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Political, economic, social, technological, legal and environmental dimensions of electric vehicle adoption in the United States: A social-media interaction analysis

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ABSTRACT

Many governments have begun to adopt aggressive targets for electric vehicles. However, studies of the drivers of electric vehicle (EV) adoption are scarce. Social media interactions can provide a new data-driven vantage point to explore such drivers. This study uses data from 36,000 public posts on Facebook to investigate intersectionality in EV-communication as per the Political, Economic, Social, Technological, Legal and Environmental (PESTLE) categories. A computational social science methodology was adopted using a mixed-method application of social network analysis and machine learning-based topic modelling through Latent Dirichlet Allocation algorithm on a 600,000-text corpus extracted from the Facebook posts. Results showed that political, economic, and legal posts had dense clusters around the technology policy of EV, the institutional discourse of electrification of the federal vehicle fleet, and tax and credit framework politics. The environmental and social dimensions had a higher discourse for social justice, clean air, and better health and well-being. A market shift towards EV as a service industry was observed in the technology and economics-related posts. These findings can help policymakers, and planners design contextualised energy policy for influencing EV adoption in the U.S. and other countries.

1. Introduction

Electric vehicles (EVs) can reduce transportation emissions, promote low-carbon mobility and a cleaner environment [1,2]. EVs are becoming more available, with sales soaring in recent years. In 2019, EV sales topped 2.1 million units globally, with 90% of sales concentrated in China, Europe and the United States [3]. Sales of all-electric light-duty vehicles (LDVs) in the U.S. grew from 0 in 2010 to 242,000 in 2019 [4]. Policy instruments like direct subsidies and tax credit have been critical in stimulating EV sales in major vehicle markets in recent years. The U.S. government has incentivised EVs' uptake through a tax credit of up to $7500 per vehicle with an additional state-specific tax credit [5].

Besides, 2019-20 saw a global EV policy shift from direct subsidies to greater reliance on regulatory and structural measures – including zero-emission vehicle mandates and fuel economy standards [3]. This shift in policy discourse has set clear, long-term signals to the auto industry and consumers that support low-carbon transition in an economically sustainable manner for governments [3,6]. The present consumer profile of the electric car market is evolving from early adopters and technophile buyers to mass adaptors. Over 200 new models are expected between 2020 and 2025 in the U.S. alone, many of which are in the popular sport utility vehicle (SUV) segment [3]. With this rapid expansion of the EV consumer segment, contextualised policies are needed to support such system changes.

Many aspects of the EV-led system changes in the U.S. were studies that include environmental consequences and health impacts [2], charging infrastructure [7,8], subsidy mechanisms [9,10], EV adoption and willingness-to-pay [11–14]. However, studies of its intersections with the Political, Economic, Social, Technological, Legal and Environmental (PESTLE) system are scant. With more EVs penetrating the U.S. market, it is crucial to identify such intersection points to sustain EV growth. This study fills this knowledge gap by investigating the demand-side PESTLE attributes of EV adoption and diffusion in the

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List of abbreviation

EV	Electric Vehicles
LDA	Latent Dirichlet Allocation
PESTLE	Political, Economic, Social, Technological, Legal and Environmental
SNA	Social Network Analysis
TM	Topic Modelling

United States.

The novelty lies in deriving an intersectional PESTLE-based overview of EV transition using crowdsourced public data from social media interactions of EV-related posts in 2020. A computational social science methodology was used to derive the PESTLE indicators using a mixed-method approach of social network analysis (SNA) and machine learning-based topic modelling to extract latent topic clusters. The use of the above methodology contributes to the state-of-the-art discussions on social data science for public policy applications. Furthermore, such computational social science methodology for PESTLE feature derivation was not used before to the best of our knowledge, and it defines the uniqueness of this study. Understanding these attributes are critical for contextualised EV policy design at the consumer level to support the low-carbon transition and translating the cultural norms from ICEVs to EVs in the United States.

2. Background: a bibliometric overview

This section explores the current state-of-the-art literature on electric vehicles (EVs) using the Political, Economic, Social, Technological, Legal and Environmental (PESTLE) framework. The PESTLE framework extends the PEST framework, developed by Fahey and Narayanan [15]. The PEST framework primarily analyses the Political, Economic, Social and Technological factors of strategic business environment from a macroeconomic perspective. The political factors mainly concern state institutions, policies and law. Economic factor includes macro-and microeconomic aspects that jointly influence industry development. Social or sociological factor includes demographic influences, lifestyle factors, income distribution, norms and culture. Technological factors include the application conditions for various techniques and technology development trends like international influences, changes in information technology and technology uptake rates. The L and E extensions to PEST outlines Legal and Environment factors. Legal factors include regulatory and policy influences, not limited to tax policies, employment laws, industry regulations, and health and safety regulations. Environment factors include the regulations and restrictions around ecological and environmental aspects such as weather, climate, and climate change. Consumer attitudes and behavioural elements are also included [16,17].

A PESTLE review offers a multifaceted approach to assess the big-picture and the intersectional factors for informed strategic management in an organisation. This tool provides an overview of the macro factors that a company needs to consider in its decision making [16]. It is now used in a broader context, including energy policymaking and renewable planning. Zalengera et al. [18] had used PESTLE for the renewable planning of Malawi and derived a sustainable development framework. Achinas et al. [19] evaluated the biofuel industry in Europe using PESTLE analysis in a similar approach that revealed the complexity of the industry faced by policymakers and production companies. This tool was also used in smart grid planning for island countries using renewable sources [20]. On automobiles, PESTLE has been used in a few studies. Tan et al. [21] assess hybrid vehicle technology in the United States. The analysis highlighted the importance of multidimensional PESTLE attributes of such technology transition. For example, it demonstrated that the economic dimension of hybrid cars in the US market would affect popularity and productivity, which will have extended social benefits. The technology, legal and environmental factors would accelerate the low-carbon transition in the transportation sector.

Recently, Capuder et al. [22] carried out risk analysis in EV integration policymaking using this framework. The authors found that high probability risks included technology and range anxiety risk among the consumers, whereas charging infrastructure risk, regulation and incentive reduction risks were categorised as low probability risk in EV integration policies. Similarly, PESTLE analysis was used to evaluate compact EV and gasoline cars [23].

Methodological advancement in the PESTLE framework space indicates a growing theoretical scoping of mixed-method approaches using data science. Campbell et al. [24] call for leveraging artificial intelligence (AI) in PESTLE and SWOT analysis in marketing research. A decision-support framework using AI and PESTLE analysis was proposed by Simões [25]. Such applications are scarce in the literature, and this paper contributes significantly to this literature gap in the mixed-method approach of the PESTLE framework with computational social sciences. We used social network analysis and topic modelling using an AI-driven Latent Dirichlet Allocation (LDA) algorithm to extract and classify latent themes on EV communications in the United States. It contributes to the state-of-the-art in energy policy applications of computational social sciences.

This section presents a detailed bibliometric analysis of the current literature on EVs. The published documents were classified using the PESTLE framework, i.e., the keyword search included the individual PESTLE elements (i.e., 'Political', 'Economic', 'Social', 'Technological', 'Legal' and 'Environmental') with 'EV' and 'electric vehicle'. The bibliometric analysis was performed using the methodological guidelines of Aria and Cuccurullo [26]. Bibliometrics is the use of statistical methods to analyse books, articles, journal articles and other publications. The bibliometric indicators used here were 'keyword/term frequency', 'word cloud' and 'co-occurrence network maps' [see Kurtz and Bollen [27] for a detailed definition of these indicators]. The bibliometric analysis data was extracted from the 'Web of Science (WoS)' database; it is the most authoritative citation database with publications of high quality. A similar approach was recently used by Debnath, Mittal and Jindal [28] to review the current challenges in the Indian Power System. Gatto and Drago [29] derived the taxonomy of energy resilience using a similar bibliometric approach. Renewable energy finance was identified through a detailed bibliometric analysis by Elie, Granier and Rigot [30]. A recent bibliometric analysis to identify suitable business models for EV provides critical clues for this section, see Secinaro et al., [31].

A total of 11,478 published documents were identified in the WoS database between 2015 and 2020 on EV with individual PESTLE elements. The documents that had different words related to individual PESTLE elements and EV simultaneously in its title, abstract or journal keywords were classified as those of the individual PESTLE group. For example, the 'Policy' group consisted of 2689 articles that words 'political/policy/politics' along with 'EV/electric vehicle' in its title, abstract or journal keyword lists (see Fig. 1). However, this classification is not mutually exclusive to any particular PESTLE element as the 'Policy' group may contain secondary words associated with other PESTLE elements. Similarly, there were 2889 'EV/electric vehicle' related articles with the term 'Economy'; 1034 articles with 'Technology', 91 articles with 'Legal', 894 articles with 'Social'; and 3881 articles with the word 'Environmental'.

The search keywords were intentionally kept broad for generalisability. This analysis was performed in the R programming language. Following the bibliometric analysis, an interpretivist approach was used to draw a storyline on the state-of-the-art EV literature.

Fig. 1. Word cloud depicting high-frequency PESTLE attributes from the current literature. [Note: the size of the word/term denote its frequency].

2.1. PESTLE attributes from EV literature

Fig. 1 illustrates the word cloud generated from the published articles with individual PESTLE attributes and EV. The size of the term denotes its frequency, i.e., a bigger word size denotes higher repeatability. Building on this context, Fig. 1a shows high-frequency words associated with 'Political' and 'EV': 'demand', 'adoption', 'policy', 'emission', 'incentive', 'preferences' and 'plug-in hybrid'. It indicates that much research on the EV-policy/politics space deals with the provisioning of incentives, adoption model and estimation of emission reduction. Low-carbon transition through EVs has a strong political connotation highlighted by Roberts et al., [32]. The authors stressed the need for more political will to accelerate low-carbon transition policies in the transportation sector deliberately. Walter et al. [33] emphasised that federal policymakers must invest in domestic EV production and deployment to support American jobs, cut emissions, and ensure national competitiveness. Additionally, the current literature shows that in the U.S., the present energy policy discourses are shifting from incentive-based to a subsidy reduction regime [3,9,14,34,35]. Such interconnections between words are also shown in Fig. 2a that illustrate term co-occurrence networks.

The economic attributes are illustrated in Fig. 1b, showing high-frequency terms like 'power management', 'optimization', 'strategy', 'design' and 'consumption'. It depicts the EV-economic literature's focus on optimising the pricing of EV systems, especially power management through charging infrastructure. The design and consumption can also be attributed to the auto manufacturer's present paradigm to increase consumer consumption through new EV models [3,36,37]. The co-occurrence network in Fig. 2b further illustrates these connections among the high-frequency terms. This figure also depicts that current EV research focuses extensively on techno-economic aspects as the technology matures.

The literature shows that EV's present social/sociological attributes have high-frequency words as 'management', 'plug-in hybrid', 'demand', 'adoption' and 'technology impact' (see Fig. 1c). It shows that the social dimension focuses on evaluating EV adoption and the technology impact, especially in contrast to plug-in hybrid vehicles, which is already a matured product [38–41]. The co-occurrence network in Fig. 2c further illustrates the interconnections in the high-frequency terms in the social attributes of EV literature. For example, the term 'adoption' has high co-occurrences with the term 'preference', 'choice', 'incentive', 'social influence', 'barriers', 'consumer attitudes', 'planned behaviour', etcetera (see Fig. 2c). It accentuates the research space in the social dimension of EV adoption, critical literature in the U.S. context can be referred to here: [14,40,42–44].

The technological attributes show a strong link with 'policy' in the co-occurrence network (see Fig. 2d), illustrating the strong technology policy link between EV technology and policy design. It can also be seen from Fig. 1d that high-frequency words are 'adoption', 'demand', 'technologies' and 'diffusion'. A higher representation of 'China' also indicates EV technology's dependency on China (see Fig. 1d). The cooccurrence network in Fig. 2d also shows critical interconnections with 'innovation' around EV technologies. Critical literature in this context is presented in Refs. [11,45–50] that focus on the intersections between technology innovation and policy design concerning charging infrastructure, EV penetration strategy and discussion on the social shaping of EV technology. A vital impetus for technology policy in the EV space is to aggressively contribute to national emission reduction efforts and low-carbon transition, as observed through the co-occurrence network in Fig. 2d.

The legal attributes associated with EV as per the PESTLE framework are illustrated in Figs. 1e and 2e. The word cloud shows that high-frequency words mimic the political attributes in Fig. 1a, depicting a coherence between political and legal elements of EV policymaking. It further shows scarcity in the literature on EV's legal aspects, as seen in the sparse co-occurrence network in Fig. 2e. A critical discourse around EV is the associated environmental and health benefits, as presented in Refs. [1,2,51]. This association has been widely discussed in the literature. Topics are around 'battery' disposal and life-cycle analysis of the lithium-ion battery (see interconnections in Fig. 2e). A recent research article by Tang et al. [52], sheds light on the possible policy mechanisms for handling the EV-batteries that have reached their end-of-life. The literature on the current discussion on the waste management and policy design around EV batteries can be referred to in Refs. [53–59].

The evidence from the bibliometric-based literature review presented here provided an overview of the EVs' current paradigm and discourse in a PESTLE framework. However, it does not necessarily emphasise what is missing or the issues that need focus. This study builds on this foundation and explores the PESTLE attributes from the demand-side spectrum by evaluating EV communications in social media-based public forums. It can provide a critical clue on the policy pinch points and aid policymakers and auto manufacturers in designing

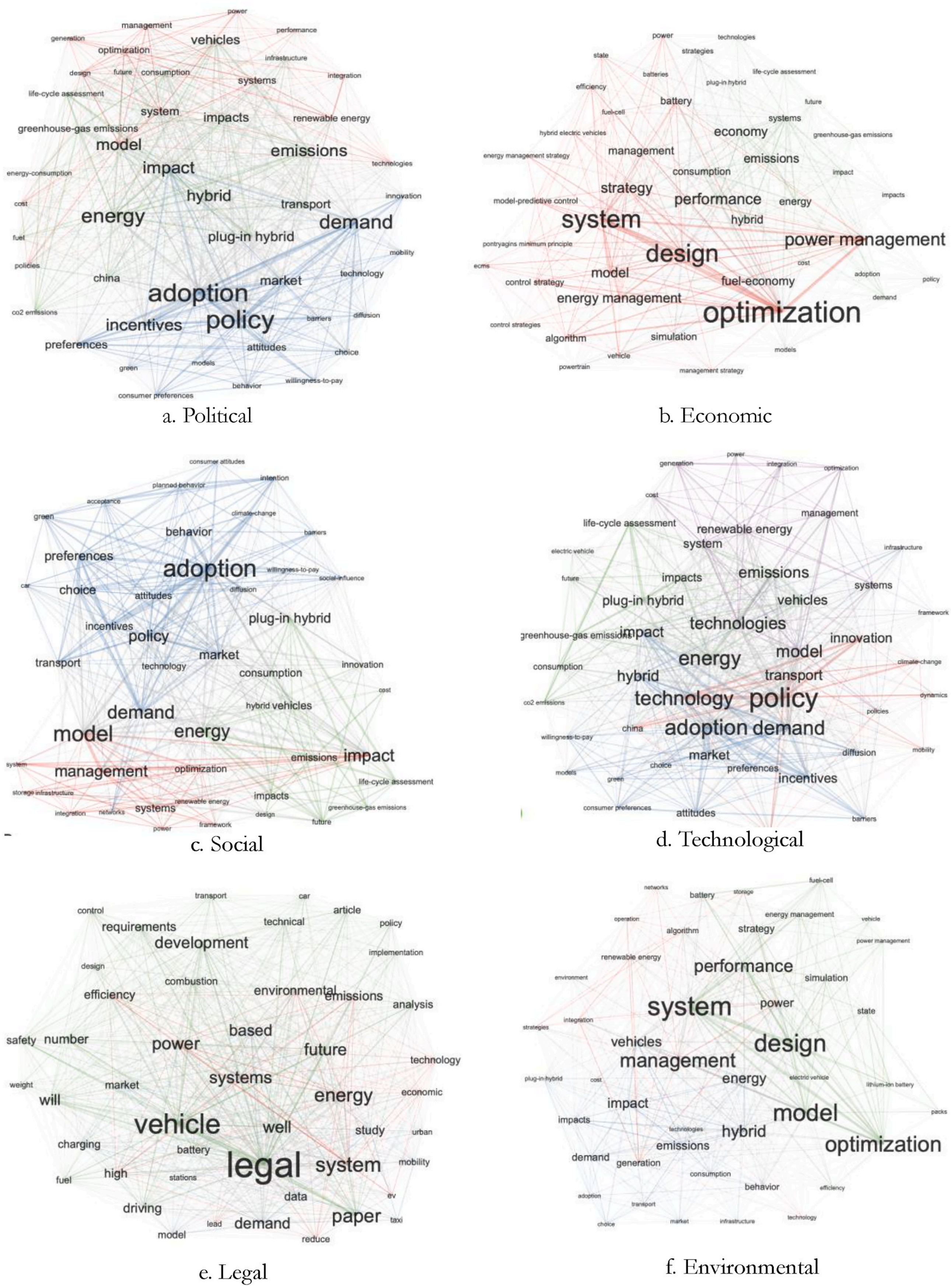


Fig. 2. Co-occurrence word network showing PESTLE attributes in the EV literature.

contextualised EV policies using crowdsourced data. A detailed description of data and methods is presented in the next section.

3. Material and methods

This section presents a detailed description of the data structure and the adopted methodology of this study. As mentioned in section 1, this study's primary data comprises social media public posts on EV-related communications. It is then evaluated based on the Political, Economic, Social, Technological, Legal and Environmental (PESTLE) framework to evaluate intersectionality and extract latent attributes using computational social sciences to contextualise EV policymaking in the United States. The computational social sciences methodology consisted of a concurrent application of social network analysis (SNA) and machine learning-based topic modelling (TM) using the Latent Dirichlet Allocation (LDA) algorithm. TM was used to complement SNA and improve its interpretability. We used SNA and TM in a nested manner to extract contextualised results and identify intersectionality in the Facebook posts as per the PESTLE categories.

3.1. Data source

This study's primary data are public posts in the English language with keywords 'EV/electric vehicle/electric cars' in the United States regional boundary and their total interactions on Facebook between the 1st of January and the October 31, 2020. The data was accessed through Facebook's CrowdTangle web-based platform. CrowdTangle is a public insight tool that tracks public content interactions from Facebook pages and groups, verified profiles. In addition, it does not include paid ads unless they began as organic, nonpaid posts that were subsequently "boosted" using Facebook's advertising tools. It does not include private accounts or posts made visible only to specific groups of followers [60].

Posts from almost 13,764 public pages that referred to electric vehicle (EV) were collected for this study between the ten months. The CrowdTangle team set the ten-month historical data limit. These posts ranged from news-media pages to public groups. Since each 'page' can contain multiple posts on related topics, we consolidated the posts with the same page ID to avoid redundancy errors in analysis. Therefore, the total number of posts extracted was around 36,000.

While analysing these 36,000 posts, we were mindful of the limitations of Facebook posts as a data source that affect the generalisability of study results. First, specific demographic and socio-economic segments are not well represented in the dataset, especially people from low-income backgrounds and lower education due to the Internet access divide [61]. Second, not all with Internet access use Facebook and other social media sites. Third, it is unclear who can effectively use the Internet for information and knowledge and who cannot [62]. Fourth, social media data presents the potential for self-selection bias. To counter the first three points and improve the generalisability of the results, we only use aggregated interaction data on public posts. This aggregated level provided a zoomed-out view of public communication on EV on the Facebook platform without weighing an individual's sentiment. We kept a wide bandwidth for PESTLE categorisation of the posts by randomly matching 40% of the post content with the categorical outcomes of the bibliometric analysis presented in section 2.1. It added a degree of randomisation in sample selection that reduced self-selection bias (as recommended by Ref. [63]).

An 'interaction' can be the number of reactions, comments and shares made on a post. This metric does not include clicks on links or the post itself [60]. We have used the 'total interaction' metric, the individual post links and the link description for constructing the nodes and edges for SNA (discussed in detail in section 3.2). The data descriptive of the number of interactions on the EV-related posts per month is illustrated in Fig. 3. In Fig. 3a, the peaks represent average page interactions in a specific month. For most months, the peaks are in the range of 1–100 interactions. The central tendency of the dataset and the outliers are illustrated in Fig. 3b.

The pages on EV-related communications from news agencies, public groups, academic communities, non-governmental organisations, and activist groups were in text. Thus, the cumulative text corpus extracted from these 36,000 posts was close to 600,000 words/terms. It served as the primary dataset for machine-learning-based topic modelling using LDA (see section 3.3. For details).

3.2. Social network analysis (SNA)

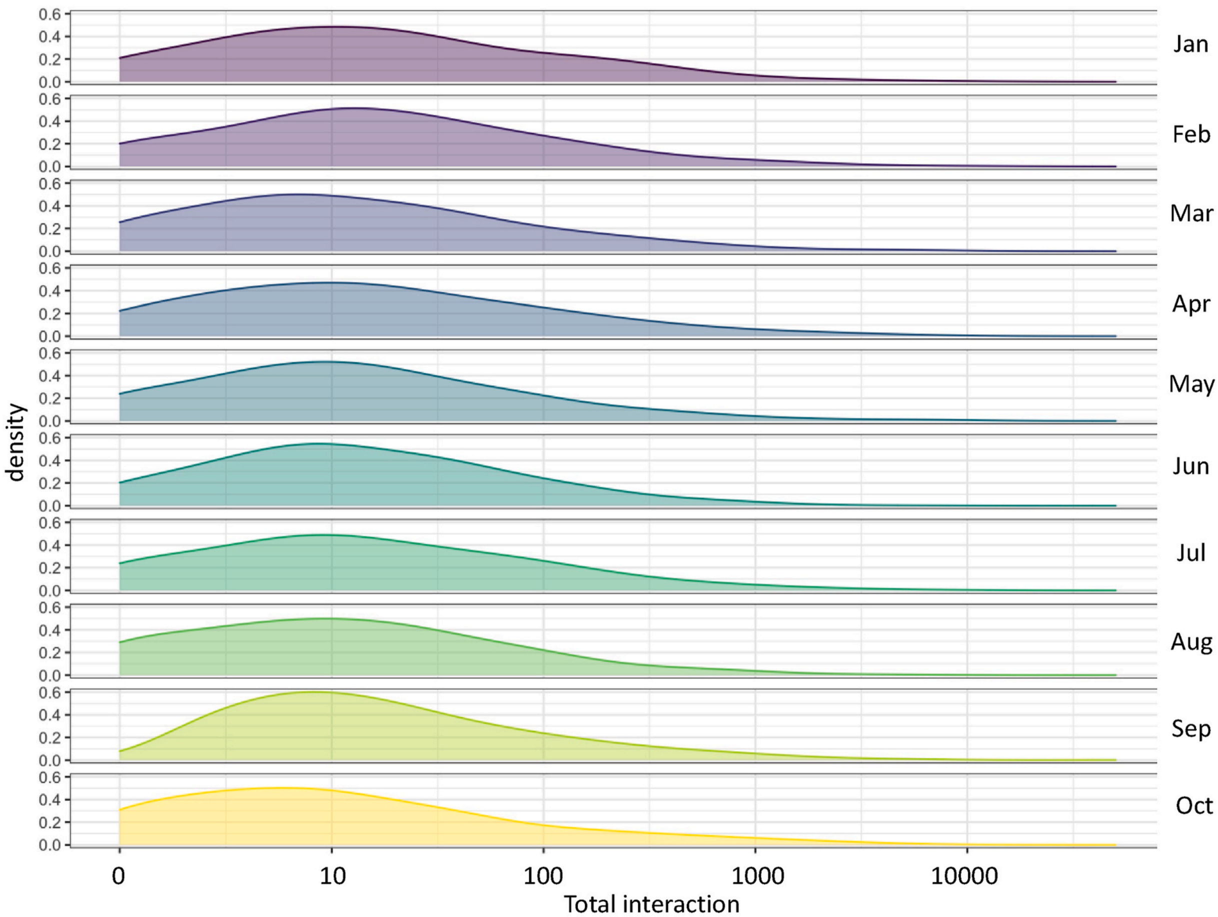
For our analysis, the downloaded CrowdTangle public page dataset (see section 3.1) was categorised into PESTLE sectors (Political, Economic, Social, Technological, Legal and Environmental) based on each page's 'link description'. This categorisation was performed by referring to high-frequency keywords extracted through the bibliometric analysis in section 2.1.

The categorised datasets were cleaned for duplicate entries, and the blank fields were removed. Then, we tabulated the post link, description, identifier and total interactions into an Excel datasheet and converted them into comma-separated value files. Finally, we created nodes and edges datasheet in Excel, with each node representing a 'page' and a 'link description'. In our case, the edges connect the page and the corresponding link description. Thus, the page became the 'source' in our dataset, and the link description became the 'target' for each PESTLE category. Important definitions regarding SNA are presented in the Appendix.

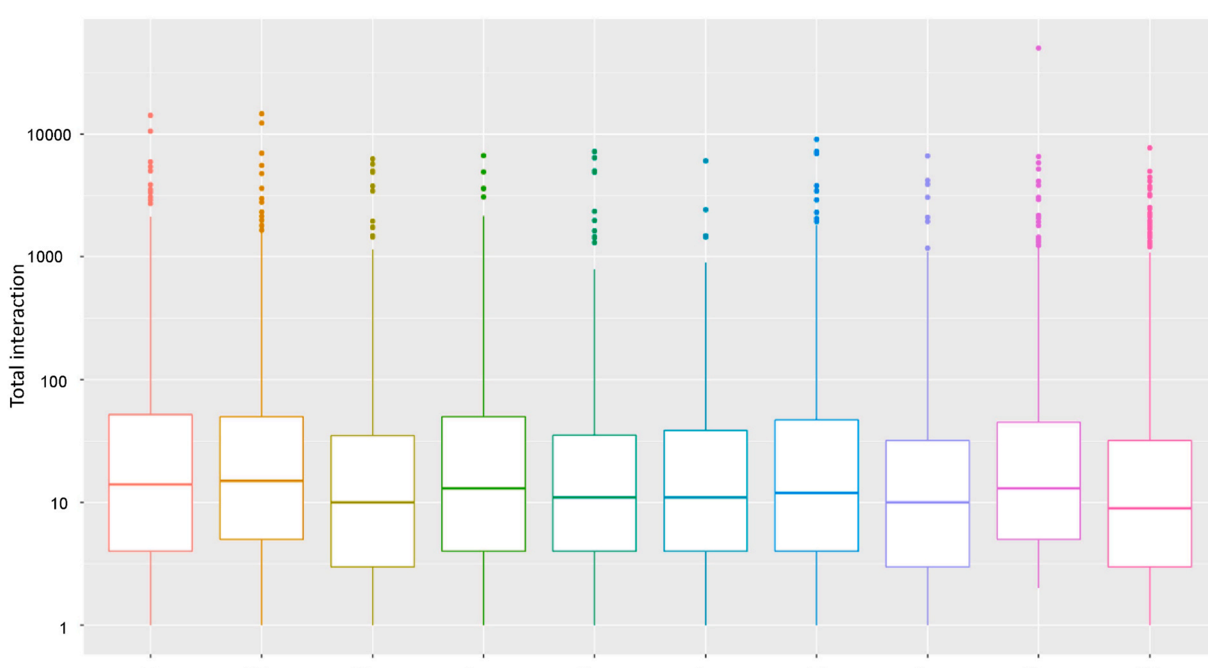
We imported the nodes and edges dataset into Gephi version 0.9.2. It is open-source software for graph and network visualisation by automatically calculating modularity and the network diameters such as betweenness centrality and visualising the network structure by adjusting spatialization algorithms [64]. In this study, modularity was calculated and applied to the nodes to divide them into differentiated community subgroups according to the closeness of their interactions and different colours were applied to distinguish these subgroups visually [65]. Furthermore, we have used in-degree ranking (see Appendix for definitions) to visualise most frequently shared links in each PESTLE category. In-degree is the number of connections that point inward at a node. The minimum in-degree size was chosen as 10, indicating that a node will at least have 10 connections, while the maximum in-degree size was set as 100. Further iterations were made to test the best values for optimal visualisation of the network.

The ForceAtlas2 (FA2) algorithm [66] was applied to achieve a visual representation in which more connected nodes are placed centrally, and ones with lower connectivity are placed towards the periphery of the network. FA2 is a force-directed layout that simulates a physical system to spatialise a network. Nodes repulse each other like charged particles, while edges attract their nodes, like springs. These forces create a movement that converges to a balanced state, representing a network. The refinement of the network visualisation was performed by applying the *LinLog, gravity* and *overlapping prevention* layout settings [see Jacomy et al. [66], for its definition and mathematical basis].

Recently, in energy policy research, a similar methodological approach was adopted by Marra et al., [67]; Wishart, [68]; Shen et al., [69]. More specifically, Zhou, Wu and Hu [70], used SNA to map the policy evolution of the EV industry in China using government EV policy documents. Matschoss and Repo [71] have used SNA to derive network typology of EV transition pathways in Finland. Marra, Antonelli and Pozzi [72], have used a similar network analysis approach to identify



a Density plot of total interactions per month



b Box plot of total interactions per month

Fig. 3. Distribution of EV-related interactions on Facebook posts.

automotive green-tech specialisation in San Francisco, New York and London. Finally, Bakker, Leguijt and Van Lente [73] have used a network-based approach to identify key actors in EV recharging plugs' standardisation.

While the network visualisation demonstrates the PESTLE dimensions in public EV communications, the latent clusters of topics extracted using topic modelling are critical to contextualised policy design, as presented in the next section.

3.3. Topic modelling using Latent Dirichlet Allocation algorithm

The 36,000 Facebook public posts on electric vehicles (EV) in the U. S. generated a text corpus of approximately 600,000 words/terms, as mentioned in section 3.1. This text corpus was used as the primary data for topic modelling (TM). TM refers to the task of identifying topics that best describes a set of documents. It is a natural language processing methodology that extracts latent clusters of closely related words based on relative probability values. It is now widely used as a computational social science tool in public policy [74–77], energy policy [78,79], disaster management [80], political science and rhetoric analysis [81–84]. It is a state-of-the-art method in policy analysis using data science-driven approaches.

TM using Latent Dirichlet Allocation (LDA) algorithm is an advanced variant of textual analysis using machine learning. LDA is an unsupervised machine learning technique that automatically analyses text data to determine a cluster of high probable words from a set of documents. The foundational background was proposed by Blei, Ng and Jordan [85], which was based on the basic idea that each document can be expressed as a distribution of topics, and the distribution of words can describe each topic. It was used to extract latent topic clusters concerning PESTLE attributes from the text corpus of ~600,000 words on EV-related public posts on Facebook (see Fig. 3).

$$p(D|\alpha,\beta)=\prod_{d=1}^{M}\int p(\theta_d|\alpha)\left(\prod_{n=1}^{N_d}\sum_{z_{dn}}p(z_{dn}|\theta_d)p(w_{dn}|z_{dn},\beta)\right)d\theta_d \tag{1}$$

The mathematical foundation for LDA is illustrated in eq [1], after Blei, Ng and Jordan [85],that shows the probability of a specific word (**w**) in a topic cluster (**z**) in unique documents (**M**). 'α' and 'β' are the hyperparameters of the Dirichlet distribution (see eq. (1)). A third hyperparameter 'γ' is needed to set the number of topics. We have used a cross-validation metric of perplexity scores [86] and the ldatuning (v0.2.0) algorithm in R [87] to determine the approximate number of topics under each PESTLE categories. Perplexity is a measure of how well a probability model fits a new set of data. It was calculated for cross-validation using the 'perplexity' function in the topicmodels (v0.2-8) package in R [88]. It included dividing the data into five subsets, and each subset gets one turn as the validation set and four turns as part of the training set. The ldatuning algorithm [87] used an iterative process to best-fit the model using the benchmarking criteria of Arun 2010, CaoJuan2009, Griffiths2004 and Deveaud2014. The cross-validation results are presented in Appendix. A similar cross-validation approach was adopted by Refs. [76,77,79].

The analysis consisted of two steps. The first step was the pre-processing of the text corpus by removing all the stop words (e.g., articles, such as "a," "an," and "the," and prepositions, such as "of," "by," and "from"), numbers, and punctuation characters and converted the text to lowercase. It also involved removing the inflectional endings of words and converting the grammatical form into its base/dictionary form. This step is usually referred to as lemmatisation in natural language processing [89].

The second step was the conversation of the lemmatised corpus into document-term-matrix (DTM), using the tidytext (v0.2.0) package in R. The DTM was converted as per the tidydata rules presented by Silge and Robinson [90]. Here, each sentence was treated as a document in the DTM that resulted in (**M**) unique documents that had **w** (words) and **z** (topics) as per eq [1]. It was created for each PESTLE category. Once the appropriate topic clusters were extracted, the results were presented in a tabulated format with the probability values (β) of each word in each topic cluster. The extracted topics were further analysed and interpreted with the network of communities derived through the ForceAtlas2 algorithm in SNA, as mentioned in section 3.2. The combined interpretation revealed critical intersectional focus points concerning EV-related crowdsourced data in the U.S., and implications were drawn for contextualised policymaking.

4. Results

4.1. Social media interactions and PESTLE dimensions

This section expands on Fig. 3 to illustrate the EV-related posts on Facebook between January and October 2020 that received the most attention (see section 3.1). Fig. 4 demonstrates the headlines/titles of the posts most interacted in the PESTLE categories, i.e., it represents the posts that received at least 4000 interactions over the analysis period.

It can be seen in Fig. 4a for the political (P) category that the most attention was given to topics related to EV tax, subsidies and federal spending plans. In Fig. 4b, economy (E) shows the highest attention topics associated with EV-market expansion, oil shock effects and EV-related consumer fees. The Social (S) dimension shows the highest interactions topics were industry-led EV investment and job creation, clean air and economic savings from EV adoption (see Fig. 4c). The post that received the most attention in the Technology (T) were related to new charging and battery tech, renewable energy infrastructure and consumer report of EV adoption (Fig. 4d). Finally, the Legal (L) and Environmental (E) dimensions had high attention topics on federal bills and legal framework, climate change and EV-related sustainability discourse (see Fig. 4e and f). The following section explores the network structure of these interactions.

4.2. PESTLE network structures using SNA

This section presents the results of social network analysis (SNA) per PESTLE categories. The network characteristics of each category are illustrated in Table 1 that reports metrics like mean path length, indegree, betweenness centrality and modulatory (detailed definition of their metrics is presented in the Appendix). The highest modularity was observed for the Economic network (0.981), followed by the Legal (0.971) and Political network (0.959), respectively. High modularity value implies there are dense connections between the nodes within modules but sparse connections between nodes in different modules. For examples for the Economic network 98.1% of the edges are inside the modules while only 1.9% connect the modules (the configuration has sparse intermodular coupling). Thus, illustrating that these networks have more significant interactions within respective modules, i.e., specific EV-related pages have higher interactions within the same clusters. The corresponding high modularity network structures are illustrated in Fig. 5.

Fig. 5a illustrates the network associated with the EV-related Political attributes that show three high modularity nodes. These nodes are associated with the government's institutional discourse, technology policy of EV and the politics around EV technology in the U.S. The institutional discourses reported communication around federal

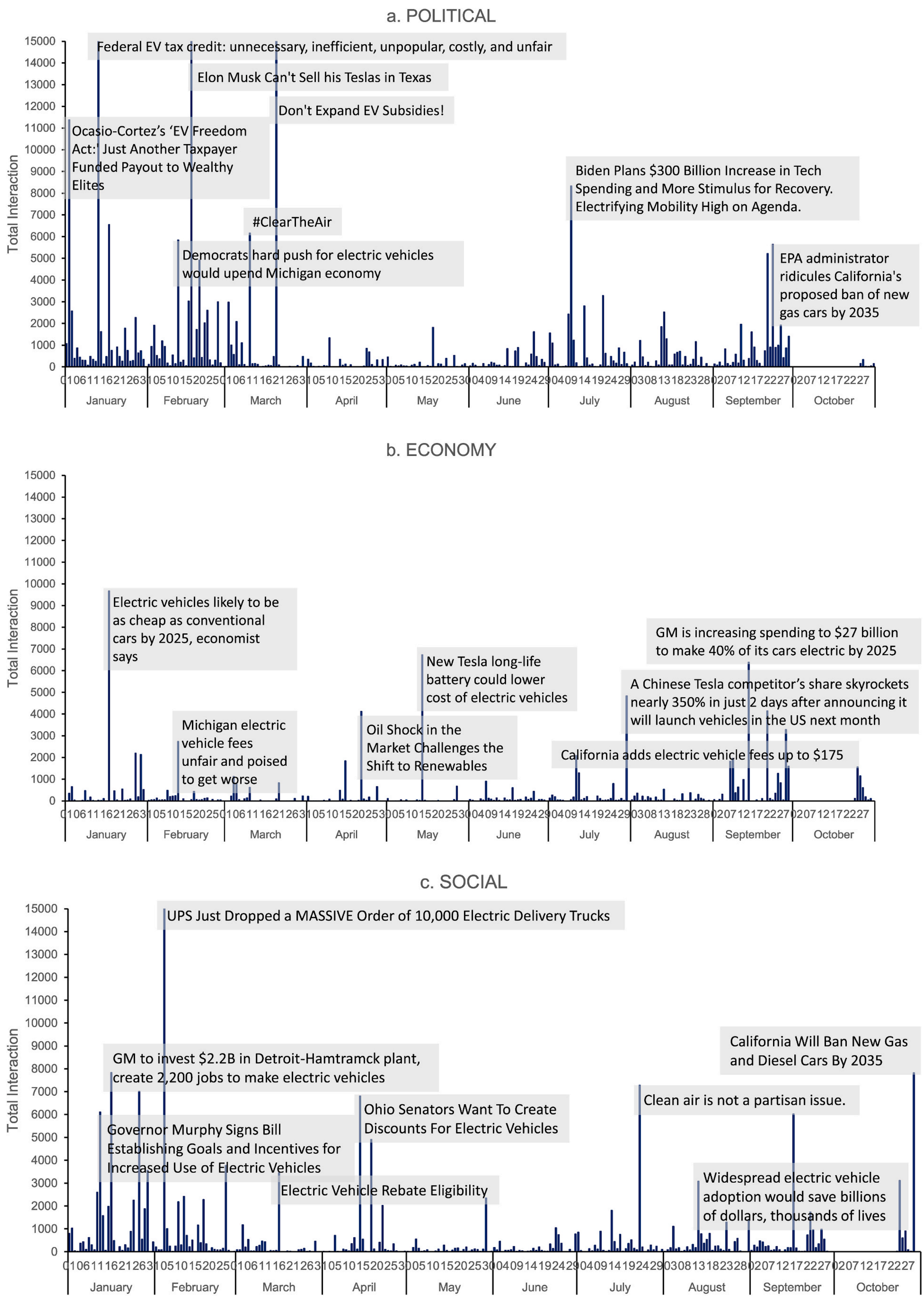


Fig. 4. Distribution of EV-related social media interactions as per PESTLE dimensions. The text boxes illustrate headlines/titles of posts with at least 4000 interactions. [Note: x-axis shows the month and the day of the post, y-axis shows the frequency of interactions].

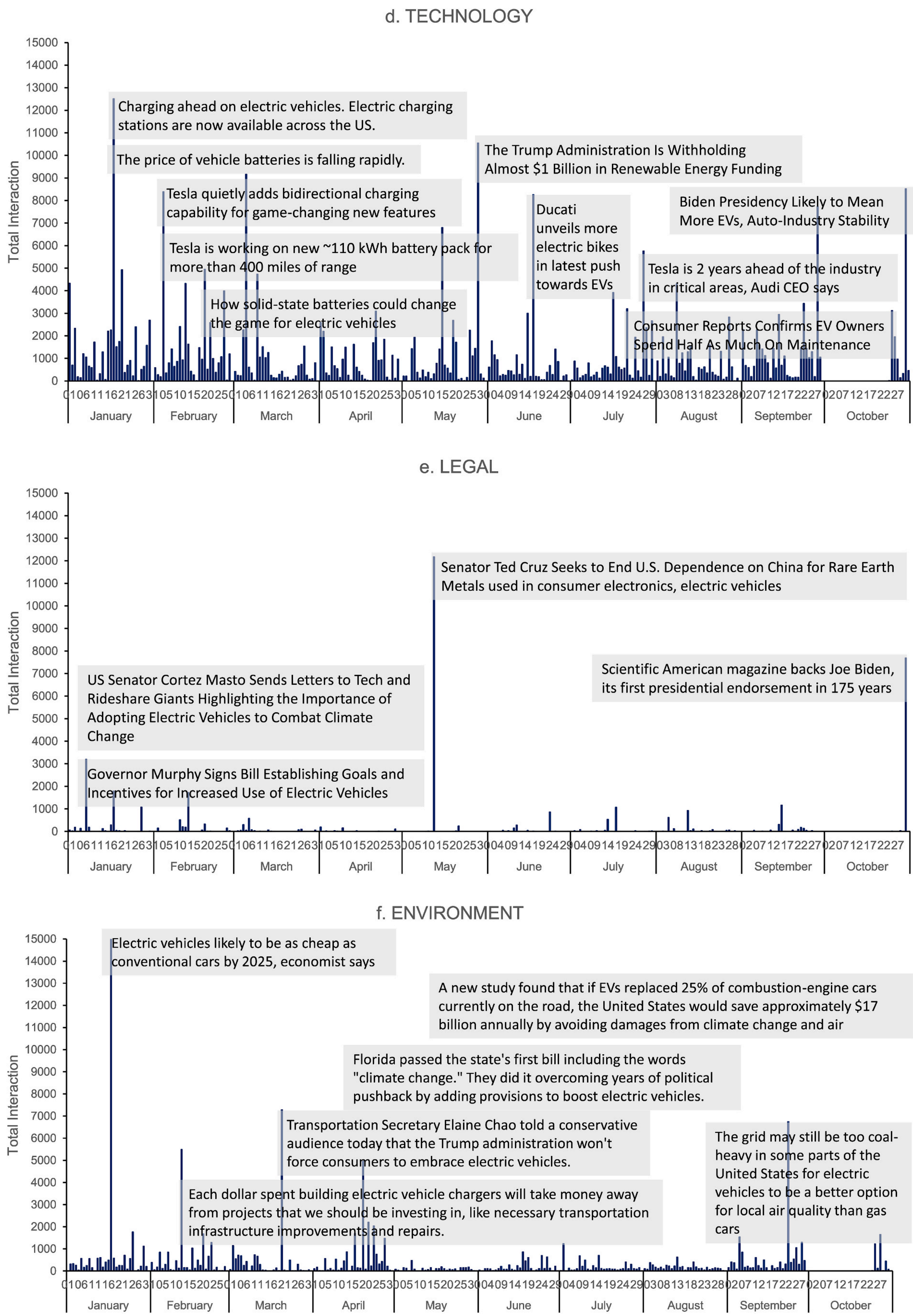
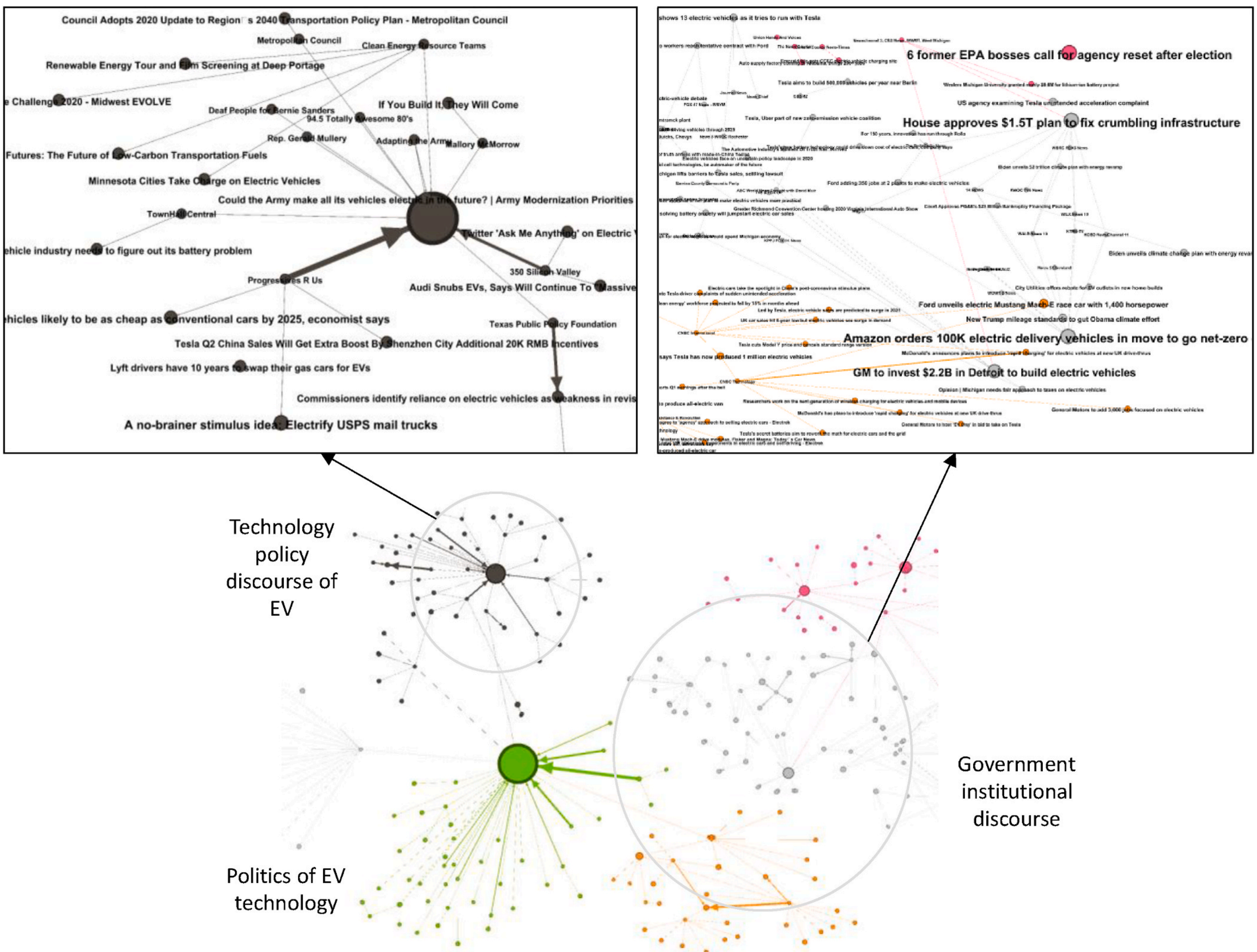


Fig. 4. (*continued*).

Table 1
Network characteristics.

Parameters	Political	Economic	Social	Technological	Legal	Environmental
Nodes	2416	991	2359	3178	364	2195
Edges	2340	1033	2237	4008	295	2643
Mean path length	1.012	1.018	1.009	1.019	1	1.014
In-degree (mean, [S.D.])	0–5 (0.652, [3.033])	0–5 (0.729, [1.122])	0–5 (0.006, [2.886])	0–9 (0.903, [1.162])	0–8 (0.895, [1.436])	0–8 (0.867, [0.911])
Betweenness centrality (mean [S.D.])	0–3 (0.014, [0.128])	0–4 (0.04, [0.085])	0–3 (0.006, [0.116])	0–15 (0.017, [0.456])	0 (0)	0–10 (0.011, [0.284])
Modularity	0.959	0.981	0.950	0.891	0.971	0.898

Note: S.D. refers to Standard Deviation.



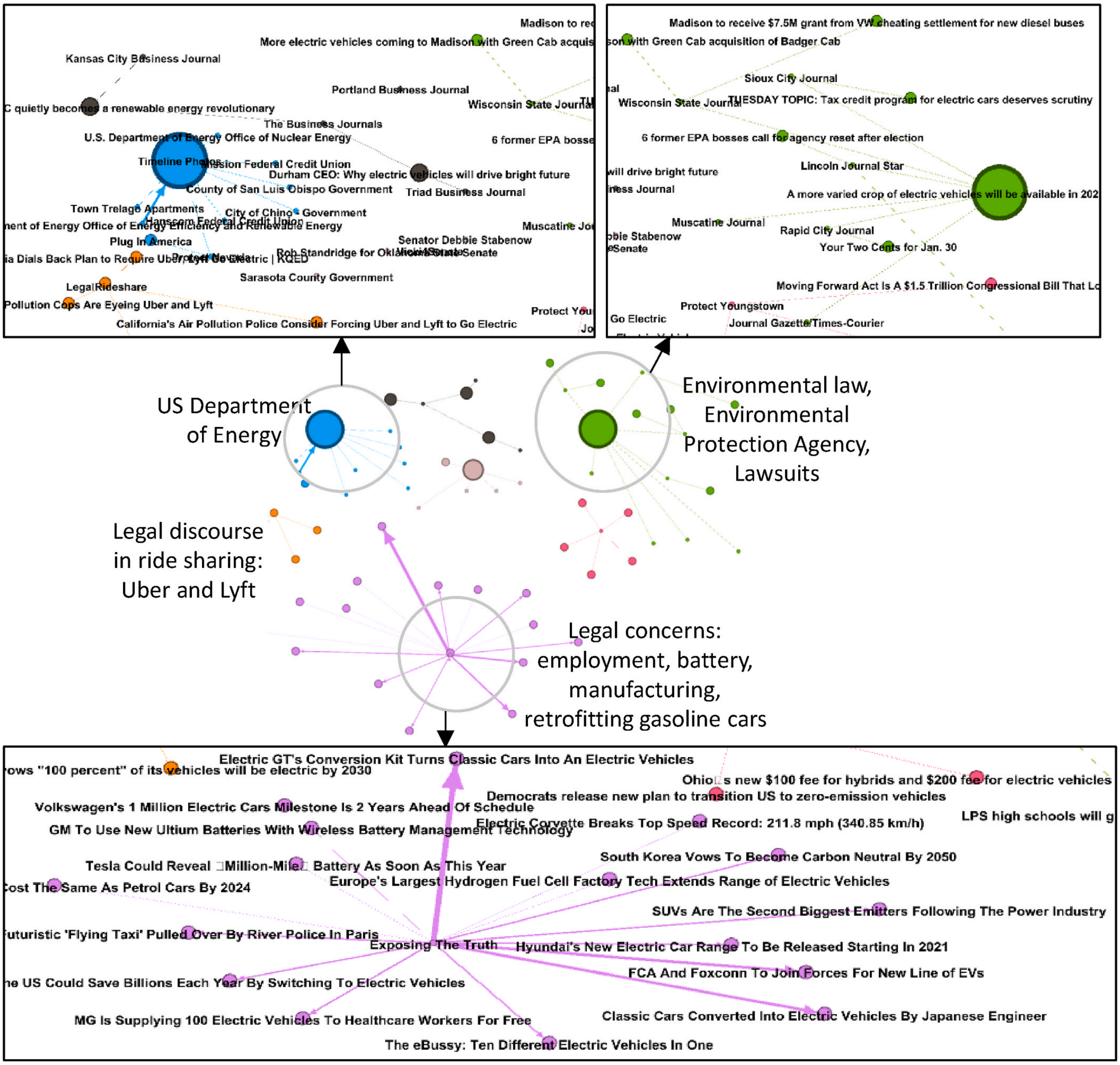
a. Political attributes of EV-related posts

[Note: Green nodes indicate the politics of EV technology cluster; Grey nodes indicate the government's institutional discourse of EV policy; and Black nodes indicate the technology policy discourse of EV policy]

Fig. 5. Networks with high modularity.

agencies like the Environmental Protection Agency (EPA) that indicated the need for structural changes following the elections (see Grey Nodes in Fig. 5a). There are also indications of funds being allocated for EV-infrastructure, like 'House approves $1.5 Trillion to fix crumbling infrastructure'. Private sector involvement helped shape the political narratives of net-zero, like 'Amazon orders 100 K electric delivery vehicles in a move to go net-zero; GM to invest $2.8 Billion to build EV'.

Public engagement events like tours to renewable energy sites,



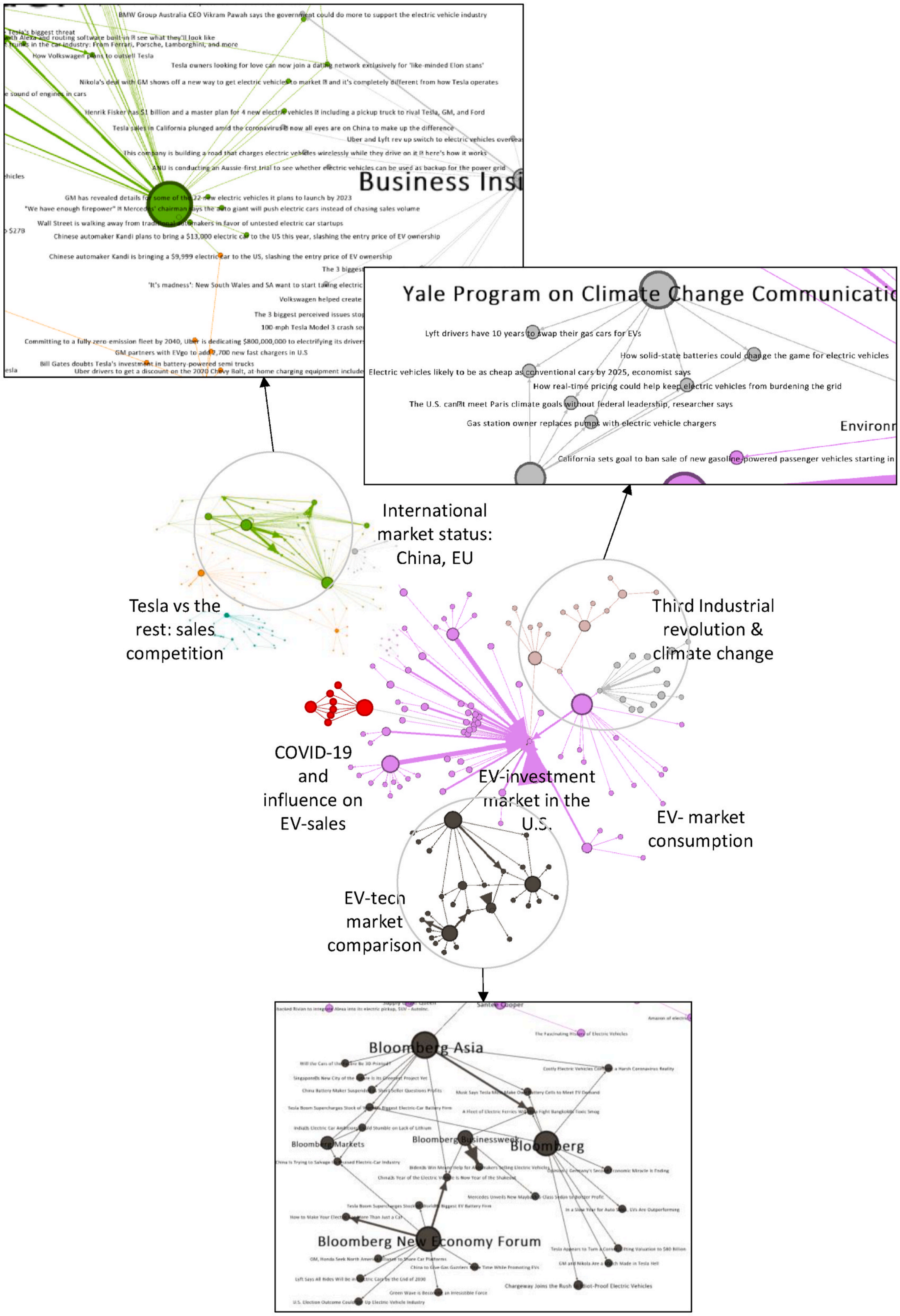
b. Legal attributes of EV-related posts

[Note: Green nodes indicate environmental law cluster; Blue nodes indicate law federal bodies responsible for EV governance; and Pink nodes indicate legal concerns on employment and manufacturing]

Fig. 5. (*continued*).

campaigns promoting EV adoption and outreach activities on EV education through social media platforms indicated efforts to create capabilities, skills, knowledge and facilities to successfully shape EV as a useful service or product to support national low-carbon goals. It showed the technology policy discourse cluster in the political category (see Black nodes in Fig. 5a).

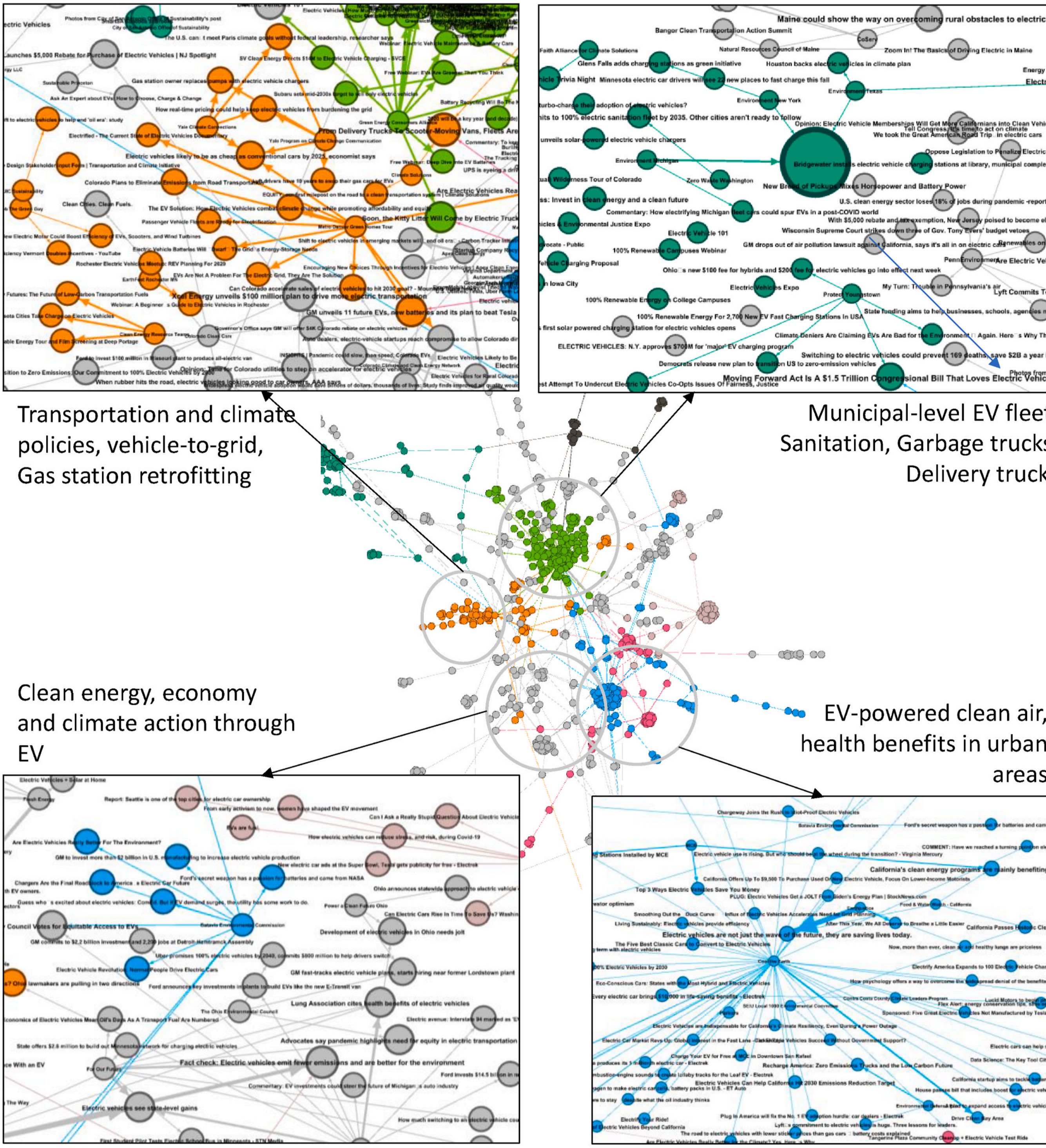
Fig. 5b demonstrated the clusters in the Legal category. It implied to focus on establishing EV-related environmental law, tax credit planning, lawsuit settlements and legal frameworks (see Green nodes) around pollution control through EV-buses, public and private transportation



c. Economic attributes of EV -related posts

[Note: Green nodes indicate Tesla sales vs the rest; Black nodes indicate EV-tech market competitiveness; and Pink nodes indicate market comparisons between US, EU and China; Grey nodes indicate discourse on EV as third industrial revolution and climate change; Red nodes indicate COVID-19 shocks and its effect on the EV market]

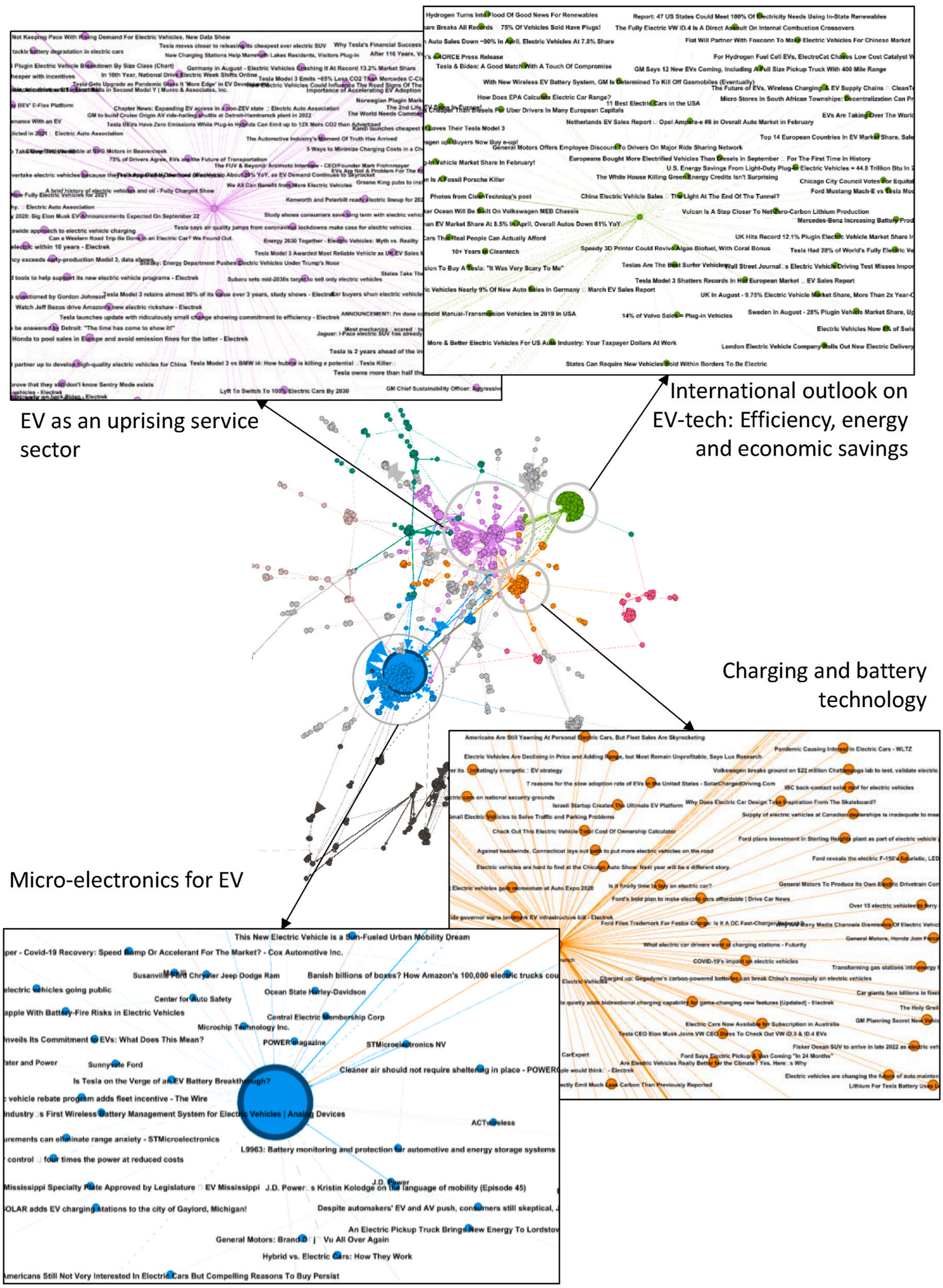
Fig. 5. (*continued*).



a. Environmental attributes of EV-related posts

[Note: Green nodes indicate discourse on electrification of federal fleets; Orange nodes indicate discourse around changing transportation policies; and Grey nodes indicate discourse on climate action; Blue nodes indicate environmental and health benefits from EV]

Fig. 6. Networks with high values of betweenness centrality.



b. Technological attributes of EV -related posts

[Note: Green nodes show the international outlook on EV tech; Pink nodes indicate EV as an upcoming service industry; Blue nodes indicate discourse on microelectronics technology for EV; and Orange nodes indicate discourse on charging and battery technology]

Fig. 6. (*continued*).

fleets like Uber and Lyft (see Orange nodes). A higher node density was observed around legal aspects concerning EV-related employment shift, infrastructural demand (charging station and manufacturing facilities) and retrofitting policies/options around gasoline to EV conversion (see Pink Nodes in Fig. 5b).

The identified Economic attributes are presented in Fig. 5c, primarily divided into the EV-tech and consumer-oriented market. The generalised economic discourse was the placement of the EV market development as the third industrial revolution (see Grey Nodes). An established benchmark was Tesla, as it makes up well over half of all US EV sales (see Green Nodes in Fig. 5c). Other aspects included EV market-based comparison to the situations in China and the EU (see Pink nodes); specifically, a significant node clustering was seen in the EV-technology segment (see Black nodes). Thus, indicating that the technical specifications around EVs can be critical policy focus points that can influence consumer acceptance. Covid-19 and its impact on EV sales also emerged as clusters showing the significance of unpredicted shocks (see Red Nodes in Fig. 5c).

The betweenness centrality measure for each PESTLE network category explained the amount of influence a node has over the flow of information in the graph. High betweenness centrality range is observed for the Technological category (0–15) and the Environmental category (0–10), as presented in Table 1 and Fig. 6. It infers that within these categories, few clusters may hold authority over disparate clusters. For example, a specific post about EV technology or environmental benefits may show higher interaction overshadowing other posts within the same network structure. On the contrary, the Legal category has 0 betweenness centrality indicating sparse nodes that do not influence the flow of information, i.e., nascent stages of EV legislation. Relatively low betweenness count was derived for Political, Economic and Social categories suggesting low information flow in the public domain (see Table 1).

Dense communities can be seen in Fig. 6a, indicating higher EV interactions and its environmental impact related posts. We detected four broader sections in the Environmental attribute network. It includes intersections around transportation and climate policies, vehicle-to-grid energy sharing and posts on the field trial of gas station retrofitting into electric charging stations (see Orange 'nodes in Fig. 6a). Environmental policy-related posts also clustered around urban planning-based measures like electrifying the garbage and sanitation trucks in all US major cities (see Green Nodes Fig. 6a). Public discourse was set around the health benefits of EV towards ng through cleaner air, identified through higher node density (see the Blue Nodes in Fig. 6a). Besides, clean energy, economy, and climate action through EV was a critical pinch point around EV-communications in the Facebook pages (see Grey Nodes in Fig. 6a). Public sensitisation on EV's environmental benefits was done through webinars, podcasts and door-to-door test drive programs. For example, several Green nodes in Fig. 6a showed topics like *'Electric Vehicle 101'*, *'100% renewable campuses webinar'*, *'Zoom in! The basics of Driving Electric in Maine'*, etcetera.

Fig. 6b shows the network structure of Technological attributes associated with the EV-related posts. This attribute also has a high range of betweenness centrality, as mentioned in Table 1. The EV-related posts have four high-density clusters, as shown in Fig. 6b. The technological development around EV has moved beyond automotive innovation and is shaping an emerging service industry. It has critical energy policy implications, especially if consumers can use electric vehicles/cars on a subscription-like any other technology-based service. It further indicates a structural shift across the EV supply chain, as it transcends towards a service sector with higher ownership.

Another critical technological attribute was the battery and charging technology innovation, as it remains a critical purchase decision factor for consumers [3]. Similarly, technological advancements can also be observed in the dense clusters around the micro-electronics and micro-controller technology in the EV (see Blue Nodes in Fig. 6b). It indicates an increased focus on developing next-generation capabilities for the EV that can, in turn, develop a service sector around the vehicle. International competition concerning EV-technology development remains high, and significant social media interactions were made in this domain, see the Green Nodes in Fig. 6b.

The social dimension of EVs showed interesting intersectionality with legal and environmental attributes. A critical discourse around it was, 'We all can benefit from more electric vehicles' (see Green Nodes in Fig. 7). It shaped EV's social justice and welfare dimensions linked with the environmental benefits like cleaner air, less pollution, climate change mitigation, and better health for all. It is further implicated in the smart city discourse (see Grey Nodes in Fig. 7). While EVs' promise (like EVs can create more jobs) is generally accepted, there is considerable criticism of EVs leading to job cuts (see Fig. 4). It can be argued that stories that highlight EV's uncertainty might be popular among the conventional ICE lovers or climate sceptics. However, assessing such sentimental differences and the impacts of EV policies on society is beyond the scope of the work.

4.3. *Topic models of PESTLE categories*

The optimal number of topic clusters derived from the 600,000-text corpus using machine learning-driven topic modelling through Latent Dirichlet Allocation (LDA) algorithm is illustrated in Table 2. The topic numbers were derived through the cross-validation process described in section 3.2, along with the theoretical basis of the topic modelling using LDA. These topic clusters present the latent semantic structures of EV-related public communications in the U.S. as per the PESTLE categories.

The topic models for each PESTLE category are presented in Table 3, with 'β' signifying the probability values of a word/term in a particular topic cluster. The top five words/terms with the highest probability are presented under each cluster for ease of interpretation. We interpreted the topic models as critical PESTLE narratives to better understand the EV-related public communications for contextualised policy design applications.

Five topics were extracted for the Political category (see Table 3). Topic 1 indicates a generalised political narrative concerning the need for infrastructural change to accelerate EV adoption. Relative high probability of the words 'state' ($\beta = 0.010$) in topic 1 further expand on the need for state-backed policies to establish adequate infrastructure for this transition from ICEVs to EVs. Topic 2, topics 3 and 5 expanded on the above narrative. They established a statement that the federal government is actively electrifying and modernising its service vehicle fleet by spending billions of funds. Words like 'mail_truck' ($\beta = 0.0075$); 'modernisation' ($\beta = 0.0050$); 'fund_bill' ($\beta = 0.010$); 'billion' ($\beta = 0.015$) supports this political narrative. Similarly, Topic 5 also illustrates policy challenges associated with increasing the demand for EVs while the current status of battery technology ($\beta = 0.011$) and charging infrastructure remains unappealing in the consumer market (($\beta = 0.005$). Interestingly, topic 4 highlights important political discourse around the Trump-Biden election and the future of climate policies (see Table 3-Political) that impacts the politics around EV in the U.S.

The topics extracted from the Economic category (see Table 3) are coherent with the network clusters identified in Fig. 5c. The economic narratives around EV are set around the market dominance of Tesla in comparison to emerging EV start-ups in the US (see Topic 2 and Topic 3). The critical intersection was observed between the Political and Legal

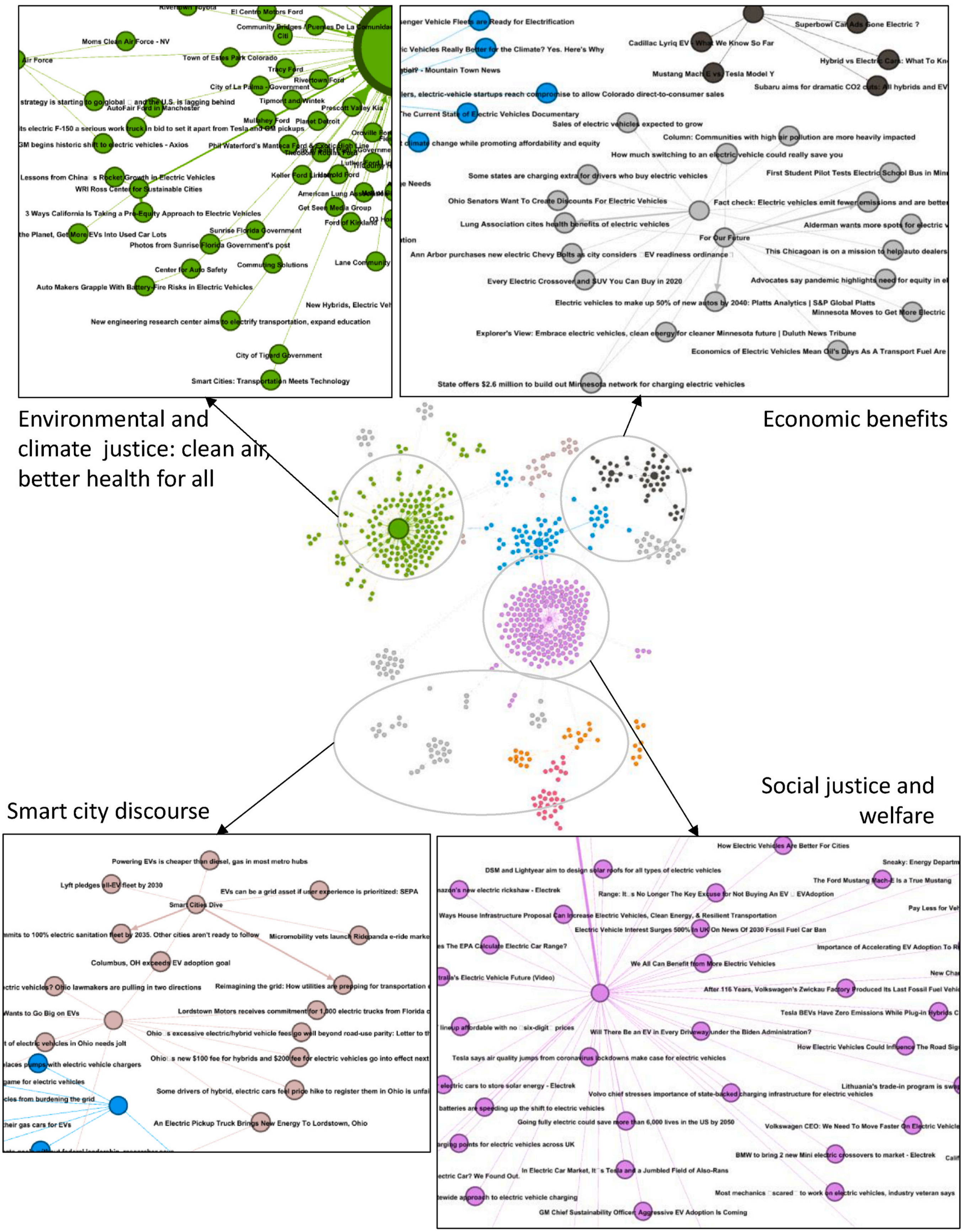


Fig. 7. Social dimensions of EV – posts in U.S. social media [Note: Green nodes indicate discourses on environmental and climate justice of EV; Black nodes indicate discourse on economic benefit of EV; Blue nodes indicate social justice and welfare benefits of EV; and Grey nodes indicate smart city discourse of EV].. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Optimal topic determination using ldatuning benchmarking criteria.

PESTLE categories	Number of topics	Benchmarking criteria[a]
Political	5	Deveaud2014; CaoJuan2009
Economic	6	CaoJuan2009
Social	4	Deveaud2014; CaoJuan2009
Technological	3	Deveaud2014
Legal	2	Griffiths2004; CaoJuan2009
Environmental	4	Deveaud2014; CaoJuan2009

[a] Detailed validation results are presented in the appendix.

discourse and topic 5 and topic 6 of the Economic category that stressed the need for tax (β = 0.006), pricing structure (β = 0.042) and policy frameworks (β = 0.005) to make EV affordable in the current market. Besides, topic 5 reiterates EV-related urban mobility challenges (β = 0.002) of high cost (β = 0.005) and battery (β = 0.005) technology limitations.

The topic extracted concerning the PESTLE framework's social dimension is also comprehensible with the network structure illustrated in Fig. 7. Four topics generalise the social justice and equity narrative associated with EV ownership in the U.S (see Table 3). For example, topic 1 expands on the need for state support (β = 0.010) to make EV affordable (β = 0.018) in the community. Topic 2 highlights the perceived welfare benefits (β = 0.008) of EV through cleaner air (β = 0.005), and its implied health benefits (β = 0.005). Thus, building the narrative on EV and social justice with questions like *'How can electric vehicles help advance social justice?'* (see Fig. 8). Topic 4 illustrate mass sensitisation and public engagement efforts to motivate the public for EV ownership through webinars, seminars, community tours and test drive sessions (also illustrated in Fig. 7). Alongside, topic 3 developed the social narrative around the need for cheaper (β = 0.008) EV to fulfil the broader objective of affordable transportation in the US.

Three topics were extracted for the Technological section (see Table 3), which aligns with the network communities illustrated in Fig. 6b. It further illustrates the existing challenges with battery and charging technologies, as the customer wants fast charging (β = 0.008) and a better driving range (β = 0.0065) (see Topic 1 – Technological section in Table 3). Improving the system efficiency (β = 0.011) and battery cost reduction (β = 0.018) was an essential element of topic 2, along with heavy research focus on electronics (β = 0.050). Topic 3 validated our assumption from Fig. 6b that the business model around EV is now shaping towards a mobility-based (β = 0.046) service industry (β = 0.038).

The legal topics extracted showed higher probability of terms like 'bill' (β = 0.025), 'state' (β = 0.011), 'tax' (β = 0.038), 'environmental_law' (β = 0.002), etcetera. It implied the growing focus on the legal framework around EV ownership concerning tax and subsidies phaseout, supporting the network-based findings in Fig. 5b. The tax and subsidies related discourses had the highest social media interactions in the Political category, as illustrated in Fig. 4, like *'Federal EV tax credit: unnecessary, inefficient, unpopular, costly, and unfair'*, and *'EV Freedom Act:' Just Another Taxpayer*-Funded *Payout to Wealthy Elites'*.

Four topics were extracted in the environment section (see Table 3) that shapes the narratives around the benefits of clean air and a pollution-free environment on the citizens' health and well-being (see Topic 1). It is complementary to the social sections, as mentioned above. Moreover, these topics explain the node clusters in Figs. 6a and 8. Interestingly, topic 3 exemplifies the effect of the Covid-19 pandemic on EV narratives as 'pandemic highlights need for equity in electric transportation'. Similar evidence can be inferred from Fig. 6a, showing that automakers pushed for EV sales with a pandemic storyline. For example, '*Coronavirus got rid of smog. Can electric cars do so permanently?*'.

5. Discussion

We studied EV-related social media communications through 36,000 public posts on Facebook in the U.S. to extract critical policy design information using the PESTLE (Political, Economic, Social, Technological, Legal and Environmental) framework. We used a mixed-method approach consisting of Social Network Analysis (SNA) and machine learning-based topic modelling using Latent Dirichlet Allocation (LDA) algorithm to derive PESTLE clusters; the results are shown in section 4.2 and section 4.3, respectively. The SNA aided in identifying EV-information clusters within the PESTLE categories and shaped the broader narratives of contextualised policy design. Parallelly, the LDA extracted latent semantic topics from a ~600,000 text corpus of EV-related posts and clustered high probability topics as per the PESTLE segmentation.

SNA results showed high modularity in the posts related to political, economic and legal categories (see Fig. 6), implying that the connectivity information is more broadly distributed throughout the PEL categories. In comparison, STE was revealed to be more integrated (i.e., high betweenness centrality). It is more so because the STE dimensions are at advanced stages, while the PEL dimensions still require multi-faceted deliberations. Hence, the higher probability of topics in this context through topic modelling, as presented in Table 3. The intersectional policy focus points derived from these categories indicate that EV-policies and legal frameworks are still at an early stage as the derived topic clusters had high probability values associated with terms like 'bill', 'state', 'tax', 'environmental_law' (see Legal in Table 3). The political-economic narrative is around how much funds are being allocated for EV projects, the tax and subsidy structure, and market advantage. Besides, a critical political attribute with EV was the posts concerning the federal vehicle fleet being electrified. It included electrification of mail delivery vans, sanitation and garbage trucks at the local government level, which is expected to create a market space for heavy-duty vehicles (see Fig. 5c and Table 3, Economic). However, the electrification of heavy-duty vehicles in practice is scarce due to technological limitations. Such market change is critical for EV incentives in the U.S. (also inferred by Ref. [9]).

In the political space, a topic cluster was extracted for the impact of the Biden-Trump election on the clean energy and low-carbon programs that significantly impact the politics of EV and its fund allocation (see Table 3, Political). It is coherent with the extracted topics in the legal categories of EV-related posts. It showed high probability words like environment law, grants and charging infrastructure (see Table 3, Legal). Topic 1 in the legal category also showed news concerning 'Biden' as a high probability term (see Table 3) that illustrated ongoing clean energy and climate action debate with the upcoming Biden administration in the United States.

The environmental dimension of EV communications showed more significant interactions with topics associated with clean air, low pollution, better health and well-being (see Table 3). Fig. 6 further illustrated greater community structures (i.e. high modularity) in the environmental category that implied more posts being shared on EV's environmental benefits. It remains a critical motivational factor for consumers [2,13]. Additionally, policy narratives connecting clean energy – health nexus were shaped through extensive webinars to sensitise

Table 3
Topic extracted by LDA as per the PESTLE categories.

Political					
Topic 1	**Prob (β)**	**Topic 2**	**Prob (β)**	**Topic 3**	**Prob (β)**
electric_vehicle	0.050	Electric	0.045	cheap	0.005
gas_car	0.025	new_company	0.012	mail_truck	0.075
Charge	0.020	billion	0.015	modernisation	0.050
State	0.010	battery	0.009	policy_bill	0.025
New	0.008	general_motor	0.002	transportation	0.025
infrastructure	0.005	funds_bill	0.010	cities	0.010
Topic 4	**Prob (β)**	**Topic 5**	**Prob (β)**		
save_climate	0.018	clean_energy	0.025		
Biden	0.015	vehicle	0.023		
Trump	0.011	low_demand	0.015		
Election	0.010	battery_tech	0.011		
Leadership	0.005	market_share	0.005		
Economic					
Topic 1	**Prob (β)**	**Topic 2**	**Prob (β)**	**Topic 3**	**Prob (β)**
electic_vehicle	0.028	ev	0.040	electric_vehicle	0.048
energy_use	0.015	business_plan	0.025	tesla	0.033
Ford	0.011	market_share	0.018	battery	0.018
market_first	0.005	company	0.007	startups	0.009
Use	0.002	launch	0.002	fleet	0.005
Topic 4	**Prob (β)**	**Topic 5**	**Prob (β)**	**Topic 6**	**Prob (β)**
manufacturer	0.028	ev_drive	0.055	city	0.033
gas_vehicle	0.008	pricing	0.042	new_platform	0.012
Climate	0.033	tax	0.015	high_cost	0.005
Clean	0.030	affordable	0.006	battery	0.005
Plan	0.002	policy	0.005	mobility	0.002
Social					
Topic 1	**Prob (β)**	**Topic 2**	**Prob (β)**	**Topic 3**	**Prob (β)**
customer_model	0.023	equity	0.035	clean_fuel	0.021
affordability	0.018	sustainable	0.012	transportation	0.010
state_backed	0.010	welfare	0.008	cheap	0.008
Solution	0.005	clean_air	0.005	infrastructure	0.0025
community	0.001	health	0.005	benefit	0.0012
Topic 4	**Prob (β)**				
Webinar	0.025				
Seminar	0.013				
ev_bill	0.009				
community	0.004				
Tour	0.002				
Technological					
Topic 1	**Prob (β)**	**Topic 2**	**Prob (β)**	**Topic 3**	**Prob (β)**
Vehicle	0.039	electronics	0.050	mobility	0.046
Battery	0.018	research	0.045	service	0.038
Charging	0.008	model	0.020	industry	0.023
Fast	0.0065	battery_cost	0.018	tesla	0.020
Plugin	0.0023	system_efficiency	0.011	competition	0.009
Legal					
Topic 1	**Prob (β)**	**Topic 2**	**Prob (β)**		
Bill	0.025	tax	0.038		
State	0.011	charging	0.015		
Vehicle	0.005	electric_vehicle	0.010		
Biden	0.003	grant	0.003		
News	0.002	environment_law	0.002		
Environmental					
Topic 1	**Prob (β)**	**Topic 2**	**Prob (β)**	**Topic 3**	**Prob (β)**
clean_air	0.030	climate	0.050	pandemic	0.055
Health	0.025	emission	0.035	covid	0.050
air_pollution	0.016	low_carbon	0.012	ev	0.050
City	0.004	clean_future	0.005	sales	0.015
Emission	0.0035	equity	0.005	environment	0.010
Topic 4	**Prob (β)**				
Sanitation	0.025				
Trucks	0.010				
local_level	0.007				
fleet_purchase	0.002				
urban	0.002				

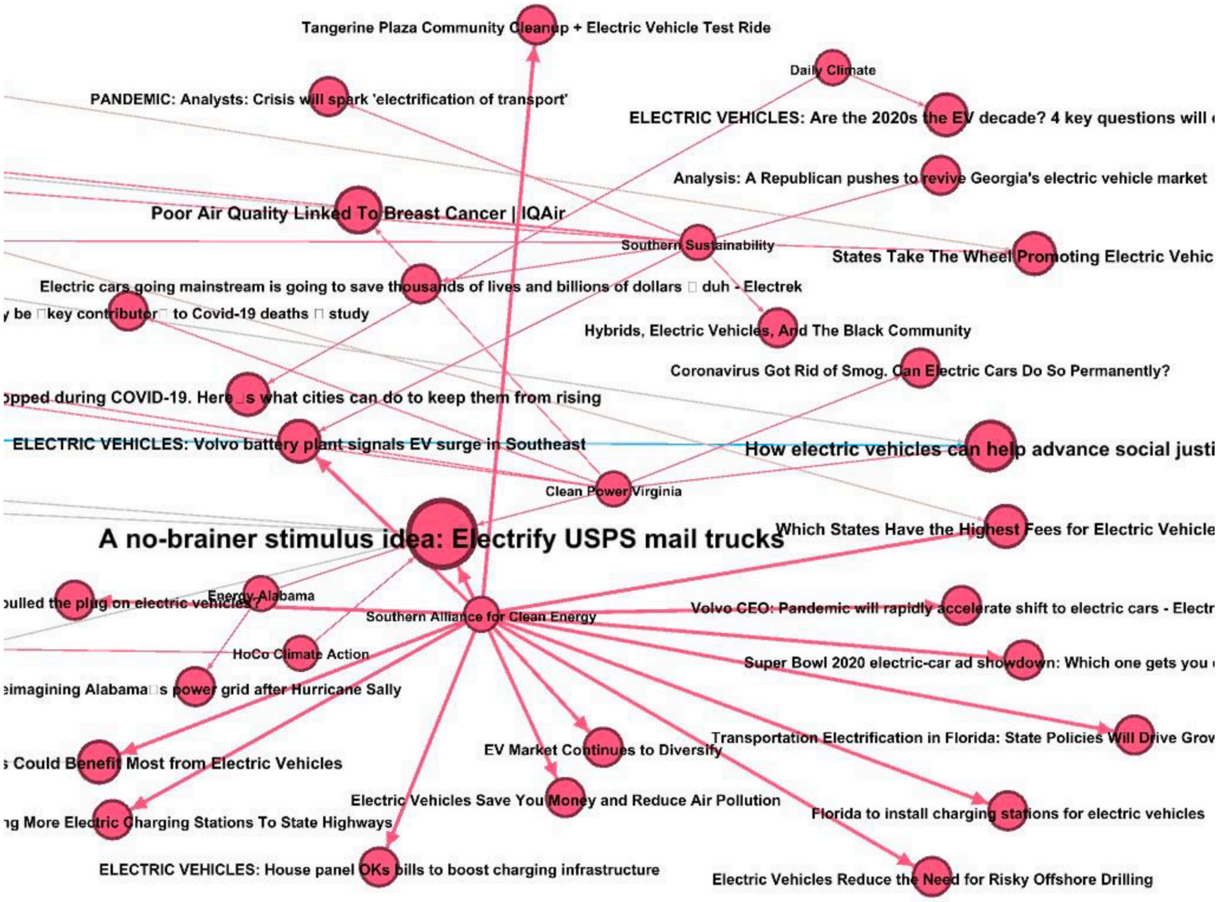


Fig. 8. Intersections in environmental and social discourse around EV-posts in public pages.

consumers on EV's benefits.

Such webinars also sensitised on the economic saving aspects of owning EVs (see Fig. 5c). The equity and equality implications of EV are illustrated in the social category (see Table 3). Social dimensions accentuated the welfare effects of EV and clean energy that connected the better health, clean air and economic saving elements, see Figs. 7 and 8. Thus, EV is presented as an enabler of distributive justice (also discussed in Refs. [91,92]).

Technology policy-shaping was observed in EV's technological dimension like high clusters in the charging and battery technology, as illustrated in Fig. 6b. It further expanded on EV as a growing service sector where consumers can avail of subscription-based electric vehicles (see Fig. 6b and Table 3). Additionally, high betweenness centrality was observed in the technology development of micro-electronics of EV. From a policy perspective, it infers manufacturers' transitioning on developing EV as a 'service'. Similar interconnections can be seen in the international market comparison cluster in Fig. 6b.

6. Conclusion

This study extracted inferences from EV-related public pages on Facebook in the United States to inform contextualised energy policymaking based on a PESTLE (Political, Economic, Social, Technological, Legal and Environmental) category. Using computational social sciences, we adopted a data-driven approach to classify policy information based on the PESTLE categories and retrieve grounded knowledge on EV-related public communications. Methodologically, social network analysis (SNA) aided in visualising the network and community structure of information around the PESTLE dimensions. In addition, the parallel use of topic modelling using the Latent Dirichlet Allocation (LDA) algorithm helped extract hidden semantic themes within the PESTLE classification.

The political posts indicated the current need for robust EV policies and funds to support national and state efforts of electrifying transportation, institutional discourse around modernisation of vehicle fleet and technology policy efforts concerning the battery and charging infrastructure. The political dimension of EV posts also revealed the influence of climate action and the clean energy debate in the Biden-Trump election campaign. Intersectionality was observed with the economic, technological and legal dimensions of EV-posts around market-oriented and development of EV as service-oriented. More than the automotive improvements and design innovation, more focus was on the micro-electronics of the electric vehicle at an industry level. It further showed a collective shift towards a service-sector model for EV ownership. Technology sensitisation through webinars and EV-tours was a norm of public engagement due to COVID-19 restrictions, which explains a critical demand-side policy action. Similarly, clean air and better health were critical environmental dimensions of EV posts.

The social dimension of the EV posts further highlighted the 'equity' and 'justice' aspects of this technology. Information on EV's energy policy implications was shared as a distributive justice element, thus influencing consumers for greater social media attention. It also has intersectional implications with the environmental dimension of climate justice and clean energy action. We also saw that the environmental and social justice discourse of EV is cumulatively shaping the legal dimensions. The key conclusion that can be drawn from this study are:

- Energy policy design of EV should leverage the social, environmental and energy justice dimensions, as it provides contexts to consumers.
- Technology policy-shaping of EV depends on the acceptability of battery and charging technology to the market and consumers.
- Political and legal dimensions of a just EV policy design require climate action and clean energy discourse across consumer groups. In addition, it places challenges around EV-tax allocations and subsidy design in the U.S.
- The disruptive innovation generated by EV startups can be leveraged to shape the economic dimension. A critical intersection was observed with the technological developments shaping a service-oriented industry associated with electric vehicles. The manufacturers are envisaging EV as a subscription-based service across the consumer groups in the U.S.
- Effective communication of social and health benefits of EV ownership can be a motivating factor for influencing higher EV uptake.

EV technology is transitioning into a service industry that may shape future mobility. While EV is centred around a robust environmental justice dimension, the social justice and welfare dimensions are critical to this technology's success. Social media-based evidence presented here already shows a higher degree of sensitisation through outreach initiatives. It is essential to understand the influential actors of EV adoption at a community level, such that subscription-based and shared ownership schemes can be designed. It was observed that climate action, clean energy and pollution-free attributes of EV over ICEV were extensively interacted within the public posts, indicating that consumers react better to these sentiments. Future consumer policies accounting for such sentiments can influence more EV adoption.

CrowdTangle's terms and conditions limited the granularity of the social media data used in this study. While it provided a cross-sectional and novel dataset of aggregated public interactions on EV-related posts, it did not provide any user-specific interactions. Demographic knowledge of the users can further enhance the understanding of context-specific factors that can influence EV adoption. Besides, this study presented the intersectionality of various PESTLE factors associated with EV-related public interactions at an industry level. Future work should build on such intersectional and data-driven approaches to counteract firm-level exclusions and include more relevant and informed stakeholders in the decision-making. Thus, expanding the applicability and complementarity of our approach is commonly used firm-level PESTLE analysis.

CRediT authorstatement

Ramit Debnath: Conceptualisation, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - original draft, Writing - review & editing, Visualisation, Project management, Funding acquisition. **Ronita Bardhan:** Validation, Writing - review & editing. **David Reiner:** Writing - review & editing. **JR Miller**: Supervision.

Declaration of competing interest

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

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Any findings, suggestion and conclusion presented in this study are that of the authors and do not represent the views of the affiliated organisations or funding bodies.

Appendix

Common terminology used in the social network analysis in this study:

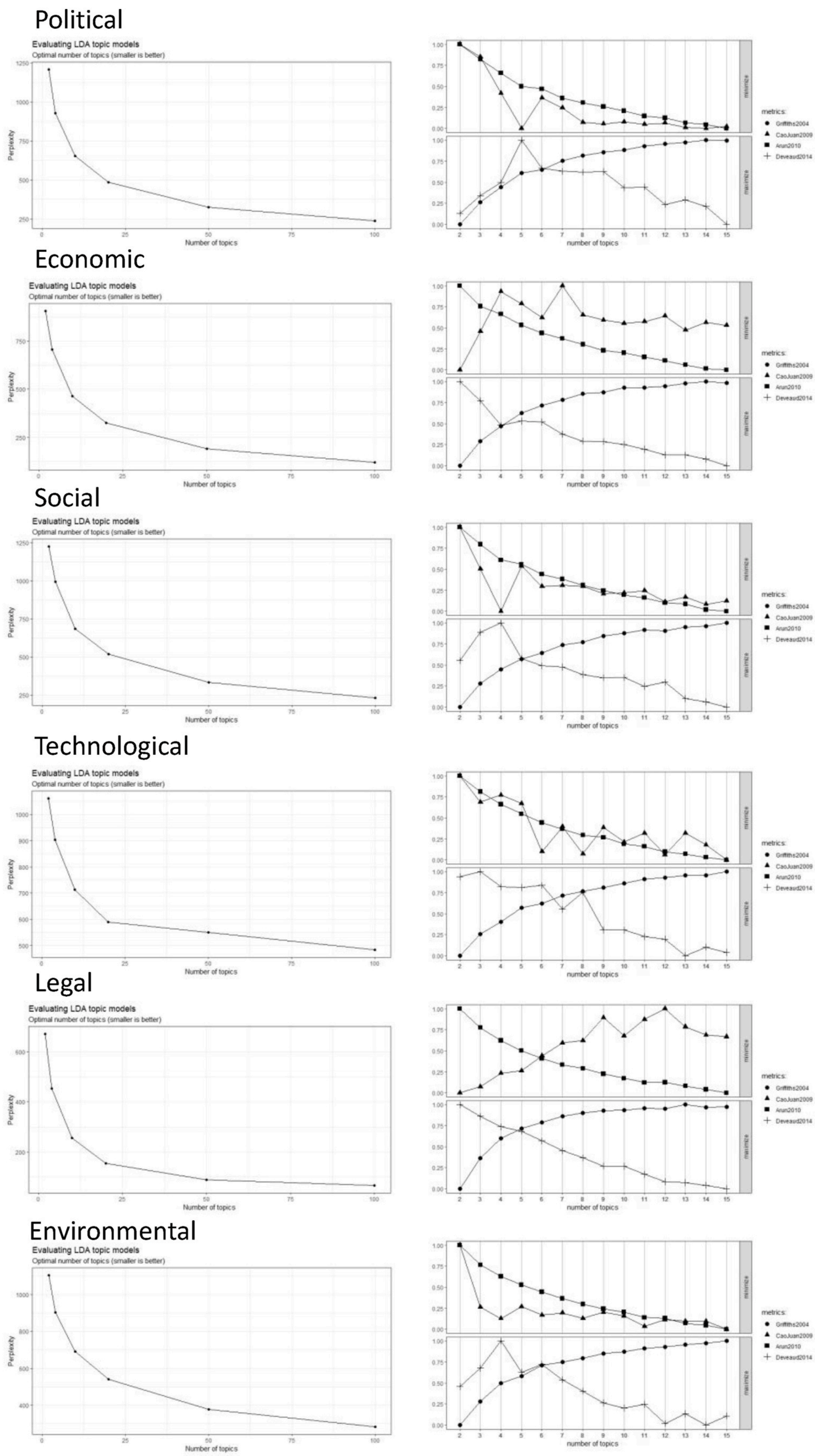
Degree centrality is a measure of the number of social interactions or links that a node has. It is expressed as an integer or count. It assigns an importance score based simply on the number of links held by each node [1,2].

The *indegree* of a node is the number of incoming links to it from source nodes and refers to the number of posts who had confirmed interaction with a given target link [2].

'Betweenness centrality measures the number of times a node lies on the shortest path between other nodes. This measure shows which nodes are 'bridges' between nodes in a network. It does this by identifying all the shortest paths and then counting how many times each node falls on one. A high betweenness count could indicate someone holds authority over disparate clusters in a network, or just that they are on the periphery of both clusters' [2].

'Modularity is a measure of the structure of network or graphs. It was It was designed to measure the strength of division of a network into modules (also called groups, clusters or communities). Networks with high modularity have dense connections between the nodes within modules but sparse connections between nodes in different modules. Modularity is often used in optimization methods for detecting community structure in networks' [2,3].

Validation results of LDA topic models: Perplexity scores and ldatuning metrics.


Political
Evaluating LDA topic models
Optimal number of topics (smaller is better)
Perplexity
Number of topics
number of topics
metrics:
Griffiths2004
CaoJuan2009
Arun2010
Deveaud2014
Economic
Evaluating LDA topic models
Optimal number of topics (smaller is better)
Social
Evaluating LDA topic models
Optimal number of topics (smaller is better)
Technological
Evaluating LDA topic models
Optimal number of topics (smaller is better)
Legal
Evaluating LDA topic models
Optimal number of topics (smaller is better)
Environmental
Evaluating LDA topic models
Optimal number of topics (smaller is better)

References

[1] Requia WJ, Mohamed M, Higgins CD, Arain A, Ferguson M. How clean are electric vehicles? Evidence-based review of the effects of electric mobility on air pollutants, greenhouse gas emissions and human health. Atmos Environ 2018;185(May):64–77.
[2] Choma EF, Evans JS, Hammitt JK, Gómez-Ibáñez JA, Spengler JD. Assessing the health impacts of electric vehicles through air pollution in the United States. Environ Int 2020;144(February):106015.
[3] International Energy Agency. Global EV outlook 2020 [Internet]. 2020 [cited 2021 Jan 2]. Available from: https://www.iea.org/reports/global-ev-outlook-2020.
[4] Oak Ridge National Laboratory. Transportation data energy book: edition 38 [Internet]. 2020 [cited 2021 Jan 2]. Available from: https://tedb.ornl.gov/wp-content/uploads/2020/02/TEDB_Ed_38.pdf.
[5] U.S. Department of Energy. Federal tax credits for new all-electric and plug-in hybrid vehicles [Internet]. 2020 [cited 2021 Jan 2]. Available from: https://www.sciencedirect.com/science/article/pii/S016041202031970X#b0165.
[6] Deloitte. Electric vehicle realities versus consumer expectations. 2020.
[7] Hardman S, Jenn A, Tal G, Axsen J, Beard G, Daina N, et al. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. Transport Res Part Transp Environ 2018;62(April):508–23.
[8] Nicholas M, Hall D, Lutsey N. Quantifying the electric vehicle charging infrastructure gap across. Washington, DC, USA.: U.S. Markets.; 2019.
[9] Jenn A, Springel K, Gopal AR. Effectiveness of electric vehicle incentives in the United States. Energy Pol 2018;119(October 2017):349–56.
[10] Sheldon TL, Dua R. Effectiveness of China's plug-in electric vehicle subsidy. Energy Econ 2020;88:104773.
[11] Tran M, Banister D, Bishop JDK, McCulloch MD. Realizing the electric-vehicle revolution. Nat Clim Change 2012;2(5):328–33.
[12] Helveston JP, Liu Y, Feit EMD, Fuchs E, Klampfl E, Michalek JJ. Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China. Transport Res Part Policy Pract 2015;73:96–112.
[13] Brückmann G, Bernauer T. What drives public support for policies to enhance electric vehicle adoption? Environ Res Lett 2020;15(9).
[14] Kumar RR, Alok K. Adoption of electric vehicle: a literature review and prospects for sustainability. J Clean Prod 2020;253:119911.
[15] Fahey L, Narayanan VK. Macro environmental analysis for strategic management (the west series in strategic management). Paperback: South-Western; 1986. p. 251.
[16] Paul D, Yeates D, Cadle J, editors. Business analysis. Swindon. British Informatics Society Limited (BISL); 2010. p. 303.
[17] Abbott RJ. Pestle analysis for students. second ed. North Charleston, SC, USA: CreateSpace Independent Publishing Platform; 2015.
[18] Zalengera C, Blanchard RE, Eames PC, Juma AM, Chitawo ML, Gondwe KT. Overview of the Malawi energy situation and A PESTLE analysis for sustainable development of renewable energy. Renew Sustain Energy Rev 2014;38:335–47.
[19] Achinas S, Horjus J, Achinas V, Euverink GJW. A PESTLE analysis of biofuels energy industry in Europe. Sustain Switz 2019;11(21):1–24.
[20] Islam FR, Mamun KA. Possibilities and challenges of implementing renewable energy in the light of PESTLE & SWOT analyses for island countries. In: Islam F, Mamun K, Amanullah M, editors. Smart energy grid design for island countries. Cham: Springer; 2017.
[21] Tan J, Chua WL, Chow CK, Chong MC, Chew BC. PESTLE analysis on toyota hybrid vehicles. In: International conference on technology management and technopreneurship. Malaysia: Melaka; 2012. p. 1–9.
[22] Capuder T, Miloš Sprčić D, Zoričić D, Pandžić H. Review of challenges and assessment of electric vehicles integration policy goals: integrated risk analysis approach. Int J Electr Power Energy Syst 2020;119(December 2019):105894.
[23] Jiang J, Blank A, Maier F, Bharthepudi A, Kumar P. Financial analysis and comparison of compact electric and gasoline cars. Portland International Conference on Management of Engineering and Technology (PICMET) 2015: 511–8. https://doi.org/10.1109/PICMET.2015.7273226.
[24] Campbell C, Sands S, Ferraro C, Tsao HY, Jody), Mavrommatis A. From data to action: how marketers can leverage AI. Bus Horiz 2020;63(2):227–43.
[25] Simões EN. A decision support system application module - for PESTLE analysis - competitive intelligence algorithm. 2020. Lisbon.
[26] Aria M, Cuccurullo C. bibliometrix: an R-tool for comprehensive science mapping analysis. J Informetr 2017;11(4):959–75.
[27] Kurtz MJ, Bollen J. Usage bibliometrics. Annu Rev Inf Sci Technol 2010;44(1):1–64.
[28] Debnath R, Mittal V, Jindal A. A review of challenges from increasing renewable generation in the Indian Power Sector: way forward for Electricity (Amendment) Bill 2020. Energy Environ; 2021.
[29] Gatto A, Drago C. A taxonomy of energy resilience. Energy Pol 2020;136 (November 2019):111007.
[30] Elie L, Granier C, Rigot S. The different types of renewable energy finance: a Bibliometric analysis. Energy Econ 2021;93:104997.
[31] Secinaro S, Brescia V, Calandra D, Biancone P. Employing bibliometric analysis to identify suitable business models for electric cars. J Clean Prod 2020;264:121503.
[32] Roberts C, Geels FW, Lockwood M, Newell P, Schmitz H, Turnheim B, et al. The politics of accelerating low-carbon transitions: towards a new research agenda. Energy Res Soc Sci 2018;44(February):304–11.
[33] Walter K, Higgins T, Bhattacharyya B, Wall M, Cliffton R. Electric vehicles should Be a win for American workers [Internet]. 2020. online, https://www.americanprogress.org/issues/economy/reports/2020/09/23/489894/electric-vehicles-win-american-workers/ [cited 2021 Jan 3]. Available from:.
[34] Gordon D, Sperling D, Livingston D. Policy priorities for advancing the U.S. Electric vehicle market. 2012. Washington DC.
[35] Borlaug B, Salisbury S, Gerdes M, Muratori M. Levelized cost of charging electric vehicles in the United States. Joule 2020;4(7):1470–85.
[36] Font Vivanco D, Freire-González J, Kemp R, Van Der Voet E. The remarkable environmental rebound effect of electric cars: a microeconomic approach. Environ Sci Technol 2014;48(20):12063–72.
[37] Wang L, Wang X, Yang W. Optimal design of electric vehicle battery recycling network – from the perspective of electric vehicle manufacturers. Appl Energy 2020;275(May):115328.
[38] Lieven T. Policy measures to promote electric mobility - a global perspective. Transport Res Part Policy Pract 2015;82:78–93.
[39] Malmgren I. Quantifying the societal benefits of electric vehicles. In: EVS29 symposium. Montréal; 2016. p. 1–12.
[40] Delmas MA, Kahn ME, Locke SL. The private and social consequences of purchasing an electric vehicle and solar panels: evidence from California. Res Econ 2017;71 (2):225–35.
[41] ICCT. Expanding access to electric mobility in the United States. 2017.
[42] Broadbent GH, Drozdzewski D, Metternicht G. Electric vehicle adoption: an analysis of best practice and pitfalls for policy making from experiences of Europe and the US. Geogr Compass 2018;12(2):1–15.
[43] Carley S, Zirogiannis N, Siddiki S, Duncan D, Graham JD. Overcoming the shortcomings of U.S. plug-in electric vehicle policies. Renew Sustain Energy Rev 2019;113(November 2018):109291.
[44] Sintov ND, Abou-Ghalioum V, White LV. The partisan politics of low-carbon transport: why democrats are more likely to adopt electric vehicles than Republicans in the United States. Energy Res Soc Sci 2020;68(April 2020):101576.
[45] Green EH, Skerlos SJ, Winebrake JJ. Increasing electric vehicle policy efficiency and effectiveness by reducing mainstream market bias. Energy Pol 2014;65:562–6.
[46] Sierzchula W, Bakker S, Maat K, Van Wee B. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. Energy Pol 2014;68: 183–94.
[47] Wesseling JH. Explaining variance in national electric vehicle policies. Environ Innov Soc Transit 2016;21(2016):28–38.
[48] Valta J, Makinen S, Kotilainen K, Rautiainen A, Järventausta P. Comparison of innovation policies for electric vehicle business ecosystems. In: 15th international conference on the European energy market (EEM). IEEE COMPUTER SOCIETY PRESS; 2018.
[49] Sun X, Li Z, Wang X, Li C. Technology development of electric vehicles: a review. Energies 2019;13(1):1–29.
[50] Giansoldati M, Monte A, Scorrano M. Barriers to the adoption of electric cars: evidence from an Italian survey. Energy Pol 2020;146(December 2019):111812.
[51] Buekers J, Van Holderbeke M, Bierkens J. Int Panis L. Health and environmental benefits related to electric vehicle introduction in EU countries. Transport Res Part Transp Environ 2014;33:26–38.
[52] Tang Y, Zhang Q, Li Y, Li H, Pan X, Mclellan B. The social-economic-environmental impacts of recycling retired EV batteries under reward-penalty mechanism. Appl Energy 2019;251(February 2019):113313.
[53] Hendrickson TP, Kavvada O, Shah N, Sathre R, D Scown C. Life-cycle implications and supply chain logistics of electric vehicle battery recycling in California. Environ Res Lett 2015;10(1).
[54] Gu H, Liu Z, Qing Q. Optimal electric vehicle production strategy under subsidy and battery recycling. Energy Pol 2017;109(January 2009):579–89.
[55] Tang Y, Zhang Q, Li Y, Wang G, Li Y. Recycling mechanisms and policy suggestions for spent electric vehicles' power battery -A case of Beijing. J Clean Prod 2018;186 (2018):388–406.
[56] Harper G, Sommerville R, Kendrick E, Driscoll L, Slater P, Stolkin R, et al. Recycling lithium-ion batteries from electric vehicles. Nature 2019;575(7781): 75–86.
[57] Beaudet A, Larouche F, Amouzegar K, Bouchard P, Zaghib K. Key challenges and opportunities for recycling electric vehicle battery materials. Sustain Switz 2020; 12(14):1–12.
[58] Li W, Long R, Chen H, He Z, Dou B, Chen F, et al. Public preference for electric vehicle incentive policies in China: a conjoint analysis. Int J Environ Res Publ Health 2020;17(1):1–16.
[59] Xiong S, Ji J, Ma X. Environmental and economic evaluation of remanufacturing lithium-ion batteries from electric vehicles. Waste Manag 2020;102:579–86.
[60] CrowdTangle Team. CrowdTangle [Internet]. 2020 [cited 2021 Nov 10]. Available from: https://help.crowdtangle.com/en/articles/3192685-citing-crowdtangle-data.
[61] Choi I, Milne DN, Glozier N, Peters D, Harvey SB, Calvo RA. Using different Facebook advertisements to recruit men for an online mental health study: engagement and selection bias. Internet Interv 2017 Jun 1;8:27–34.
[62] Wei L, Hindman DB. Does the digital divide matter more? Comparing the effects of new media and old media use on the education-based knowledge gap. Mass Commun Soc 2011 Feb 28;14(2):216–35.
[63] Pannucci CJ, Wilkins EG. Identifying and avoiding bias in research. Plast Reconstr Surg 2010 Aug;126(2):619–25.
[64] Bastian M, Heymann S, Jacomy M. Gephi: an open source software for exploring and manipulating networks. In: International AAAI conference on web and social media; 2009. p. 361–2.
[65] Newman MEJ. Modularity and community structure in networks. Proc Natl Acad Sci Unit States Am 2006;103(23).
[66] Jacomy M, Venturini T, Heymann S, Bastian M. ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. PloS One 2014;9(6):1–12.

[67] Marra A, Antonelli P, Dell'Anna L, Pozzi C. A network analysis using metadata to investigate innovation in clean-tech - implications for energy policy. Energy Pol 2015;86:17–26.
[68] Wishart R. Class capacities and climate politics: coal and conflict in the United States energy policy-planning network. Energy Res Soc Sci 2019;48(September 2018):151–65.
[69] Shen N, Deng R, Liao H, Shevchuk O. Mapping renewable energy subsidy policy research published from 1997 to 2018: a scientometric review. Util Pol 2020;64 (April):101055.
[70] Zhou N, Wu Q, Hu X. Research on the policy evolution of China's new energy vehicles industry. Sustain Switz 2020;12(9).
[71] Matschoss K, Repo P. Forward-looking network analysis of ongoing sustainability transitions. Technol Forecast Soc Change 2020;161(September):120288.
[72] Marra A, Antonelli P, Pozzi C. Emerging green-tech specializations and clusters – a network analysis on technological innovation at the metropolitan level. Renew Sustain Energy Rev 2017;67:1037–46.
[73] Bakker S, Leguijt P, Van Lente H. Niche accumulation and standardization - the case of electric vehicle recharging plugs. J Clean Prod 2015;94:155–64.
[74] DiMaggio P, Nag M, Blei D. Exploiting affinities between topic modeling and the sociological perspective on culture: application to newspaper coverage of U.S. government arts funding. Poetics 2013;41(6):570–606.
[75] Zirn C, Stuckenschmidt H. Multidimensional topic analysis in political texts. Data Knowl Eng 2014;90:38–53.
[76] Walker RM, Chandra Y, Zhang J, van Witteloostuijn A. Topic modeling the research-practice gap in public administration. Publ Adm Rev 2019;79(6):931–7.
[77] Debnath R, Bardhan R. India nudges to contain COVID-19 pandemic: a reactive public policy analysis using machine-learning based topic modelling. PLOS ONE 2020;15(9):1–25. https://doi.org/10.1371/journal.pone.0238972.
[78] Debnath R, Darby S, Bardhan R, Mohaddes K, Sunikka-Blank M. Grounded reality meets machine learning: a deep-narrative analysis framework for energy policy research. Energy Res Soc Sci 2020;69.
[79] Debnath R, Bardhan R, Darby S, Mohaddes K, Sunikka-Blank M, Coelho ACV, et al. Words against injustices: a deep narrative analysis of energy cultures in slum rehabiliation housing of Abuja, Mumbai and Rio de Janeiro for just policy design. Energy Res Soc Sci 2021;72(101892). https://doi.org/10.1016/j.erss.2020.101892.
[80] Wang Y, Taylor JE. DUET: data-driven approach based on latent dirichlet allocation topic modeling. J Comput Civ Eng 2019;33(3).
[81] Balasubramanyan R, Cohen WW, Pierce D, Redlawsk DP. Modeling polarizing topics: when do different political communities respond differently to the same news. ICWSM 2012 - Proc 6th Int AAAI Conf Weblogs Soc Media; 2012. p. 18–25.
[82] Grimmer J, Stewart BM. Text as data: the promise and pitfalls of automatic content analysis methods for political texts. Polit Anal 2013;21(3):267–97.
[83] Song M, Kim MC, Jeong YK. Analyzing the political landscape of 2012 Korean presidential election in twitter. IEEE Intell Syst 2014;29(2):18–26.
[84] Jacobs T, Tschötschel R. Topic models meet discourse analysis: a quantitative tool for a qualitative approach. Int J Soc Res Methodol 2019;22(5):469–85.
[85] Blei DM, Ng AY, Jordan MI. Latent dirichlet allocation. J Mach Learn Res 2003;3 (4–5):993–1022.
[86] Hankerson D, Harris GA, Peter D, Johnson J, editors. Introduction to information theory and data compression. second ed. Washington DC: CRC Press; 2003.
[87] ldatuning Moor N. Tuning of the latent dirichlet allocation model parameters: R package version 0.2.0 [Internet]. 2019 [cited 2019 Nov 27]. p. 4. Available from: https://cran.r-project.org/web/packages/ldatuning/ldatuning.pdf.
[88] Grün B, Hornik K. Topicmodels: an R package for fitting topic models. J Stat Software 2011;40(13):1–30.
[89] Manning CD, Raghavan P, Schutze H. Introduction to information retrieval. first ed. Cambridge, England: Cambridge University Press; 2009. p. 461.
[90] Silge J, Robinson D. In: Tache N, editor. Text mining with R: a tidy approach. first ed. Sebastopol, CA: O'Reilly Media; 2017. p. 194.
[91] Sovacool BK, Griffiths S. The cultural barriers to a low-carbon future: a review of six mobility and energy transitions across 28 countries. Renew Sustain Energy Rev 2020;119(November 2019):109569.
[92] Sovacool BK, Martiskainen M, Hook A, Baker L. Decarbonization and its discontents: a critical energy justice perspective on four low-carbon transitions. Climatic Change 2019;155:581–619.

Reference

[1] Golbeck J. Degree centrality - an overview [Internet]. Introduction to Social Media Investigation; 2015 [cited 2021 Jan 9]. Available from: https://www.sciencedirect.com/topics/computer-science/degree-centrality.
[2] Disney A. Social network analysis 101: centrality measures explained [Internet]. Cambridge Intelligence; 2020 [cited 2021 Jan 9]. Available from: https://cambridge-intelligence.com/keylines-faqs-social-network-analysis/#:~:text=Definition%3A Degree centrality assigns an,other nodes in the network.&text=A bit more detail%3A Degree,simplest measure of node connectivity.
[3] Newman MEJ. Modularity and community structure in networks. Proc Natl Acad Sci Unit States Am 2006;103(23).