, tracking sentiment during the rollout of new EV models or significant policy announcements can reveal the impact of these events on consumer perceptions.

Finally, future research should delve deeper into subgroup dynamics. Understanding the nuanced concerns of specific user groups, such as tech enthusiasts, environmentally focused consumers, and budget-conscious skeptics, can inform more targeted communication and marketing strategies. By addressing the unique priorities of these segments, stakeholders can foster greater alignment between public expectations and the capabilities of EV technology.

10. Data Visualization

Figure 2. Below illustrates the Top 20 keywords in EV discussions on Reddit.

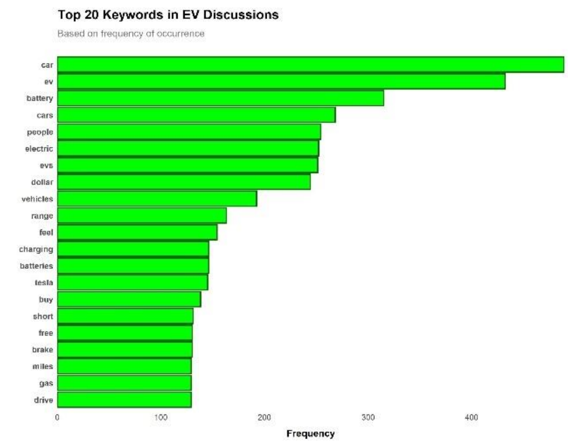

Figure 4. Top 20 keywords.

Figure 3. Below illustrates the Top 20 words by TF and TF*IDF in EV discussions on Reddit

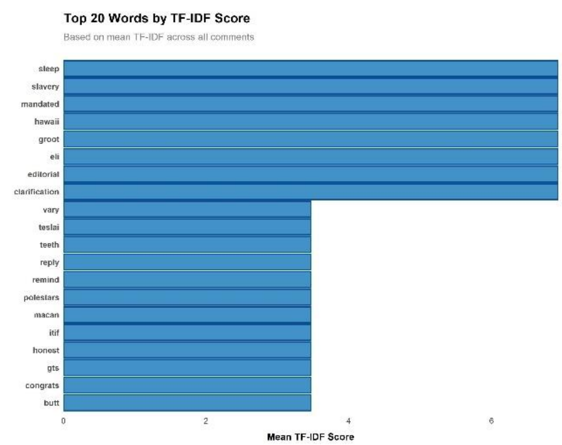

Figure 5.Top 20 words by tf & tf*idf.

Figure 4. Below illustrates the Top 10 bigrams by sentiment category in EV discussions on Reddit.

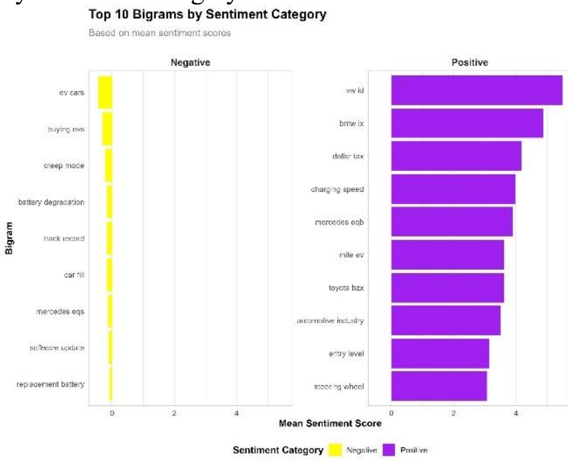

Figure 6. Top 10 bigrams by sentiment category.

Figure 5. Below illustrates the Top 10 terms in each LDA topic in EV discussions on Reddit.

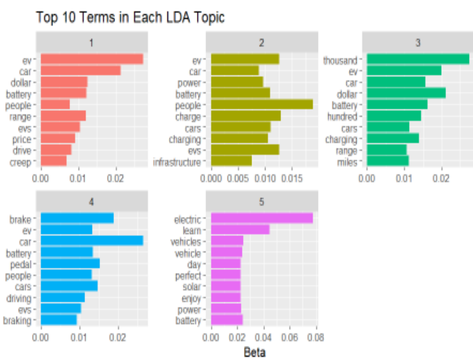

Figure 7. Top 10 terms in each LDA topic

Figure 6. Below illustrates the LDA topic similarity in EV discussions on Reddit.

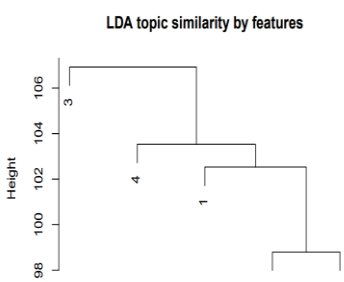

Figure 6. LDA topic similarity by features

Figure 7. Below illustrates the sentiment variation across use subgroups in EV discussions on Reddit.

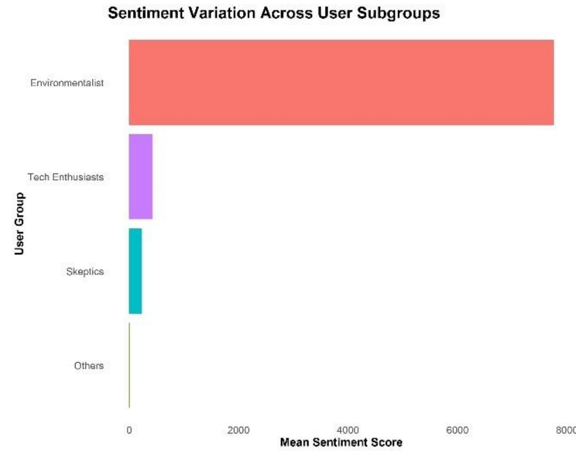

Figure 8. Sentiment variation across subgroups.

Figure 7. Below illustrates the Correlation analysis for sentiment variables in EV discussions on Reddit.

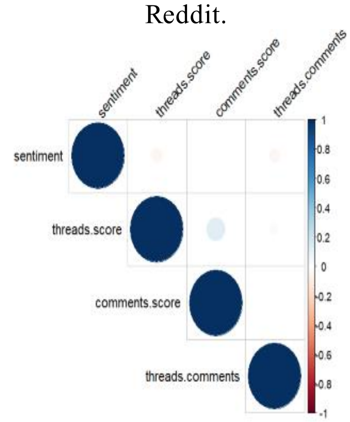

Figure 7. Correlation of variables

Figure 8. Below illustrates the linear regression model showing key variables for sentiment prediction in EV discussions on Reddit

```
Call:
lm(formula = sentiment ~ threads.score + comments.score + threads.comments,
    data = sentiment_variables)

Residuals:
    Min      1Q  Median      3Q     Max
-5.7584 -0.8979 -0.2629  0.6521 16.3245

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       9.073e-01  6.238e-02  14.545  < 2e-16 ***
threads.score    -2.090e-05  7.863e-06  -2.658  0.00791 **
comments.score    5.386e-05  8.095e-05   0.665  0.50586
threads.comments -3.378e-04  7.969e-05  -4.239 2.32e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.703 on 2672 degrees of freedom
Multiple R-squared:  0.009558,  Adjusted R-squared:  0.008446
F-statistic: 8.595 on 3 and 2672 DF,  p-value: 1.12e-05
```

Figure 8. Regression model

Figure 9. Below illustrates a basic word cloud of terms in EV discussions on Reddit

Figure 9. Word cloud

Figure 10. Below illustrates comparison word cloud using sentiment analysis in EV discussions on Reddit indicating both positive and negative.

Figure 10. Sentiment comparison word cloud

Figure 11. Below illustrates shows the distribution of comments about EV discussions on Reddit.

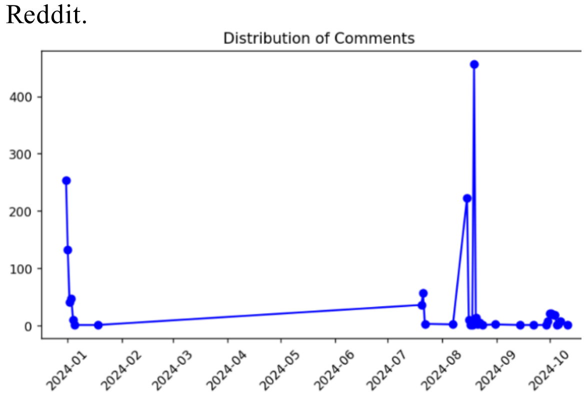

Figure 11. Comments timeline

Figure 12. Below illustrates sentiment polarity distributions amongst EV discussions.

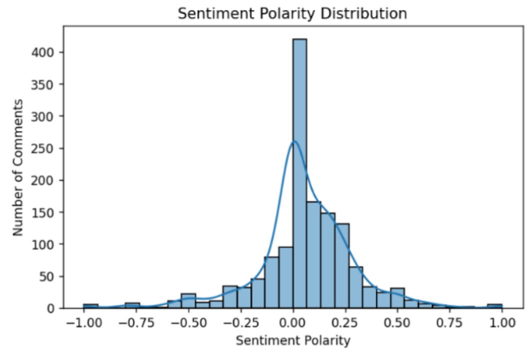

Figure 12. Sentiment polarity distribution

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