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Attention and attitudes of Chinese social media users towards autonomous vehicles: sentimental, statistical and spatiotemporal perspectives

Yuan Li[1,8] · **Justin Hayse Chiwing G. Tang**[1,2] · **Shengyou Wang**[3] · **Zhenhan Peng**[1,7] · **Chengxiang Zhuge**[1,4,5,6,9]

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Abstract

In recent years, autonomous driving technology has progressed rapidly, promising to transform current transportation systems significantly and attracting growing public attention. Previous studies have predominantly relied on interviews and surveys to examine public perceptions of autonomous vehicles (AVs), which come with inherent limitations. This study utilizes a substantial dataset of 616,355 samples from Sina Weibo, one of China's most prominent social media platforms, to examine variations in statistical, temporal, spatial, and emotional dimensions to gain insights into the Chinese populace's perceptions and sentiments towards AVs. From 2015 to 2023, public attention and engagement have steadily risen, with individual users representing the largest group interested in AVs. Among individual users, males and young adults (aged 18–30) have demonstrated heightened interest. Attention levels are particularly pronounced in economically developed regions such as Beijing, Guangdong, and Shanghai. Overall, the public attitude towards AVs is positive; however, there has been a significant rise in negative sentiment since 2020, primarily related to concerns about safety and technological reliability. Based on public attention, this study also discusses potential challenges and corresponding strategies. These insights gained will aid automobile manufacturers, technology firms, and public agencies in addressing emerging challenges and facilitating the development of AVs.

Keywords Autonomous vehicle · Public attention · Social media · Text mining

Introduction

Transportation is an important component of modern society, continuously evolving alongside emerging technologies (Z. Peng et al. 2024a, b). Among these innovations, Autonomous Vehicles (AVs), which are highly automated or fully autonomous vehicles capable of assisting or completely replacing human drivers (SAE 2021), have garnered significant attention in recent years. This interest is primarily due to their potential to reduce traffic

Extended author information available on the last page of the article

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accidents caused by human driving errors (Yu et al. 2021; Zhang et al. 2024), transform mobility patterns (Fagnant and Kockelman 2015; Grindsted et al. 2022), enhance fuel economy (Noroozi et al. 2023; Qin et al. 2024) and mitigate environmental challenges (Kopelias et al. 2020; Rahman and Thill 2023; Ma et al. 2024). Consequently, AVs have attracted significant involvement from numerous technology companies and automobile manufacturers (Tennant et al. 2019). Since the launch of Google's Self-Driving Car Project in 2009, now under Alphabet, a diverse array of companies has entered the AV development space. This includes IT giants such as Apple and Nvidia, ride-hailing platforms like Uber and DiDi, major Asian technology firms including Baidu, Softbank, Alibaba, and Tencent, as well as traditional automobile manufacturers such as Tesla Motors, General Motors, Ford, and Daimler (Alvarez León and Aoyama 2022). By 2019, approximately 31 million vehicles equipped with varying levels of automation were operational worldwide (Placek 2023). Furthermore, the global market for AVs surpassed 24 billion U.S. dollars in 2021 (Placek 2023), while the Chinese AV market alone reached a valuation of 28.94 billion Chinese yuan (approximately 4.13 billion U.S. dollars) in 2022 (Liu 2024).

In recent years, AVs have gradually gained prominence in public discourse. An increasing amount of research has concentrated on public attitudes, acceptance, and intentions regarding AV adoption. These studies typically employ descriptive methods, including interviews (Eden et al. 2017) and questionnaire surveys (Zhang et al. 2020; Zhu et al. 2020), to explore public perceptions and attitudes. Findings indicate that factors such as safety (Moody et al. 2020), trust (Das 2021), demographic variables including gender and age (Asmussen et al. 2020; Nielsen and Haustein 2018), perceived usefulness, perceived ease of use (Panagiotopoulos and Dimitrakopoulos 2018), and cost (Bösch et al. 2018) significantly influence public acceptance of AVs. Understanding these key factors is indeed crucial for policymakers and industry stakeholders as they formulate strategies for developing and implementing AVs, which directly impact technology advancement.

While previous studies have predominantly used interviews or questionnaire surveys to investigate public attitudes and opinions towards AVs, this approach may overlook the dynamics of public attention. In addition, such methods often suffer from limited geographical coverage and relatively smaller sample sizes, which can lead to biases and insufficient representation of varied viewpoints. To bridge this research gap, this study collected social media data from Sina Weibo (one of the most-used social media platforms in China), employing text mining and deep learning techniques to explore public attention and sentiment towards AVs. By integrating analyses of temporal and spatial properties, social attributes, and contents of posts, this study reflects public perceptions towards AVs. Furthermore, this study enriches the AV literature by developing a methodological framework based on social media data to explore public attention and sentiments towards AVs. This approach allows for a more representative understanding of public opinion, capturing dynamic reactions and diverse perspectives from a broader geographical and demographic spectrum.

Literature review

Public attention and attitude towards autonomous vehicles (AVs)

Over the past decade, AVs have emerged as one of the most significant breakthroughs in transportation technology. A variety of research studies have been undertaken to gain a more comprehensive understanding of public attention and attitudes towards AVs from multiple perspectives, as shown in Table 1. Gkartzonikas and Gkritza (2019) reviewed that stated preference (SP) and choice modeling studies have explored public attitudes, perceptions, and willingness-to-pay (WTP) for AVs through experimental designs. SP survey questionnaires, crafted for choice experiments, are widely utilized as the primary tool for gathering

Table 1 Summary of key studies on public attention and attitudes towards AV

Reference	Methods	Key Findings
(Morita and Managi 2020)	Stated preference survey	AV credibility is a critical factor influencing WTP
(Rahimi et al. 2020)	Stated preference survey; Structural equation model	Privacy concerns are the main barrier to AV adoption
(Asgari and Jin 2019)	Stated preference survey	Individuals who derive pleasure from driving show lower WTA and WTP; A high level of technological proficiency demonstrates a greater WTA and WTP
(Daziano et al. 2017)	Stated preference survey	Average households willing to pay significantly for both partial and complete automation
(Clayton et al. 2020)	Questionnaire survey; Discrete choice experiment	Investigating user acceptance of AVs and their willingness to share them
(Wang et al. 2020a, b)	Online survey; Factor analysis; Multinomial logit models	Risk-taking, early adopters, and driving pleasure correlate with positive SAV attitudes
(Krueger et al. 2016)	Stated choice survey; Mixed logit model	Service attributes like waiting time, and travel costs impact SAV adoption
(Cartenì 2020)	Interviews; Mixed logit model	Technological and psychological factors hinder SAV adoption
(Patel et al. 2023)	Stated preference survey; Structural equation model	Sociodemographic attributes mediate willingness to use SAVs
(Rice and Winter 2019)	Questionnaire survey	Females show lower willingness to ride in AVs; Age effects were significant only in certain aspects of the study
(Liu et al. 2019)	Questionnaire survey	Previous knowledge, education, and income impact AV acceptance
(Charness et al. 2018)	Questionnaire survey	Personality traits affect attitudes towards AVs
(Yoo and Managi 2021)	Questionnaire survey	Education and income influence AV acceptance

information and opinions regarding AVs. Morita and Managi (2020) identified the credibility of AVs as a critical factor influencing WTP. In a study conducted by Rahimi et al. (2020), data from 1,194 respondents in the US was collected through an SP survey. A structural equation model (SEM) was employed to estimate willingness-to-adopt (WTA) and WTP for AVs across different user classes. They found that data privacy concerns is the biggest barrier to the shift to AVs. Similarly, Asgari and Jin (2019) analyzed WTA and WTP for various levels of autonomous features. They discovered that individuals who derive pleasure from driving show lower WTA and WTP for AVs, whereas those possessing a high level of technological proficiency demonstrate a greater WTA and WTP. Daziano et al. (2017) studied early responses to AV ownership and gathered SP survey data from 1,260 participants. The study concluded that the average household is ready to allocate considerable funds for both partial and complete automation, with substantial heterogeneity in preferences.

Given the potential for AVs to function as shared cars, many studies have investigated the attitude toward shared AVs (SAVs). Clayton et al. (2020) employed a survey (N= 899), incorporating a discrete choice experiment (DCE) and cluster analysis, to investigate user acceptance of AVs and their willingness to share them. Wang et al. (2020a, b) utilized an online panel of 834 participants from the US to examine attitudes towards SAVs, employing factor analysis and multinomial logit (MNL) models. Their findings revealed that individuals inclined towards risk-taking, early adoption, and those who find pleasure in driving show more positive attitudes towards SAVs. Similarly, Krueger et al. (2016) conducted a stated choice survey and a mixed logit model to investigate individual preferences and WTP for different service attributes of SAVs in Australia. They discovered that waiting time, travel costs, and other service-related attributes are likely to be key determining factors for the adoption of SAVs. Cartenì (2020) utilized interviews and a mixed logit model to estimate the acceptability value of SAVs. The findings revealed that technological and psychological factors are the primary obstacles hindering the widespread adoption of SAVs. Patel et al. (2023) employed SEM to analyze data collected from a survey of 250 participants. The study identified the elements affecting individuals' willingness to utilize SAVs and highlighted the mediating role of sociodemographic attributes. In addition to stated preference (SP) studies, some research has analyzed respondents data from questionnaire surveys and found that sociodemographic attributes significantly influence public attention and attitudes towards AVs. Rice and Winter (2019) recruited 300 participants to complete five established scales and offer six emotional reactions to scenarios. Their findings revealed gender differences, with females showing lower willingness to ride in AVs than males, whereas age effects were significant only in certain aspects of the study. Beyond gender and age, various studies have investigated the impact of variables like previous knowledge (Liu et al. 2019), personality traits (Charness et al. 2018), education, and income (Liu et al. 2019; Yoo and Managi 2021) on attitudes towards AVs. These factors have been examined to understand their impact on individuals' acceptance of AV and to guide the creation of efficient tactics for encouraging extensive AV adoption.

Analysis of public attention to emerging technologies via social media

Over the past few years, social media platforms have emerged as the primary means for individuals to share their views and experiences. Social media platforms, for instance, Sina Weibo, Facebook, Twitter (or X), Instagram, Threads, (He et al. 2022; Park et al. 2024), and others are valuable sources of extensive data, often surpassing traditional survey data. With nearly 3.6 billion people worldwide sharing their preferences and opinions on various topics daily, these platforms offer a wealth of information (Wu et al. 2023). Such social media big data has been used in studies of emerging technologies, e.g., electric vehicles (EVs) (Kühl et al. 2019; Ruan and Lv 2023), hydrogen energy technology (Schreiber et al. 2023), and green buildings (Liu and Hu 2019). Text mining has become a prevalent and efficacious approach for extracting meaningful insights from vast, extensive, disorganized social media data. This technique enables researchers to analyze large volumes of data without requiring prior knowledge of the content. For instance, Balla et al. (2023) examined changes in public discussions regarding EV adoption over the past decade using data mining techniques on Twitter data. Ruan and Lv (2022) analyzed the evolution of public perception of EVs on Reddit from 2011 to 2020, highlighting active discussions in fringe communities like conspiracy, particularly on environmental impact. Priyam et al. (2024) explored how different demographic groups perceive EVs on Reddit and Twitter, examining the factors influencing their views. Wu et al. (2023) utilized data from Sina Weibo to survey Chinese attitudes towards new energy vehicles (NEVs), revealing that the Chinese public generally holds a positive sentiment towards NEVs. Other research has focused on consumer sentiments, preferences, and their impact on EV sales (Wang et al. 2022), along with the construction of charging infrastructure (Wang et al. 2021, 2022). Austmann and Vigne (2021) utilized a keyword analysis of Twitter to gauge how environmental awareness influences the EV market, but the results suggest that environmental awareness has a minimal impact on the expansion and demand of EVs. The text mining method was employed to explore the differences in media framing of conventional, electric, and hydrogen vehicles using data gathered from Twitter and newspapers. They found that discussions about consumer and alternative fuel adoption issues are more prevalent on Twitter (Schreiber et al. 2023).

Certain studies on emerging technologies have also utilized social media big data to investigate the general public attention and sentiment towards AVs. Several studies have investigated public perception of AVs following accidents, with a primary focus on analyzing changes in sentiment and attention during extreme events (Chen et al. 2021; Jefferson and McDonald 2019). In order to explore the Chinese public perception of AVs following accidents, Jing et al. (2023) gathered 42,111 comments from popular Chinese social media platforms, specifically examining gender distinctions in public view regarding AVs, analyzing the sentiments expressed in the collected comments. Penmetsa et al. (2021) analyzed 1.7 million tweets in the 15 days before and after incidents to study public perceptions and sentiments related to AVs. They observed that the tweets became more negative, and the percentage of negative tweets specifically about AVs increased after fatal crashes involving AVs. These studies aim to understand how public attitudes and attention towards AVs may fluctuate in response to incidents or accidents involving AVs.

It is important to highlight that there is a limited number of research papers that directly study the long-term public attention of AVs using social media data. Ding et al. (2021) proposed a machine learning (ML) framework to analyze public sentiments through Twitter feeds, detect sentiment bias related to AV terms, summarize public concerns, and discuss potential policy implications. Nonetheless, the methodology is only applicable to English-language social media data, and the study's scope is confined to a three-month period, which may impact the generalizability of the results. Similarly, Bakalos et al. (2020) used sentiment analysis and deep learning (DL) models to analyze social media posts from Twitter

(N= 5047) and Reddit (N= 495), capturing and classifying public opinions as positive or negative, and providing insights into fears and factors influencing negative opinions on AVs. Chen and Tomblin (2021) incorporated data from Reddit, surveys, and public deliberation to gauge public sentiment regarding AVs, with a specific focus on contrasting the specific features of these three types of data. S. Wang et al. (2022) amassed a two-year dataset from Twitter regarding AVs, along with 53 candidate independent variables through web scraping techniques. The findings unveiled that the preponderant public sentiment towards AVs was generally positive, with terms e.g., "drunk", "blind spot", and "mobility" exerting the most profound impact on shaping these attitudes. Das et al. (2019) undertook an analysis of the 15 most popular AV-related YouTube videos, employing text analysis to identify crucial topics and public attitudes towards AVs. However, one must bear in mind that the study had a limited sample size, and the comments analyzed were inevitably influenced by the content of the selected videos. Consequently, leveraging long-term social media data mining can effectively offer insights into the evolving public attention and sentiments towards AVs (Ding et al. 2021).

Comments on previous work

As discussed earlier, previous studies have predominantly relied on stated preference (SP) surveys, discrete choice experiments, and structural equation modeling (SEM) to understand the willingness-to-adopt (WTA) and willingness-to-pay (WTP) for AVs (Rahman and Thill 2024). However, this approach mainly employs survey data, which comes with several limitations, as conducting and distributing questionnaires can be costly, and the process of collecting responses often requires considerable time (Lietz 2010). What is more, the sample size of valid data obtained from surveys is frequently limited, which can restrict the generalizability of the findings (Gkartzonikas and Gkritza 2019). Moreover, numerous studies have focused on public perceptions within specific regions or countries, e.g., the US or Australia, while research on China is indeed lacking. In the past few years, many social media platforms have emerged as rich and easily accessible sources of data, offering opportunities to gather public opinions on emerging mobility technologies, including electric vehicles, hydrogen vehicles, Mobility-as-a-Service (MaaS), and so on. While several studies have explored public opinion on AVs, they have often concentrated on immediate reactions to specific events, such as accidents involving AVs. This short-term focus may fail to capture the gradual shifts in public sentiment or the underlying trends that impact the adoption and acceptance of AVs over time.

To fill these gaps, this study employed a social media-based approach, leveraging text mining and sentiment analysis, to objectively examine the Chinese populace's perceptions and attitudes towards AVs. A significant volume of data sourced from Sina Weibo, a well-known Chinese social media platform, was employed to gain a more reliable understanding of the current dynamics, as well as long-term trends in public attention and attitudes towards AVs. Furthermore, we examined the attention towards AVs through the lens of urban heterogeneity across different provinces in China. In addition, we explored the variations in attitudes towards AVs among diverse demographic groups. A thorough grasp of the public attitudes and perceptions regarding AVs can aid policymakers and automobile manufacturers in comprehending and tackling specific challenges, thereby easing the development and adoption of AVs.

Data and methods

Development of AVs in China

Since 2014, the Chinese automotive industry has entered a phase of moderate growth. In 2023, vehicle production and sales in China amounted to 30.161 million and 30.094 million units, respectively, representing annual growth rates of 11.6% and 12%, thereby setting new historical highs (Agency 2024). The sales of new energy vehicles (NEVs) experienced even more remarkable growth, with yearly increases of 35.8% and 37.9%, respectively, further deepening public awareness of AVs (Agency 2024; Peng et al. 2024a, b). Transitioning from advanced driver assistance systems (ADAS) technology, the Chinese automotive industry is now focusing on the development of autonomous driving technology (Xu and Fan 2019). The State Council introduced the "Made in China 2025" plan in May 2015, which for the first time proposed a strategy for autonomous driving technology. The plan aimed to enable China to master key technologies in intelligent driving assistance systems by 2020 and to achieve fully autonomous driving capabilities by 2025 (Xu and Fan 2019). Following this initiative, the Chinese government implemented a range of supportive policies to promote the advancement of autonomous driving technology, strengthen standardized management of AVs, and encourage their commercial use. Several significant policies from 2015 to 2023 are outlined in Table. A in the Supplementary Materials. Additionally, several cities, including Beijing, Shanghai, Shenzhen, and Chongqing, have introduced policies and regulations to drive the commercial operation and deployment of AVs on public roads.

In August 2021, the State Administration for Market Regulation issued the national standard "Taxonomy of Driving Automation for Vehicles" (Regulation 2021), as depicted in Table. B in the Supplementary Materials. The autonomous driving level of passenger vehicles is transitioning from L2 to L3 in China. With the progress of hardware platforms and software algorithms, L2 automated driving features are becoming increasingly prevalent in new vehicles. In 2022, the penetration rates of L2 and L3 automated driving systems in new vehicles reached 35% and 9%, respectively (Daily 2023b). Several technology companies have been developing and testing L4 automated driving systems in certain urban areas or specific scenarios. The penetration rate for L4 automated driving stood at 2% in 2022 (Daily 2023b). Additionally, since 2018, the Chinese government has gradually issued regulations and implementation guidelines for the road testing of intelligent and connected vehicles, as shown in Table. C in the Supplementary Materials, to meet the requirements for public road testing of AVs. The cumulative total of testing roads open nationwide has exceeded 15,000 km, with over 2,800 testing licenses issued. The total mileage covered in road testing has surpassed 70 million kilometers (Daily 2023b).

In the Chinese AV market, AV companies can be broadly categorized into three types: internet tech giants, traditional automakers, and startups. Internet tech giants such as Baidu, Alibaba, and Huawei have been actively involved in intelligent vehicle projects. They entered the field early and primarily focused on the development of autonomous driving platforms and chips. Traditional automakers (e.g., GAC, Geely, BYD, Changan, Xiaopeng, and NIO) started with lower-level driving assistance systems and gradually implemented L1-L3 driving capabilities. Startups like Didi, AutoX, Momenta, Pony.ai, and WeRide mainly focus on autonomous driving operation services (Mu 2024). To cater to individual and public transportation needs, they have conducted extensive testing of Robotaxi and Robobus across various urban scenarios (CAAM 2023).

An analytical framework based on social media data

Figure 1 illustrates the analytical framework, detailing the specific steps as outlined below:

(1) Data collection. We utilized the keywords "autonomous vehicle (AV)" and "unmanned vehicle" and web crawler technology to gather data, including posts and associated user information from Sina Weibo.

(2) Data pre-processing. The data underwent a cleaning process, during which irrelevant posts were discarded and extraneous information removed. Then, we performed Chinese word segmentation and eliminated stop words to prepare the dataset for further analysis.

(3) Analysis. We employed a multi-faceted analytical approach to extract comprehensive insights from the cleaned data. Firstly, we performed statistical analyses from both posts and user perspectives. Following this, we conducted a spatial analysis to explore the geographical distribution of post quantities and the average number of posts per user, as well as the public attention flow across China. For those provinces with the highest flow of public attention, topic analysis was utilized to generate and identify major topics/themes and assess the importance scores of relevant keywords. Moreover, we adopted sentiment analysis to classify all posts into positive and negative categories, enabling us to explore temporal changes in sentiment across different genders and ages of users. To enhance our comprehension of

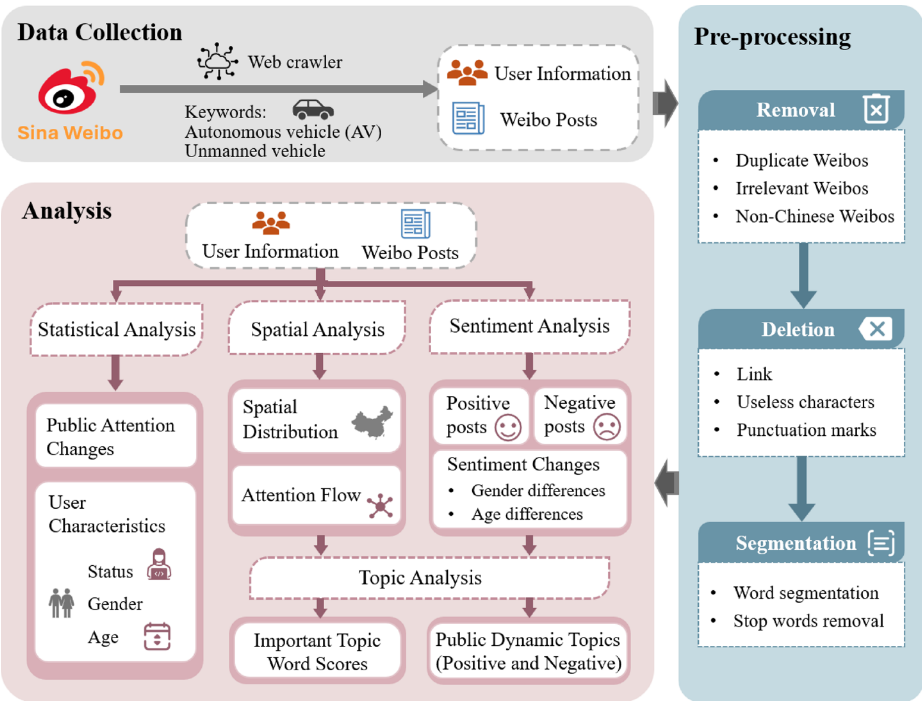


Fig. 1 Analytical framework based on social media data

the underlying topics driving positive and negative sentiments, we then conducted separate topic analyses for each sentiment category.

Data collection and pre-processing

As of December 2023, China boasted 1.092 billion internet users, with an internet penetration rate of 77.5% (CNNIC 2024). Among the popular social media platforms in the country are WeChat, Weibo, Douyin, and Little Red Book, with Weibo standing out as a leading microblogging platform for real-time content creation, discovery, and distribution in China. In December 2023, Sina Weibo reported 605 million monthly active users and 257 million daily active users (SWDC, 2024; Weibo 2024), rendering it a valuable source for collecting public online opinion data. In addition, web crawlers have proven to be exceptional tools for gathering large-scale data, demonstrating high effectiveness in many studies (Kumar et al. 2018; Lee et al. 2021; Sun et al. 2023; T. Wang et al. 2020a, b). Therefore, we used Weibo as a data source and employed web crawler technology implemented in Python to collect data related to AVs. We took "autonomous vehicle" and "unmanned vehicle" as the keywords to retrieve Weibo posts and related user details spanning from January 1, 2015, to December 31, 2023. The collected data on Weibo posts included post links, content, publishing times, and user interaction metrics such as the number of reposts, likes, and comments. For Weibo users, we gathered data on names, genders, birthdays, types of authenticated users, addresses, and IP locations. Specifically, the address refers to the information displayed on the user's account profile, while the IP location refers to the provincial-level location determined by the IP address of the user's connected device. We primarily utilized IP location data, supplemented by user-provided address information when IP location data is unavailable. Although users may have migrated across provinces during the nine-year study period, China's interprovincial migration rate of 3.61% between 2015 and 2020 was relatively low (Wang 2022), suggesting its impact on our key findings is likely to be minimal.

To ensure data quality and facilitate subsequent analysis, we performed pre-processing on the collected 616,355 Weibo data. The specific steps for data pre-processing were as follows:

(1) Remove duplicate, irrelevant and non-Chinese Weibo. We removed duplicate Weibo posts with identical links, irrelevant posts pertaining to airplanes, ships, trains, and other forms of transportation, as well as posts that originated from outside China.

(2) Noise removal. We deleted interference information from Weibo posts, such as emojis, punctuation symbols, user names from interactions, and numerous URL links.

(3) Text Processing. In Chinese text, words are not separated by formal delimiters. Consequently, we employed a Chinese word segmentation dictionary, in order to divide the Chinese text into distinct words. To enhance the precision of subsequent analysis, we augmented the existing word segmentation dictionary by adding new domain-specific terms related to our research, such as "intelligent connected vehicles", "Xiaopeng", "NIO", and "Momenta". Additionally, we expanded the existing stop word dictionary by adding custom stop words such as "client (computing)", "web link", and "hotline" to reduce the dimensionality of text features. After completing these pre-processing steps, we obtained a cleaned dataset of 320,469 Weibo posts, ensuring a high-quality corpus for further analysis.

Methods

Sentiment analysis

Sentiment analysis is employed to identify the attitude expressed in text data (Wankhade et al. 2022). To extract public attitudes towards AVs from the large volume of collected Weibo post data, this study employed the Bidirectional Encoder Representations from the Transformers (BERT) model. BERT is a pre-trained model that utilizes deep bidirectional representations by considering both left and right contexts in all Transformer layers (Devlin et al. 2018). Previous research has demonstrated the effectiveness of BERT as a sentiment classification tool (Briskilal and Subalalitha 2022; Li et al. 2021; Singh et al. 2021; Zhao and Yu 2021). Since the analysis involved Chinese texts, we used the "chinese-bert-wwm" model, which is a pre-trained BERT model specifically designed for the Chinese language. It incorporates the whole word masking (wwm) strategy, making it easier for the model to predict and understand Chinese words (Cui et al. 2021). The pre-training process for this model consists of two unsupervised tasks, including the Masked Language Model (MLM) and the Next Sentence Prediction (NSP) (Arase and Tsujii 2021).

- MLM: This task trains the BERT model to infer the missing words within a sentence. Specifically, it randomly masks certain tokens in the input sentence. In the context of Chinese text, which is typically segmented at the character level without adhering to traditional word segmentation, we employed the whole word masking (wwm) strategy. If a portion of a complete word is masked, the other parts belonging to the same word will also be masked. The BERT model is then required to predict these masked words in the surrounding context (Cui et al. 2021).
- NSP: This task trains the BERT model to understand the relationship between pairs of sentences. Given two input sentences, A and B, the model needs to predict whether sentence B logically follows sentence A.

The flow of steps of sentiment classification is shown in Fig. 2. To establish a pre-labeled dataset for training and fine-tuning the sentiment analysis model, we leveraged our knowledge of AV-related terminologies, transportation systems, and existing literature to manually label 5,000 Weibo posts. This pre-labeled dataset consisted of 3,026 posts labeled as positive (1) and 1,974 posts labeled as negative (0). Table 2 provides examples of manually labeled posts, showcasing the sentiment annotation. We then divided the pre-labeled dataset into a training dataset (80%) and a test dataset (20%). These datasets were then used to fine-tune the pre-trained Chinese BERT model for the specific task of sentiment classification on AV-related Weibo posts. The fine-tuning process involved the following steps:

(a) **Input Embeddings**: The input data was tokenized using the BertTokenizer provided by the BERT model. Each input sequence was marked with $[CLS]$ at the beginning and $[SEP]$ between sentences. Each word was mapped to a vector denoted as Tok.
(b) **Fine-tuning and Classification**: The pre-trained Chinese BERT model was fine-tuned for sentiment classification. By utilizing the input embeddings from the model, contextually relevant word embeddings E were obtained. The output vector C corresponding to the $[CLS]$ was extracted from the final layer of the BERT model, which encapsulates

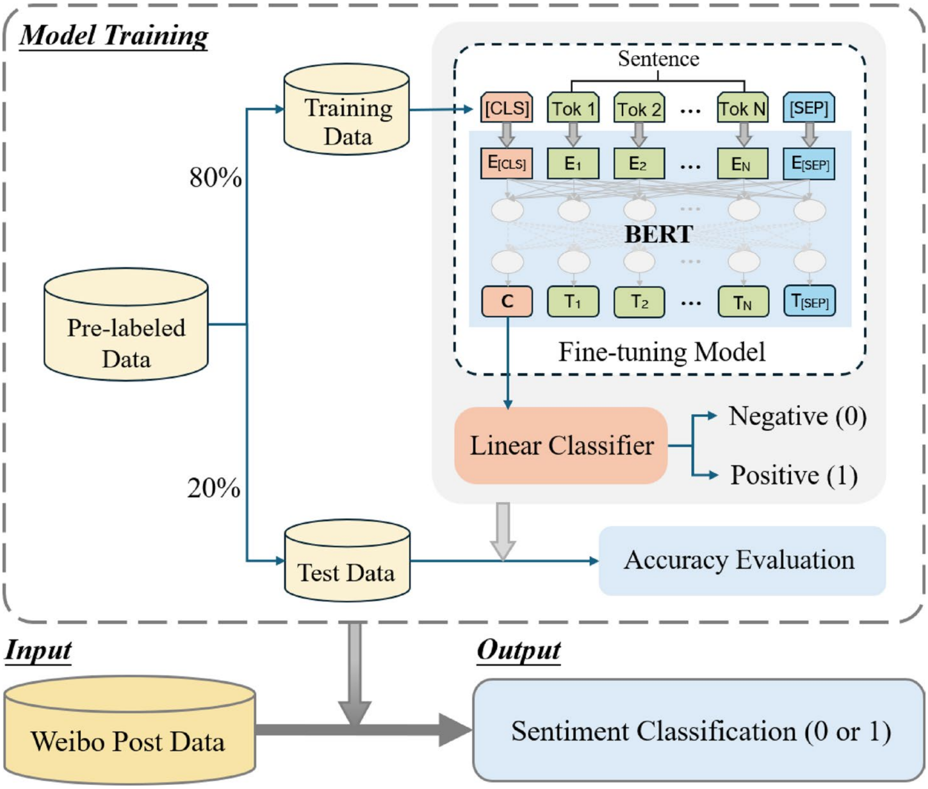


Fig. 2 Flow of steps of sentiment classification

Table 2 Examples of manually labeled posts

Categories (label)	Content of posts
Negative (0)	Another fatal accident involving a Tesla was once again caused by autonomous vehicles. It is evident that autonomous vehicles and intelligent modes are still not mature.
	There is already a crisis emerging even before the widespread adoption of autonomous vehicles.
Positive (1)	I really think the autonomous vehicle is so cool. Humans need autonomous vehicles. Autonomous driving is really good at driving.
	Autonomous driving technology is truly becoming more and more mature! With research and development investment exceeding hundreds of billions, there will definitely be even better outcomes.

the representation of the entire input sequence. C was then passed through a fully connected layer (linear layer) to map it to a new two-dimensional space. The fully connected layer is demonstrated in Eq. (1).

$$Z = W \times C + b \tag{1}$$

where, Z denotes the vector of the fully connected layer, W denotes the weight matrix, and b denotes the bias vector.

To convert the output of the fully connected layer into a probability distribution, a softmax activation function was typically applied. This function can transform any real-valued vector into a valid probability distribution. For the two-class classification problem in this study, softmax function is shown in Eq. (2).

$$p_i = Softmax\left(Z_i\right) = \frac{e^{Z_i}}{\sum_{j=1}^{2} e^{Z_j}} \tag{2}$$

where, p_i denotes the predicted probability of belonging to the i-th category, and Z_i denotes the value of the i-th element in the output vector Z.

(c) **Optimization**: The loss function was computed using labeled data, and the parameters of the BERT model and the classification layer were updated through backpropagation. The cross-entropy loss function was utilized, as depicted in Eq. (3).

$$L = -\sum_{i=1}^{2} y_i \log\left(p_i\right) \tag{3}$$

where, L denotes the value of the loss function, and y_i is the one-hot representation of the real label.

(d) **Evaluation**: The performance of the fine-tuned model was assessed on the test set using accuracy as the evaluation metric. Accuracy is shown by Eq. (4).

$$Accuracy = \frac{\sum_{k=1}^{N} 1(\widehat{y}_k = y_k)}{N} \tag{4}$$

where, N is the total number of predictions, $\widehat{y}_k$ is the predicted category of the k-th sample by the model, y_k is the true category of the k-th sample, and $1(\widehat{y}_k = y_k)$ is an indicator function whose value is 1 when the predicted category is equal to the true category, otherwise it is 0.

Finally, we used the fine-tuned model to perform sentiment classification on the entire Weibo post data.

Topic modeling

Topic modeling is an unsupervised learning technique in natural language processing (NLP) that clusters textual documents based on their underlying semantic structure (Papadimitriou et al. 1998). This approach allows for extracting topics from a large corpus of social media post text and provides insights into the underlying reasons contributing to their evolution. Unlike supervised learning methods that require manual labeling before analysis, topic modeling can automatically discover clustered topics within the text, making it more efficient (Chen et al. 2023). This study used BERTopic, a topic modeling technique based on BERT embeddings and Class-based Term Frequency - Inverse Document Frequency (c-TF-IDF), to generate dense clusters with interpretable topics while retaining important words in the topic description (Grootendorst 2022). BERTopic has been demonstrated as an effective framework for topic modeling (Falkenberg et al. 2022; Karabacak and Margetis 2024; Šćepanović et al. 2023), particularly in terms of topic coherence and interpretability. It offers advantages over other topic modeling techniques, such as Latent Dirichlet Allocation (LDA) and Probabilistic Latent Semantic Analysis (PLSA) (Ebeling et al. 2023; Invernici et al. 2024; Wang et al. 2023). The workflow of BERTopic for topic extraction is depicted in Fig. 3.

In this study, BERTopic was employed in two ways. On the one hand, BERTopic was used to analyze the Weibo posts from regions with high flow of attention to identify popular topics within those regions, along with representative keywords for each topic. On the other hand, BERTopic was used to extract themes from positive and negative Weibo posts respectively. Next, dynamic topic modeling was applied to the top topics, enabling a thorough analysis of the progression of these themes over time.

The BERTopic model typically includes embeddings, dimensionality reduction, clustering, and topic representation. In this study, the Sentence-BERT-based (SBERT-based) embedding model, specifically sbert-chinese-general-v2, was utilized to embed the input documents, as SBERT has been shown to excel in capturing semantic details as well as conveying sentence meanings (Reimers and Gurevych 2019). For dimensionality reduction, the Uniform Manifold Approximation and Projection (UMAP) was employed to lower the dimensionality of the documents for improved clustering, because UMAP can reduce the dimensionality of the original data while effectively preserving important features and accelerating the computation process (Abuzayed and Al-Khalifa 2021; McInnes et al. 2018). Next, Hierarchical Density-based Spatial Clustering of Applications with Noise (HDBSCAN) was used for clustering the embeddings. This algorithm can automatically determine the optimal clustering outcomes and efficiently recognize clusters of varying shapes as well as outliers. Lastly, in order to create topic descriptions (i.e., clusters), the Cluster-based

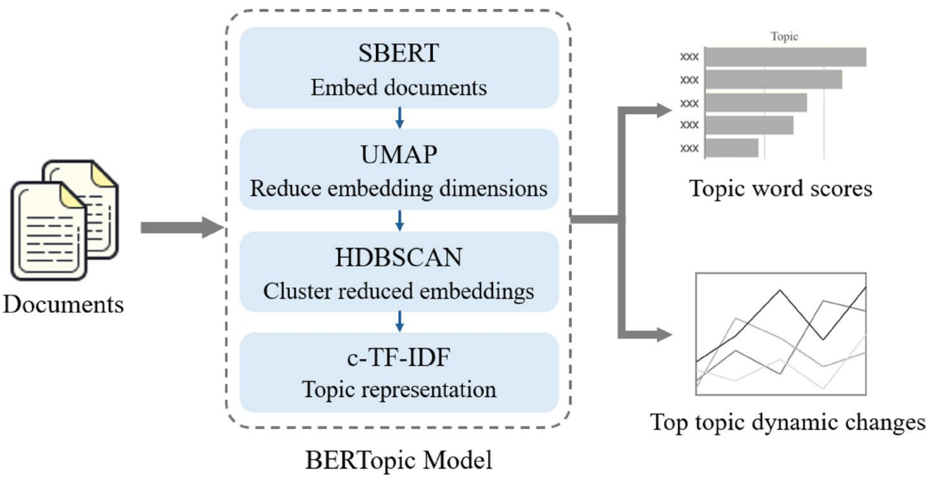


Fig. 3 Workflow of BERTopic

Term Frequency-Inverse Document Frequency method (c-TF-IDF) was utilized to assess the significance of words within a specific cluster and to extract key terms that represent the topic. The formula of c-TF-IDF is represented in Eq. (5).

$$c - TF - IDF_{x,c} = tf_{x,c} \times \log\left(1 + \frac{a}{f_x}\right) \tag{5}$$

where, $c - TF - IDf_{x,c}$ is the weight of a word x in class c, $tf_{x,c}$ is the frequency of word x in the class c, f_x is the frequency of word x across all the classes, and a is the mean value of words per class.

Results

Statistical results

Patterns of Weibo posts

This section examines the level of attention afforded to AVs by social media users, as evidenced by fluctuations in the number of posts and interaction volume, including the numbers of likes, reposts, and comments per day. Figure 4 illustrates this analysis, with time plotted on the x-axis and the quantity of AV-related posts and interaction volume on the y-axis. The overall trend in the number of posts indicates a consistent upward trajectory. From 2015 to 2017, the number of posts gradually increased from nearly 500 to around 20,000. During this period, the interaction volume also rose gradually, primarily consisting of likes and comments, although it remained relatively low overall. Between 2017 and 2019, the growth rate became notably rapid. Simultaneously, the interaction volume increased substantially, with a significant growth in the number of likes. In 2020, the number of posts

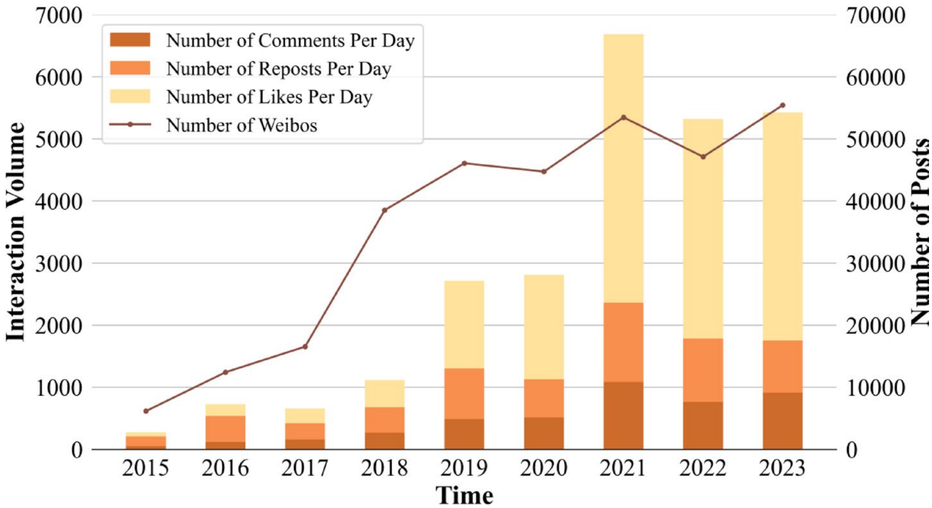


Fig. 4 The number of Weibo posts and the user interaction volume

slightly decreased, but the interaction volume remained. From 2021 to 2023, the post count remained consistently around 50,000, with a peak in 2023, while the level of interaction remained consistently high, reaching its zenith in 2021. Overall, there was a steady rise in discussions surrounding AVs on Weibo over time, with a corresponding increase in user interactions, reflecting growing public interest and engagement in the topic.

Characteristics of Weibo users

This section examines the distribution and proportions of Weibo users interested in AVs based on user type, gender, as well as age.

Individuals and organizations are the two main categories of Weibo users. Within the individual category, accounts are further divided into unverified and verified, with the latter comprising prominent figures or celebrities. Organizations can be subdivided into several types, primarily including educational institutions, enterprises, administrative agencies, and media outlets. Figure 5 presents Weibo user counts, the total volume of posts, and the mean value of followers across these various categories. Upon analyzing individual users, it becomes evident that unverified accounts represent the largest segment in terms of quantity. Nonetheless, their mean follower count per user is relatively modest, suggesting a limited influence, with their Weibo activity primarily reflecting personal views on AVs. On the contrary, verified individual users, despite being a minority, demonstrate a higher posting frequency compared to unverified users. Moreover, they have a notably higher mean follower count per user, indicating a more substantial impact and the capacity to advocate for AVs through their Weibo activity. In terms of organizations, the top three influential categories are media outlets, educational groups, and institutions, followed by government agencies. This indicates that media outlets, educational groups, and institutions play a prominent role in endorsing AVs, facilitating public comprehension of the potential safety, convenience, and benefits linked with autonomous driving. Their efforts bolster the acceptance as well as

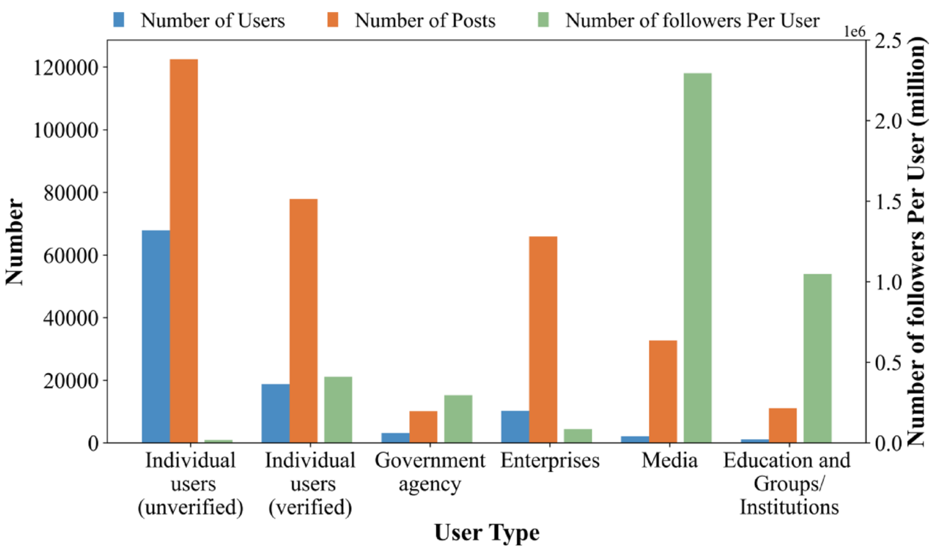


Fig. 5 The quantity of Weibo users and their followers in different categories

utilization of AV tech, along with the development and improvement of emerging transportation systems.

As gender division does not apply to organizations, our analysis focuses solely on the gender distribution among individual users. We identified 86,759 individual users through statistical analysis, comprising 54,582 male users and 32,177 female users. This indicates that, to some extent, men exhibit a greater interest in AVs compared to women. This observation aligns with the general notion that men tend to have a relatively higher interest in technology and engineering fields (Hudson et al. 2019; Li et al. 2024). They may be more inclined to explore and study the technical details, algorithms, and working principles of autonomous driving technology, as well as to show greater interest in the performance and driving experience of AVs. Figure 6 illustrates the number of Weibo users by gender from 2015 to 2023. For both male and female users, the number was relatively low from 2015 to 2017 but saw a sharp increase in 2018 and peaked in 2020. The number of male users decreased in 2021 and 2022, before experiencing another rise in 2023. The number of female users experienced a decline after 2020 and consistently remained below 6,000 from 2021 to 2023. Overall, the number of male users consistently outnumbered female users throughout the years, with both genders demonstrating similar trends. The engagement of Weibo users indicated a substantial increase from 2018 onwards, reflecting broader attention to AV during these years.

In addition to examining the number of users across different gender groups, we also investigated the proportions within different age categories. As Weibo users have the option to include their birth dates in their profiles, the data on user ages is somewhat incomplete. Here, we exclusively focused on individual users even though some may have left the age field blank, as organizations do not possess age classifications. Thus, we identified 45,832 individual users with ages ranging from 18 to 75 years old, as driving is illegal for those under 18 in China. Within this demographic, there are 15,966 individuals aged 18 to 30, 22,775 aged 31 to 45, 6,289 aged 46 to 60, and 802 aged 60 to 75. As shown in Fig. 7, youngsters (ages between 18 and 30 years) exhibit a nearly linear increase in interest in AVs

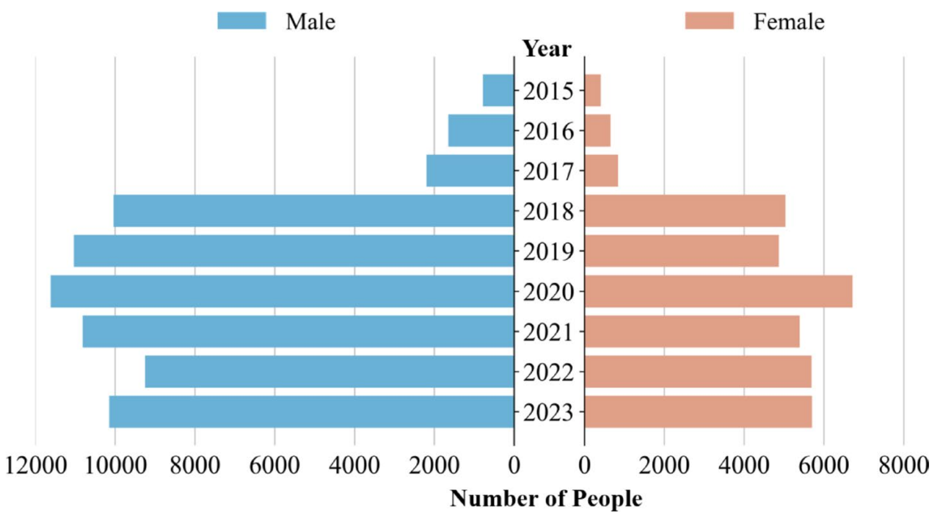


Fig. 6 Gender of Weibo users

from 2015 to 2023, whereas that among users in the 46 to 60 age group has shown a steady decline.

Spatial and flow analysis of public attention

This section explores the level of attention and the flow of interest among users across twenty-three provinces, four municipalities, five autonomous regions, and two special administrative regions, namely Hong Kong and Macao. Figure 8 illustrates the spatial distribution of posts related to AVs and the average post counts per user in various regions. Regions with more posts are represented in darker colors, indicating a greater level of attention and discussion surrounding AVs in these areas. The average number of posts per user who posted about AV posts is represented by the different sizes of circles, measuring engagement among users interested in AVs across different regions. Our result reveals that the central, eastern, and coastal provinces exhibit a higher total number of posts, suggesting that these regions either have a larger population of users interested in AVs or are more active on social media platforms. It is noteworthy that the economically developed regions in China, such as Guangdong, Jiangsu, Shandong, Zhejiang, Fujian, Shanghai, and Beijing (Daily 2023a), serve as primary hubs for representative companies in the AV industry (Qianzhan 2024). Moreover, these regions' governments have implemented more policies regarding AVs, such as scenario testing, technological research and development, and commercial applications (Qianzhan 2021). Therefore, it is plausible that regions with higher economic development or a significant concentration of AV-related enterprises may demonstrate greater attention and activities. There appears to be a correlation between the total number of posts and the average number of posts per user, suggesting that regions with more overall activity also have higher engagement among users interested in AVs. Conversely, some regions, such as Tibet and Taiwan, might show high engagement levels despite having fewer total users interested in AVs.

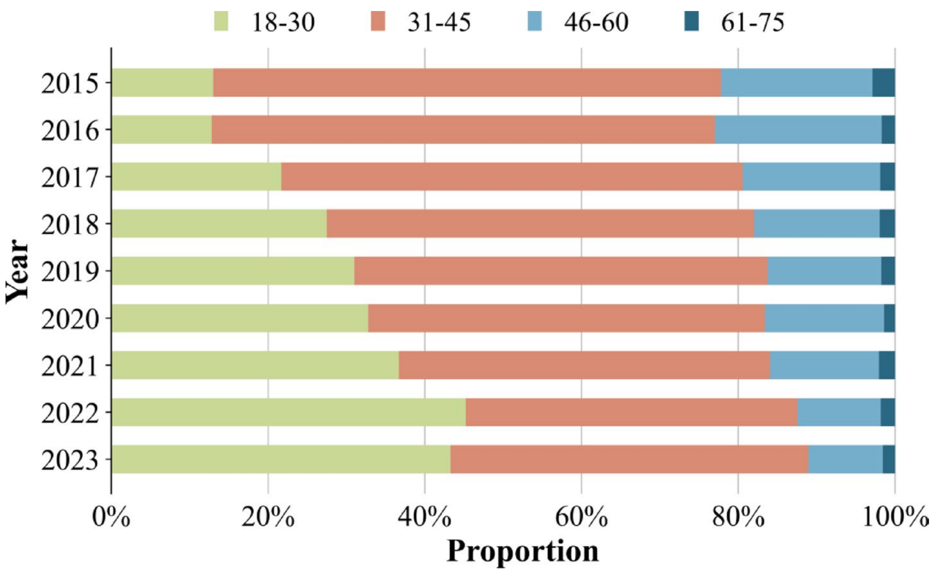


Fig. 7 Age ratio of Weibo users

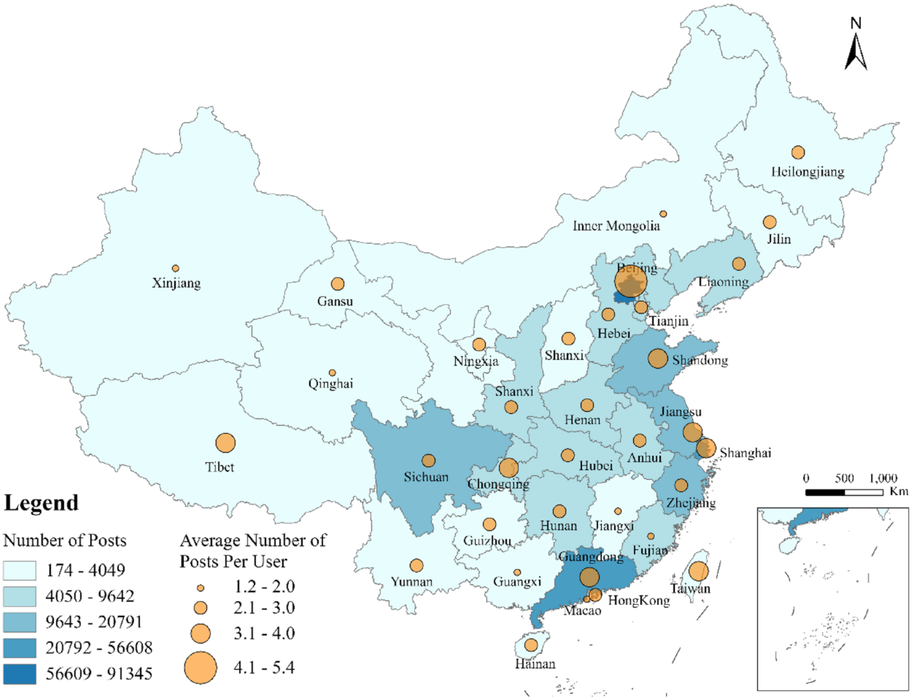
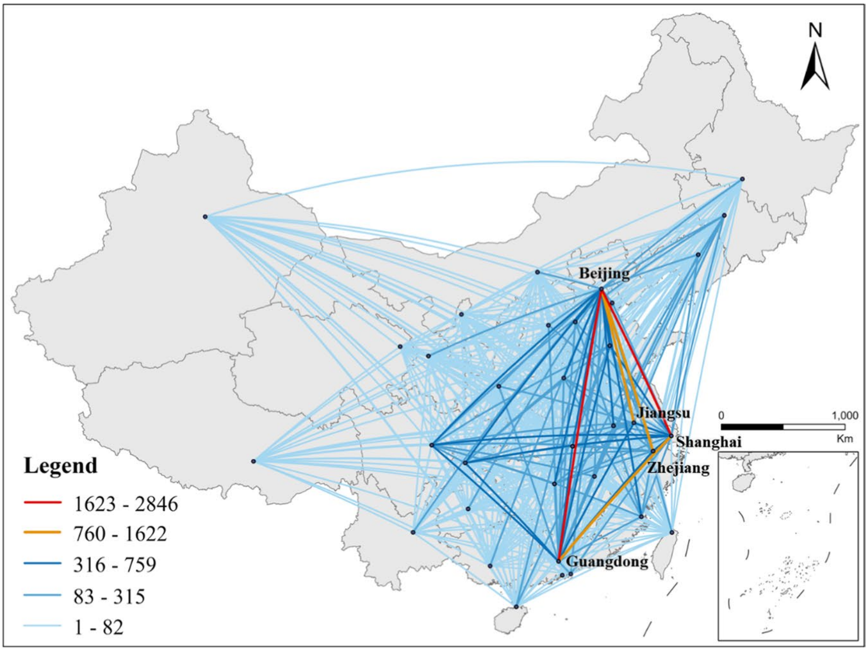
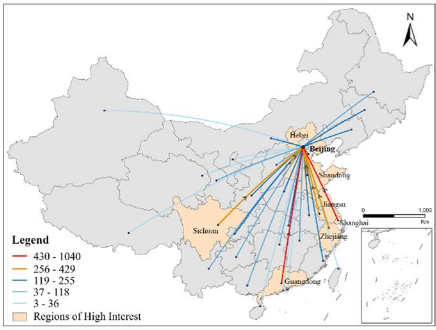


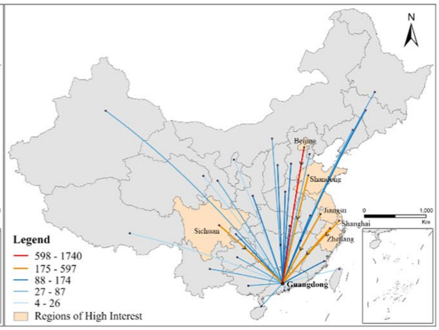
Fig. 8 Spatial distribution of the post counts and average post counts per user

To investigate the primary areas of interest among various provinces, we analyzed the attention flow of users, using their locations as the start points of attention flow and the locations mentioned in posts as the endpoints, transforming locations to a provincial level of granularity. Finally, we obtained 54,044 compliant blog posts, accounting for 16.86% of the total. According to Fig. 9(a), the attention flow in AVs across all provinces in China is illustrated, with the intensity of attention represented by different colors of lines. Provinces like Beijing, Shanghai, Guangdong, Zhejiang, and Jiangsu emerged as active, drawing considerable attention towards AVs while also showing attention to the development of AVs in other regions. Among these, the top four provinces receiving attention from other regions are Beijing, Shanghai, Guangdong, and Zhejiang. In Fig. 9(b), the orange area indicates that AVs in Beijing are receiving high public attention from regions such as Shanghai, Guangdong, Sichuan, Zhejiang, Jiangsu, Shandong, and Hebei, primarily coastal areas and surrounding areas of Beijing. Their attention mainly centers around two topics in Beijing: the AV road testing and the construction of demonstration zones, as illustrated by the topic keywords of Beijing in Fig. 10. In 2015, Volvo conducted the first AV road test and showcase in Asia in Beijing, attracting significant attention. Subsequently, companies like Baidu, Changan, NIO, and Mercedes-Benz obtained licenses for AV road testing. Additionally, Beijing took the lead in establishing AV demonstration areas in China, equipped with full 5G coverage, which garnered attention from other regions. In Fig. 9(c), the public of Beijing, Shandong, Shanghai, Sichuan, Jiangsu, and Zhejiang pay attention to AVs in Guangdong. As indicated by the topic keywords related to Guangdong in Fig. 10, the public is mainly focused on three topics: AV taxis, 5G strategic collaborations, and intelligent connected vehicle man-



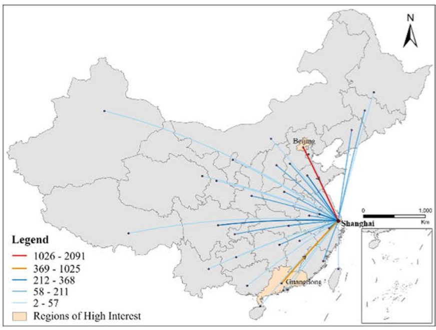
(a) Flow map of China

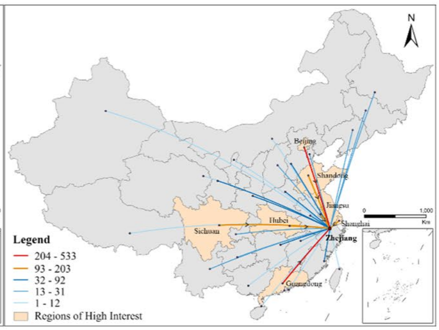




(b) Flow map of Beijing

(c) Flow map of Guangdong





(d) Flow map of Shanghai

(e) Flow map of Zhejiang

Fig. 9 Public attention flow in China

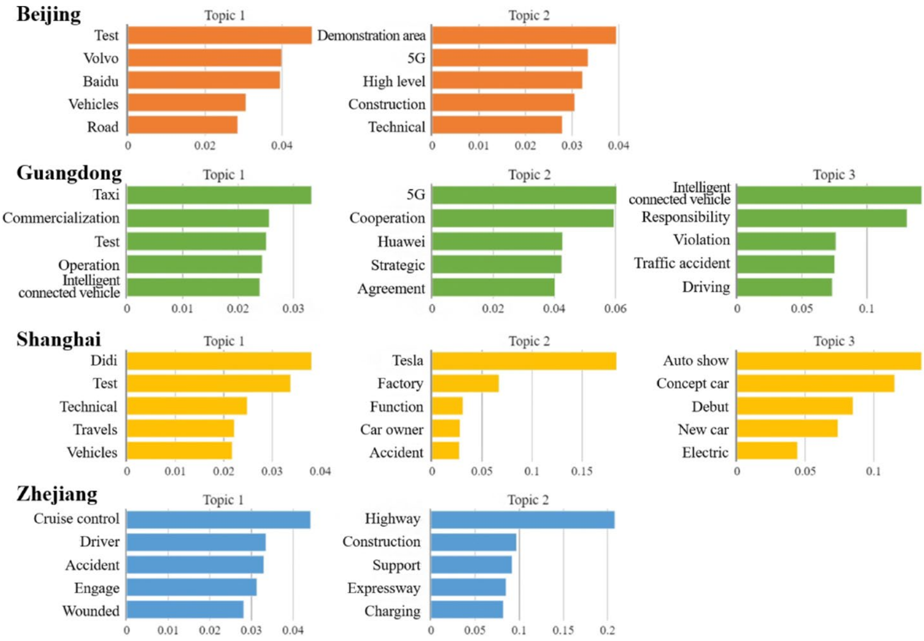


Fig. 10 Topic keywords scores based on c-TF-ID

agement regulations. The first AV taxi commenced trial operation in Guangzhou in 2019, drawing public attention to the commercialization of AV technology. Subsequently, the first AV 5G internet of vehicles demonstration island was established, with full 5G network coverage and strategic cooperation with companies like Huawei and the Chinese Academy of Sciences Software Institute. Additionally, Shenzhen, Guangdong, issued the Intelligent Connected Vehicle Management Regulations, the nation's first official regulatory document that provides detailed delineations on important issues such as responsibility, violation, and traffic accidents for L3 and higher-level AV (Southcn 2022), attracting significant attention. In Fig. 9(d), the attention flow of Shanghai shows that the AVs of Shanghai are of relatively higher attention to users from Beijing and Guangdong. As indicated by the topic keywords related to Shanghai in Fig. 10, users from other regions are interested in topics related to Didi, Tesla, and auto shows. Didi established a subsidiary involving AV technology and launched autonomous taxi services for travel in Shanghai. Regarding Tesla, two aspects garner more attention: the construction of a factory in Shanghai and incidents involving Tesla's autonomous driving function causing traffic accidents on highways in Shanghai. Shanghai, being China's largest international economic center and a cultural metropolis, hosts numerous car shows annually (SMPGIO 2024). Some new or concept cars related to AV at these exhibitions attracted much attention from the public. In Fig. 9(e), it is shown that users from Beijing, Guangdong, Shanghai, Shandong, Sichuan, Hubei, and Jiangsu exhibit relatively higher interest in Zhejiang. As indicated by the topic keywords related to Zhejiang in Fig. 10, topic 1 is about cruise control. Some drivers enjoy using cruise control to enhance their driving experience, but it is different from autonomous driving. In Zhejiang, accidents have occurred due to the misuse of cruise control, resulting in wounded. Topic 2 focuses on highways. Zhejiang is planning to construct China's first highway that supports autonomous driving and wireless charging while in motion. Both of these topics have captured the attention of the public in other regions.

Public sentiment analysis

To evaluate public sentiments regarding AVs, we performed an in-depth analysis of Weibo post content using sentiment analysis. Following model training and validation set testing, the model exhibits good classification performance, achieving an accuracy rate of 91.88%. Figure 11 illustrates the proportion and number of positive and negative posts concerning AVs from Weibo users over a span of nine years. Between 2015 and 2019, both positive and negative Weibo posts experienced a consistent annual increase, accompanied by relatively minor fluctuations in their proportions. The proportion of positive posts remained around 90%. In contrast, from 2020 to 2023, the quantity of positive posts stabilized at approximately 40,000, whereas the count of negative posts exhibited a marked increase. Moreover, the proportion of negative posts also showed an upward trend. Throughout the years, most posts were positive, indicating generally favorable public attitudes towards AVs. Although positive sentiment remained dominant, the proportion of negative posts has notably increased since 2020, peaking in 2023. This rise in negative sentiment may indicate growing public concerns or criticisms regarding AVs.

In addition to conducting sentiment analysis on all posts, we also conducted sentiment analysis on Weibo users of different genders and ages. Since gender and age division is not applicable to organizations, our analysis focuses solely on the post ratio of individual users. We obtained 131,830 posts from male users and 52,871 posts from female users

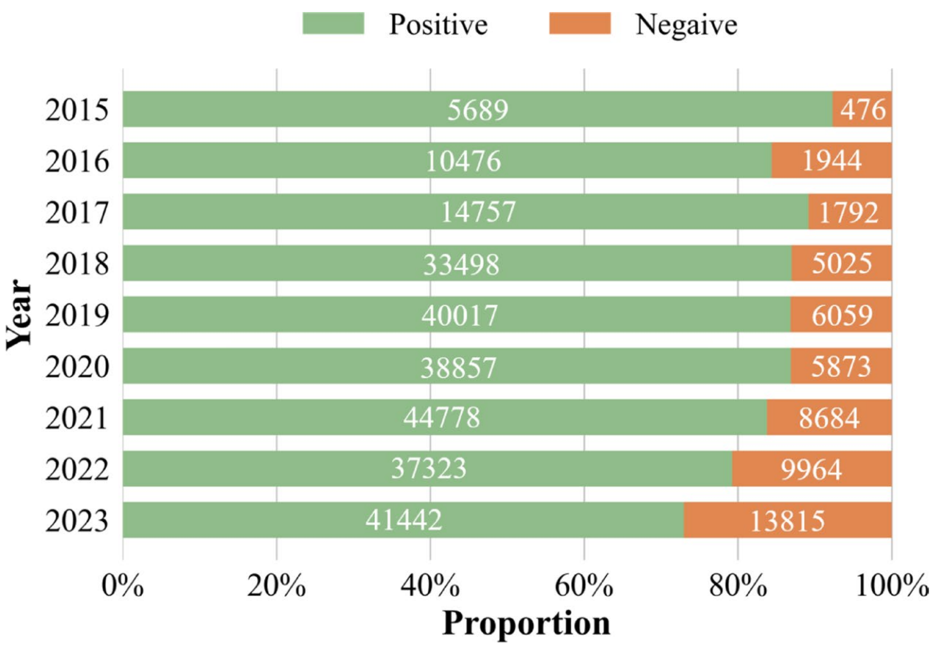


Fig. 11 Number and proportion of positive and negative posts

through statistical analysis. Of these, we identified 90,363 individual posts that included age information. Among these users, there are 28,314 posts in the 18–30 age group, 44,604 posts in the 31–45 age group, 10,366 posts in the 46–60 age group, and 1,886 posts in the 61–75 age group. Due to the relatively small data size and missing values in certain years for the 61–75 age group, it is not representative, and therefore we did not discuss it in this analysis. Figure 12 presents the proportion of positive posts about AVs on Weibo from 2015 to 2023, segmented by gender and age groups. The top graph compares the overall proportion of positive posts between female and male users, while the bottom graphs break down this data further by age groups (18–30, 31–45, and 46–60) for each gender. In the top graph, both female and male users had a similar trend of proportion. From 2015 to 2019, the proportion of positive posts fluctuated slightly but generally remained high (above 0.8), and the proportion of positive posts from female users consistently surpassed that of male users during this period. From 2020 onwards, there was a noticeable decline in the proportion of positive posts for both genders, with female users exhibiting a sharper decline in positive sentiment. This trend may be attributed to the greater societal influence on women and their higher risk perceptions (Kapser et al. 2021). As shown in Fig. 11, the proportion of negative posts increased significantly around 2021, and female users appear to be more affected by this negative information. Additionally, much of this negative content is related to AV safety and technological reliability, which may have further contributed to the decline in positive sentiment among female users. In the bottom graphs, similar fluctuation trends are observed among different gender groups within the same age range. Among different age groups, the difference in the proportion of positive posts is more prominent among female users compared to male users. The 18–30 age group of both genders exhibited more significant fluctuations in the proportion of positive posts over the years, while the 31–45 age group

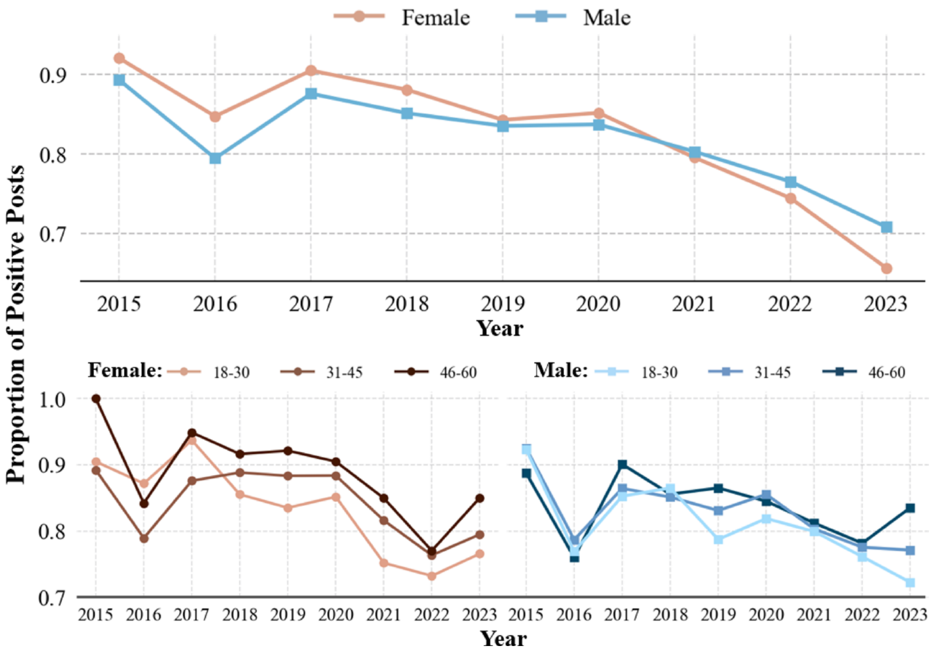


Fig. 12 Proportion of positive posts in different gender and age group

showed a relatively stable proportion. The 46–60 age group, based on the available data, consistently demonstrated a high proportion of positive posts.

Public dynamic topic

To explore how public sentiment is influenced, we extracted the top 10 topics influencing public sentiment from positive and negative posts and analyzed the dynamic changes in these topics from 2015 to 2023. Figure 13 illustrates the evolutionary process of the top 10 positive topics, including the application of AV technology, cruise control and driving assistance, software technology collaboration, Volvo entering into Asia, vehicle appearance recognition, car exhibition test drive experience, infrastructure construction, concept cars, road testing, and reducing accident risks. Among these, the "Application of AV technology" (Topic 1) shows a significant and sustained increase in frequency, peaking around 2019 and maintaining a high level of attention thereafter. "Cruise control and driving assistance" (Topic 2) also exhibits a steady rise, particularly prior to 2021. Other topics, such as "Software technology collaboration" (Topic 3) and "Volvo enters into Asia" (Topic 4), show more moderate trends with occasional fluctuations. The remaining topics (from Topic 5 to Topic 10) remain relatively low in frequency but show minor increases over time. Overall, public attention to AV technology and related topics is on the rise, which significantly contributes to the prevailing positive attitudes. Since 2017, the Chinese government has been increasingly emphasizing AV technology, introducing a series of policies and regulations to promote its development (Mallesons 2017). Therefore, AV technology has seen greater application and advancements, while AV-related infrastructure has been constructed. The application and implementation of features like cruise control and driver assistance functions not only enhance driving experiences but also help mitigate accident risks to a certain extent.

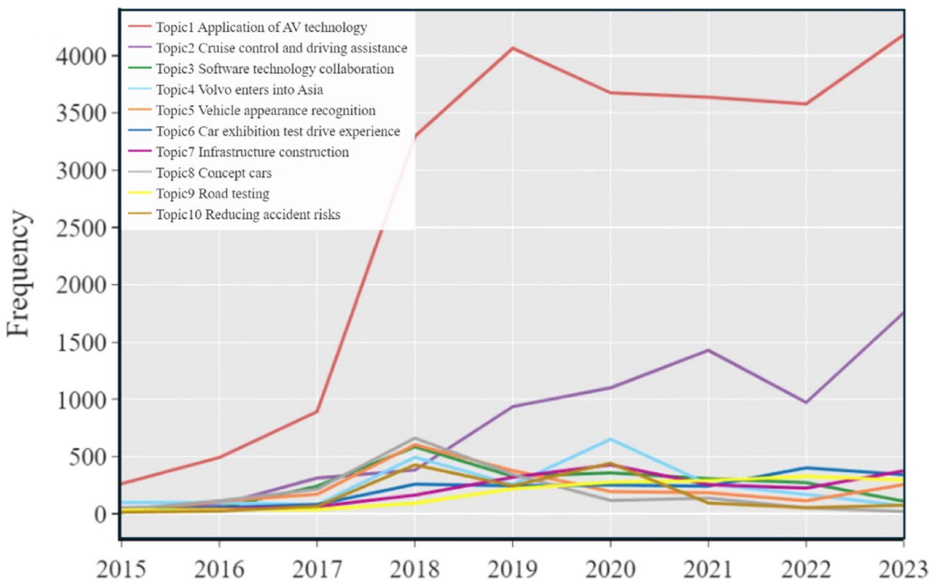


Fig. 13 The dynamic evolutionary process of positive topics

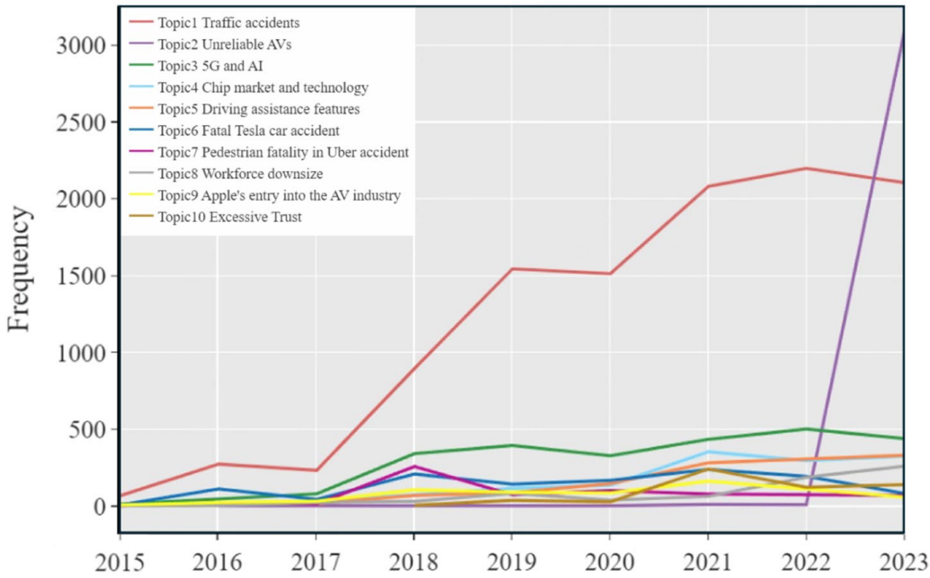


Fig. 14 The dynamic evolutionary process of negative topics

Figure 14 illustrates the dynamic evolutionary process of the top 10 negative topics, including traffic accidents, unreliable AVs, 5G and AI, the chip market and technology, driving assistance features, the fatal Tesla car accident, pedestrian fatality in Uber accident, workforce downsize, Apple's entry into the AV industry, and excessive trust. "Traffic accidents" (Topic 1) is the most prominent concern, showing a sharp rise beginning in 2017 and maintaining a high frequency of discussion. Recently, in 2023, "Unreliable AVs" (Topic 2) witnessed a substantial spike, indicating growing concerns about the reliability of AV technology. Specific incidents such as the "Fatal Tesla car accident" (Topic 6) and the "Pedestrian fatality in Uber accident" (Topic 7) show spikes, indicating heightened media and public attention during those periods. Emerging technological issues like "5G and AI" (Topic 3) as well as challenges in the "Chip market and technology" (Topic 4) have gained increased scrutiny over time, highlighting potential obstacles in technological infrastructure and advancement. Additionally, topics such as "Workforce downsize" (Topic 8) and "Excessive trust" (Topic 10) also generate negative discussion, possibly due to societal and ethical concerns related to job displacement and overreliance on automated systems.

Comparing the dynamic evolutionary processes of positive and negative topics, both exhibited an overall upward trend from 2015 to 2019. However, starting around 2021, positive topics showed little change in trend, whereas negative topics continued to rise. As shown in Fig. 14 and Table. D2 in the Supplementary Materials, "Traffic accidents" (Topic 1) and "5G and AI" (Topic 3) experienced continuous growth from 2020 to 2022, while "Unreliable AVs" (Topic 2) surged sharply in 2023. These three negative topics primarily reflect concerns about AV safety and technological reliability, and their increasing trends coincide with the rise in both the number and proportion of negative posts in Fig. 11 since around 2021.

Conclusion

This study collected Weibo posts and user data concerning AVs from 2015 to 2023. The analysis examined Chinese social media users' attention and attitudes towards AVs from sentimental, statistical, and spatiotemporal perspectives. The findings indicate a significant increase in public attention and engagement over time, characterized by a consistent upward trend in both post quantity and interaction volume. Examination of Weibo user categories indicates that unverified individual users form the largest group expressing opinions on AVs, while media, education, and institutional sectors exhibit higher levels of engagement and impact. Demographically, men show more attention to AVs than women, and the proportion of young users (18–30 years old) is rising annually. In terms of spatial distribution, public attention correlates with regional economic development, with central, eastern, and coastal provinces, including Beijing, Shanghai, Guangdong, and Zhejiang leading in discussions and engagement. Sentiment analysis further explores the factors influencing the development of AVs, revealing that while overall attitudes towards AVs have been predominantly positive over time, there has been a noticeable uptick in negative sentiment since 2020. The rise in negative sentiment, especially concerning safety and technological reliability, highlights the growing public scrutiny and challenges confronting the AV industry, even as interest and technological advancements continue to progress.

Drawing from the results, this research proposes the following recommendations, in order to improve the development and public perception of AVs in China. In the short term, given the substantial influence of high-profile incidents on public sentiment, companies and regulators should establish robust crisis management strategies. This includes strengthening crisis communication by swiftly and transparently responding to any accidents or failures involving AVs and providing timely public updates to maintain trust. Additionally, AV developers should regularly provide updates on safety measures, successful road tests, and the integration of new technologies aimed at reducing accident risks to further reassure the public. In the long term, policymakers and AV developers should collaboratively develop comprehensive AV safety standards and clear legal frameworks and consider implementing more targeted regulations that address public concerns, such as those related to workforce displacement and the ethical implications of AV technology. Moreover, policymakers are encouraged to facilitate cooperation between AV-related enterprises and technology firms on innovations like 5G and AI, which possess the potential to enhance AV performance and public perception. Furthermore, expanding AV demonstration zones and pilot programs in economically developed regions, as well as underserved areas, could also help demonstrate the practical benefits of AVs, to increase user confidence and enhance long-term acceptance.

This study aids in understanding public attention and attitudes towards AVs and informs policy development while addressing existing challenges. However, certain limitations persist. First, due to limitations on Weibo user authorizations, the data collected is not comprehensive. For example, some posts are visible only to friends, rendering this data inaccessible. Secondly, Weibo users tend to be relatively young. For a more thorough analysis of Chinese public attention to AVs, future studies could incorporate data from additional social media platforms. Thirdly, there may be a correlation between regional attention on AVs and regional Weibo penetration rates, but this cannot be explicitly examined with our data. This limitation should be considered when the empirical findings of this study are applied in any real-world policy making and planning. Lastly, while this study only focuses on Chinese AVs, future research could expand its scope globally to contrast public opinions and viewpoints on social media platforms both domestically and internationally.

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Author contributions Y.L.: Acquisition of data, Methodology, Visualization, Formal analysis, Writing - Original draft - Review & Editing. J.T.: Formal analysis, Writing - Review & Editing. S.W.: Methodology, Writing - Review. Z.P.: Formal analysis, Writing - Review. C.Z.: Conceptualization, Formal analysis, Writing - Review & Editing.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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Yuan Li is a PhD student in the MOBI Research Group at Vrije Universiteit. She received her B.S. degree from Hunan Normal University in 2020, and her M.S. degree from The Hong Kong Polytechnic University in 2024. Her research interests include text mining, smart mobility, and spatial big data analysis.

Justin Hayse Chiwing G. Tang is a PhD student in the Department of Land Surveying and Geo-Informatics (LSGI) at the Hong Kong Polytechnic University (PolyU). He received his B.S. degree from the Hong Kong Polytechnic University and his M.S. degree from the Hong Kong University of Science and Technology. His research is focused on transportation planning, travel behavior, geoinformatics, and spatial agent-based modeling.

Shengyou Wang earned her Ph.D. degree from Beijing Jiaotong University, Beijing, China, in 2022. She is currently an assistant professor at the School of Traffic Management, People's Public Security University of China. Her research interests include intelligent transportation, deep learning, and traffic flow theory.

Zhenhan Peng is a PhD student in the Centre for Industrial Management/Traffic and Infrastructure at KU Leuven. His research work focuses on the deployment of electric vehicle (EV) infrastructure, fuel options for electric mobility, spatial big data analysis, and large-scale micro-simulation.

Chengxiang Zhuge received his B.S. and first Ph.D degrees in transportation from Beijing Jiaotong University and a second Ph.D. degree in geography from the University of Cambridge. He is an Assistant Professor in the Department of Land Surveying and Geo-Informatics (LSGI) at the Hong Kong Polytechnic University (PolyU). Prior to joining PolyU, he was a Senior Research Associate at the University of East Anglia, United Kingdom. His research tries to investigate complex dynamic urban systems, primarily using agent-based modeling and big data.

Authors and Affiliations

Yuan Li[1,8] · Justin Hayse Chiwing G. Tang[1,2] · Shengyou Wang[3] · Zhenhan Peng[1,7] · Chengxiang Zhuge[1,4,5,6,9]

✉ Chengxiang Zhuge
chengxiang.zhuge@polyu.edu.hk

Yuan Li
yuan-ly.li@connect.polyu.hk

Justin Hayse Chiwing G. Tang
jhcwgtang@connect.ust.hk

Shengyou Wang
sywang618@foxmail.com

Zhenhan Peng
zhenhan.peng@connect.polyu.hk

1 Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China

2 Division of Environment and Sustainability, The Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong, China

3 School of Traffic Management, People's Public Security University of China, Beijing, China

4 Research Institute for Sustainable Urban Development, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China

5 Smart Cities Research Institute, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China

6 The Hong Kong Polytechnic University Shenzhen Research Institute, Shenzhen, China

7 Centre for Industrial Management/Traffic and Infrastructure, KU Leuven, Leuven, Belgium

8 Department of Business Technology & Operations, MOBI Research Group, Vrije Universiteit Brussel, Pleinlaan 2, 1050 Brussels, Belgium

9 The Hong Kong Polytechnic University Shenzhen Technology and Innovation Research Institute (Futian), Shenzhen, China