Fuel Costs and the EV Conversation: Tracking Public Sentiment Through Social Media

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This study investigates the impact of gas prices on public sentiment toward electric vehicles (EVs) through Social Media data analysis. Using Natural Language Processing (NLP) techniques, we collected and pre-processed posts related to EVs, employing tools such as NLTK, VADER, and Python-based machine learning methods. Topic mining was conducted using Latent Dirichlet Allocation (LDA), and sentiment analysis and word cloud visualizations were applied to identify patterns in public online discourse. We hypothesized that rising gas prices would reduce barriers to EV adoption, resulting in more positive sentiment and increased EV-related discussion. Our findings support this hypothesis, while also revealing that positive sentiment correlates more strongly with gas prices during periods of decline than during increases.

Keywords: electric vehicle, gas price, topic mining, Latent Dirichlet Allocation (LDA), sentiment analysis, Natural Language Processing (NLP), word cloud, VADER, NLTK, Python, machine learning

INTRODUCTION

To meet future mobility needs, reduce climate- and health-related emissions, and phase out dependence on oil (i.e., "peak oil"), today's propulsion technologies must be replaced by more efficient and environmentally friendly alternatives. In the transition to a sustainable society, particularly efficient mobility technologies are needed worldwide. Electric vehicles (EVs) have been identified as one such technology (Helmers & Marx, 2012). EVs have gained significant attention in recent years due to their

potential to reduce greenhouse gas emissions, improve air quality, and increase energy security (Electric Vehicles, n.d.).

The purpose of this paper is to investigate how gas prices influence mentions of electric vehicles (EVs) on Social Media. While previous studies have examined EV adoption drivers, a gap remains in the literature regarding how fluctuations in gas prices affect public sentiment and discussion around EVs on social media platforms. This study seeks to address that gap by analyzing how EV-related sentiment varies with changes in gas prices. We hypothesize that EV mentions and positive sentiment correlate with gas prices to some degree, indicating that fuel cost dynamics shape public discourse and emotional responses toward EVs.

The scope of this study includes collecting posts with EV-related keywords, followed by data cleaning, analysis, and visualization to explore how sentiment varies with average gas prices over time. Gas price data are obtained from the U.S. Energy Information Administration (EIA.gov).

While tax credits and subsidies have been used to increase demand for EVs and foster positive sentiment, this study explores whether *negative economic incentives*, such as rising fuel costs, might produce similar effects. EVs are typically more expensive than standard gas vehicles or hybrids and often fall outside the average consumer's budget. However, government incentives like EV tax credits have helped overcome these barriers and stimulated demand. These credits are often capped by manufacturer, resulting in high demand but limited supply. Increasing or extending these incentives has been shown to promote positive public sentiment and adoption.

This paper considers whether rising gas prices—akin to a "reverse incentive"—could similarly enhance EV sentiment. The U.S. government typically intervenes to keep gas prices low, but if the policy goal is to accelerate EV adoption, it is worth considering whether reducing such interventions (e.g., halting gas subsidies) might serve as an indirect but effective motivator.

To analyze EV sentiment, this study collects Social Media data using SNSCRAPE with keywords related to EVs (e.g., "electric vehicle," "Tesla," "electric motor") and stores them in a database. The dataset is then cleaned using Natural Language Processing (NLP) techniques to remove emojis, hyperlinks, duplicate content, and irrelevant characters. Python libraries such as Matplotlib and Seaborn are employed to visualize the results.

The analysis includes tables and graphs comparing gas prices (in dollars per gallon) to the number and percentage of positive EV-related Posts. Our findings indicate that correlations between EV sentiment and gas prices are stronger during price downtrends than uptrends. When gas prices fall, public interest and positive sentiment toward EVs decline. While rising gas prices are also associated with increased EV sentiment, this relationship is less consistent. These trends suggest that consumer sentiment toward EVs is more sensitive to falling gas prices than to rising ones.

Motivated by these observations, this study addresses the following research questions:

- How does electric vehicle activity on social media change with gas prices over time?
- How does gas price affect electric vehicle adoption in the United States, as reflected in Social Media sentiment?
- What topics and keywords do users discuss in EV-related Posts during different gas price trends?

The remainder of this paper includes a literature review, methodology, empirical findings, and a conclusion. This study draws on four analytical frameworks: Popularity Analytics, Sentiment Analytics, Voice Analytics, and Opinion Mining.

LITERATURE REVIEW

A comprehensive literature review was conducted in addition to data exploration and uncovered three main themes of prior work. These themes include Electric Vehicle (EV) barriers to adoption and social sentiment, gas prices over time and gas prices as a predictor of vehicle purchases as well as the validity of Sentiment Analysis (SA) and Natural Language Processing (NLP).

Many instances of recent literature focused on one of the above themes or a blend of each. Each of these themes influenced the research conducted in this study, especially in regard with the methods used to

web scrape, clean, visualize and analyze the data. Very few publications explored all three themes, and none explored how EV sentiment on social media varies with gas prices over time. This publication seeks to address this gap in knowledge. And We will discuss these themes in the next 3 subsections.

EV Barriers to Adoption and Social Sentiment

The main barriers to adoption of EVs include the prices of EVs (including gas, maintenance and tax incentives), lack of EV driving range, and a lack of customer awareness regarding the benefits of reducing fossil fuel emissions (Adepetu & Keshav, 2017; Hosseinpour et al., 2015; Jena, 2020; Kester et al., 2018; Murugan & Marisamynathan, 2022; Novizayanti et al., 2021, p.). One study ranked these barriers by dividing them into technical, social, economic, infrastructure and policy barriers (Adhikari et al., 2020).

A lack of battery range (the miles that an EV can travel before it needs to be recharged) was found in several studies to be the largest consumer concern that discouraged EV adoption (Egbue & Long, 2012; Tarei et al., 2021).

However, one study shows that in the next years, electric cars will be mostly small- or mid-size cars due to two main reasons: First, the weight , limits the range of operation, which is a factor of suitability for daily use. Second, battery costs establish an other main regulating factor: larger cars need bigger and much more expensive batteries.(Helmers & Marx, 2012).One study found that gas prices had the strongest effect on EV market share, and was quantified to show that a 10% increase in gas prices correlates with a 70-90% increase in hybrid market share (Egbue & Long, 2012). Some key benefits to consumers that adopt EVs include helping reduce fossil fuel emissions and long-term gas cost savings; however, consumers weigh these benefits against their willingness to pay premium prices for EVs (Hidrue et al., 2011). The willingness-to-pay method reveals consumers are unwilling to pay large premiums for EVs, even when given information on future fuel savings(Larson et al., 2014). Plug-In Hybrid EVs were found in one study to be less expensive than gas vehicles long-term when factoring in greenhouse gas abatement costs (Tseng et al., 2013). EV battery costs are one of the most significant barriers to entry, and one study estimated that increasing fuel costs coupled with decreasing costs (and increasing potential milage) of batteries would make EVs cost competitive with gas vehicles by the year 2030 (Newbery & Strbac, 2016). A similar study found that oil prices, when compared to electric unit prices, has an indirect effect on EV adoption (Yildiz, 2000). One study covered a predictive model that shows that areas with higher gas prices and higher income tax deductions/credits have a greater demand for hybrid vehicles (Beresteanu & Li, 2011).

One study showed that people who drove EVs were more likely to share positive sentiment about them (Shaheen et al., 2020). Despite these benefits, the high initial cost of EVs as compared to Gas Cars (GCs) has resulted in a slow adoption of EVs. Survey results also support the hypothesis that EV rollout has focused too much on technology, and not enough on consumers(Larson et al., 2014). Governmental incentives have contributed to EV adoption (Diamond, 2009), but even including these incentives EVs are significantly more expensive than GCs (Rosales-Tristancho et al., 2022). One study found that the share of EVs to total vehicles in 31 countries was correlated with EVs' relative prices in comparison to GCs (Dixit & Singh, 2022). a couple of countries (like Germany, Denmark, and Sweden) have decided to switch electricity production from fossil fuel to renewable sources, further improving the sustainability of electric cars when compared with ICEV (internal combustion engine) (Helmers & Marx, 2012).

A study found that the Energy Policy Act of 2005 increased hybrid sales by up to 20% in the United States, but large and paid-upfront monetary incentives were key to increasing hybrid vehicle adoption (Jenn et al., 2013). One study found that exposure to EVs through carsharing apps has been shown to increase the likelihood of consumers purchasing EVs (Shaheen et al., 2020, p.). Subsidies could drive increased EV adoption as they have done in the US and China in the past (Helveston et al., 2015). In one study of European cities, a combination of a large charging network, high EV incentives and a large number of EV models significantly decreased EV costs long-term (Wappelhorst et al., 2020). Many US lawmakers, including current US President Joe Biden, have sought to increase the monetary value of EV Federal Tax Credits to address these barriers to entry in order to reduce fossil fuel emissions. Lower EV costs decrease EV barriers to adoption; similarly, increased gas costs may decrease EV barriers to adoption and increase mentions/sentiment on social media platforms as a result. Despite the challenges facing electric vehicles,

there is optimism about their future prospects. Many governments around the world have implemented policies to encourage the adoption of electric vehicles, including tax incentives and subsidies. In addition, automakers are investing heavily in electric vehicle technology, with many announcing plans to phase out gasoline-powered vehicles in the coming years (*Energy Efficiency*, n.d.).

NLP and SA in Opinion Mining

Opinion Mining is a relatively new field but has proven to be an effective means of data exploration. Social media platforms house large numbers of untapped data that can be used to explore communication in ways that has never been possible before (Jyoti & Rao, 2016).

Word-based and document-based sentiment analysis has been used effectively with both supervised and unsupervised models when applied to news sentiment for EVs in one study (Jiang & Everts, 2021). Latent Dirichlet Analysis (LDA) is a leading technique in the field and has great potential for research (Chen et al., 2016). Python's VADER, NLTK, Word Cloud and Text Blob libraries have been effectively used in previous publications to identify trends in text sentiment, especially as it relates to polarity and subjectivity (Ahuja & Dubey, 2017; Bengaluru & Kuman, 2021; Millstein, 2018). Sentiment Analysis has become more accessible than in the past as computer processing speeds increase, and great insights can be gathered from Posts with few lines of code (Millstein, 2018).

Sentiment Analysis involves quantifying the polarity and subjectivity based on previously trained models (Jyoti & Rao, 2016). N-gram modeling techniques as well as using a supervised machine learning algorithm (KNN, SVM, etc.) can lead to effective sentiment analysis models (Parikh & Shah, 2020). Different models are more effective for different types of data, as demonstrated in one study which compared several models in predicting sentiment toward oil and gas companies (AlRawi & Ashour, 2020).

Text mining is valuable in using real-time information to observe trends that previously could only be collected by delayed surveys (Surjandari et al., 2014). Sentiment analysis showed in one study that stock returns can be predicted based on news sentiment (Vijay et al., 2018). Another study showed that a sentiment analysis model could predict individual stock prices with 72% accuracy (Biswas & Ghosh, 2022).

Sentiment analysis has been used to gauge EV sentiment in several studies; in several such studies, it was found that Tesla is the most positively viewed EV vehicle brand on Social Media (Bhatnagar & Choubey, 2021; Suresha & Kumar Tiwari, 2021). Another study showed that even new EV manufacturers are discussed positively on social media internationally- this study examined Turkey's Automobile Joint Venture Group in Turkey (Demirer & Buyukeke, 2022).

Opinion mining has been used to determine that there is the overwhelmingly positive sentiment towards EVs on social media, but has not been used to determine how this sentiment compares to gas prices.

Gas Prices

The impact of electric vehicles (EVs) on gasoline prices is a topic of much debate among researchers and policymakers. While some argue that the growth of EVs could lead to a decrease in demand for gasoline, others suggest that the impact will be negligible. Gas prices have been found in many studies to correlate with consumer vehicle choices. Gas prices themselves have been accurately predicted over several studies (Baghestani, 2015; Baumeister et al., 2017). One study forecasted gas prices based on consumer surveys and found that consumer sentiment can accurately predict gas prices, with strong evidence supporting "causality from Google searches to gas prices" (Anderson et al., 2011). A similar study found that investor sentiment (positive or negative) can explain changes in oil prices, which then affect gas prices (Du et al., 2016). Another study examined the correlation between Google searches for gas prices and the actual price of gas (Molnár & Bašta, 2017). One study successfully forecasted oil prices using sentiment analysis (Zhao et al., 2019).

Consumers have in the past purchased more fuel-efficient vehicles as a response to higher gas prices (Busse et al., 2016); in one study, it was found that higher gas prices help to sell smaller, more fuel-efficient vehicles (Wheatley & Leekley, 2010). Another study by the National Renewable Energy Laboratory (NREL) in the United States suggests that the impact of electric vehicles on gasoline prices will depend on the rate of adoption of EVs and the responsiveness of gasoline demand to changes in price. The study found

that if electric vehicle adoption rates were high, gasoline prices could decrease significantly. However, if adoption rates were low, the impact on gasoline prices would be negligible(*Global EV Outlook 2017 – Analysis*, n.d.). Concerns over the costs of refueling are primarily what drive this, although environmental concerns such as air quality are also a significant factor (Cho, 2021). One study found that grocery shopping behavior changed when gas prices increased, showcasing how consumer budgets are affected by gas price spikes (Ma et al., 2011).

One study by Cargurus.com showcases that increasing gas prices stimulates electric vehicle demand; this study surveyed prospective EV buyers in 2021 and 2022, and over time those surveyed became more sensitive to higher gas prices in terms of their willingness to purchase an EV (Shaheen et al., 2020). Another study by Roger Duncan found that gas prices influence gas vehicle sales in a predictable formulaic manner (Duncan, 1980). Gas prices have proven to be predictable, and EV sentiment on social media platforms may be able to both determine and be determined by gas prices. As the present trend suggests, this

mode of transport is likely to replace internal combustion engine (ICE) vehicles in the near future. Therefore, the shift in the vehicle world created by EVs impacts the environment, the economy, and being electric, the electrical systems to a great extent. EVs are gaining popularity because of the benefits they provide(Un-Noor et al., 2017).

METHODOLOGY

Data Collection and Preprocessing

A scraper for social networking services, SNSCRAPE, is used to scrape Posts from social media. 5 criteria are set to collect Posts for the study.

Given the penetration and usage of EVs in the US, US cities with a population of more than 1.5 million are selected for the study. The study covers Posts from within 15 miles of 37 cities among 20 states.

Since the study is meant to explore gas price impacts on EVs, Posts from Jan 1st, 2019 to February 28th, 2022 are collected that possess keywords related to "EVs" and the top 5 most popular brands in the EV industry (Tesla, Rivian, etc.).

Given that there is some geographic overlap during coverage of 2 selected cities, unique Post ids are required in order to not collect duplicated Posts. With the above tool and criteria, 128,994 of Posts in total are collected for preprocessing (Table 1).

TABLE 1
TOOLS AND CRITERIA OF POSTS COLLECTION

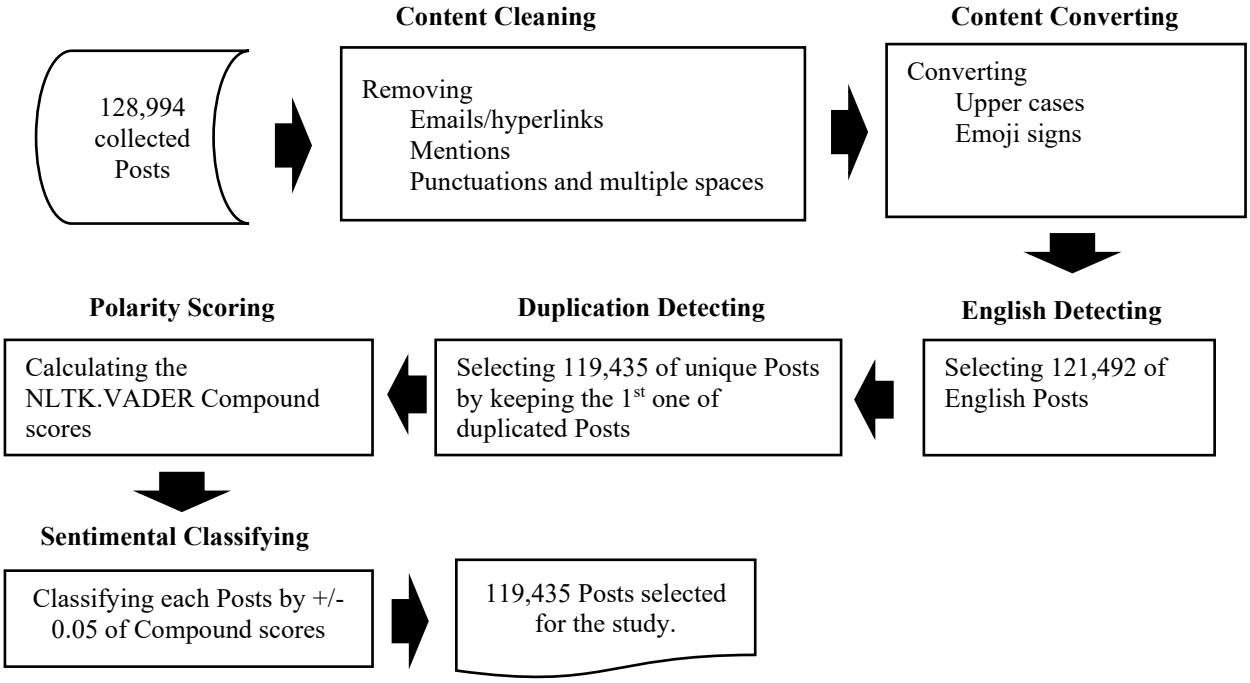
Tools and Criteria	Details
Post Scraping Tool	SNSCRAPE
Criteria of Posts Collection	Cities: All cities in the U.S with a population of more than 1.5 million Coverage: within 15 miles of the selected cities Time: Jan 1st, 2019 to February 28th, 2022 A set of keywords (electric vehicle) OR (electric vehicles) OR (electricvehicle) OR (electric vehicles) ' OR (electric car) OR (electric cars) OR) OR (electriccars) ' OR (electric motor) OR (electric motors) OR (electric motor) OR (electricmotors) ' OR (tesla) OR (tsla) ' OR (lucid motors) OR (lucidmotors) OR (lcid) OR (lucidair) OR (lucid air) ' OR (rivian) OR (rivn) ' OR (nio) ' OR (li auto) OR (liauto) OR ($li) '

	Unique Posts' id.
Number of Posts Collecting	128,994 of Posts in total

There are three objectives of the preprocessing. The first objective is to clean Posts for sentiment scoring. The second is to score each Post with the Compound of polarity scores using NLTK.SENTIMENT.VADER and to classify each Post as "Positive", "Neutral", and "Negative" by the threshold of +0.05 and -0.05 of Compound (Figure 1). The Posts after preprocessing are used to analyze in later steps.

The gas price in this work is from the U.S. Energy Information Administration. These data have a weekly update and can be downloaded in EIA.GOV. Weekly U.S. All Grades All Formulations Gas Prices (Dollars per Gallon) from December 31st, 2018 to February 21st, 2022 are used in the study.

FIGURE 1
POST PREPROCESSING



The Popularity Analytics and Voice Analytics in this work are inspired by Social Listening. Social Listening, otherwise known as Social Media Measurement, is a way to compute the popularity of key words or terms by extracting information from social media channels. Social Listening allows researchers to monitor what people are discussing regarding any topic online, and to evaluate the volume with which any given topic is mentioned (Awario, 2021). Popularity Analytics monitors the weekly number of Posts with a set of keywords, including "EV" and the top 5 most popular EV brands. Voice Analytics further monitors the ratio in the number of EV-related Posts with "gas" related keywords as compared to the total number of EV Posts.

The Sentiment Analytics in this work is inspired by many previous works outlined in the literature review. Sentiment Analysis, also known as Opinion Mining, is one of the most commonly researched tasks in NLP. Its basic purpose is determining and classifying the polarity of a given text as positive, negative, or neutral. The COMPOUND score of VADER and its threshold of 0.05/-0.05 are one of the most common metrics for sentiment analysis (Hugo, 2014). In this study, positive EV Post metrics are generated by

NLTK.SENTIMENT.VADER. The objectives, key measurements, and methods used in these 3 analytics are explained as follows.

Popularity Analytics

Popularity Analytics emphasizes the popularity of EVs in online discussions. The objective in these analytics is to identify the impacts of gas price on EV discussion (on Social Media) by comparing the variations in the weekly number of EV Posts with gas price uptrends and downtrends. Time series analysis is used in this methodology.

Sentiment Analytics

Sentiment Analytics emphasizes the psychological angle of EV discussion. Its key objective is to identify the impacts of gas price during perception of EV discussion by comparing the variation in the ratio of positive EV Posts (to the total) to gas price uptrends and downtrends. Time series analysis is also used here.

Voice Analytics

Voice Analytics with gas related keywords among EV Posts helps to explain the impacts from gas prices on EV discussions. The key objective of this analysis is to identify the intensity of impacts from gas prices on EV discussions by comparing variations in the ratio of EV Posts with gas related keywords to total EV Posts during gas price uptrends and downtrends. Time series analysis is also used.

Path Pattern Analytics

Path Pattern Analytics explores the direct and indirect positive associations between gas prices with EV popularity and positive sentiment on Social Media. Specifically, the key objective in this analysis is to test the hypotheses of H1 and H2 and further to build and demonstrate the path via which retail price exerts its impacts on EV popularity and positive sentiment. Simple linear regression is used to explain these trends. Table 2 shows the key measurements and their definitions applied in the aforementioned analytics.

TABLE 2
KEY MEASUREMENTS AND DEFINITIONS APPLIED IN THE POPULARITY, SENTIMENT, AND VOICE ANALYTICS

Analytics	Measurement	Definition
Popularity Analytics	Weekly Moving Average Number of Gas Price	Simple moving average of 8 weeks on Weekly U.S. All Grades All Formulations Gas Prices
	Weekly Moving Average Number of EV Posts	Simple moving average of 8 weeks on weekly number of EV Posts
sentiment Analytics	Weekly Moving Average Ratio of EV Positive Sentiment	Simple moving average of 8 weeks on ratio of weekly number of EV Positive Posts to total weekly number of EV Posts
Voice analytics	Weekly Moving Average Ratio of EV Posts with Gas Related Keywords	Simple moving average of 8 weeks on ratio of weekly number of EV Posts with Gas related keywords to total weekly number of EV Posts The following words and terms are considered as a set of Gas related keywords: “gas/gas”, “petrol/ petroleum”, “diesel”, “oil”, “fuel”, “tank”, “$ **/** dollars/** miles per gallon”.

Topic Mining Analytics

The objective of Topic Mining Analytics is to future answer the question of "how retailer gas price exerts its impacts via the internal intermediary variable – the Voice of Gas – on Social Media" (H3). The Analytics only focus on positive and negative EV Posts in periods of Price Uptrend and Price Downtrend. Log likelihood word cloud analytics and LDA model are used to mine the latent topics in the Analytics.

LDA model

The Latent Dirichlet allocation (LDA) model is used to investigate the topics underlying the prepared data during the modeling step. "LDA is a generative probabilistic model of a corpus, and its basic idea is that documents are represented as random mixtures over latent topics, where each topic is characterized by its word distribution (Blei et al., 2003)." LDA could be used "as an intuitive approach for the calculation of similarity between source files and obtain their respective distributions of each document over topics (Jelodar et al., 2019)." Figure 2 shows the process and methods used in the LDA model in this work. Extraction of representative 2&3 grams of nouns and of highly used nouns/hashtags based pooling scheme are used to enhance the effectiveness and coherence of the LDA model.

All hashtags are extracted to set up a highly correlated hashtag set for pooling. Mehrotra et al. (2013) mentioned that hashtag-based pooling scheme is to create pooled documents for each hashtag. If any Post has more than one hashtag, this Post gets added to the Post-pool of each of those hashtags. However, given that parts of hashtags in this work are highly likely to appear together in a Post such as 'growth', 'money', and 'millionaire', unlike Mehrotra's pooling scheme, the hashtag pooling scheme in this work is first generating a subset of highly correlated hashtags (Pearson correlation > 0.7) and then supplementing all other hashtags to create a full hashtag pooling set. This helps reduce the redundancy of Posts after pooling. Since this work emphasizes the comparison of Price Uptrends and Downtrends, the Posts are further pooled by periods. Table 3 shows the number of documents used in the LDA model after hashtag pooling.

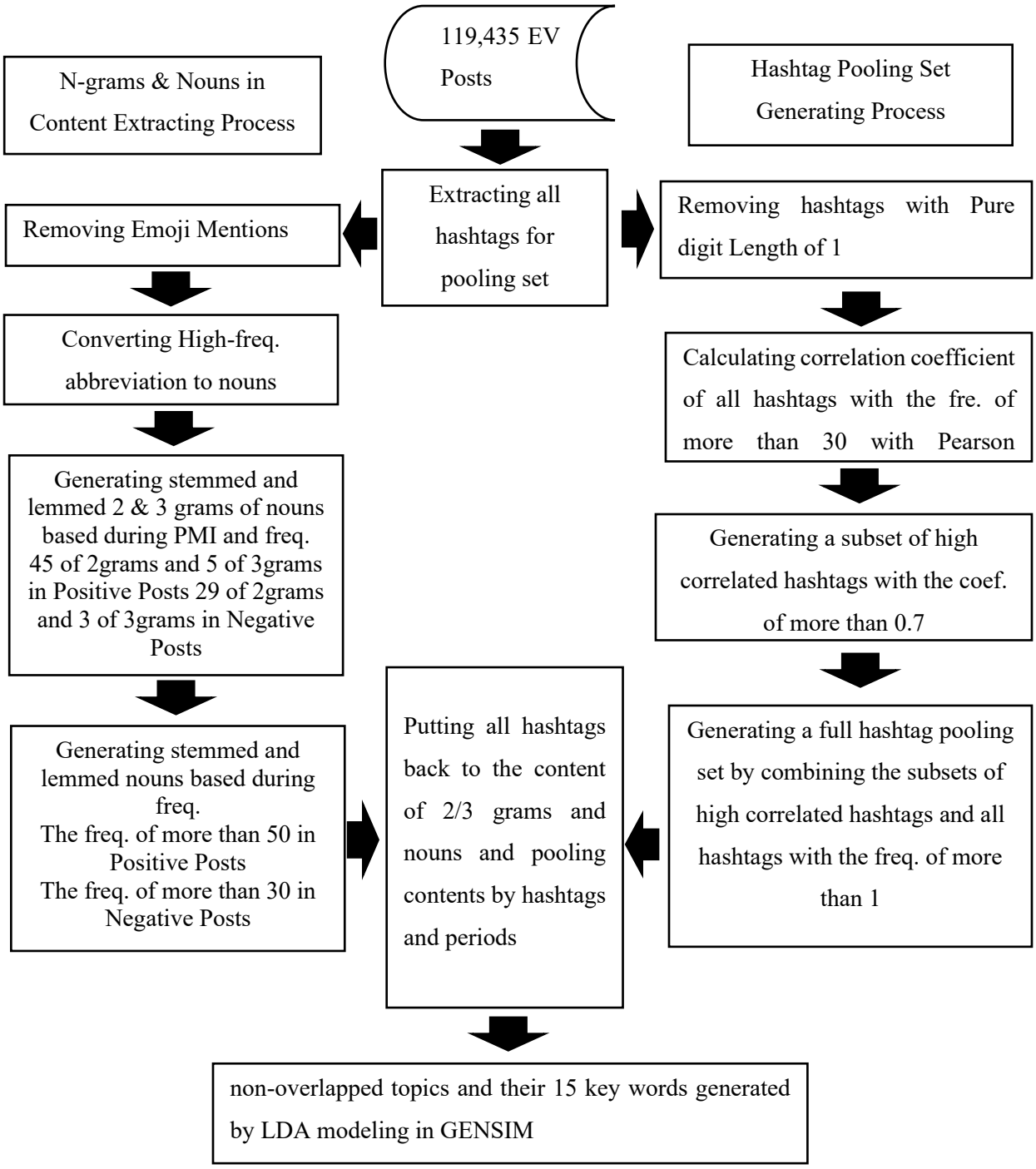
TABLE 3
NUMBER OF DOCUMENTS USED IN LDA MODEL AFTER HASHTAG POOLING

	Positive Posts	**Negative Posts**
Price Uptrend	40,974	16,279
Price Downtrend	18,695	7,825

Extraction of representative 2&3 grams of nouns and frequently used nouns is to extract the most relevant nouns and phrases to build the topic model. To achieve this objective, 2 grams and 3 grams are firstly generated and then filtered to the semantic ones by the threshold of their frequency and Pointwise Mutual Information (PMI) values. Given that the combination of adjectives/nouns and nouns are most relevant here, 2 and 3 grams which have their first words as adjectives or nouns, and their last words are nouns, are selected to use in the topic model after filtering them by their frequency and PMI values.

In positive Posts, 2 grams with a frequency of more than 100 and PMI of more than 6.0, 3 grams with the frequency of more than 100 and PMI of more than 10.0, and the nouns with the frequency of more than 50 are also selected to add in the model as the context. In negative Posts, 2 grams with a frequency of more than 50 and PMI of more than 6.0, 3 grams with a frequency of more than 50 and PMI of more than 10.0, and the nouns with a frequency of more than 30 are also selected to add in the model as the context.

FIGURE 2
PROCESS AND METHODS IN LDA MODELING



FINDINGS AND RESULTS

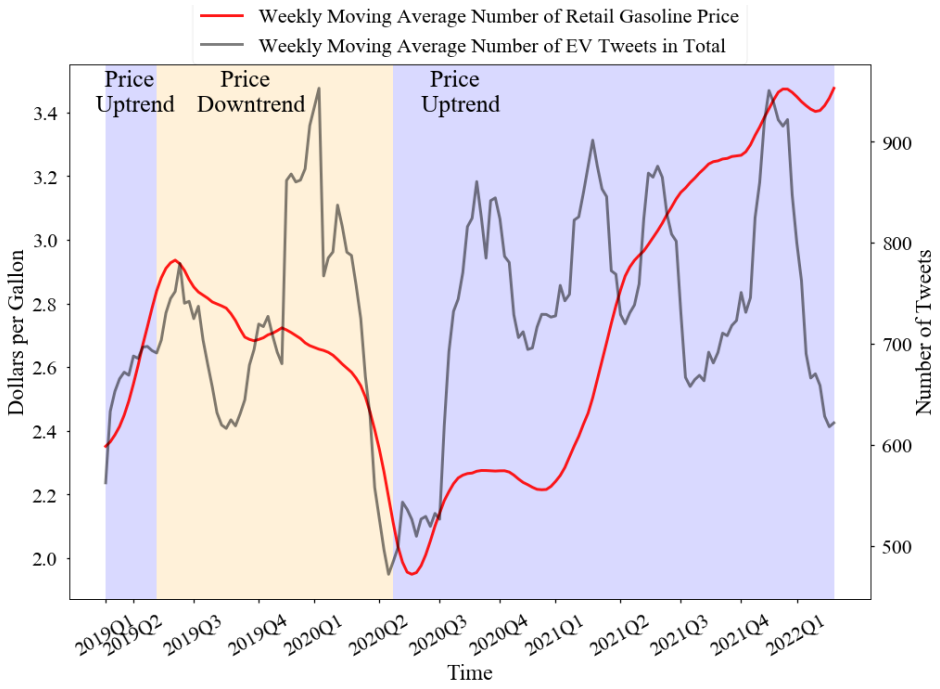
In this section, the results and findings are discussed and organized under the following five subsections: popularity analytics, sentimental analytics, voice analytics, path pattern analytics and topic mining analytics.

Popularity Analytics

In summary, the result shows that Gas prices had a tight positive association with EV popularity during Price Downtrends, meaning that EV popularity decreased during Price Downtrends; additionally, this positive association was quite loose during Price Uptrend, given that the EV popularity had much more rapidly rebounded during Price Uptrend**.**

Figure 3 shows the 8-week simple moving average (sma-8w) number of all grades, all formulations gas price, and EV posts in the U.S. the 1st price uptrend is from January 1st, 2019, to May 6th, 2019. The price downtrend is from May 6th, 2019, to April 27th, 2020. The 2nd price uptrend is from April 27th, 2021, to February 28th, 2022. The sma-8w of DEV posts had a corresponding increase during 1st price uptrend. When the gas price started its downtrend, EV posts decreased. The sma-8w number of EV posts saw a quick rebound when the price entered the 2nd price uptrend. The number of posts varied at the plateau while gas prices climbed during 2nd price uptrend.

FIGURE 3
WEEKLY MOVING AVERAGE NUMBER OF GAS PRICE AND EV POSTS IN TOTAL

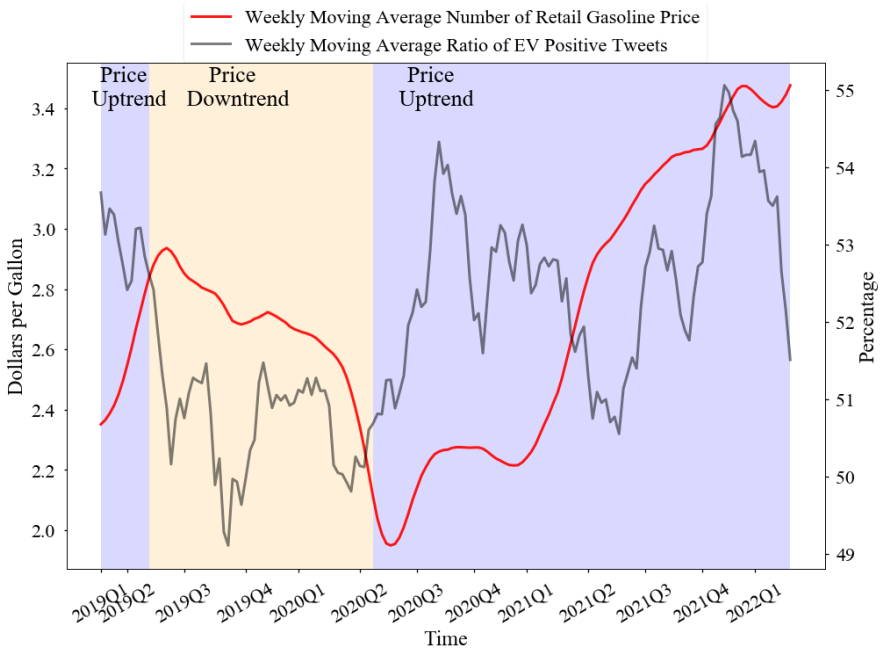


Sentiment Analytics

In summary, Gas prices have a tight positive association with the ratio of positive EV Posts to the total of EV Posts during Price Downtrend, and this positive association is loose during Price Uptrend.

Figure 4 shows the SMA-8W number of all grades, all formulations gas price, and the SMA-8W ratio of the number of EV positive posts to the total number of EV posts. The ratio was at the plateau during the 1st price uptrend and decreased and maintained a low position when gas prices started a price downtrend. However, the ratio had a steep increase when the price entered the 2nd price uptrend. The ratio varied at a higher percentage when the price was climbing during the 2nd price uptrend.

FIGURE 4
WEEKLY MOVING AVERAGE NUMBER OF GAS PRICE AND WEEKLY MOVING AVERAGE RATIO OF EV POSITIVE POSTS

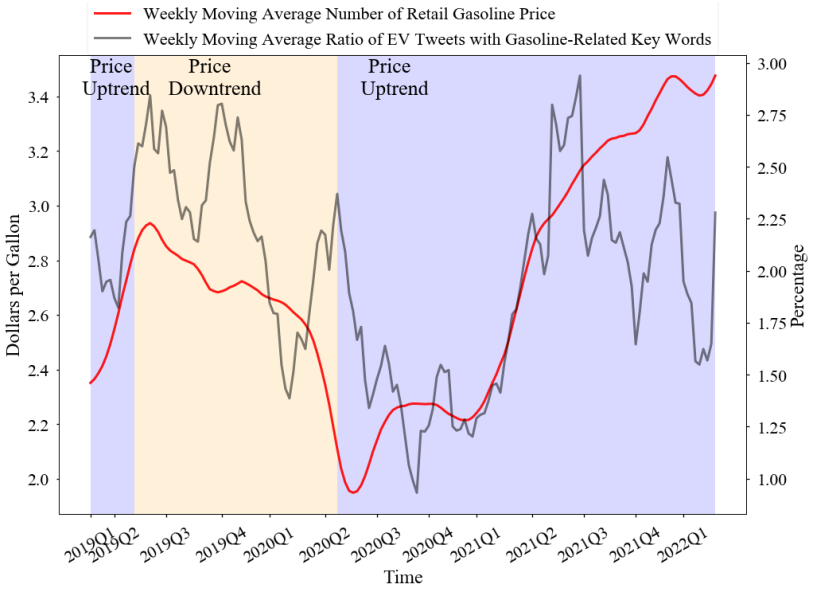


Voice Analytics

In summary, the variance of gas prices has a tight positive association with the Voice of Gas in EV Posts on both Price Uptrends and Downtrends.

Figure 5 shows the SMA-8W number of all grades, all formulations, gas prices, and the SMA-8W ratio of the number of EV posts with gas-related keywords to the total number of EV posts. The ratio had a corresponding increase during 1st price uptrend. When the price started to downtrend, the ratio had a corresponding drop from its peak. When the price started its 2nd uptrend, the ratio changed to increase with the price climb.

FIGURE 5
WEEKLY MOVING AVERAGE NUMBER OF GAS PRICE AND WEEKLY MOVING AVERAGE RATIO OF EV POSTS WITH GAS-RELATED KEYWORDS



Path Pattern Analytics

In summary, During Price Uptrends, gas prices had an indirect positive association with EV popularity and positive sentiment as evidenced by the Voice of Gas. However, during Price Downtrends, gas prices had both direct and indirect positive associations. The Voice of Gas may have triggered changes in positive sentiment and the number of Posts.

To quantify the evolving relationship between gas prices and posts of electric vehicle (EV), we first conducted a correlation analysis with the annual EV sales volume and average yearly U.S. gas prices from 2010 to 2022. The yearly gas price data were aggregated from weekly prices, and Pearson's correlation were employed for two distinct temporal periods: before 2019 and 2019 to 2022. The correlation results disclosed a moderate negative correlation before 2019 ($r = –0.43$). The rising gas prices did not increase the EV volume, most likely because EV was still an immature market that drivers were not familiar with and few discourses occurred online. However, the correlation during 2019–2022 was strongly positive ($r = 0.94$), indicating that with an increase on gas prices, EV volume surged—possibly because of the market maturity, more EV models availability, policy incentives, and greater public awareness. These findings align with the results in Figure 6—9.

Figure 6 shows the single linear regression outcome from SciPy. Stats to test the hypotheses in the path pattern during price uptrends. The outcome shows that gas price had neither a significant association with the number of EV posts in total nor the number of EV positive posts. Even though gas prices triggered the sales of EVs on its uptrend, the price had few direct incentives to the EV popularity and positive sentiment on social media. Instead, gas price had an indirect path to trigger the EV popularity and positive sentiment on its uptrend. The price had a significant positive association with the number of EV gas related posts. The number of EV and gas related posts had a significant positive association with the number of EV posts in total and the number of EV positive posts respectively. Price uptrends showed a more distinct voice of gas presence among EV discussions on social media. The voice of gas further brought more discussion regarding EVs and spread positive sentiment on EVs on social media. Figure 7 summarizes this tested path pattern during price uptrends.

FIGURE 6
SINGLE LINEAR REGRESSION OF PATH PATTERN ANALYTICS DURING PRICE UPTREND

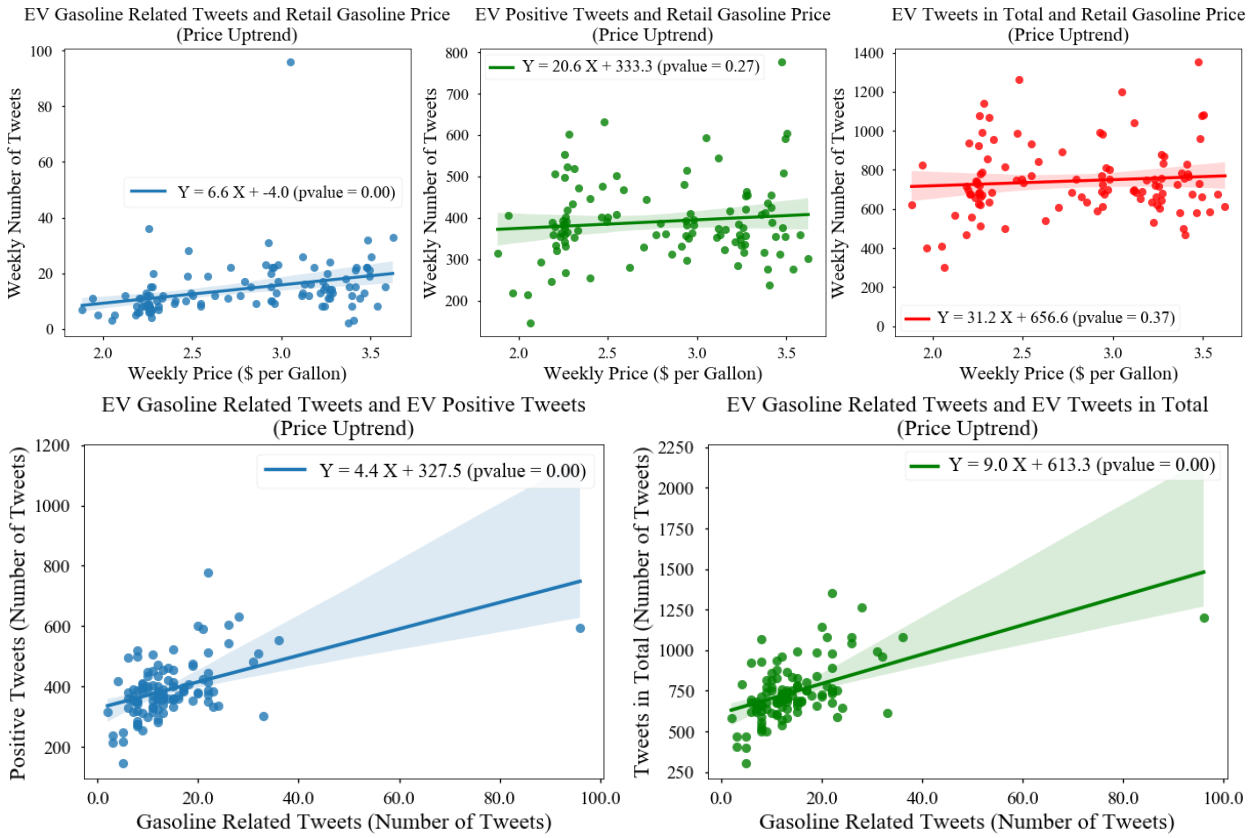
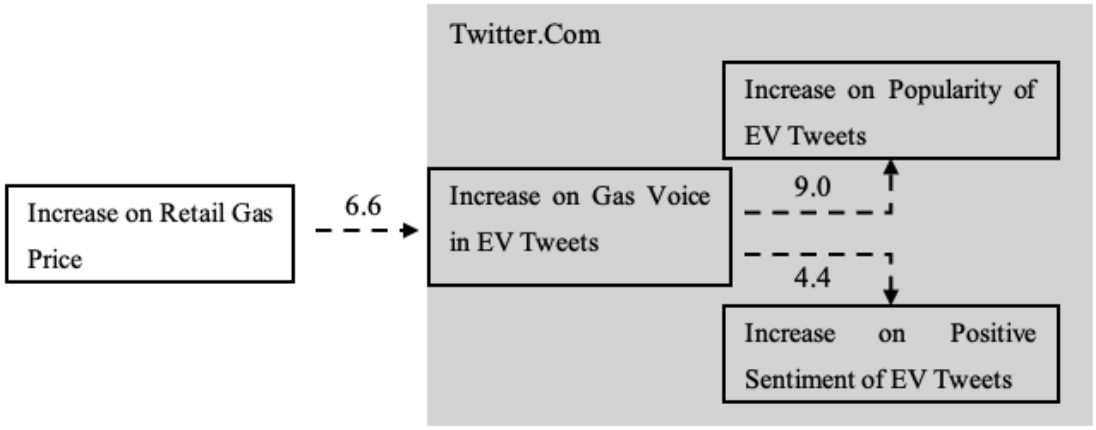


Figure 8 shows the linear regression outcome from SciPy.Stats to test the hypotheses in the path pattern during price downtrends. The outcome shows that gas prices impacted EV popularity and positive sentiment during price downtrends. The price had a significant positive association with the number of EV posts in total and the number of EV positive posts, respectively, meaning that both popularity and positive sentiment decreased with the decline of the price. The price had direct impacts on both EV popularity and positive sentiment. When the price was decreasing, EV discussion on social media decreased with the decline in EV sales. Gas prices had an additional indirect path of impact during EV popularity and positive sentiment during its downtrend. The price had a significant positive association with the number of EV gas-related posts. With the price decreasing, the voice of gas among EV discussions has declined. The number of EV gas-related posts further had a significant positive association with the number of EV posts in total and the number of EV positive posts. The price downtrend decreased gas-related voices, and further, the decline of the voice of gas resulted in less discussion on EVs and weakened positive sentiment on EVs on social media. Figure 8 summarizes this tested path pattern during price downtrends.

FIGURE 7
PATH PATTERN OF GAS PRICE IMPACTS DURING EV POPULARITY AND POSITIVE SENTIMENT ON SOCIAL MEDIA DURING PRICE UPTREND



Solid line means (H1) paths of direct association from retail gas price to EVs' popularity and positive sentiment; Dash line means (H2) paths of indirect association from retail gas price to EVs' popularity and positive sentiment via gas voice on Twitter.Com

FIGURE 8
SINGLE LINEAR REGRESSION OF PATH PATTERN ANALYTICS DURING PRICE DOWNTREND

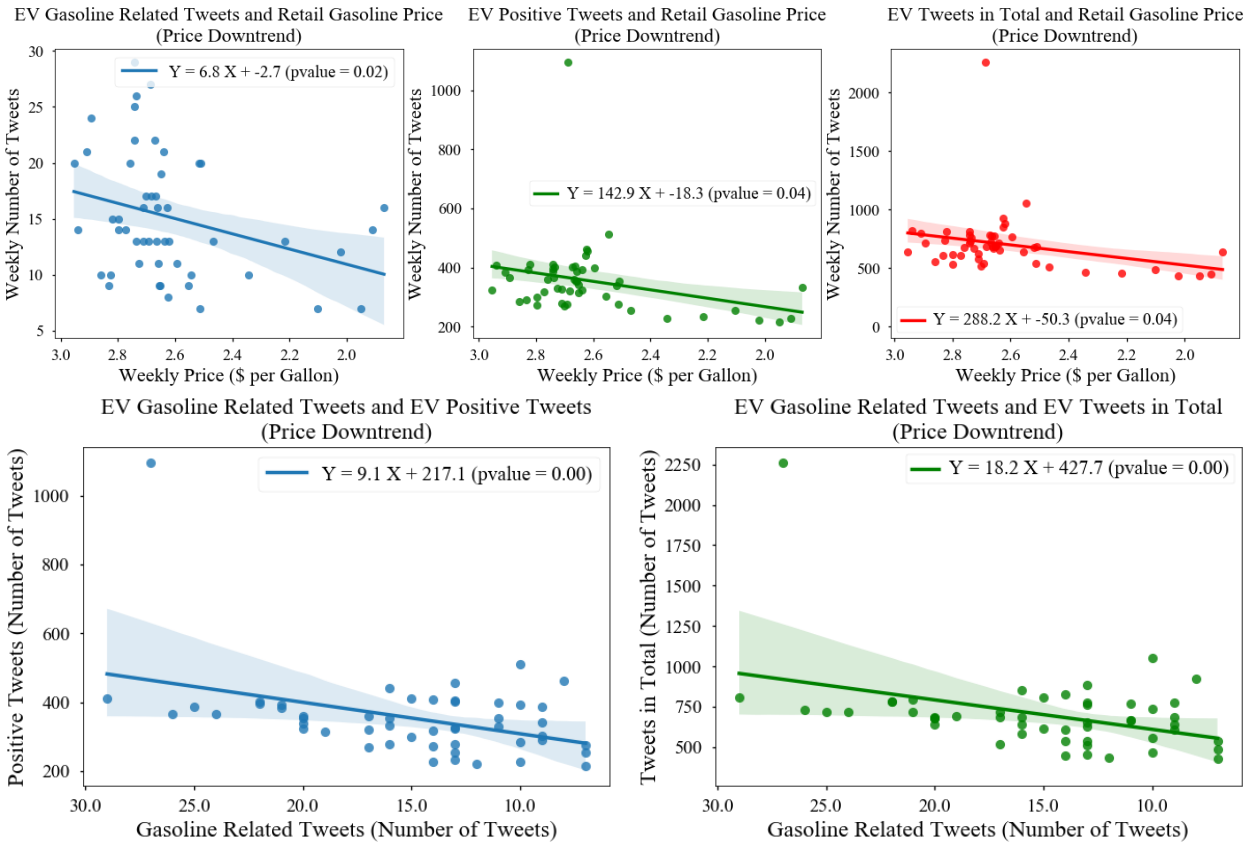
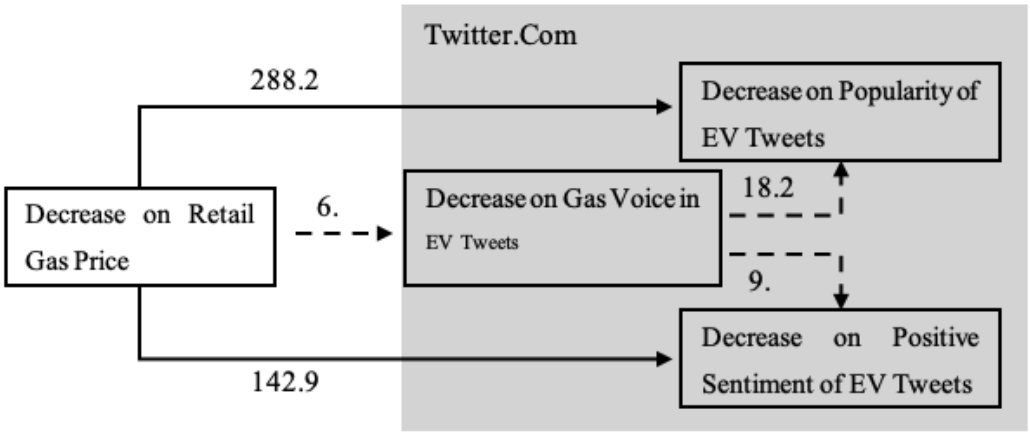


FIGURE 9
PATH PATTERN OF GAS PRICE IMPACTS DURING EV POPULARITY AND POSITIVE SENTIMENT ON SOCIAL MEDIA DURING PRICE DOWNTREND



Solid line means (H1) paths of direct association from retail gas price to EVs' popularity and positive sentiment; Dash line means (H2) paths of indirect association from retail gas price to EVs' popularity and positive sentiment via gas voice on Twitter.Com

Topic Mining Analytics

In summary, there are different topics that were more relevant during gas price uptrends versus downtrends in EV Posts as demonstrated by word clouds.

Log-Likelihood Word Cloud of Hashtags

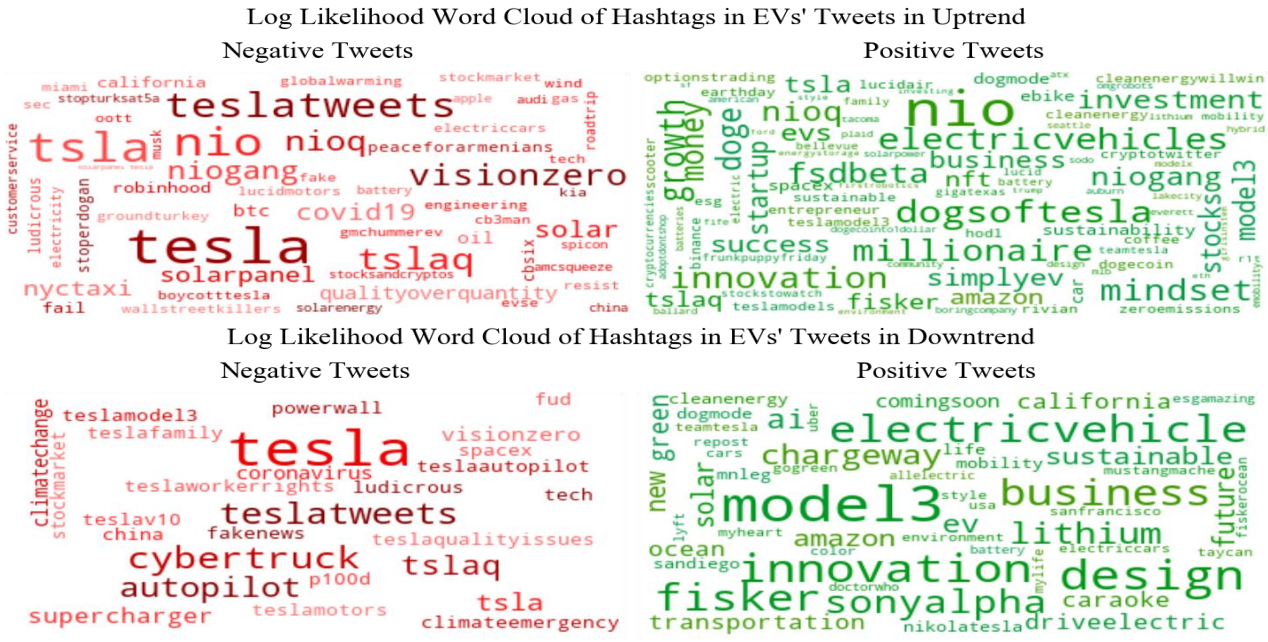
Figure 9 shows the log-likelihood-based word clouds pulled from the most popular 5% of hashtags for positive and negative EV posts during price uptrends and downtrends. During the price uptrend, hashtags of stocks and investments such as "nioq", "tsla", "nft", and "doge" were popular in the positive posts. The growth of EV sales triggered hashtags such as "growth" in positive posts. Innovation related to EVs triggered the appearance of hashtags such as "innovation" and "fsdbeta" in the positive posts. None of gas related hashtags appeared in the positive posts during uptrends.

Similarly, hashtags of stocks and investment were also popular in negative Posts during Price Uptrends such as "tsla", "niog", and "btc". Hashtags of products and quality, such as "solarpanel", "battery" and "qualityoverquantity" also appeared in the negative Posts. COVID-19 brought an unpredictable impact during EV market, and thus hashtags of "COVID-19" also appeared in the negative Posts. Hashtags of traffic fatalities and severe injuries, such as "visionzero" appeared in the negative Posts. The increase in gas prices triggered some hashtags of "oil" and "gas" in the negative Posts.

During the price downtrend, hashtags of stock and investment were not popular in both positive and negative Posts. Instead, hashtags of innovation and future such as "ai", "chargeway" and "design" were shown in positive Post. Meanwhile, hashtags of sustainability advocacy such as "green", "cleanenergy", "solar" were shown in positive Posts. None of gas related hashtags were in the positive Posts during Downtrends.

Hashtags of "visionzero" and "coronavirus" appeared in negative Posts during Price Downtrends. Meanwhile, concerns on Tesla's autopilot triggered some hashtags of "autopilot" and "teslaautopilot" in the negative Posts. None of gas related hashtags were in the negative Posts during Downtrends.

FIGURE 10
LOG LIKELIHOOD WORD CLOUD OF HASHTAGS IN POSITIVE AND NEGATIVE EV POSTS DURING PRICE UPTRENDS AND DOWNTRENDS



Since hashtags can be regarded as topics in Posts, word cloud analytics with the frequency of hashtags is an effective means to explore the overall picture of EV related Posts. Furthermore, it is usual that the most frequently used hashtags would appear in both positive and negative Posts. Log Likelihood is used to maximize the difference between positive and negative Posts. Log Likelihood is a logarithm of the ratio of the conditional probability of each word appearing in the positive and negative groups (Mourri, 2021). In this work, the log score of a word in the positive group and the negative group of Posts are calculated as follow:

$$\lambda post(word) = \frac{p(word|post)}{(p(neg)+p(neu))}) \quad (1)$$

$$\lambda neg(word) = log\ log\ (\frac{p(word|neg)}{(p(post)+p(neu))}) \quad (2)$$

In this work, all non-digit hashtags with a length of more than 1 are used to calculate the log likelihood scores, and the hashtags with the top 5% log scores are shown in the word cloud.

Topic Mining of Gas Price from EV Posts

This work explores the path pattern via which gas prices impact EV popularity and positive sentiment. It also explores the latent topics of gas among EV Posts; in other words, it explores if the Voice of Gas has a positive association with EV popularity and positive sentiment. The topics of gas and its related keywords underlie both positive and negative Posts; this provides insight into the impacts of gas prices – which we will refer to as the Voice of Gas – on Social Media. Thus, if the Voice of Gas in EV Posts shows a positive association with the EV popularity and positive sentiment, the third hypothesis is proven correct.

Hypothesis. Path Patterns demonstrate that Gas Prices Impact EV Popularity and Positive Sentiment on social media.

The 1st question that this work manages to answer is how gas prices influence EV popularity and positive sentiment on social media. This work explores a path pattern via which weekly gas price impacts EV popularity and positive sentiment on social media. Two scenarios are considered in building this path pattern.

In the first scenario, monthly EV sales – including hybrid electric vehicles (HEV) and plug-in electric vehicles (PEV) – are correlated with the variations of monthly gas prices (Argonne National Laboratory, n.d.). Increases in gas prices trigger more conventional internal combustion engine (ICE) vehicle drivers to purchase EVs (O'Dell, 2022). The more EVs are used daily, the more likely EV drivers are to share their reviews and usage experiences regarding EVs on social media; this enhances EV popularity and positive sentiment on social media. The reverse reasoning could also apply when gas prices decline. Thus, the first hypothesis is that there is an impact from increasing gas prices on EV popularity and positive sentiment on social media, via a path out of social media.

H1: *Gas prices have a direct positive association with both EV popularity and positive sentiment on social media.*

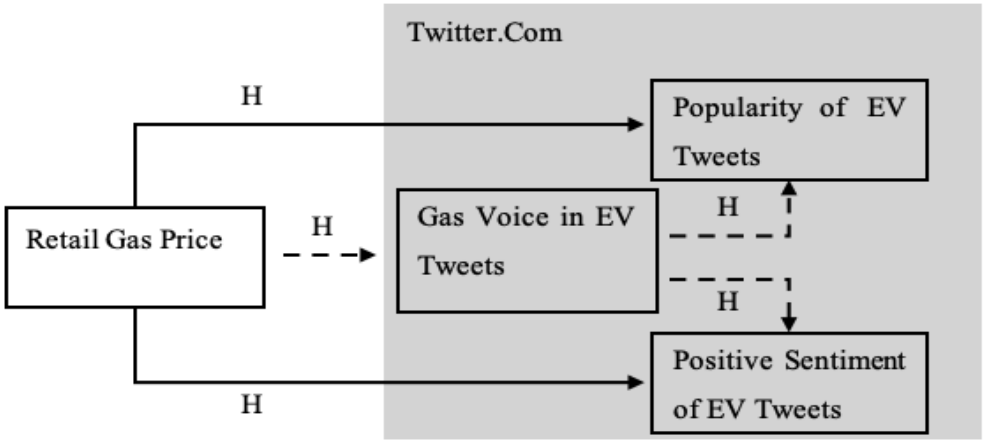
In the second scenario, from social media itself, the increase in gas prices would trigger more discussion amongst EV drivers regarding gas-related topics on social media, such as gas prices, gas efficiency, and daily fuel cost comparisons. This gas-related voice would enhance both EV popularity and positive sentiment on social media. Similarly, the reverse reasoning would also be applied to the decrease in gas prices. Thus, the second hypothesis represents a path of impact that occurs internally on social media.

H2: *Gas prices have an indirect positive association with EV popularity and positive sentiment on social media via an intermediary variable – the online Voice of Gas.*

This work examines Posts on Social Media. Posts with keywords related to electric vehicles were collected from January 1st, 2019, to February 28th, 2022. Gas prices are sourced from Weekly U.S. All Grades All Formulations Gas Prices (Dollars per Gallon) from the U.S. Energy Information Administration (EIA.GOV). Data used in this work will be outlined in the Data Collection and Preprocessing Section.

Figure 11 shows the path pattern and hypotheses of gas price impacts on EV popularity and positive sentiment on social media. These patterns and hypotheses will be explored and explained in the popularity analytics, sentiment analytics, voice analytics of gas-related keywords, and path pattern analytics sections in this paper.

FIGURE 11
PATH PATTERN OF GAS PRICE IMPACTS DURING EV POPULARITY AND POSITIVE SENTIMENT ON SOCIAL MEDIA



Solid line means (H1) paths of direct association from retail gas price to EV popularity and positive sentiment; Dash line means (H2) paths of indirect association from retail gas price to EV popularity and positive sentiment via gas voice on Twitter.Com

H3: *As gas prices increase, the Voice of Gas related topics appears more often in EV-related Posts. Typically, when gas price is during downtrend, topics about gas appear in negative Posts, and decrease the positive sentiment of EV-related Posts.*

Topic and top 15 keywords of positive and negative Posts

Table 6 shows the 4 topics and their top 15 key words of the positive and negative EV posts during price uptrends as generated by the LDA model. Topics of "stock & invest", "EV & gas", and "car & service" were dominant in both positive and negative posts during price uptrends. The topic of the EV manufacturers' "stock & investments" such as "tsla", "nio", "profit", and "share" appeared in either positive or negative posts were mainly owing to the increase in EV sales and the profits of EV manufacturers during price uptrends. Meanwhile, the acceptance of bitcoin for Tesla purchasing led to a variance in bitcoin's sentiment value, triggering the appearance of keywords "bitcoin" during the topic of "stock & invest " in the positive posts.

The increase in gas prices triggered more discussion about gas during Uptrend. The topic of "EV & Gas" appeared in both positive and negative Posts. The discussion was mainly about the "cost" of electric cars and comparison during usage of "batteri" and "gas" "oil".

> "…in 2023 is when the cost to own a light electric vehicle will be cheaper than a gas vehicles…"

> "…Senator, the auto industry sees the future as electric vehicles or some hydrogen. A 15-20 year transition would allow costs of EVs to come down, quality of batteries to improve. Texas is in a good spot - natural gas as key transition fuel, lots of solar and wind generation…."

Verbatim in the positive Posts in the topic of "EV & Gas" during Uptrend

> "…the disaster would be on another scale if all those cars were electric. you can't just add 2 gallons of gas in less than a minute to get it going like with an ice vehicle. how

depleted would an ev be after 12 hours in sub-freezing temps? how do you recharge 100s of stranded EVs?....”

“…why doesn't tesla sell portable single use power packs in case someone's battery dies? if your car runs out of gas you can buy a gas canister. but if your car battery dies there's no way to carry "fuel" to your tesla and get it to the nearest charging station...”

Verbatims in the negative Posts in the topic of “EV & Gas” during Uptrend

*Underlined words are key words in the top 15 key words of “EV & Gas”

“Car and Service” was also popular in both positive and negative Posts during Uptrend. The discussion on “Tesla and Elonmusk” such as “spacex” and “giga_texa” mainly appeared in the positive Posts while the topic of “Need & Manufacture” such as “factori”, “employe”, and “need” mainly appeared in the negative Posts.

Table 7 shows the 4 topics and their top 15 key words of the positive and negative EV posts during the price downtrend generated by the LDA model. Given that the e voice of gas in EV posts and the EV sales decreased with the drop in gas price during the downtrend, “ev & gas” and “stock & invest” were not popular in the positive posts. Instead, topics of “design & innovation”, “photo & kol”, “model and autopilot”, and “company & stock” were popular in the positive posts.

The corresponding drop during positive sentiment of EV Posts during Price Downtrend could be explained by the appearance of “EV & Gas” in the negative Posts. The discussion of “EV & Gas” here is mainly concerned about the EV necessity and efficiency such as keywords “need” and “ people”.

“….we don't need cheaper gas. we need no gas. we need more housing near more transit so that we don't have cars spewing emissions and sending up break pad and tire particulates, so that we aren't burning carbon to power electric vehicles, so that people don't need to drive to work….”

“….and people say electric cars aren't as efficient as gas sum….”

“….electric cars need not run on fossil fuels but they still further car-dependence and anti-pedestrian designs. … Further, spikes in oil and gas prices aren't the needed signals to get off fossil fuels….”

Verbatims in the negative Posts in the topic of “EV & Gas” during Downtrend

Besides of the “EV & Gas”, the topics of “Fire & Crash” and “Car & Service” appeared in the negative Posts. They mainly showed the concerns during safety and service of EVs such as “crash”, “fire”, “autopilot”, “issu” and “problem”.

TABLE 6
LDA TOPICS’ OUTCOME OF POSITIVE AND NEGATIVE EV POSTS IN THE UPTREND

	Negative Posts in the Uptrend				Positive Posts in the Uptrend			
Top 15 Key Words	Stock & Invest	Car & Service	EV & Gas	Need & Manufacture	Car & Service	Stock & Invest	EV & Gas	Tesla & Elonmusk
0	tsla	tesla	car	electr_car	car	Tsla	electr_vehicl	Tesla
1	stock	peopl	way	elon_musk	time	Stock	electr_car	Model
2	money	model	electr_vehicl	truck	thank	Share	Batteri	Elonmusk

3	market	car	gas	Tax	tesla	Nio	Ev	Cybertruck
4	today	thing	batteri	damn	peopl	Compani	Energi	Love
5	nio	driver	cost	california	way	Money	Gas	Fun
6	day	lot	product	Need	thing	Lol	Electricvehicles	Supercharg
7	price	one	mile	Citi	year	Price	Power	model3
8	fuck	servic	engin	report	lot	Market	Car	Space
9	share	time	vehicl	Tesla	owner	Day	Future	Spacex
10	Post	someth	rang	factori	drive	Bitcoin	State	Elon
11	As	owner	auto	world	friend	Today	Ford	Fsd
12	lol	man	oil	Texa	servic	Appl	Rang	Dream
13	facebook	autopilot	state	compani	work	Week	auto	giga_texa
14	week	guy	hour	employe	driver	Profit	motor	Austin

TABLE 7
LDA TOPICS' OUTCOME OF POSITIVE AND NEGATIVE EV POSTS IN THE DOWNTREND

	Negative Posts in the Downtrend				Positive Posts in the Downtrend			
Top 15 Key Words	Fire & Crash	EV & Gas	Car & Service	Truck & EV	Company & Stock	Design & Innovation	Photo & KOL	Model & Autopilot
0	Tesla	car	model	Tesla	car	truck	Ev	Tesla
1	driver	tsla	Tesla	Truck	tesla	cybertruck	Electricvehicles	Thank
2	cybertruck	Money	Thing	peopl	peopl	fisker	Sonyalpha	Model
3	elon_musk	electr_car	Day	Guy	year	drive	Electric	model3
4	Drive	gas	Service	Ev	tsla	design	Aov	Love
5	teslamodel3	time	Today	Mile	time	electricvehicle	Igcars	Autopilot
6	Fire	electr_vehicl	Elon	Car	compani	Suv	loves_transports	Supercharg
7	Shit	compani	Autopilot	electric vehicles	way	Cars	Agameoftones	Wow
8	supercharg	googl	Wheel	someth	electr_vehicl	Evs	Sonyimages	Man
9	Year	facebook	Car	Busi	electr_car	innovation	Instagoodmyphoto	Wheel
10	Game	twtr	Part	Way	stock	planet	splendid_transport	teslamodel3
11	Crash	oil	Issu	Damn	thing	electriccar	Visualsgang	Mode
12	Stock	power	Video	Ford	market	Show	autos_of_our_world	Today

13	Appl	peopl	Anyth	Fan	model	clean	Killeverygram	California
14	elonmusk	need	Problem	Bitch	day	travel	freddyp3d	Park

CONCLUSION

This work uncovered some interesting findings relating to EV sentiment vs gas prices. These findings are that:

1. Gas prices were highly positively correlated with EV popularity as gas prices decreased. Gas prices were less correlated with EV popularity as gas prices increased.
2. EV Positive Sentiment and EV Popularity shared similar correlations with gas prices.
3. The variance of gas prices has a positive association with the Voice of Gas in EV Posts.
4. The Voice of Gas affects EV popularity and positive sentiment.
5. There are different topics that were more relevant during gas price uptrends or downtrends.

Sentiment Analysis has been used in the past to investigate similar trends and is only becoming more popular and accessible. Overall, this study showcases that EV sentiment on social media varies with gas prices over time. This main conclusion follows up on previous research that found gas prices to be an attribute that influences EV adoption; this study builds on this theory by quantifying the social media sentiment underlying gas price changes over time. What this means is that to influence people to have positive opinions and discuss EVs, increased gas taxes and similar economic disincentives may be effective governmental policy.

Future Research

Future research could include investigating why EV sentiment varies with gas prices, how negative governmental incentives could persuade prospective car buyers to purchase EVs and how vehicle demand can be predicted based on consumer sentiment. Governmental incentives meant to increase gas prices may increase positive EV social sentiment and adoption similar to how government imposed high taxes on tobacco in the United States curb tobacco usage.

Our study highlights the significance of the online discourse of Gas price in mediating the relationship between gas prices and EV sentiment on Social Media. Future research could drill into the types of discourse and framing that influence EV sentiment during price fluctuations. This could involve extending topic modeling and sentiment analysis to include framing theory and narrative analysis, identifying whether specific themes—such as environmental concern, energy independence, or economic burden—become more prominent in shaping public sentiment during gas price uptrends or downtrends. Such work could clarify how social and traditional media co-produce public opinion shifts around EVs.

Future research also investigate how policy interventions—such as EV subsidies—interact with public discourse to shape not just sentiment, but behavioral engagement and actual purchase intention. This could include experimental designs (e.g., survey experiments or natural experiments) that test whether gas price expectation increases consumer intention and social media sentiment on EVs. Integrating behavioral economics with sentiment dynamics would offer a more causal understanding of how to translate public attention into adoption behavior.

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