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A Multi-Layered Analysis of Digital Public Discourse on Electric Vehicles: Integrating Sentiment, Emotion, and Network Structures in Social Media

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Abstract. This study analyses the structure and dynamics of digital public discourse on electric vehicles using a data-driven social media analytics approach. A total of 219 tweets were collected through the SocialX data mining system and analysed using Natural Language Processing (NLP), Social Network Analysis (SNA), Text Network Analysis (TNA), sentiment analysis, emotion analysis, trend analysis, and zero-shot classification. The analytical process included word cloud extraction, transformer-based sentiment and emotion classification, network mapping, and temporal trend analysis. The results indicate that electric vehicle discourse is highly dynamic and event-driven, with discussion peaks influenced by policy developments and technological innovations. Sentiment analysis shows a predominance of neutral content, suggesting that users mainly engage in information sharing, while positive and negative sentiments reflect support and criticism. Emotion analysis reveals optimism as the dominant emotion, accompanied by concern and critical perspectives. TNA identifies interconnected themes related to electricity, vehicles, policy, and economic issues, whereas SNA highlights a hybrid interaction structure in which several influential actors play key roles in information dissemination and discourse amplification. This study contributes an integrated analytical framework that combines textual, emotional, structural, and temporal dimensions of online discourse. The findings provide valuable insights for policymakers, industry stakeholders, and communication practitioners in developing more effective electric vehicle communication strategies and policies.

Keywords: Electric vehicles, Social media analytics, Sentiment analysis, Network analysis, Digital discourse.

1 Introduction

The rapid expansion of digital communication technologies has transformed social media into a central arena for public discourse, particularly in relation to emerging issues such as electric vehicles and sustainable transportation technologies [1], [2]. Platforms such as X/Twitter enable users to exchange information, express opinions, and respond collectively to ongoing developments in real time, thereby creating a dynamic environment in which public perception is continuously constructed and reconstructed. In this context, discussions surrounding electric vehicles are not limited to technological

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aspects but extend to broader socio-economic dimensions, including pricing mechanisms, government policies, infrastructure readiness, and user experience [3]. Empirical observations derived from social media data indicate that digital discourse tends to evolve in response to external stimuli, such as policy announcements or technological updates, resulting in fluctuating levels of engagement over time. However, despite the increasing intensity of online discussions. EV-related discourse remains fragmented, reactive, and event-driven nature of discourse on digital platforms [4].

The growing body of research on social media analytics highlights the importance of computational approaches in understanding how public discourse is formed and evolves. Previous studies have employed techniques such as sentiment analysis, text mining, and network analysis to examine communication patterns, information diffusion, and opinion formation. These approaches demonstrate that digital discourse is inherently influenced by external events and collective attention, whereby users tend to engage simultaneously when particular issues gain prominence [5][6] [7]. Furthermore, recent advancements in Natural Language Processing (NLP) and network science have enabled more sophisticated analyses, allowing researchers to explore not only the content of discourse but also its structural and relational characteristics [8]. Methods such as Text Network Analysis (TNA) and Social Network Analysis (SNA) have been increasingly utilised to identify thematic clusters, key actors, and patterns of interaction within digital ecosystems.

Despite these advancements, existing studies have often focused on isolated analytical dimensions, such as sentiment distribution or keyword frequency, without integrating multiple perspectives into a comprehensive analytical framework [9][10]. Consequently, the multidimensional nature of digital discourse has not been sufficiently explored. In particular, limited attention has been paid to how temporal dynamics, emotional expressions, and network structures interact to shape the collective understanding of issues such as electric vehicles. This gap indicates the need for an integrative approach that can capture the complexity of digital communication, where multiple layers of meaning, interaction, and temporal evolution coexist simultaneously [11].

While previous studies have successfully applied sentiment analysis, network analysis, and NLP techniques independently or in limited combinations, few studies have explicitly examined how textual content, emotional expressions, interaction structures, and temporal dynamics interact within a unified analytical framework. This study addresses this gap by proposing a multi-layered framework that integrates these dimensions simultaneously. The novelty of the framework lies not merely in combining computational techniques, but in explaining how discourse content, emotions, network structures, and collective attention mutually reinforce one another in shaping public understanding of electric vehicles [12][13].

This study addresses this gap by proposing a multi-layered analytical framework that integrates Natural Language Processing, Text Network Analysis, Social Network Analysis, sentiment analysis, emotion analysis, trend analysis, and zero-shot classification to examine public discourse on electric vehicles [14][15]. By combining these approaches, this study provides a more holistic understanding of how discourse is structured, evolves over time, and interacts with various analytical dimensions. This research is grounded in the theoretical perspectives of the Digital Public Sphere and the Social Construction of Technology, which emphasise that technological meanings are socially constructed through interaction within digital environments. Through this integrative

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approach, this study aims to analyse the structure, dynamics, and evolution of public discourse on electric vehicles; identify dominant themes and patterns; examine sentiment and emotional distributions; and explore temporal trends and interaction networks within social media platforms [16][17].

Accordingly, this study addresses the following research questions:

1. How is public discourse on electric vehicles expressed and distributed through social media interactions on X/Twitter?
2. What dominant sentiments, emotions, thematic structures, and temporal patterns characterize digital discussions related to electric vehicles?
3. Who are the key actors within the interaction network and how do they influence the dissemination and amplification of information regarding electric vehicles?
4. To what extent can the integration of sentiment analysis, emotion analysis, Text Network Analysis, and Social Network Analysis provide a comprehensive understanding of digital public discourse on electric vehicles?

2 Literature Review

The increasing relevance of digital platforms in shaping public discourse has attracted significant scholarly attention, particularly in the context of technology adoption and sociotechnical transformation. Social media has been widely recognised as a digital public sphere in which individuals participate in the construction of meaning through interaction, information exchange, and collective interpretation [18][19]. Within this environment, discourse is not static but continuously evolves in response to emerging issues, external events, and user engagement patterns. Studies have shown that public conversations on technological innovations, including electric vehicles, are strongly influenced by policy interventions, economic incentives, and perceived benefits, indicating that discourse is shaped by the intersection of technological, regulatory, and socioeconomic factors [20].

In the field of computational social science, Natural Language Processing has become a key methodological approach for analysing large-scale textual data derived from social media [21]. Sentiment analysis has been widely used to identify public attitudes, revealing that digital discourse often contains a combination of informational, supportive, and critical perspectives. At the same time, emotion analysis provides a more nuanced understanding of affective responses, highlighting how emotions such as optimism, fear, or dissatisfaction contribute to the formation of public opinion [22][23]. These approaches demonstrate that digital communication is inherently heterogeneous and combines descriptive content with evaluative and emotional elements.

Beyond textual analysis, network-based approaches such as Text Network Analysis and Social Network Analysis have been employed to examine the structural characteristics of discourse. Text Network Analysis focuses on co-occurrence relationships between words, enabling the identification of thematic clusters and conceptual connections within the discourse [2][24]. Meanwhile, Social Network Analysis examines interaction patterns among users, revealing the presence of key actors, community structures, and information flow dynamics. These methods provide valuable insights into how discourse is organised and how influence is distributed within digital

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environments. While previous studies have successfully identified public attitudes toward EV adoption through sentiment analysis, they often neglect interaction structures and temporal fluctuations that shape discourse evolution

However, most existing studies have applied these analytical techniques separately, resulting in fragmented insights that do not fully capture the complexity of digital discourse. The lack of integration between textual, emotional, structural, and temporal analyses limits our ability to understand how different dimensions of discourse interact and evolve over time. In addition, temporal dynamics are often underexplored despite evidence that public engagement on social media is highly responsive to external triggers and exhibits patterns of escalation and decline [25][26]. This limitation highlights the need for a comprehensive analytical framework combining multiple approaches to provide a deeper and more holistic understanding of digital communication [27].

To address the complexity of digital public discourse, this study adopts a multi-layered discourse framework that conceptualises online communication as a sequential process involving informational inputs, cognitive interpretation, emotional responses, network diffusion, and temporal evolution. This perspective is consistent with information-processing approaches, which suggest that individuals first receive information, subsequently interpret and evaluate it, develop emotional reactions, and ultimately express behavioural responses through communication activities.

Within this framework, Text Network Analysis represents the textual layer of discourse by identifying dominant narratives, themes, and semantic relationships embedded within public conversations. These textual structures function as informational inputs entering the digital public sphere and provide the foundation upon which public understanding is constructed. The cognitive layer is represented through sentiment analysis and zero-shot classification. These analytical approaches capture how users interpret and evaluate information related to electric vehicles, revealing whether discourse is perceived positively, negatively, neutrally, or through specific thematic categories. Cognitive interpretation plays an important role in transforming textual information into meaningful public perceptions[28].

Beyond cognitive evaluation, discourse also involves affective responses. Therefore, emotion analysis is employed to identify emotional expressions such as happiness, fear, anger, sadness, and other affective reactions that emerge from public engagement with electric vehicle-related issues. This emotional layer provides a deeper understanding of how individuals respond psychologically to technological, economic, and policy developments. The structural layer is represented through Social Network Analysis, which examines how discourse is disseminated, amplified, and circulated through interaction networks. In this context, influential actors facilitate information diffusion and contribute to the formation of collective attention by connecting different segments of the communication network[29].

Finally, the temporal layer is represented through trend analysis, which captures fluctuations in discourse intensity over time. Temporal patterns reveal how public attention evolves in response to external events such as policy announcements, technological innovations, market developments, or other significant triggers. Accordingly, textual, cognitive, emotional, structural, and temporal dimensions are not treated as independent analytical components. Instead, they are conceptualised as interconnected layers within a unified discourse-processing system. This integrated framework enables a more comprehensive understanding of how public discourse on electric vehicles is

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constructed, interpreted, amplified, and transformed within digital environments[30][31].

3 Methodology

This study employed an exploratory social media analytics approach to investigate the dynamics of public discourse related to electric vehicles on X/Twitter [32]. The research design was structured to ensure a systematic, logical, and reproducible process, enabling a comprehensive analysis of textual data and interaction patterns. The dataset consisted of 219 tweets collected using the SocialX platform. Prominence was assessed based on interaction frequency, network position, and visual network connectivity pattern. Although the dataset size may appear limited compared with large-scale social media studies, the objective of this research is exploratory rather than predictive. The purpose is to identify discourse structures, thematic relationships, emotional patterns, and interaction dynamics within a bounded observation period. In discourse-oriented and network-based investigations, analytical value derives from the richness of relationships and communication patterns rather than from sample size alone, an artificial intelligence-based tool designed for structured social media data extraction. The data collection process captured not only textual content but also relevant metadata, including timestamps, engagement metrics, and interaction structures, such as mentions and retweets, thereby providing a robust foundation for multidimensional analysis [33][34].

For analytical consistency, this study operationalises several key concepts used throughout the manuscript. First, dynamic discourse refers to fluctuations in communication intensity measured through variations in tweet volume, engagement patterns, and discourse activity over time.Second, event-driven discourse refers to communication patterns characterised by sudden increases in public attention triggered by external stimuli, such as policy announcements, technological developments, market changes, or viral events. Third, multidimensional discourse refers to discourse that simultaneously contains textual, cognitive, emotional, structural, and temporal characteristics. These dimensions are captured through the integration of Text Network Analysis, sentiment analysis, emotion analysis, Social Network Analysis, and temporal trend analysis. Finally, integrated discourse refers to the interaction between these dimensions, whereby textual narratives influence cognitive interpretation, cognitive interpretation generates emotional responses, emotional responses are amplified through social interaction networks, and the resulting discourse evolves over time in response to external events [35][36].

Prior to the analysis, the dataset underwent a preprocessing stage to ensure data quality and consistency. This process includes the removal of irrelevant elements such as URLs, emojis, and nonstandard characters, as well as the elimination of duplicate entries [37][38]. Text normalisation was conducted through tokenisation and lowercasing to standardise the data and reduce variability in textual representation. These steps are essential for enhancing the validity and reliability of the analysis, particularly given the diverse and unstructured nature of social media data [39].

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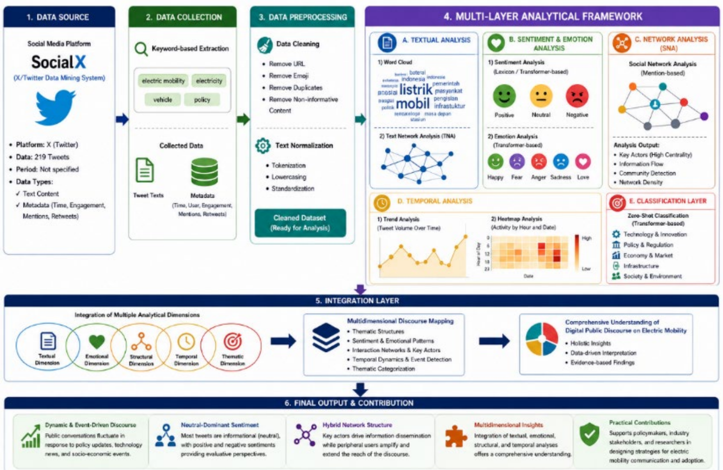

Fig. 1. Research Framework for Methodology

Sentiment analysis was performed using transformer-based language models implemented through the Hugging Face ecosystem. Specifically, pre-trained transformer architectures were selected due to their strong performance in social media text classification and their ability to capture contextual semantic relationships beyond traditional lexicon-based approaches. These models leverage contextual embeddings that enable more accurate interpretation of user-generated content, including short and informal social media texts. Previous studies have demonstrated that transformer-based models consistently outperform conventional machine-learning and lexicon-based methods in sentiment and emotion classification tasks. Nevertheless, classification outcomes should be interpreted as probabilistic estimates rather than definitive representations of user intent because sarcasm, irony, cultural references, multilingual expressions, and context-dependent meanings may not always be accurately recognized[40].

Table 1. Analytical Dimensions and Methods

Dimension	Method	Purpose
Textual	Text Network Analysis	Identify themes and semantic relationships
Emotional	Sentiment & Emotion Analysis	Capture attitudes and affective responses
Structural	Social Network Analysis	Identify influential actors and information flow
Temporal	Trend Analysis	Examine discourse evolution over time
Interpretive	Zero Shot	Categorise discourse themes

All analytical results were visualised using statistical- and network-based representations to facilitate interpretation and pattern identification [41]. The findings were

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interpreted within the theoretical frameworks of the Digital Public Sphere and the Social Construction of Technology, which emphasise the role of social interaction in shaping technological meaning and public perception The methodological approach adopted in this study ensures validity through the use of established computational techniques, reproducibility through clearly defined procedures, and transparency through the explicit documentation of data sources, analytical methods, and tools. This integrative framework enables a comprehensive understanding of digital discourse by capturing textual, emotional, structural, and temporal dimensions within a unified analytical model [42].

4 Result and Discussion

Data Overview

To further examine the daily rhythm of online engagement, this study presents a Tweet Activity Heatmap (Hour vs. Date) that visualises the intensity of tweet distribution across both temporal dimensions. The heatmap indicates that tweet activity is not evenly distributed throughout the observation period, but instead exhibits a gradual and significant increase over time. During the early phase, tweet frequency remained relatively low and sporadic, generally ranging between 0 and 2 tweets per day. However, toward a later period, a substantial surge was observed, with peak activity exceeding 25 tweets on specific dates.

From a temporal perspective, this pattern reflects a progressive escalation in public discourse, in which the initial low activity transitions into a steady increase before reaching a pronounced peak at the end of the observation window. This trend suggests that growth in tweet volume is likely driven by external stimuli, including emerging issues, policy-related developments, or technological updates relevant to the topic under discussion. This reinforces the notion that digital discourse is inherently reactive and closely aligns with real-world events.

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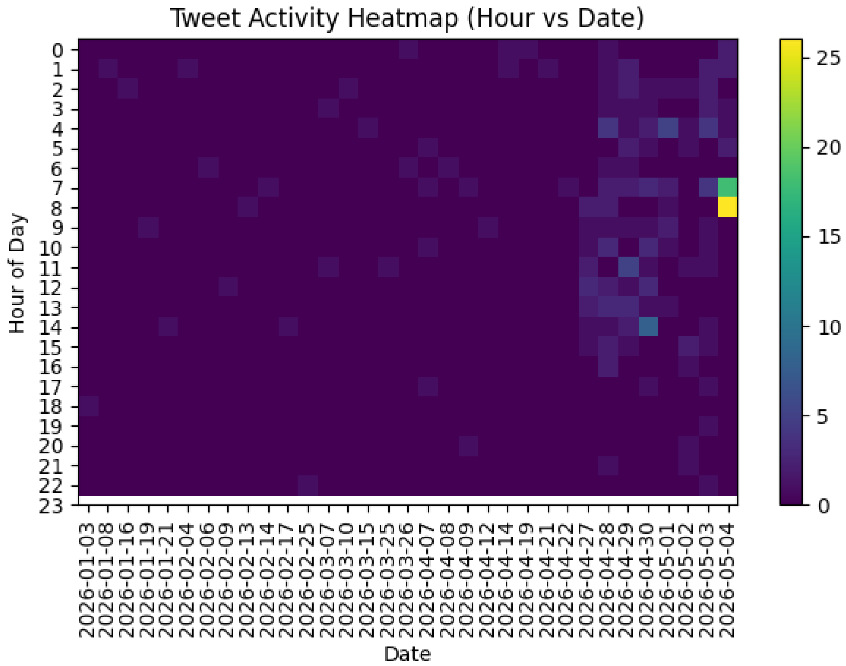

Fig. 2. Tweer Activity Heatmap

In terms of hourly distribution, the heat map revealed that tweet activity was predominantly concentrated within specific time intervals, particularly between 08:00 and 14:00. The highest intensity was observed around 09:00–10:00, when the tweet frequency reached its maximum, as indicated by the darkest colour gradient in the visualisation. In contrast, activity during the early morning hours, particularly between 00:00 and 05:00, remained consistently low, with frequencies approaching zero. This pattern reflects typical user behaviour, in which engagement is aligned with active daily routines and decreases during resting periods. Furthermore, the clustering of activities within certain hourly blocks suggests a synchronised pattern of user engagement, in which individuals respond collectively to shared information or trending topics within a relatively narrow timeframe. This phenomenon highlights the role of collective attention in shaping the dynamics of digital communication, as users tend to participate simultaneously when particular issues gain prominence.

Overall, the heatmap demonstrates that public discourse follows a structured temporal pattern characterised by both gradual increases in daily tweet volume and concentrated activity during peak hours. The observed escalation to more than 25 tweets at peak periods, combined with the concentration of activity between 08:00 and 14:00, underscores the interplay between external triggers and habitual user behaviour. These findings provide a robust foundation for subsequent analyses, including trend identification, event detection, and modelling of user engagement patterns within digital ecosystems.

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Word Cloud Analysis

The word cloud generated from the overall dataset illustrates the most frequently occurring terms within public discourse related to electric vehicles, energy, and technology-driven transportation systems. Visually, the size of each word represents its frequency of occurrence, with larger words indicating greater prominence in the conversation. In this visualisation, dominant terms such as “electricity”, “vehicle”, and “motorcycle” appear most prominently, suggesting that these concepts form the central core of discourse. The presence of terms such as “speed”, “control”, and “distance” further indicates that the discussion extends beyond the existence of technology itself, encompassing operational aspects, performance considerations, and user experience.

In addition, the emergence of policy- and economy-related terms such as “tariff”, “subsidy”, “price”, and “government” reflects the strong influence of regulatory frameworks and economic factors within the discourse. This pattern suggests that public conversations are not solely focused on technological innovation but are also shaped by government interventions, pricing mechanisms, and broader market dynamics that affect adoption and accessibility. The appearance of consumer-oriented terms such as “buy”, “discount”, and “save” reinforces the role of economic considerations in influencing public perception and decision-making regarding electric vehicles.

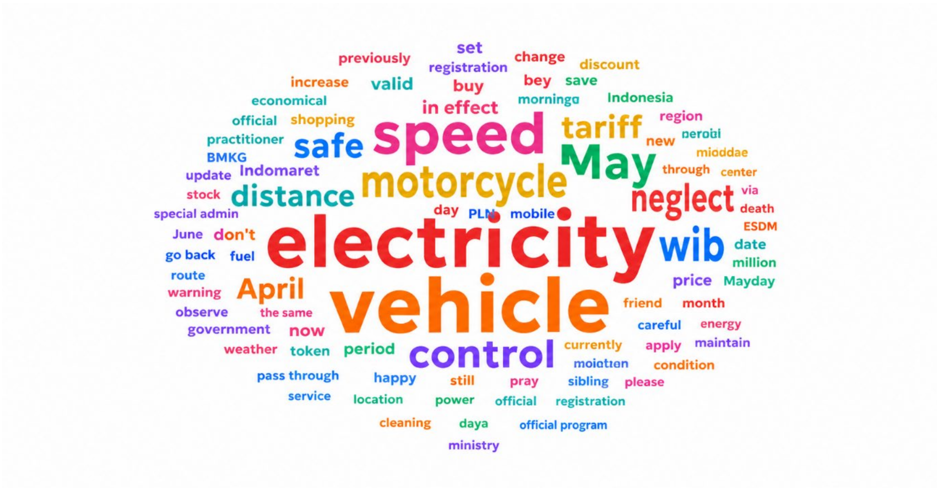

Fig. 3. Word Cloud Anlysis

Temporal expressions including “April”, “May”, “date”, and “period” indicate the presence of a time-related dimension within the discourse. These terms suggest that conversation intensity may be linked to specific events, policy announcements, or periodic developments that trigger increased engagement. Such temporal patterns highlight the dynamic nature of digital discourse, which evolves in response to external stimuli and contextual changes.

Overall, the word cloud highlights several key patterns. First, the discourse is dominated by themes related to electric vehicles and energy transition. Second, regulatory

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and policy-related elements play a significant role in shaping narratives. Third, user experience and technical performance have emerged as important components of public discussion. Finally, economic and temporal factors contribute to the evolving dynamics of conversations. Taken together, these findings indicate that discourse is inherently multidimensional, wherein technological, regulatory, economic, and experiential aspects are closely interconnected to shape public narratives in digital environments.

Sentiment Analysis

Sentiment analysis of 219 tweets indicates that public discourse on the examined topic on the X/Twitter platform is predominantly characterised by neutral sentiment, accounting for 78.08% (171 tweets). This substantial proportion indicates that most tweets were classified without explicit positive or negative polarity. Such neutrality may reflect informational communication, factual reporting, or descriptive discussion. However, it should be acknowledged that automated sentiment classification models may not fully capture implicit sentiment, sarcasm, irony, or context-dependent meanings frequently encountered in social media communication. Such as by sharing news, announcements, or general updates, rather than expressing strong emotional positions. The dominance of neutral sentiments implies that discourse is largely driven by information dissemination rather than by subjective or affective engagement. The dominance of neutral sentiment may indicate that discourse is largely driven by information dissemination rather than explicit emotional expression.

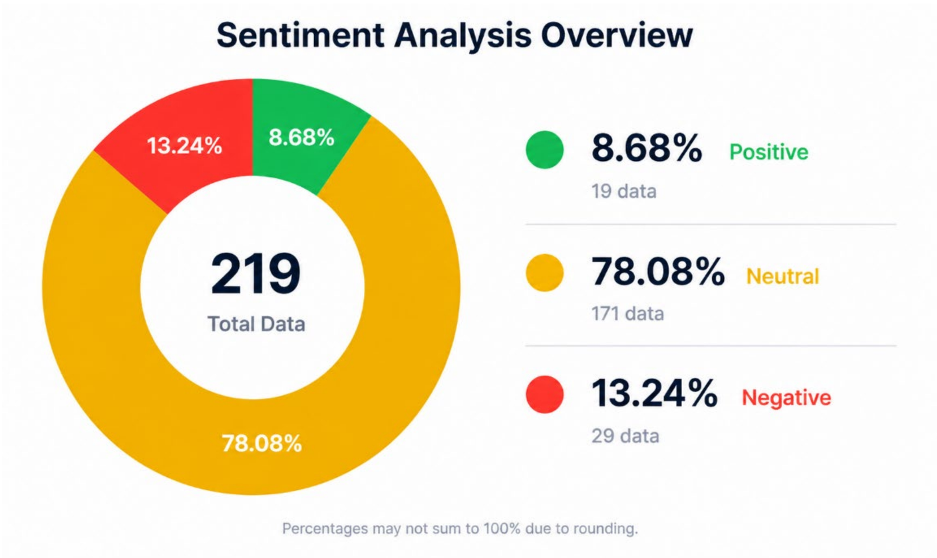

Fig. 4. Sentiment Analysis Overview

Positive sentiments represented 8.68% (19 tweets) of the dataset. Although relatively limited in proportion, these positive expressions reflected supportive, optimistic, or appreciative responses to the topic under discussion. Such tweets are typically associated

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with perceived benefits, opportunities, or favorable developments related to technological advancements, policy initiatives, or broader socioeconomic dynamics. The presence of positive sentiment indicates the degree of public acceptance and endorsement within certain segments of the discourse.

Conversely, negative sentiments accounted for 13.24% (29 tweets) of tweets, highlighting the existence of critical perspectives within the conversation. Negative expressions are generally linked to concerns regarding policy effectiveness, technical challenges, or the perceived risks associated with the issue. Although not dominant, the presence of negative sentiment remains analytically significant, as it reflects areas of contention and potential barriers to broader public acceptance.

The sentiment distribution demonstrates that public discourse is primarily informational, with neutral sentiment prevailing, whereas positive and negative sentiments contribute to additional layers of support and critique. The dominance of neutral sentiment suggests that EV-related discourse is still primarily driven by informational dissemination rather than strong ideological polarization. This pattern underscores the heterogeneous nature of digital communication, in which information exchange, favorable perception, and critical evaluation coexist within the same discourse environment. Such findings are consistent with prior research emphasizing that digital public discourse is shaped by the interplay between information dissemination, user perception, and evolving socio-contextual dynamics

Text Network Analysis

Text network analysis provides a comprehensive overview of how lexical elements within a dataset are interconnected, forming a structured representation of public discourse. The network visualization reveals that key terms such as “electricity,” “vehicle,” “motorcycle,” and “control” occupy central positions, indicated by larger node sizes and higher connectivity. These nodes function as core elements within the discourse, suggesting that conversations are strongly anchored in the technological and operational aspects of electric vehicles.

The network structure not only reflects word frequency but also illustrates co-occurrence patterns, allowing the identification of several thematic clusters. A primary cluster is centered on “electricity,” which is strongly associated with terms such as “car,” “motorcycle,” “subsidy,” “tariff,” and “energy.” This cluster highlights the dominance of discussions related to electric vehicles and energy transition, where technological development is closely linked to policy frameworks and economic incentives. The strong interconnections within this cluster indicate that public discourse is shaped by the intersection of innovation, regulation, and resource management.

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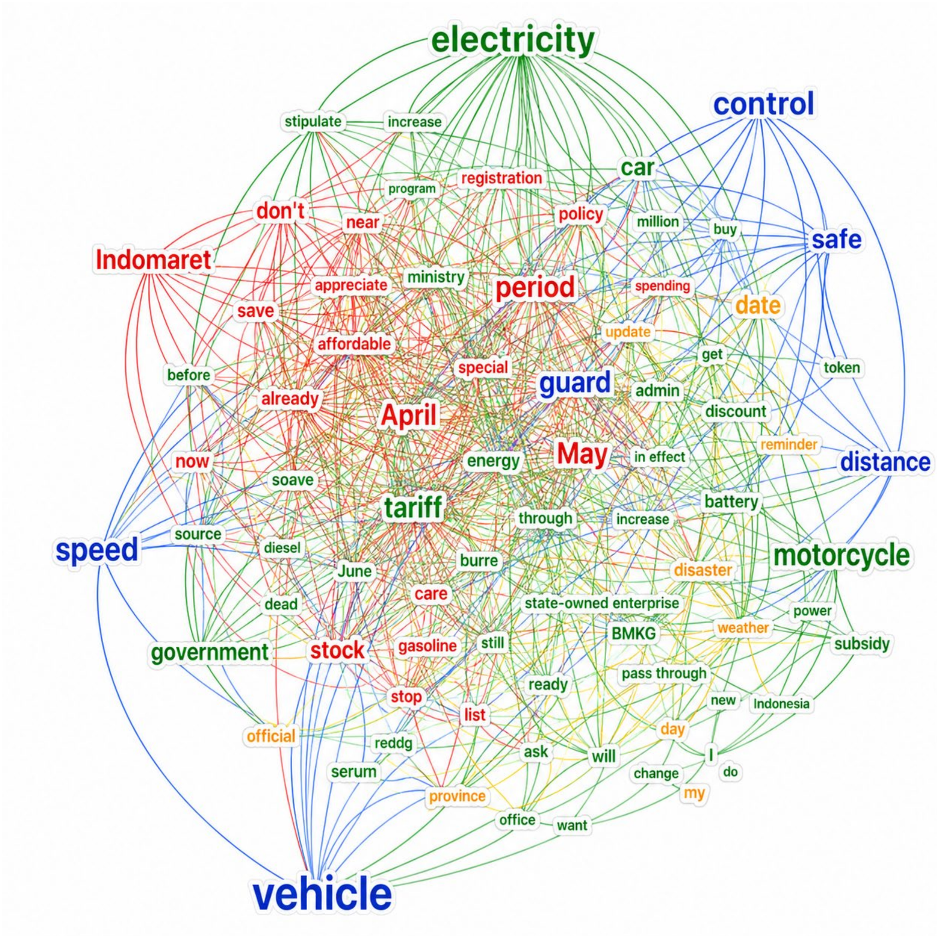

Fig. 5. Text Network Analysis

A second cluster emerges around the concept of “vehicle”, particularly linked with terms such as “speed”, “distance”, “safe”, and “control”. This cluster reflects the operational and experiential dimensions of the discourse, emphasizing issues related to performance, safety, and efficiency. This suggests that public engagement is not limited to abstract discussions of policy or infrastructure but extends to practical considerations that directly affect user experience. This finding underscores the importance of perceived usability and safety in shaping the public acceptance of emerging technologies.In addition to technological and operational themes, the network also reveals a temporal-policy cluster characterized by terms such as “April,” “May,” “period,” and “in effect.” The presence of these temporal markers indicates that public discourse is influenced by time-specific events, such as policy announcements, regulatory changes, or market-driven developments. This temporal dimension highlights the dynamic nature of digital communication, in which the intensity and focus of discussions fluctuate in response to external stimuli.

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Furthermore, the network incorporates socioeconomic dimensions, as reflected by the presence of terms such as “government,” “price,” “shopping,” and references to national contexts such as “Indonesia.” These elements suggest that the discourse is embedded within broader economic and policy frameworks, where public attention is shaped by pricing mechanisms, subsidies, and consumer behavior. The inclusion of everyday consumption-related terms further indicates that the adoption of electric vehicles is perceived not only as a technological shift but also as part of daily economic decision-making.

The text network analysis demonstrates that public discourse on electric vehicles and energy systems is inherently multidimensional. The interaction between technological innovation, regulatory structures, economic considerations, and user experience forms a complex and interconnected narrative. This structure indicates that digital conversations are not shaped by a single dominant factor but rather emerge from the interplay of multiple domains that collectively construct public understanding of the issue. This pattern reflects the characteristics of the digital public sphere, where meaning is continuously negotiated through dynamic interactions among users, technologies, and socioeconomic contexts.

From an integrated discourse perspective, the identified co-occurrence structures represent more than simple lexical associations. The textual narratives revealed through Text Network Analysis constitute the informational inputs entering the digital public sphere. These narratives are subsequently interpreted by users through cognitive evaluation processes, reflected in sentiment distributions, and affective responses, reflected in emotional expressions. Furthermore, these interpretations and emotions are disseminated and amplified through interaction networks, creating broader patterns of public engagement over time.

The strong connections between electricity, vehicles, subsidies, tariffs, government policies, and economic considerations indicate that electric vehicles are not interpreted solely as technological artefacts. Instead, they are socially constructed through continuous interaction among technological developments, policy narratives, economic concerns, and public perceptions. This finding supports both the Digital Public Sphere perspective and the Social Construction of Technology framework, demonstrating that technological meaning emerges through ongoing communication processes within digital environments.

Emotion Analysis

The emotion analysis of 219 tweets revealed that public discourse is predominantly characterized by the emotion “happy,” accounting for 71.69% (157 tweets). This dominant proportion indicates that most online conversations are positive in nature, reflecting optimistic, appreciative, or supportive responses to the issue under discussion. The high prevalence of positive emotions suggests that public perception tends to align with favorable views, highlighting a general sense of acceptance and perceived benefit associated with the topic.

The second most prominent emotion is “fear,” representing 15.53% (34 tweets). The presence of this emotion indicates that a segment of users expresses concern or uncertainty regarding an issue. Such emotional responses are often associated with perceived

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risks, policy ambiguity, or potential challenges to implementation, all of which can influence public confidence and trust.

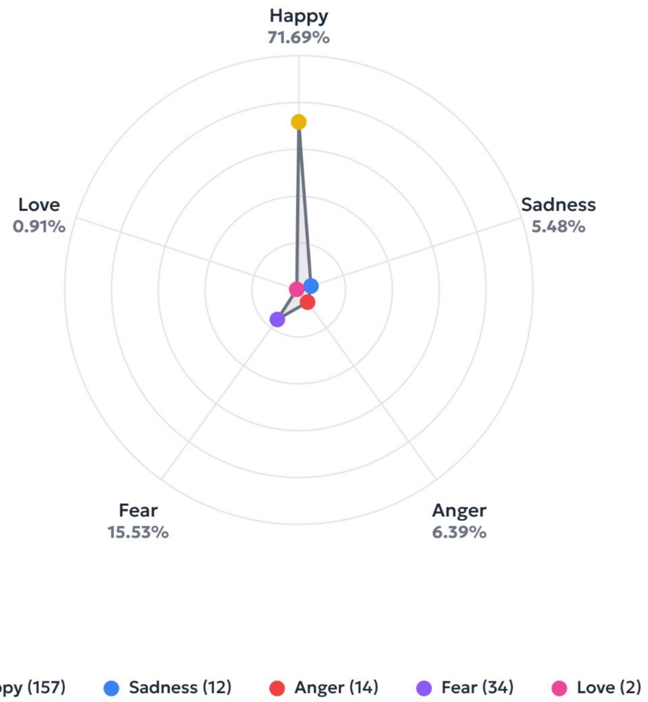

Fig. 6. Emotion Analysis

In contrast, “anger” accounts for 6.39% (14 tweets) and “sadness” for 5.48% (12 tweets), indicating the existence of negative emotional responses, although in relatively smaller proportions. The emotion “anger” typically reflects dissatisfaction or criticism toward specific aspects of the issue, whereas “sadness” represents disappointment or emotional responses to perceived unfavorable conditions.

The least represented emotion is “love,” comprising only 0.91% (two tweets), suggesting that deeply personal or affective expressions are minimal within the discourse. This pattern indicates that conversation is largely driven by informational and evaluative content rather than strong emotional attachment. The distribution of emotions highlights that public discourse is largely dominated by positive sentiments while still incorporating elements of concern and critique. This pattern reflects the inherently complex nature of digital communication, in which supportive attitudes coexist with uncertainty and critical perspectives. Such findings align with the broader understanding that digital public discourse is shaped by the interaction between user experience, perceived risks, and responses to policy and technological developments

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Trend Analysis

Temporal trend analysis of the dataset revealed a significant evolution in public discourse over the observation period. During the initial phase, spanning from early January to mid-March, tweet activity remained relatively stable at a very low level, with frequencies close to zero. This pattern indicates that the topic had not yet gained substantial attention within public discourse during this period.

A gradual increase in activity began to emerge from late March to mid-April, although the overall volume remained relatively modest. This suggests an early stage of public engagement, likely driven by the emergence of new information or initial developments related to the topic.

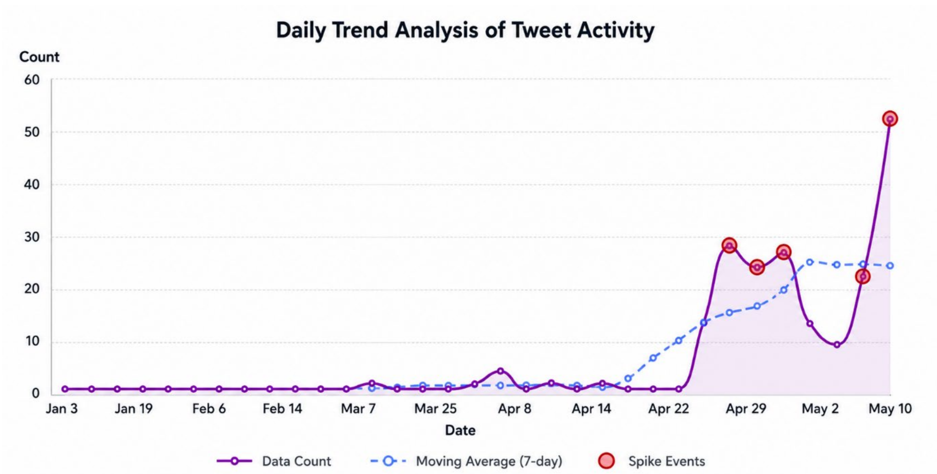

Fig. 7. Trend Analysis of Tweet Activity

A substantial surge in activity was observed from late April to early May, as indicated by the prominent spike events in the graph. During this period, the tweet volume increased sharply, reaching a peak of more than 50 data points. This spike suggests the occurrence of significant external triggers, such as policy announcements, viral content, or major events that intensify public attention and engagement. Furthermore, the 7-day moving average demonstrated a consistent upward trend toward the end of the observation period. This indicates that the increase in activity is not merely episodic but reflects sustained growth in public discourse.

These findings highlight that digital discourse evolves dynamically over time and is strongly influenced by external stimuli. The transition from low-level activity to a sharp increase in engagement reflects the responsive nature of social media, where public attention rapidly intensifies in reaction to emerging issues and information flows.

Zero-Shot Classification

The sentiment analysis of 219 tweets revealed a more balanced distribution compared to previous findings, although positive sentiments remained dominant. Positive

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sentiment accounted for 44.29% (97 tweets), indicating that a substantial proportion of users expressed supportive, optimistic, or favorable perceptions of the issue under discussion. This dominance suggests a relatively strong level of public acceptance, particularly regarding the perceived benefits or positive developments associated with a topic.

Neutral sentiments represented 37.90% (83 tweets) of the tweets, occupying the second-largest proportion within the dataset. This indicates that a significant portion of the discourse continues to be informational in nature, with users primarily sharing descriptive content such as news, updates, or general information without strong emotional expression.

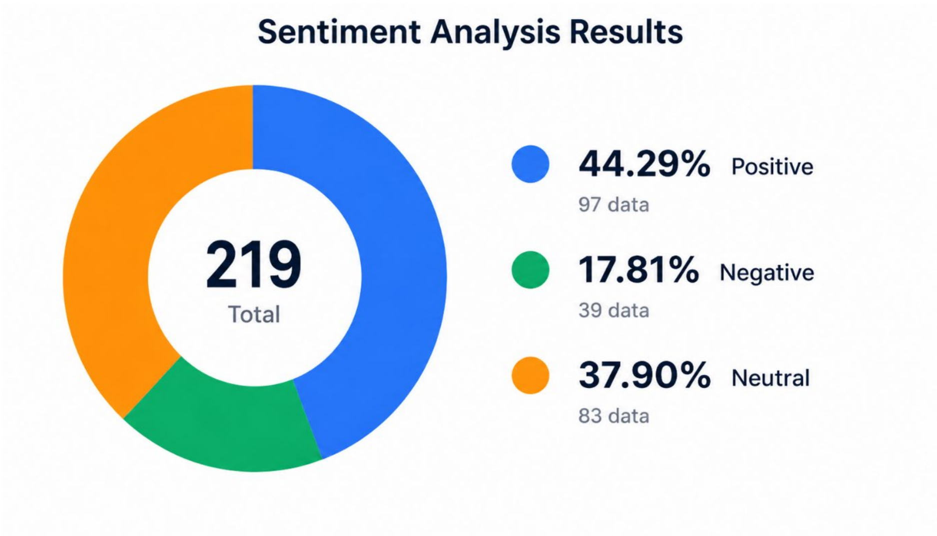

Fig. 8. Sentiment Analysis Result

Negative sentiments accounted for 17.81% of the tweets (39 tweets). Although not dominant, the presence of negative sentiments reflects the critical perspectives, concerns, or dissatisfaction expressed by a segment of users. These negative responses may be associated with policy-related issues, implementation challenges, or user experiences that do not fully meet expectations. This distribution suggests a shift in the nature of public discourse, moving beyond purely informational communication toward more evaluative and opinion-driven exchange. The increased presence of both positive and negative sentiments indicates that users are not only disseminating information but are also actively engaging in assessing and interpreting the issue.

These findings highlight the dynamic nature of digital discourse, in which communication evolves with increasing public engagement. The discourse reflects an interaction between information sharing, user perception, and experiential responses to ongoing developments within the digital environment. The integration of textual, emotional, structural, and temporal analyses reveals that discourse surrounding electric vehicles operates as a multilayered sociotechnical communication system. Temporal spikes indicate periods of heightened collective attention triggered by external events. During

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these periods, thematic clusters identified through Text Network Analysis become more prominent, reflecting the issues that dominate public discussion.

Sentiment and emotion analyses demonstrate how users interpret these issues, revealing a combination of informational communication, optimism, concern, and criticism. At the same time, Social Network Analysis shows that discourse visibility is influenced by a limited number of strategically positioned actors who facilitate information dissemination across the network. These findings support the Digital Public Sphere framework by demonstrating that public understanding emerges through the interaction of content, emotions, network structures, and collective attention. Likewise, the Social Construction of Technology perspective is supported by evidence that electric vehicles are interpreted not solely as technological artefacts but as socially negotiated innovations shaped by policy, economics, public perception, and communication dynamics.

5 Conclusion

This study demonstrates that public discourse on electric vehicles on X/Twitter is expressed through dynamic and interconnected interaction patterns shaped by informational exchange, emotional responses, and event-driven communication. The findings reveal that digital conversations are distributed within a hybrid interaction structure, where discourse intensity fluctuates in response to external triggers such as policy developments, technological updates, and socioeconomic issues.

The study further identifies that public discourse is predominantly characterized by neutral and positive sentiments, while emotional expressions are strongly dominated by happiness and optimism. Nevertheless, the presence of fear, criticism, and negative sentiment indicates that public perception remains multidimensional and reflects both support and concern regarding electric vehicle adoption. Text Network Analysis confirms that discussions are structured around interconnected themes related to electricity, vehicles, government policy, subsidies, infrastructure, and economic considerations, while temporal analysis demonstrates that discourse activity is highly reactive and concentrated during specific peak periods.

In addition Social Network Analysis reveals the existence of prominent actors who occupy important positions within the interaction network and contribute substantially to information dissemination. The findings suggest that digital communication is not evenly distributed across users but is influenced by a relatively small number of actors who facilitate the circulation of information within the broader communication ecosystem. And amplifying discourse visibility. The network structure indicates that digital communication is not evenly distributed but instead depends heavily on key nodes that accelerate the spread of information across user communities.

Rather than examining discourse from a single analytical perspective, this study demonstrates that textual content, emotional responses, network structures, and temporal dynamics are mutually reinforcing dimensions that collectively shape public understanding of electric vehicles. This integrated perspective provides a richer explanation of digital discourse processes than isolated analytical approaches.

Overall, this study confirms that the integration of sentiment analysis, emotion analysis, Text Network Analysis, Social Network Analysis, and temporal analysis provides

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a comprehensive framework for understanding digital public discourse on electric vehicles. The findings contribute theoretically to the understanding of digital public sphere dynamics and socially constructed technological narratives, while practically offering insights for policymakers, researchers, and industry stakeholders in designing more effective communication strategies and policy interventions related to electric vehicle adoption.

6 Limitations and Recommendations for Further Research

This study has several limitations that should be considered when interpreting the findings. First, the dataset is limited to 219 tweets collected from the X/Twitter platform within a specific observation period, which may not fully represent the broader dynamics of public discourse on electric vehicles across different social media platforms or over longer timeframes. In addition, the use of keyword-based data collection introduces potential selection bias, as only tweets explicitly containing predefined terms were included in the analysis, potentially excluding relevant discussions expressed using alternative wording or implicit references. Furthermore, the application of computational models such as sentiment analysis, emotion analysis, and zero-shot classification involves inherent limitations in capturing contextual nuances, including sarcasm, cultural references, and ambiguous expressions that are commonly found in online communication. Therefore, the findings should be interpreted as an exploratory representation of discourse patterns within a specific observation period rather than as a statistically representative picture of all electric vehicle discussions on X/Twitter.

Considering these limitations, future research is recommended to expand both the temporal scope and data sources by incorporating multiple social media platforms such as Instagram, TikTok, and YouTube, thereby enabling a more comprehensive and multidimensional understanding of digital discourse. Extending the observation period to cover longer timeframes or specific policy cycles may also provide deeper insights into recurring patterns and long-term trends in public engagement. In addition, more advanced analytical techniques, such as topic modeling, network centrality measures, and causal inference approaches, can be applied to explore the relationships between discourse themes and their influence on public perception and behavior. Future studies may also consider integrating mixed-method approaches by combining computational analysis with qualitative methods to better capture contextual meanings and user perspectives. Through these enhancements, subsequent research can contribute to a more robust understanding of how digital public discourse shapes the adoption and perception of electric vehicles within evolving socio-technical environments.

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