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Analyzing Public Sentiment on Electric Vehicles Through BERTopic and Emotion-Based Data Clustering

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Abstract

The escalating impact of technological advancements on worldwide society prompts a closer examination of their profound consequences. Enhanced communication methods and the significant influence of social media platforms stand out as critical factors, with the automotive industry responding to environmental concerns through the emergence of electric vehicles (EVs). In this work the relationship between the trends of EV evolving and social media was utilized using X (aka, Twitter) data. Specifically, this work studies the increasing market demand for EVs due to the impact of social media. Consequently, the study is crucial for both clients and EV manufacturers. To identify the primary discussion themes on Twitter, this article utilizes a topic modelling technique (BERTopic) a data mining method and analyses the production and sales of EV manufacturers. We utilized The National Research Council Canada's Emotion Lexicon (NRCLex) for emotion analysis. Trust, surprise, anger, anticipation, positive, negative, disgust, fear, sadness, and joy are the eight emotions of NRCLex that can provide awareness of the present dynamics. We compared current media coverage of EVs and topic-modeled data. The results showed that BERTopic and NRCLex provided a depth of analysis via the emotional analysis. Consequently, this study contributes to improving the understanding of public sentiment's influence on EV trends.

Keywords: AI; BERTopic; data mining; electric vehicles; NRCLex; Topic Modelling

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1. Introduction

Electric Vehicles (EVs) are a revolutionary transport and energy consumption innovation because of zero tailpipe emissions and high energy efficiency. Moreover, EVs hold potential opportunities of reducing air pollution. The EVs have environmental advantages that can be enhanced in combination with a low-carbon power generation mix. Additional work, progress, and policymaking are essential in helping to popularize EVs, which can change and highlight its importance [1]. With a target of 20 million EVs by 2020, the global EV inventory surpassed one million in 2015 [2].

In recent years, social media platforms have frequently discussed electric and hybrid vehicles. Regularly generating a large amount of textual data is an enormous challenge for these platforms. Classifying textual data into different topics and themes is crucial to getting significant insights [3]. The above topics are essential for developing tools that facilitate decision-making, generate additional information for chance findings, and ultimately enhance learning in subject domains. Like mentions and hashtags, X (aka: Twitter - as an example of the platforms) enables mining over attributes [4].

Nevertheless, although these features are important for monitoring prevalent subjects in real time, they frequently employ non-English words, hashtags, or specific names to denote these trends. Consequently reducing their interpretability [5]. Hence, we require a critical research area in Natural Language Processing (NLP) to improve information retrieval and classify

these subjects into broader categories with high accuracy and precision [6].

This paper introduces a new AI-driven method to categorize and model EV-related topics gleaned from Twitter data using a unique dataset related to electric and hybrid vehicles. We use BERTopic (Bidirectional Encoder Representations from Transformers), a leading topic modeling and data mining approach, known for outstanding classification results. Analysis of emotions also uses the National Research Council Canada's Emotion Lexicon (NRCLex), focusing on eight core feelings (positive, negative, anger, anticipation, disgust, fear, joy, sadness, surprise and trust). We combine research methods such as topic modelling, data mining and studying emotions to better assess how social media changes the automotive sector.

A push to introduce EVs into the mainstream car industry occurred in the early 1990s [7]. Therefore, many countries' auto manufacturers pay more attention to manufacturing electric and hybrid cars in response to increasing challenges from fuel price increases, climate CO2 emissions, and change [8], [9]. However, from a global perspective, the public opinion or acceptability rate of this idea remains unknown. Yet, for future transportation systems, the widespread distribution and adaptation of EVs would be promising solutions. Nevertheless, mass distribution in EVs presents more significant challenges than conventional vehicles due to technological differences and infrastructure limitations [10].

In recent years, many studies have taken the elements impacting EVs' rejectability and acceptance [11]. For instance, they studied the size and features of the potential market for EVs in business fleets, such as fleet size, range needs, and usage patterns [12]. In addition, issues like charging rate, driving range, and price that impact the usage and ownership of EVs are shown to be influential [13]. Similarly, the flexibility of EVs was strongly contingent the public lifestyle, and clients were unwilling to pay the price of EVs in the context of future fuel-saving advantages [14].

Although challenges may vary across countries, they often include lacking charging infrastructure, extremely high achievement costs, worries about range and battery permanence, and a lack of customer education and awareness about EVs [15]. Furthermore, social and culture preferences, for example for bigger size vehicles or the absence of motivations, can impact EV adoption across countries [16]. The overcoming of these problems can be done practically through policy interventions and motivations that promote charging infrastructure, lower upfront charges, educate clients about EVs, and provide stakeholders with the opportunity to collaborate on addressing issues related to range and battery [17].

For instance, in Singapore, important concerns elevated by clients were the expensive cost of EVs and Certificate of Entitlement [18]. Furthermore, several participants estimated the driving range and resale value [19]. In addition to significant challenges and considerations when promoting the adoption of EVs, addressing pricing concerns and ensuring competitive pricing could make vehicle prices considerably cheaper and more attractive to clients [20]. Lack of consumer knowledge and awareness, high initial costs, and limited availability of charging facilities have all been identified as obstacles and enablers to EV adoption in the United Kingdom [21]. Nevertheless, several factors contribute to the anxiety related to EV adoption have been identified in the United States [10]. The issues concern limitations on charging capabilities, increased initial costs in comparison to gasoline-powered vehicles, and insufficient consumer knowledge and understanding regarding EVs [22].

Societal preferences for larger vehicles and Insufficient charging infrastructure are among the numerous barriers that obstruct the broad adoption of EVs in many countries. However, several recent papers argued that there are feasible options through understanding public sentiment and adapting strategies accordingly. Therefore, the evaluation of individuals' views, attitudes, and emotions regarding a product is known as sentiment analysis. It contains transfer learning, resource development, and feeling detection [23]. Accordingly, EV companies can collect public opinion to assess product awareness and monitor the reputation of their EVs.

Topic modeling can support more nuanced sentiment and emotion analysis by revealing the underlying themes and topics associated with people's opinions and feelings. Rather than just classifying sentiment as positive or negative, topic modeling provides valuable context about what people are expressing positive or negative sentiments about [24]. For example, Lin et al. [25] developed semi-supervised topic models that jointly model discovered topics alongside overall sentiment labels, allowing the model to learn associations between different topics and the sentiment expressed around those topics. Similarly, Rui et al. [26] applied topic modeling to social media data to analyze how sentiment towards entities like brands can vary based on the topic being discussed.

Topic modeling approaches have also been combined with emotion analysis to identify emotional themes and language use around specific topics. Bao et al. [27] used topic models to mine expressions of social emotions from text and connect them to underlying topics. More recently, contextual topic modeling techniques have been utilized to model emotions through learned associations between detected topics and related emotion labels [28].

In addition, various researchers have employed an emotional analysis technique utilizing social media during dust and for EVs [29]. For example, Kamal et al. [30] suggested a crowdsource sensing approach based on Twitter data and a word model that can categorize emotions and is more efficient when the analysis is

performed by location. Many Twitter datasets do not specify the location from which the tweet is sent. In such cases, word models aid in the precise categorization of emotions. Twitter allows individuals to disclose their feelings. Some research even blends deep-learning-based language modeling with traditional topic modeling approaches. Using a Deep Neural Network, ALP et al. [31] sorted Turkish Tweets into fundamental emotions. The analysis of our suggested technique is based on data obtained from Twitter users worldwide. Building on these emotional analyses, Kiichi Tago et al. [32] hypothesized the effect of emotional behavior on user connections. Felipe et al. [33] analyzed Facebook data emotionally, categorizing Facebook reactions as good, negative, or neutral and examining if they are connected to Ekman's emotion categorization.

The global discourse on EVs goes beyond technical standards and environmental concerns to include people's emotional emotions. Emotional analysis employing Twitter data from around the world can help comprehend and handle public EV attitudes, preferences, and valuations. Such insights help overcome personal and societal hurdles, impacting electric and hybrid car commercial distribution and acceptance.

The subsequent sections of this paper are organized as follows: Section 2 outlines the methodology employed in this study. Section 3 presents and discusses the results of our topic modeling and classification algorithms. Finally, Section 4 provides conclusions, and our future work focuses.

2. Methods

The methodology of this study presents five phases, these phases are as following: Phase 1 (Data Collection) serves to collect data from several sources, laying the groundwork for our analysis. The phase 2 (Preprocessing) is when the collected data is thoroughly cleaned, filtered and transformed to maintain its quality. Phase 3 (Methodology) involves analysis of emotions with numerous techniques among which are mood, opinion, feeling and emotion. This implies that essential morphological aspects must be used to elucidate the problem in question. In Phase 4 (Topic Modeling), we focus on key areas of the data and our artificial intelligence tools allow us to find the main components hidden behind the unconscious information in the data. During Phase 5 (Visualization), outcomes are shared using data visualization tools which turn information into images that are easy for the audience to grasp.

In the subsequent sections, each methodology phase is discussed in detail, providing a comprehensive and systematic number of the processes and methodologies utilized to address the research questions effectively. Figure 1 illustrates the structure of the proposed model.

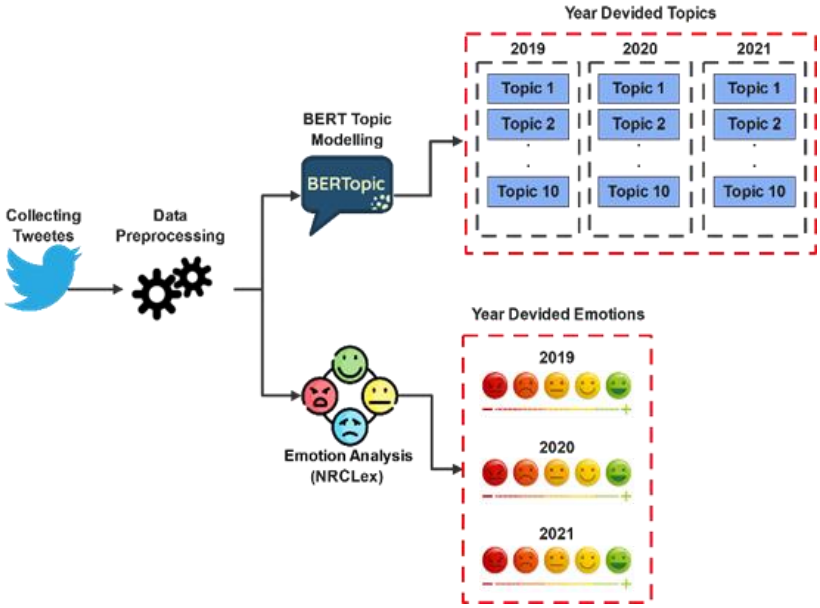


Figure 1. The structure of the proposed model

2.1 Data Collection

Since the dataset was used in our experiments, we collected Tweets between the 1st of January 2019 and the 31st of December 2021. In this step, the social media data accessed from Twitter is collected using Python. Since the Twitter API needs to be admitted for registration and is limited in gathering daily tweets, we have used our developed Python Twitter Scraper to collect the tweets.

We collected data about electric and hybrid cars to extract raw data. The following hashtag has been used: #electriccars, #ElectricCar, #ElectricVehicles, #HybridCars, #Hybridelectricvehicle, #EV, #EVgo, #DriveElectric,#EVroadtrip,#evcharging,#getthepowe, #NewElectricCarfriendly, #Builtforabetterdco, #Electriccars, #HybridElectricCars, #electricfuel, #EVandHybridcar, #ElectricCityCar, #chargeway, and #HybridTechnology.

The Hashtags with user comments found in the tweets will be beneficial. The hashtag tagging the respective discussion topic or opinion will help other users find related comments quickly with hashtags. A total of 848,470 tweets were randomly filtered within the given year ranges. Next, various elements apart from their texts were extracted from the collected tweets, including tweet ID, tweet date, language, and hashtags. These were saved as comma-separated values for the analysis. The collected data were preprocessed before the analysis, as described in the following section.

2.2 Preprocessing

The initial data preprocessing stage was performed to remove noise from our text data. In the context of Twitter data for natural language processing and data mining, we considered the following noises: Non-standard text and punctuations, URLs and whitespaces, hashtags, names of users, and duplicate tweets [34]. Language filtering was then applied to the collected tweets to extract only those written in English for the next stage. The outcomes after preprocessing 841,252 tweets are listed in Table 1 regarding the preprocessing for each year.

Table 1. Preprocessing for each year

Years	Number of Tweets	
	Before Preprocessing	After Preprocessing
2019	262,064	260,060
2020	248,150	245,318
2021	338,256	335,874
Total	848,470	841,252

In preparing our data for analysis, several steps were undertaken to ensure the quality and relevance of the information. Initially, all words were converted to lowercase, a process known as Lowercase, to reduce dimensionality and increase topic coherence. Then, the process is followed by removing commonly used words that do not change the meaning of the data, a step referred to as Stop Words Removal.

As a rule-based method for ensuring data consistency and accuracy, the following stage is text normalisation, in which out-of-vocabulary words, misspellings and abbreviations in our extracted data are identified and normalized. Following this, according to the link removal procedure, we deleted every link to a tweet comprising HTML elements, numerals, special characters, punctuation and URLs. Concerning topic modelling, these elements were not important to the text. In the same way, the tweets' emojis were removed.

Lemmatization, a final step we applied, involves the removal of suffixes and affixes from words to convert them back into their words (referred to as lemmas), which convey meaning. For instance, "go" is the lemmatization of "going". We ensured that our data had been applied for further analysis by applying this process to the entire dataset.

2.3. NRC Emotions

However, the NRC Lexicon (NRCLex) is now seen as one of the main resources for identifying emotional content in written text resulting in the application of this technology in psychological research, product marketing, public opinion analysis and consumer profile analysis [35]. The vocabulary of the lexicon is derived from many English words, each thoroughly annotated and assigned to two sentiment categories (negative and positive) and eight fundamental emotions (joy, hate, anticipation, trust, surprise, pity, fear, and anger). Through the instrument of NRCLex, academicians and practitioners can gain an in-depth knowledge about the emotional composition of the texts in focus by leveraging data mining techniques to uncover underlying patterns.

Additionally, NRCLex helps with extensive re-analysis and interpretation of the numerous sentiments and feelings communicated by the audience in their comments [36]. These detailed details about emotional content, extracted through data mining, are the key to understanding patterns, trends and associations that would have remained provocatively unseen in all textual data.

2.4 BERTopic Modeling

Although BERTopic is an effective Natural Language Processing (NLP) model based on the Transformer architecture and synonyms, it concurrently uses pre-trained on a large corpus of text data to identify contextual representations of words [37]. This model facilitates the research of key topics and automatic clustering of text data, yielding solid and basic concepts present in a specified text collection. Document-related tasks, document classification, and sentiment analysis are among the cases in which BERTopic can be extremely useful [38]. Secondly, the BERTopic modeling ability to track trends by analysing large volumes of text is just as incomparably important for companies that want to remain competitive and have data-based decision-making [39].

Furthermore, this modeling is capable of demining the relation among diffident topics and identifying hidden connections. Consequently, aiding in knowledge discovery and decision-making processes provides a deeper understanding of complex datasets [40].

3. Results and Discussions

From two perspectives, this part discusses the findings as follows. First, we will discuss the results of applying BERTopic modelling and then discuss the emotions of the users on Twitter regarding EVs. The following subsection will discuss the main topics discovered after using BETopic modelling over three years.

3.1. Topics generated using BERTopic

In this subsection, we report extracting the ten most essential topics based on the number of topics assigned to each. Furthermore, it presents the keyword-based

"names" of the topic electric and hybrid cars for the three years (2019, 2020, and 2021), which shows the number of documents within each topic in Table 2.

Table 2. The number of documents within each topic per year

Topic	Number of Tweets		
	2019	2020	2021
0	112,553	102,934	144,945
1	1,268	1,249	1,385
2	826	1,221	1,256
3	700	895	1,166
4	698	881	1,139
5	666	747	1,056
6	663	682	915
7	659	673	863
8	644	571	861
9	608	554	818

The intertropical distance map on BERTopic included tooltips with counts of topic, document and the top five frequent terms. The hierarchical clustering results were validated using cross referenced events from online news. As shown in Figure 2, topic 3 ("Harley", "Davidson", "motorcycle", "Livewire", "bike") is closely related to topic 4 ("Mustang", "Mach", "Ford", "inspire", "pony"), indicating that leading motorcycle companies are adopting EV technology while continuing to offer traditional riding experiences [41]. Topic 9 ("diesel", "petrol", "anal", "cheap", "emit") links to topic 1 ("noise", "sound", "pedestrian", "emit", "quiet") which highlights the fact that EVs are quiet (a positive once, but now becoming a pedestrian safety issue) [42]. Topics 5 ("pollution", "air", "quality", "asthma", "breathe") and 6 ("climate", "crisis", "change", "ClimateGroup", "action") also show that EVs can help reduce urban air pollution and tackle climate change. Topics 2 ("guideline", "infrastructure", "charge", "EVs", "consultation") and 8 ("retort", "energy", "consult", "become", "clean") highlight the uneven deployment of EV charging infrastructure throughout the EU and how such expansion is essential for EVs to become deployed more broadly.

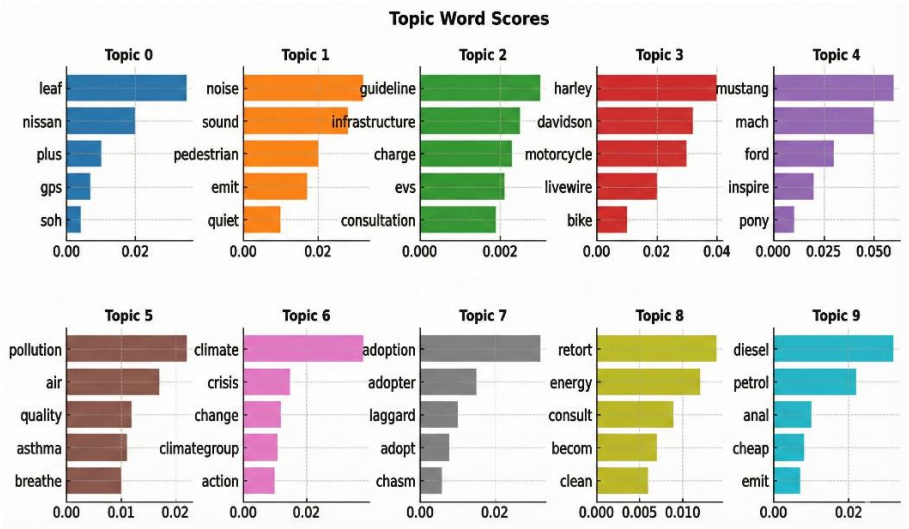


Figure 2. Top 10 related word topics in 2019

Figure. 3 shows the date and duration of the frequency of the topics over a given time duration. The figure provides a temporal analysis of various topics during 2019. The figure shows certain topics, such as "diesel, petrol, cheap" and "pollution, air quality, asthma," exhibit a consistent presence throughout the period, indicating their sustained relevance in the dataset. Also, the figure indicates dynamic changes in the representation of different topics over time. These variations could be influenced by a multitude of external factors, which necessitates a comprehensive analysis for accurate interpretation.

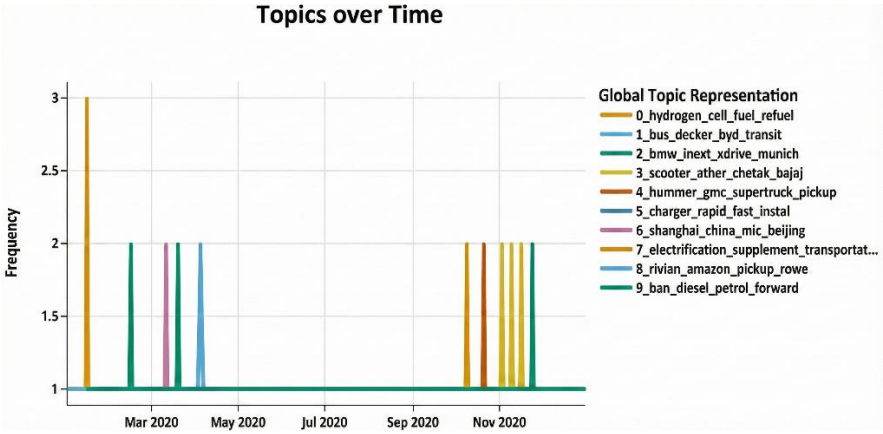


Figure 3. Topics frequency during 2019

Related topic words from 2020 are shown in Figure 4. In Topic 4 ("Hummer", "GMC", "supertruck", "pickup", "horsepower"), we see Topic 8 ("Rivian", "Amazon", "pickup", "Rowe", "configurator") again, with GM's effort to bring traditional truck users to electric mobility with its Hummer EV [43]. Topic 3 (scooter, Ather, Chetak, Bajaj, scoot) is linked to topic 5 (charger, rapid, fast, install, portable), with Bajaj Auto's successful introduction of the Chetak EV scooter, with over 2,000 bookings in 15 days, indicating increasing acceptance of EVs in India's urban centres [44]. With a robust 3 kWh battery and 4,080 W motor, the Chetak fully charges in five hours and provides practical urban mobility [45].

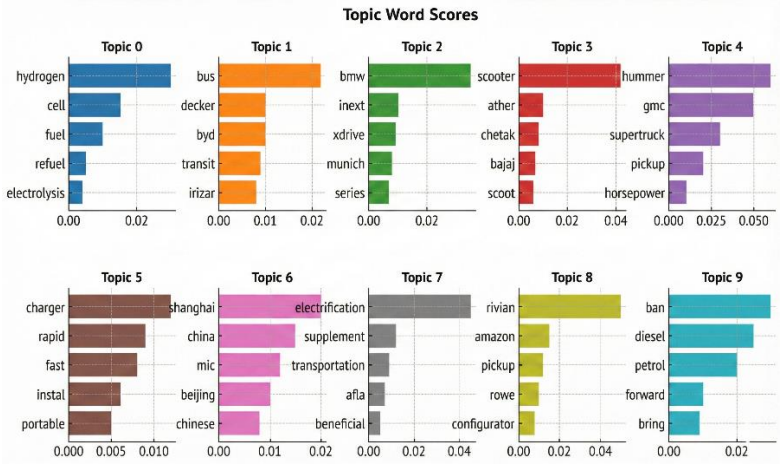


Figure 4. Top 10 related word topics in 2020

In the same way, topic 2 ('BMW', 'iNEXT', 'xDrive', 'Munich', 'series') is very close to topic 6 ('Shanghai', 'China', 'MIC', 'Beijing', 'Chinese'), as BMW launched the fully electric i4 Gran Coupé at Auto China Beijing 2020 emphasizing China's role in BMW's EV market strategy [46]. Topic 1 ("bus", "decker", "BYD", "transit", "Irizar") is directly linked to topic 0 ("hydrogen", "cell", "fuel", "refuel", "electrolysis") due to Europe's greater uptake of electric buses and its search for the use of hydrogen fuel cell technology for sustainable urban transport [47].

Topic 7 ("electrification", "supplement", "transportation", "afla", "beneficial") focuses on new power solutions, highlighting the use of battery electric cars for smaller vehicles and hydrogen cells for larger vehicles potentially and influencing strategies for sustainable urban mobility and greenhouse gas reduction [48]. Furthermore, topic 9 ("ban", "diesel", "petrol", "forward", "bring") is connected to topics 0, 1 and 7 which include the UK's rushed 2035 ban on petrol, diesel and hybrid vehicle sales in line with the ambitious climate action plan to create zero emission transportation [49]. The topic frequency over time in 2019 (Figure 5) shows that global events can drive the trends of topics, e.g., the spike in the "oxygen_cell_fuel" topic in March 2020 which highlights the importance of temporal analysis to understand driving factors.

Figure 6 presents the connections between topics and words from the previous year. We find a strong relationship between topic 0 ("retort", "renewable", "energy", "renewables", "clean") and topic 8 ("innovation", "invention", "technological", "technology", "disruptive") in the automotive industry, indicating that EVs are becoming more affordable due to novel ideas, new technology and less expensive batteries. As a result, OEMs have to introduce new technologies to ensure their cars are clean and can communicate with users which indicates that a future of clean energy is likely [50].

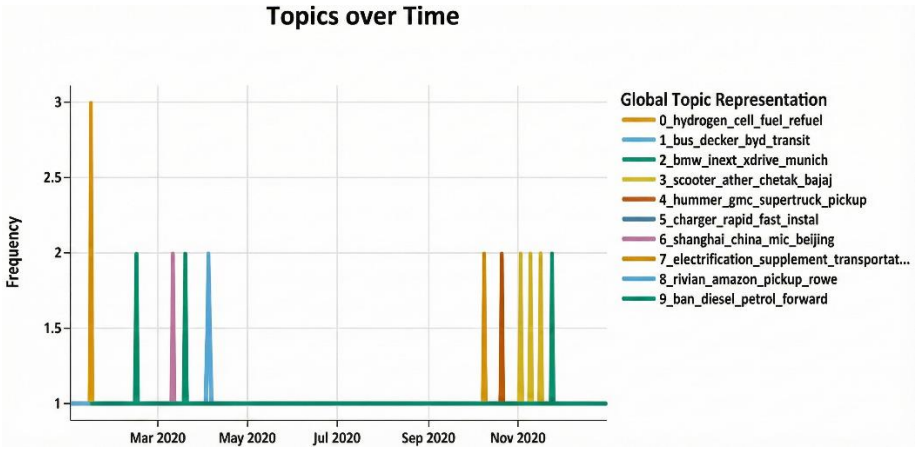


Figure 5. Topic frequency during 2020

Topic 3 describes aspects of gas and fuel, while topic 4 introduces hybrid vehicles, showing that EVs run why not look here on electricity with no internal combustion, PHEVs give more options by using both fuel and electricity [51].

Both topic 5 ("retort", "renewable", "energy", "renewables", "clean") and topic 9 ("innovation", "invention", "technological", "technology", "disruptive") are connected by the Transport Minister's support of the COP26 electric bus tour aiming for net-zero methods [52]. Another important note (on topic 7, "charger", 'Ohme', "install", "installation", "instal") explains how using home EV smart charging solutions can save money and be more convenient [53]. This subject highlights hydrogen-powered FCEVs, which are efficient, easy to use and produce zero pollution from their tailpipes, making them promising for clean travel [54].

Additionally, topic 1 merges with topics 0, 7 and 8, indicating that the US is taking action through the Bipartisan Infrastructure Investment and Jobs Act to develop a country-wide EV charging network that can increase EV use [55]. Finally, topic 6 ("suvs", "suv", "stymie", "gravity", "compact") points out that big automakers like Tesla, Ford, Audi and Volkswagen are growing their electric SUV markets, causing big changes in how people travel sustainably [56].

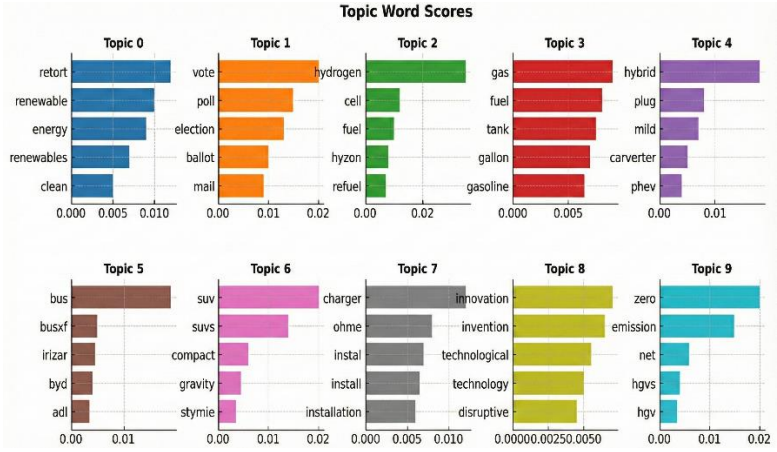


Figure 6. Top 10 related word topics in 2021

Figure 7 shows the topics frequency in 2021. For instance, the figure displays a noteworthy point in discussions about "zero_emission_net_news" in November 2021, suggesting an event or shift in focus that catalyzed this conversation. Other topics like "retort_renewable_energy_renewables" and "innovation_invention_technological_technique" also appearance but with less frequency. The figure provides valuable insights into the sequential dynamics and importance of several themes within the broader discourse on renewable energy. The detected patterns can be focus on the influence of many factors, including technological improvements, policy modifications, or global events. Among these topics, additional examination is necessary in order to understand the fundamental causes of the patterns and correlations.

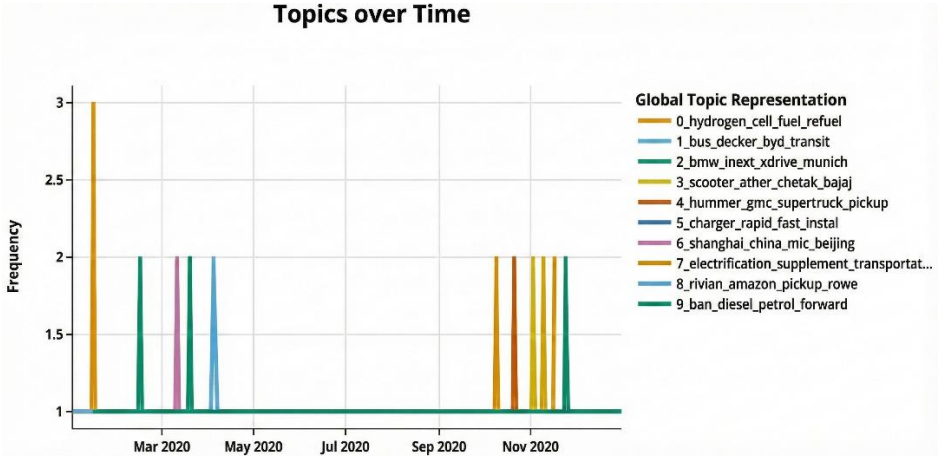


Figure 7. Topic frequency during 2021

3.2. Emotion Analysis

Emotion research holds significant importance for all auto manufacturers as it helps gauge the demand and level of interest in transitioning to electric cars. This study utilized emotion analysis to understand individuals' sentiments regarding electric and hybrid vehicles compared to conventional ones. This study revealed interesting insights after analyzing the findings of emotion extraction for the previous years. In the year

2019, The study exhibits a domination of benevolent sentiments as well as a shortage of unwanted sentiments towards EVs, demonstrating a growing focus on and positive vibes about their future. Such messages are a source of information for carmakers to find out the public attitude towards the new product and decide on the volume of production. Positive sentiments expressed on social media regarding EVs are channels for the managers or the marketing strategies of the automobiles manufacturers or the vehicle manufacturers. Tracking down sentiment of public via consumption, manufacturers can satisfy consumer demand, making more people tend to be favorable towards green ones. Throughout the years 2019 and 2020, our computed emotions continued to grow in an equally positive trend where there was more than 100,000 occurrences of positive feelings as enthusiasm and trust in our product continued to be noticed. Amazingly, there was a remarkable diminution of difficult feelings like tickling, sadness, fear, anger, and negativism as shown on Figure 8 and Figure 9 which trailed the previous 2 years.

The fact that positive emotions have continued for two years means people are still very interested and open to electric and hybrid vehicles. Because of both ecological advantages and new technology in electric vehicles, more people are now choosing eco-friendly transport. Having such confidence reduces common mistakes, allowing electric cars to stand in for gas-powered vehicles. Trust in electric vehicles grew during 2019 and early 2020, indicating the market can expect to expand. Analyzing emotions helps manufacturers and policymakers design strategies that fit with the public's feelings which boosts innovation and adoption. In general, the trend of more positive and fewer negative comments indicates that EVs are gaining support and contributing to sustainability.

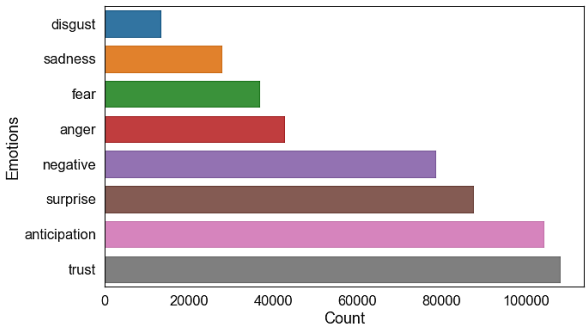


Figure 8. Emotion counts in 2019

The apparent global increase has notably influenced the emotional results of the analysis of oil prices in 2021. This impact is evident in the significant turnout and growing inclination for electric cars as a preferred choice among clients. Figure 10 shows that positive emotional responses are on top of other emotions. The emotions of trust, astonishment and delight steward their way over the ones known as negativity. This upsurge of positive experiences outlines trust in EVs. It is one of the significances that can arise from the increasing environmental issues and the motivating to use less fossil fuels. The higher price of oil will make EV's an significant environmentally substitute.

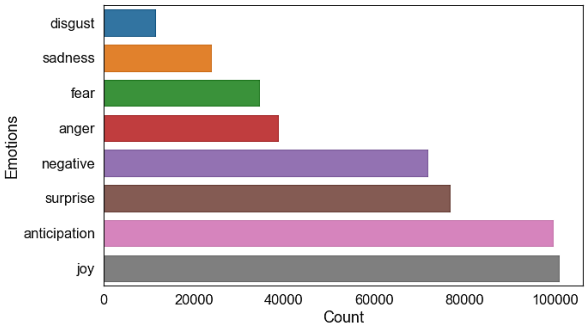


Figure 9. Emotion counts in 2020

The changing emotions between clients are not only a sign of shifting opinions, but also of a growing move towards EVs because of climate change. As more people know about EVs, they are seen as practical options, helping energy transition and emissions descend. Emotional analysis helps organizations and marketers make informed changes to their strategies, products and facilities as EV demand increases. Having a positive attitude is significant for market success.

There is a general shift toward protecting the environment through transport, because more people are considering electric vehicles. The analysis highlights the economic and environmental advantages of EVs, particularly because climate change is pushing towards using less fossil fuel. The main reasons for increased adoption are likely to be lower costs, easier operation and less dependence on oil. Yet, to scale EVs, we must develop better batteries, build more charging points and get additional backing from laws. Goals for reducing pollution from vehicles may not be achieved without a strategy. Problems such as finding energy and reducing costs should be dealt with. Green transportation can be achieved only if people and organizations work together and participate.

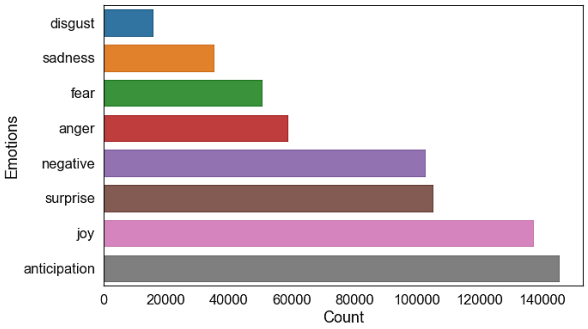


Figure 10. Emotion counts in 2021

4. Conclusions

The study applied BERTopic modelling and NRCLex to detect emotion in EVs through different aspects of EVs. We provided a detailed comprehension of EVs' importance and sustainability. This investigation covers four critical factors of EV-that including, countries

producing electric cars, technological inventions, economic benefits and public awareness, extending our consideration of the EV economy. The clustering outcomes concentrated by BERTopic have nevertheless been valuable in determining the core topics and the major discourse revolving around e-cars. They have also shown that the positive emotions and excitement connected with using EVs drive interest among the population willing to help build up a cleaner planet and reduce their personal carbon footprint. The conversations building up around EVs prove how this act feels outstanding and leads to global acceptance of a cleaner world. On top of that, EV usage patterns also show the rising uptake of EVs alongside the importance of environmental considerations and technological innovations. These factors are worth the mention in the context of public opinion shaping regarding EVs. The consistent addition of charging stations of different sorts as well as emergence of newer EV models from different car brands essentially ensure the bright future of electric vehicles. Inclusion of BERTopic, social media analysis, emotions, and trend of EVs, we have come up to a common understanding concerning the extent of EVs revolution and the impact of digital media on market sphere. These findings, therefore, emphasize the importance of positive sentiment, increasing the interest, and adoptions as ELV industry drivers. We encountered several limitations during our investigation. Thus, the data collection mainly consists of digital social media platforms, which could not necessarily reflect the sentiment for the electric cars of every group. Besides, BERTopic is one of the great tools, this tool has the bias and limitation just like other tools that extract information from the different data and these bias and limitations are connected to the model architecture. Future research should try to overcome these obstacles and extend them to more investigative fields. First, an omnibus survey and panel interview among a large population cross-section would give a towering understanding of the general mindset and ideas concerning EVs. Previously, the analysis would be improved by surveying other data sources, e.g. government files and industrial databases, adding to accuracy and dependability. Conclusively, analysing the future environmental and economic impacts of converting EVs on a large scale is respectful for policymakers and researchers alike.

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