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Drivers of Public Engagement in Social Media Discourse on Self-Driving

Vehicles: Psychological and Emotional Determinants

Abstract

Research on self-driving vehicles (SDVs) has largely overlooked the influence of framing strategies on public interests and public engagement on social media discourse regarding SDVs. We address this gap by analysing 102,174 Twitter posts to examine how emotional sentiment and psychological distance shape engagement across private, public, and commercial SDV contexts. Grounded in Construal Level Theory and Appraisal Theory of Emotion, we identify thematic and emotional drivers of interaction. By leveraging large-scale social media analysis, this study advances understanding of the cognitive and emotional mechanisms underlying SDV discourse, offering insights for more effective public communication and consumer engagement strategies. Our analyses show that psychologically proximal topics (e.g., safety or pricing) elicit stronger engagement in private vehicle discourse due to personal relevance. Further, high-arousal negative emotions (fear, anger) spark immediate, intense responses, while low-arousal positive emotions (happiness) encourage sustained, reflective engagement.

Keywords: Self-driving vehicles, public transport, commercial vehicles, public engagement, Construal Level Theory, Appraisal Theory of Emotion.

1. Introduction

The transportation sector is undergoing a rapid technological transformation, with artificial intelligence (AI) emerging as a key enabler in creating more efficient mobility solutions (Turienzo, Cabanelas and Lampón, 2023; Innovate UK, 2024; Liu *et al.*, 2025). Among these innovations, self-driving vehicles (SDVs) or autonomous vehicles (AVs) have gained significant attention due to their potential to address numerous systemic challenges across passenger and freight mobility. Autonomous mobility technologies are being deployed to revolutionise services such as robo-taxis and last-mile delivery, using aerial drones (Beninger & Robson, 2025) and ground-based robots (De Maio *et al.*, 2024). Beyond their gains in operational efficiency, SDVs also offer solutions to critical societal challenges, including mobility for elderly and disabled individuals (Porru *et al.*, 2020), the shortage of freight drivers (Sindi & Woodman, 2021), and the need to reduce road traffic accidents (Petrović, Mijailović and Pešić, 2020). To support the development and deployment of SDVs, governments and industries around the world have made major investments. Most recently, the Automated Vehicles Act, passed in May 2024, provides a legal framework for SDV deployment on UK roads by 2026, aiming to unlock a £42 billion industry and generate 38,000 skilled jobs by

2035 (GOV.UK, 2024). Globally, the autonomous vehicle market could reach revenues of \$300–400 billion by 2035 (McKinsey & Company, 2023).

While advances in technology and regulation are necessary, they are not sufficient to ensure the widespread adoption of SDVs. Public acceptance remains a critical barrier, as societal concerns continue to shape the trajectory of autonomous mobility. Scholars have pointed to potential downsides, such as increased congestion from empty vehicle circulation (Simoni *et al.*, 2019), and the risk of deepening social inequalities by limiting access for underrepresented or vulnerable populations (Hall, Matos and Martin, 2014). These concerns have elevated issues of inclusivity, ethics, and trust in public discourse around SDVs (UK Government, 2023; Yoo *et al.*, 2024). Understanding how the public perceives and emotionally responds to SDVs is therefore essential, not only for anticipating the key success factors but also for shaping policies, technologies, and communication strategies that promote equitable and trusted implementation.

Existing research on the factors influencing consumer acceptance of SDVs spans government-sponsored studies (GOV.UK, 2023), industry reports (Lang *et al.*, 2020; PwC, 2023), and academic literature (Talebian and Mishra, 2018; Wang and Zhao, 2019; Yoo, Kumagai and Managi, 2024). For instance, Manfreda *et al.* (2021) and Dubey *et al.* (2022) employed structured questionnaires to explore determinants of SDV acceptance, while Gopinath and Narayanamurthy (2022) advanced the field through a meta-analysis of 65 studies involving 37,076 participants, synthesising key topics in SDV and consumer attitude. Despite these contributions, much of the existing research remains limited by its reliance on traditional survey methodologies, which are often constrained by small sample sizes, temporal limitations, and a narrow focus on specific transport modes (Sindi and Woodman, 2021; Laurell and Sandström, 2022). In contrast, the potential of social media data, where individuals spontaneously express opinions, preferences, and emotions, remains largely untapped in the context of SDV adoption. This gap is significant, given the increasingly influential role of social media in shaping and reflecting public discourse (Ramanathan, Subramanian and Parrott, 2017). As Kaplan and Haenlein (2010) observe, social media platforms serve as modern digital public squares, where users actively generate and consume content.

Zhan *et al.* (2020) highlight the positive impact of social media on new product development, underscoring its relevance to innovation and market responsiveness. Platforms such as X (formerly Twitter), YouTube, and Reddit provide real-time, large-scale access to diverse public perspectives (Liu, 2012; Sun, Luo and Chen, 2017), making them ideal for mining sentiment around emerging technologies. Analysing such data can offer policymakers

and SDV manufacturers valuable insights into the drivers of public engagement with SDV-related content and how these vary across segments of the transport and technology industries. Building on this foundation, the present study addresses three central research questions:

RQ1: What are the predominant topics in social media discourse regarding self-driving vehicles (SDVs)?

RQ2: How do relationships between various topics and emotions influence the public engagement with SDV-related social media content?

RQ3: To what extent do these relationships differ across key SDV market segments (e.g., commercial, public, and private)?

To address these questions, this study aims to contribute to the emerging body of research on public opinion on SDV by applying opinion mining techniques to a large-scale dataset of social media posts. Drawing on psychological and information processing theories and using a dataset of 102,174 tweets posted between March and June 2022, we conducted a multi-step analysis involving emotion detection. (Text2Emotion, 2020), topic modelling via Latent Dirichlet Allocation (Blei, Ng and Jordan, 2003), lexicon-based sentiment scoring (Hutto and Gilbert, 2014), and finally econometric analysis. The econometric model was revalidated in a multi-group study focusing on three key market contexts: commercial vehicles, public transport, and private cars. By synthesising these methods, we aim to uncover nuanced insights into public engagement and its implications for SDV deployment strategies.

Our findings reveal that public sentiment toward SDVs is generally positive, but engagement patterns vary substantially across topics, emotional expressions, and transport segments. While happiness remains a strong predictor of engagement, particularly within the Private Cars subset, our results show that engagement is not uniformly driven by positive affect. Instead, topic relevance and psychological distance play a decisive role. In the Commercial segment, infrastructure-related content framed at a high construal level generated the strongest positive engagement, reflecting the strategic, system-level priorities of fleet and industry stakeholders. In the Public Transport segment, infrastructure framed at a low construal level produced the highest engagement, indicating that concrete, near-term improvements resonate most strongly with public transport users. Across the Whole dataset and the Private Cars subset, safety, traffic, and infrastructure consistently evoked strong emotional responses, confirming their centrality in public perceptions of SDVs. Engagement patterns further varied across market segments. In the public transport category, traffic, both in low- and high-construal contexts, generated the second- and third-highest levels of interaction, while commercial SDV discussions centred on low-construal, concrete employment and technology topics, suggesting

that practical, operational concerns dominate this space. Traffic and infrastructure consistently emerged as high-engagement topics across all segments, underscoring their salience in public attitudes toward SDVs.

Theoretically, this study advances SDV-related transportation policy research by combining psychological theory with large-scale social media data. Drawing on Construal Level Theory, we show that psychological proximity increases engagement with personally relevant issues such as safety, infrastructure, and traffic. However, our findings also reveal that CLT effects are not uniform: psychological proximity amplifies engagement primarily in identity-relevant domains (e.g., private vehicles), whereas public transport and commercial contexts exhibit attenuated or even reversed sentiment–engagement relationships. This demonstrates that psychological distance is not solely a property of content but is dynamically shaped by audience–segment identity. We further extend the Appraisal Theory of Emotion by demonstrating that high-arousal negative emotions (e.g., fear, anger) drive reactive engagement, especially in personally relevant contexts (e.g., private vehicles), while low-arousal positive emotions (e.g., happiness) foster more reflective, sustained interaction. Machine-learning interpretability analyses reveal additional non-linear mechanisms: happiness and fear follow inverted U-shaped patterns, safety sentiment shows diminishing returns at high positivity, and traffic sentiment exhibits a U-shaped effect, suggesting polarised reactions. By examining these dynamics across transport segments, we refine the conceptualisation of psychological distance as a dynamic, context-sensitive factor influencing SDV-related engagement.

From a managerial perspective, our findings offer strategic guidance for public communication around SDVs. Emotionally resonant, psychologically proximal messages, particularly those focused on safety, pricing, infrastructure, and traffic, enhance engagement, especially among private vehicle users. However, while high-arousal negative emotions can capture attention, they risk backlash if not countered with transparent, reassuring messaging. In contrast, low-arousal positive content builds trust and long-term receptivity. The variation in emotional responses across private, public, and commercial contexts points to the need for tailored messaging: emphasising personal relevance in private transport, and highlighting innovation, efficiency, and public benefit in broader mobility narratives. These insights provide a nuanced foundation for designing communication strategies that align with audience motivations, emotional dynamics, and the evolving public discourse around autonomous mobility.

2. Literature Review

2.1. Self-driving Vehicles: Adoption and Public Opinions

Traditional research in the domain of SDV adoption has used established models, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Manfreda, Ljubi and Groznik, 2021) and the Innovation Diffusion Theory (IDT) (Talebian and Mishra, 2018, 2022; Ghasri and Vij, 2021). Additional frameworks, including trust and risk-based theories (Lee and Mirman, 2018; Wang and Zhao, 2019; Bertrandias *et al.*, 2021; Yoo, Kumagai and Managi, 2024), and Construal Level Theory (CLT) (Schandl, Lermer and Hudecek, 2024), have provided valuable psychological and contextual insights into user acceptance of emerging technologies. Existing research indicated that the public opinion on SDVs is shaped by a multifaceted interplay of social and socio-technical factors, including safety concerns, technological advancement, infrastructure readiness, traffic efficiency, employment implications, pricing strategies, and social influence. (Gopinath & Narayanamurthy, 2022; Lee & Mirman, 2018; Talebian & Mishra, 2018, 2022; Yoo *et al.*, 2024; Zhu *et al.*, 2020).

Safety remains the most decisive factor influencing trust and attitude. Gopinath and Narayanamurthy (2022), in a meta-analysis of 65 studies ($n = 37,076$), found trust, perceived safety, and perceived risk to be the most cited safety factors shaping public acceptance. Wang and Zhao (2019) further underscored the significance of risk preferences in SDV design through a survey of 1,142 participants in Singapore. Ethical considerations also matter—Karnouskos (2020) highlighted that cross-cultural norms influence perceptions of SDV decision-making, especially in accident scenarios, and suggests pluralism as a framework for developing ethical algorithms. Manfreda *et al.* (2021) showed that improved perceptions of safety can offset other concerns, particularly among younger users. Technology readiness is another key determinant. Lee and Mirman (2018), in a U.S. survey of 985 parents, found that acceptance was significantly driven by intentions to use SDVs and tech-readiness, influenced by demographics like location and child age. Similarly, Schandl *et al.* (2024) found that psychological proximity, such as a near-future timeline, increases openness to autonomous shuttles. Yoo *et al.* (2024), surveying over 69,000 individuals in Japan, showed that SDV adoption increases among disaster-affected communities when supported by reliable infrastructure and social networks. Commercial SDV segments also reflect unique dynamics. Talebian and Mishra (2022) surveyed 400 U.S. trucking professionals and found strong belief in the superiority of autonomous trucks. In contrast, Sindi and Woodman (2021) highlighted

UK freight experts' concerns about job displacement; 60% viewed the employment impact negatively. This “dual-edged sword” (Carbajal-Pina and Acur, 2025) underscores the tension between automation benefits and labour disruption. Pricing and financial incentives are also pivotal. Talebian and Mishra (2018) demonstrated that wide SDV adoption by 2050 would require annual price drops of 15–20%. Word-of-mouth also shapes uptake. Dubey et al. (2022) caution that ignoring Word-Of-Mouth in models may bias forecasts by 20%.

Social influence, especially via media, is pervasive. While existing studies on SDV have extensively employed traditional surveys, which, despite their value, are often limited by small sample sizes, time-bound data, and a narrow focus on specific transportation modes. This leaves critical gaps, particularly in social media-based studies and market-segment-specific insights. Unlike surveys, social media offers organic expressions of public opinions, preferences, and emotions, yet remains understudied in SDV-related research. Our study addresses this gap by leveraging social media data to analyse SDV acceptance across public, commercial, and private vehicle contexts.

2.2. Social Media Discourse on SDV

While several studies, as discussed in section 2.1, have focused on key factors of acceptance of SDVs, they have mainly adopted structured, static survey environments, often overlooking the dynamic and affect-rich discourse available on social media platforms. On the other hand, a few studies have also focused on social media discourse on SDVs. Chen et al. (2021) found that the opinions received in surveys and the opinions expressed in social media such as Reddit are systematically different. Ding *et al.* (2021) addressed this by analysing 365,465 tweets on SDVs, manually labelling 800, and using SVM to classify the rest. Time-series and topic modelling (via LDA) revealed five discussion topics, noting that general users were more reactive to social events than high-frequency tweeters. Laurell and Sandström (2022) conducted a multi-platform analysis of 100,283 posts related to Tesla's Autopilot in Sweden, showing platform consistency and slightly stronger sentiment trends on blogs and Facebook. Despite limitations due to the black-box nature of the data collection platform, the study offers insights into cross-platform sentiment dynamics. Kohl *et al.* (2017) manually labelled 7,482 out of 601,778 SDV tweets to classify sentiment into risk, benefit, or neutral. Their SVM model found that neutral sentiment dominated (76.4%), while risk-oriented tweets slightly exceeded benefit-related ones. Li et al. (2025) captured the changing sentiment with autonomous vehicles in the Chinese context.

While existing studies have examined various theories influencing public attitude towards SDV and focused on public discourse in social media, they have largely overlooked the critical role of engagement drivers, key elements that influence public discourse and willingness to adopt the technology. Understanding these drivers is essential for designing effective strategies to encourage SDV adoption. Addressing this gap, we examine large-scale Twitter datasets to identify not only the dominant topics surrounding SDVs but also the underlying engagement drivers that shape public perception and SDV adoption intentions. By doing so, we provide implementable insights into how social media discourse influences technology acceptance, offering a data-driven complement to traditional survey-based methodologies.

Moreover, in contrast to prior approaches, this study utilises large-scale social media data to explore how emotional and psychological factors shape public engagement with SDVs across different transport segments, including private, public, and commercial applications. Such contextual difference of the engagement drivers provides a nuanced understanding for the policy makers and managers, which is otherwise not available in the extant literature.

3. Theoretical Model

3.1. Construal Level Theory

We develop our theoretical model based on the Construal Level Theory (CLT). CLT is a psychological framework that explains how people perceive, evaluate, and react to objects, events, or information based on their perceived psychological distance from them. Developed by Trope and Liberman (2010), CLT posits that individuals mentally represent psychologically near events in more concrete, detailed, and contextual terms (low-level construal), whereas psychologically distant events are construed more abstractly, with broader, generalised features (high-level construal). Psychological distance can be temporal (time), spatial (physical location), social (interpersonal closeness), or hypothetical (likelihood of occurrence) (Trope and Liberman, 2010).

CLT has been increasingly used in transport policy research to study public support for future mobility systems, climate-friendly transport options, and infrastructure planning. Empirical studies consistently show that low-emission transport policies receive greater support when they are framed in temporally immediate and socially relevant ways. For instance, Wang *et al.* (2021) show that when people see themselves as globally mobile “citizens of the world,” spatial distances collapse and they are more willing to help far-away beneficiaries, a mechanism that transport scholars now borrow to make futuristic mobility feel

personally relevant. Nguyen and Fujita (2024) extends this logic to climate-friendly transport, demonstrating that policy messages framed around near-term, personally experienced benefits (e.g., cleaner air this year) elicit stronger regulatory support than abstract, long-horizon appeals. Likewise, Schandl *et al.* (2024) show that temporal and psychological proximity increases the intention to use autonomous shuttle buses. At the network-design scale, Thompson Sargoni and Manley (2023) embed CLT directly into an agent-based pedestrian model, revealing that travellers alternate between high-level neighbourhood goals and low-level street choices—evidence that planners must match information granularity to travellers’ mental zoom. Empirical policy work echoes the same pattern: Zhai and Wolff (2021) find that London’s Low-Emission Zone has gained traction once officials foregrounded immediate local health gains, linking temporal and social proximity to higher compliance. Similarly, Haboucha *et al.* (2017) found that when AV policies were framed in terms of personal utility and safety (psychologically close), they received more public support than when framed in terms of urban planning or industry-wide effects (psychologically distant). These applications affirm that how transport innovations are communicated, especially across psychological dimensions, significantly shapes public attitudes and engagement.

3.2. Appraisal Theory of Emotion

We also rely on the Appraisal Theory of Emotion for the theoretical model. Emotion Appraisal Theory posits that emotions arise from individuals’ cognitive evaluations of events along dimensions such as goal relevance, certainty, control, responsibility, and novelty (Lazarus, 1991; Roseman, 1991; Roseman and Smith, 2001; Moors *et al.*, 2013). Rather than treating emotions as automatic reactions, the theory emphasizes that discrete emotions are generated through systematic appraisals of how events relate to personal goals and situational interpretations (Roseman, 1991). These appraisal-driven emotions subsequently shape behavioural tendencies, including approach, avoidance, expression, and communication (Roseman and Smith, 2001).

In social media contexts, users continuously appraise posts, narratives, and visual content before engaging through likes, comments, or shares. (Syrdal and Briggs, 2018; Trunfio and Rossi, 2021). Research increasingly recognizes that engagement is not driven solely by emotional intensity but by the type of emotion elicited, which reflects underlying appraisal processes. (Lazarus, 1991; Nabi, 1999). For instance, appraisals of novelty and unexpectedness often generate surprise or amusement, leading to immediate but short-lived engagement. (Berlyne, 1960; Scherer, 2001), whereas appraisals of certainty, stability, and long-term benefit

tend to evoke emotions such as admiration, contentment, or trust, which are associated with more sustained and deliberative forms of engagement (Scherer, 2005; Algoe and Haidt, 2009). Similarly, appraisals involving perceived injustice or external blame give rise to anger, which has been shown to strongly motivate sharing and collective discourse. (Lerner and Keltner, 2001; Brady *et al.*, 2017).

Although much social media research operationalizes emotions using broad valence–arousal frameworks, appraisal theory provides a deeper explanatory mechanism by linking content characteristics to discrete emotional outcomes and engagement behaviours. (Lazarus, 1991; Scherer, 2001). Linguistic and text-analytic studies further suggest that appraisal dimensions are embedded in users’ language, enabling indirect measurement through discourse features such as evaluative stance, affective markers, and attributional patterns (Martin and White, 2005; White, 2015). Moreover, discrete emotions such as happiness, anger, sadness, fear, and surprise have been shown to possess distinct neural, behavioural, and linguistic signatures (Lench, Flores and Bench, 2011; Saarimäki *et al.*, 2016), reinforcing the appropriateness of categorical approaches alongside dimensional models. Overall, applying appraisal theory to social media research advances understanding of why specific posts elicit emotional responses and how these responses translate into heterogeneous engagement patterns.

3.3. Role of topics on Social Media Engagement

To understand how public engagement with self-driving vehicle (SDV) content varies across different psychological distances and vehicle types, this study draws upon Construal Level Theory (CLT) (Trope and Liberman, 2010) as introduced in Section 3.1. Psychologically close topics, such as personal transport use, which could involve safety issues, traffic and infrastructure experiences, or test drives and other promotional events, tend to evoke stronger and more immediate emotional responses than distant, abstract issues like global technological shifts, manufacturers’ pricing strategies, or employment trends (Trope and Liberman, 2003; Liberman and Trope, 2014; Wang, Kirmani and Li, 2021; Thompson Sargoni and Manley, 2023; Nguyen and Fujita, 2024; Schandl, Lerner and Hudecek, 2024). According to CLT, public engagement (e.g., likes, retweets, replies) increases when individuals perceive content as concrete and personally relevant (Packard and Berger, 2021). We argue that positive sentiment around psychologically close topics (e.g., safety, traffic, infrastructure) leads to higher engagement, as these issues directly impact daily life and are easier to relate to. For instance, tweets about improved safety features or private SDVs are more likely to be shared

or liked, as they offer reassurance and align with self-relevant concerns. This supports the idea that reducing psychological distance enhances the emotional impact of content, with positive affect acting as a key driver of public responsiveness (Trope and Liberman, 2010).

H1a: The sentiment on topics that are psychologically closer to the audience will have a positive relationship with public engagement

Private vehicles are closely tied to personal identity, lifestyle, and autonomy, making them psychologically closer than public or commercial transport. (Belk, 1988; Steg, 2005). This perceived proximity amplifies emotional responses and increases engagement with sentiment-rich content. As a result, users are more likely to interact with positive messages about private SDVs, such as those highlighting convenience, safety, or affordability. In contrast, public and commercial SDVs, while socially relevant, may feel less personally impactful, leading to weaker engagement. (Anable, 2005; Gatersleben and Uzzell, 2007). Thus, the sentiment-engagement link is strongest for private vehicles, underscoring the influence of psychological closeness.

H1b: For private cars, the above-mentioned relationship will be stronger than for public transport and commercial vehicles

Topics that are construed at a high level, such as employment shifts, regulatory policies, manufacturers' pricing strategies, or technological advancements, etc., are typically perceived as abstract, uncertain, and temporally distant (Trope and Liberman, 2010; Liberman and Trope, 2014). When sentiment expressed around such topics is negative, it may exacerbate the audience's disengagement or indifference (Trope and Liberman, 2003). For instance, content discussing job losses in logistics due to commercial SDVs or abstract policy failures may generate cognitive dissonance or fatigue, leading to reduced engagement. According to CLT, high-level construal is less likely to evoke strong emotional responses, and when coupled with negative sentiment, they further reduce perceived relevance (Trope and Liberman, 2010). As a result, people may ignore or avoid interacting with such content.

H2a: The sentiment on topics that are psychologically distant to the audience will have a negative relationship with public engagement

Even for distant topics, if they are loosely associated with private car usage, the psychological distance may still be perceived as somewhat reduced due to personal relevance. For instance, even a discussion around global regulations may become engaging if it is linked to how an individual might purchase or use a private SDV (Belk, 1988; Steg, 2005). In contrast, commercial and public transport, often seen as less personal and more institutional, remain distant regardless of the topic (Anable, 2005). Therefore, the negative impact of distant-topic

sentiment on engagement is likely attenuated for private cars, as individuals maintain a base level of involvement. This makes the sentiment-engagement relationship less negative for private vehicles.

H2b: For private cars, the above-mentioned relationship will be weaker than for public transport and commercial vehicles

3.4. Role of Emotions on Social Media Engagement

To explain the relationship between emotional content and public engagement on social media, particularly in the context of SDVs, this study draws on the Appraisal Theory of Emotion (Lazarus, 1991) as introduced in Section 3.2. It highlights how emotional arousal and valence shape user attention, cognitive processing, and behavioural outcomes, such as sharing, liking, and commenting, on social media platforms (Syrdal and Briggs, 2018; Trunfio and Rossi, 2021).

High-arousal negative emotions such as anger and fear often signal the presence of threats, injustice, or urgency. According to Appraisal Theory, these emotions arise from evaluations of situational harm or danger, prompting action-oriented responses (Lazarus, 1991; Nabi, 1999). In the context of SDVs, content related to accidents, safety risks, or ethical dilemmas may evoke fear or anger. These high-arousal states encourage users to act quickly by sharing content, commenting, or participating in online debates. Conversely, low-arousal negative emotions like sadness are typically associated with loss or helplessness and evoke disengagement or passive reflection, thereby reducing immediate interaction (Scherer, 2005). As a result, posts that generate high-arousal negative emotions are more likely to yield stronger engagement.

H3a: High arousal negative emotion will have a stronger positive relationship with public engagement than low arousal negative emotion

High-arousal negative emotions (e.g., anger, fear) are typically triggered by events perceived as immediate threats or injustices (Lazarus, 1991). In the context of private cars, such emotions are more personally relevant due to ownership, control, and identity investment (Belk, 1988; Steg, 2005). According to appraisal theory, individuals assess emotionally charged events based on personal relevance, and high ownership involvement amplifies both the intensity and public expression of negative emotions (Lazarus, 1991).

Construal Level Theory (CLT) further explains this: private cars are psychologically “close” objects, making emotional responses more visceral and engaging (Trope and Liberman, 2010). If a safety issue, pricing concern, or infrastructure-related limitation affects private

vehicles, people are more likely to express outrage, dissatisfaction, or concern, leading to stronger public engagement (Scherer, 2005; Algoe and Haidt, 2009).

In contrast, public transport and commercial vehicles are psychologically distant. The emotional responses are diffused because users feel less individual agency or responsibility over these systems (Anable, 2005; Gatersleben and Uzzell, 2007). Even if a transport policy failure occurs, users may perceive it as a systemic issue, not a personal one, leading to lower engagement, even when the emotional arousal is high.

H3b: The positive relationship between high-arousal negative emotions and public engagement will be stronger for private cars than for public transport and commercial vehicles.

From the perspective of Emotion Appraisal Theory, different positive emotions arise from distinct cognitive appraisals of events and therefore generate different behavioural tendencies (Lazarus, 1991; Roseman, 1991; Roseman and Smith, 2001; Moors *et al.*, 2013). High-arousal positive emotions such as joy and surprise are typically elicited by appraisals of novelty or sudden goal congruence, but they are often short-lived because they are weakly associated with appraisals of certainty, control, or personal relevance (Scherer, 2001; Ellsworth and Scherer, 2003). As a result, these emotions tend to prompt immediate but shallow reactions, such as quick expressions of approval, without motivating sustained engagement (Fredrickson, 1998).

In contrast, low-arousal positive emotions such as happiness, contentment, and admiration emerge from appraisals of stability, predictability, and enduring goal congruence (Scherer, 2005; Algoe and Haidt, 2009). These emotions are linked to appraisals of confidence and perceived control, which foster approach-oriented behaviours that extend beyond momentary reactions (Ellsworth and Smith, 1988; Fredrickson, 2001). When users appraise technological developments as reliable, safe, or beneficial over time, the resulting emotions encourage more deliberate forms of engagement, including endorsement, advocacy, and reflective discussion. Accordingly, posts that elicit admiration for technological progress or contentment with safety improvements are more likely to generate deeper and more meaningful public engagement, particularly in contexts involving emerging technologies such as self-driving vehicles.

H4a: Low arousal positive emotion will have a stronger positive relationship with public engagement than high arousal positive emotion

From a Construal Level Theory perspective, engagement outcomes depend on the psychological proximity of the transportation mode to the individual (Trope and Liberman, 2010). Private cars are psychologically proximate objects, closely tied to users' daily routines,

personal identity, and direct control (Belk, 1988; Steg, 2005). As a result, even mildly positive experiential evaluations—such as comfort, smooth performance, or design appreciation—are construed at a low level and processed in a concrete, detail-oriented manner. This low-level construal increases the salience of these evaluations and makes them more likely to translate into active engagement, including sharing experiences or expressing satisfaction online (Liberman and Trope, 2014; Packard and Berger, 2021).

In contrast, commercial vehicles are psychologically more distant for most users, as they are typically encountered in instrumental or professional contexts rather than as objects of personal ownership. Consequently, positive evaluations related to efficiency or reliability are construed at a higher level and interpreted in abstract, functional terms (Trope and Liberman, 2003). Engagement arising from such evaluations is therefore more utilitarian, manifesting in informational exchanges or technical discussions rather than expressive or experiential content.

Public transport represents the greatest psychological distance due to limited personal control and weak identity association (Anable, 2005; Gatersleben and Uzzell, 2007). Positive experiences in this context are construed abstractly and episodically, reducing their perceived relevance. As a result, even when favourable evaluations occur, they are unlikely to trigger sustained or meaningful engagement.

H4b: The positive relationship between low-arousal positive emotions and public engagement will be stronger for private cars than for public transport and commercial vehicles.

Figure 1 gives the theoretical model of the study.

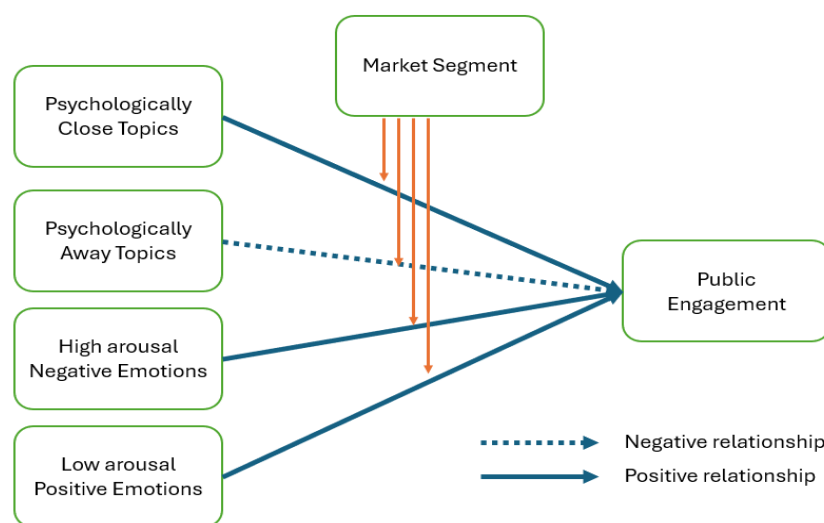


Figure 1 Theoretical Model for the Study

4. Empirical Studies

4.1. Data

We collected tweets posted between 1 March 2022 and 1 June 2022 on 4 June 2022. The keywords used were “Autonomous” OR “Self-drive” OR “Driverless”, and tweets were filtered for the English language. A total of 198,597 tweets were gathered under these conditions. To support the assessment of dataset reliability, we note that 5.2% of accounts in our sample were verified. At the time of data collection, prior to Elon Musk’s acquisition, Twitter’s verification system was restricted to public-facing entities such as companies, brands, and celebrities. As a result, verification status should be interpreted as an indicator of institutional or public visibility rather than a general measure of user authenticity. To further reduce the influence of automated or coordinated activity, as well as to prevent retweets from disproportionately amplifying individual posts, we removed duplicated tweets and retained only the first instance of each unique message. Removing retweets does not affect model predictions, as the retweetCount variable on the original post already captures all subsequent shares and is used as one of the dependent variables in our models. Table S1 in the supplementary file summarises the dataset variables, along with their respective descriptions and coding rules. Notably, there are no missing values in the variables used for analysis. Table S2 in the supplementary file provides full details of the python libraries used in this study.

Figure 2 shows the methodology applied along with their interconnection.

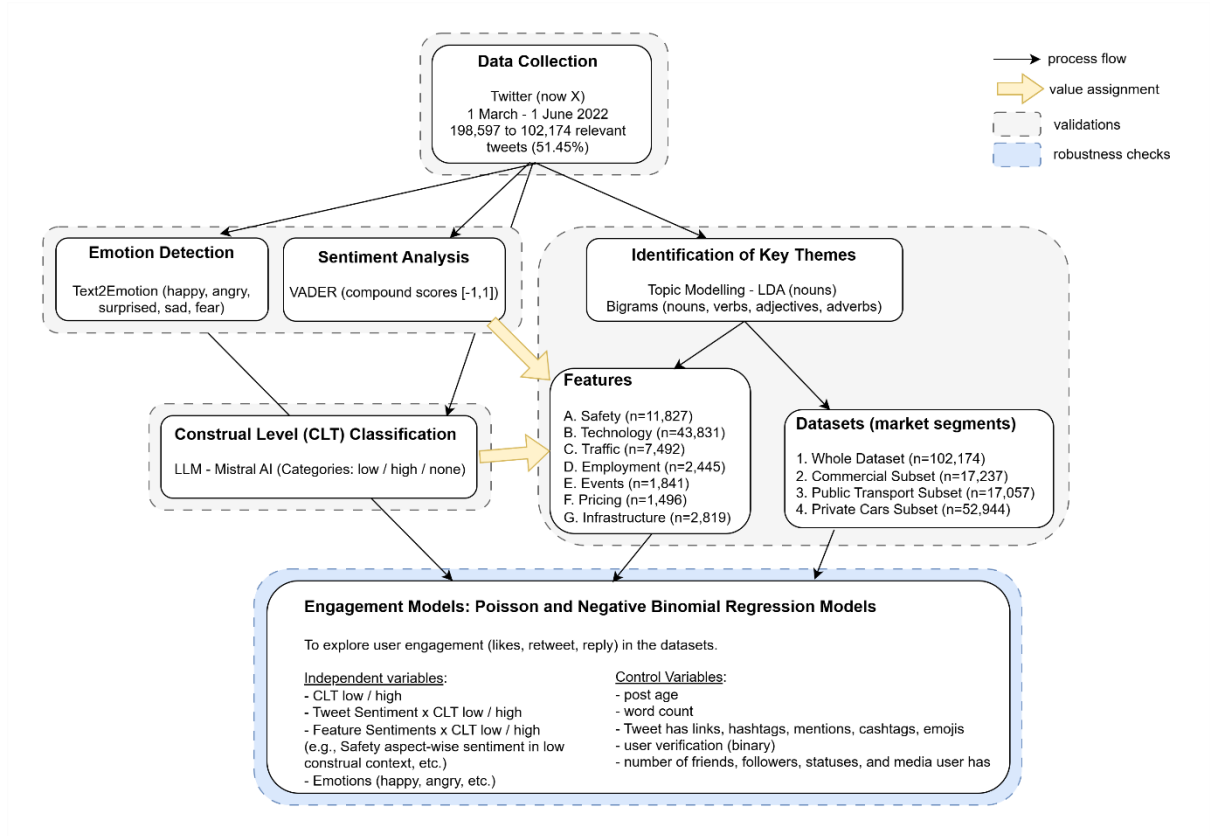


Figure 2 Methodology applied

4.2. Text pre-processing

To remove off-topic tweets, we first extracted the 50 most frequent bigrams from the dataset. However, increasing this number did not improve filtering, as many irrelevant entries remained within the 171,391 tweets. To refine the dataset, we randomly sampled 1,000 tweets and manually classified them as on- or off-topic using extended domain knowledge and a keyword heuristic method (Huyen, 2022). The final set of applied keywords is available in the Supplementary file (Supplementary Table S3). Although this reduced the dataset to 170,749 tweets, many unique off-topic tweets persisted. Instead of eliminating off-topic terms, we then extracted on-topic expressions from the manually labelled sample to improve accuracy. This two-step approach ultimately reduced the dataset from 198,597 to 102,174 relevant tweets (51.45%). The Standard Natural Language Processing (NLP) approach for preprocessing was applied to remove URLs, mentions, special characters, and whitespaces, and to convert text to lowercase.

4.3. Topic Modelling

Topic modelling (TM) is a widely used unsupervised machine learning method for analysing large-scale textual data and identifying latent topics across numerous documents (Mustak *et al.*, 2021). While several TM techniques exist, three have become particularly prominent: Latent Semantic Analysis (LSA) (Landauer, 2006), Probabilistic Latent Semantic Analysis (pLSA) (Hofmann, 2013), and Latent Dirichlet Allocation (LDA) (Blei, Ng and Jordan, 2003). Both LSA and pLSA use matrix factorisation to reduce dimensionality—LSA via singular value decomposition and pLSA through maximum likelihood estimation. LDA extends these approaches by incorporating a Bayesian generative model, which enables better generalisation to new documents. Studies have found LDA to perform more accurately than other TM methods (Vaid et al., 2023), which is why we employed LDA for this study. LDA assumes each document (tweet) is a mixture of latent topics, each comprising a distribution of words (Blei, Ng and Jordan, 2003).

To optimise the model, we tested six topic numbers (10, 15, 20, 25, 30) across three learning decay rates (0.5, 0.7, 0.9). The 10-topic model with a 0.5 decay rate performed best, showing the highest log-likelihood (-1,666,227.63) and lowest perplexity (845.95). From the final model, we identified seven feature-related topics (safety, technology, traffic, employment, events, pricing, infrastructure) and three market-segment-related topics (commercial, public transport, private cars). A keyword-based heuristic was then applied to refine and expand the final topic word lists, as shown in Table 1. The ten most frequent words for each feature-wise subset, along with their TF-IDF weights, are presented in the Supplementary file (Figure S1). The validation of the topic assignments is detailed in Section S2.3 in the Supplementary file.

Table 1 Keywords for features

	Keywords for the Features	No. of Tweets within
A) Safety	'security', 'risk', 'collision', 'accident', 'error', 'recall', 'faulty', 'death', 'fatal', 'safe', 'safety', 'human', 'pedestrian'	11,827
B) Technology	'ai', 'technology', 'tech', 'startup', 'fintech', 'beta', 'fsd', 'feature', 'software', 'automation', 'robot', 'engineering', 'autopilot', 'cruise control'	43,831
C) Traffic	'traffic', 'control', 'speed', 'parking', 'control', 'city', 'congestion'	7,492
D) Employment	'employment', 'driver shortages', 'unemployment', 'job', 'taxi driver', 'uber driver', 'human driver', 'career', 'human work', 'people work', 'software engineer'	2,445
E) Events	'event', 'expo', 'car show', 'truck show', 'vehicle show', 'fun day', 'autonomous vehicle day', 'show room', 'test drive', 'festival', 'marketing', 'trade show'	1,841
F) Pricing	'price', 'pricing', 'expensive', 'cheap', 'value for money'	1,496

	Keywords for the Features	No. of Tweets within
G) Infrastructure	'infrastructure', 'charging', 'supercharg', 'lane'	2,819

4.4. Emotion mining and Topic wise sentiment mining

Sentiment analysis is a common NLP method for examining large volumes of unstructured text. Two major approaches are typically used: lexicon-based methods, which rely on predefined sentiment scores for words; and machine learning (ML)-based approaches that use techniques like Bag-of-Words or Term Frequency-Inverse Document Frequency for training predictive models.

For this study, sentiment compound scores were generated using the VADER lexicon. This tool calculates the overall polarity of a tweet by summing individual word valence scores and normalising the result to a range between -1 (completely negative) and +1 (completely positive). To identify emotional expressions, we used `Text2Emotion` library, which assigns scores for five emotions: Happy, Angry, Surprise, Sad, and Fear. While dimensional models of affect (valence and arousal) provide complementary perspectives, we adopt these discrete categories in line with appraisal theory and prior research showing that emotions such as happiness, anger, sadness, fear, and surprise have distinct neural and behavioural signatures (Lench, Flores and Bench, 2011; Saarimäki *et al.*, 2016). In social media contexts, surprise is frequently expressed as positive amazement (Masciantonio, Heiser and Cherbonnier, 2025), and happiness often manifests as low-arousal contentment (McManus, Nakamura and Siegel, 2024), making these categorical distinctions practically relevant for text-based emotion analysis.

To compare the accuracy of these automated tools, a random sample of 100 tweets was manually labelled by three human annotators (L1–L3). Inter-annotator agreement was substantial for sentiment (Krippendorff’s $\alpha = 0.646$) as well as for emotion categories ($\alpha = 0.736$ – 0.859). We attempted to scale the validation to a 1,000-tweet sample using an LLM (Mistral AI) as fourth annotator (L4), but its performance on the initial 100-tweet test set was very poor, as summarised in Table 2. This difficulty in capturing fine-grained sentiment and affect is well documented in the literature (Zhang *et al.*, 2024; Herrera-Poyatos *et al.*, 2025). Consequently, we rely on human annotators for sentiment and emotion validation and retain VADER and `Text2Emotion` for all subsequent analyses. Full details of this validation procedure are provided in Supplementary File S2.2.

Table 2 Inter-annotator agreement measures for the sample of 100 tweets. Annotators 1–3 correspond to human coders, and annotator 4 corresponds to the LLM. Pairwise Cohen’s κ coefficients are reported using the notation `cohen_ij`, indicating

agreement between annotators i and j . Krippendorff’s α is reported for the subset of human annotators (_123) and for the full set of annotators (_1234), as presented in the final two columns.

category	cohen_12	cohen_13	cohen_14	cohen_23	cohen_24	cohen_34	Krippendorff alpha_123	Krippendorff alpha_1234
sentiment	0.656	0.647	0.130	0.635	0.031	0.112	0.646	0.238
happy	0.765	0.748	-0.094	0.701	-0.152	0.030	0.736	0.287
angry	0.834	0.863	0.497	0.879	0.476	0.557	0.859	0.686
surprise	0.885	0.788	-0.182	0.900	-0.105	-0.030	0.858	0.249
sad	0.834	0.864	0.188	0.840	0.228	0.247	0.846	0.482
fear	0.836	0.811	0.099	0.773	0.135	0.110	0.806	0.312

Topic-wise sentiment mining, also known as topic-based, feature-wise, or aspect-level sentiment analysis, is an emerging research area that integrates topic modelling and sentiment analysis in NLP. This method allows researchers to assign sentiment scores to specific aspects discussed within a given text. For example, in the tweet “High speed (long distance) rail is the only large-scale public transportation infrastructure I support, self-driving cars will be revolutionary for local transportation and make all other forms of local public transport obsolete well before there is any +ROI for things like LRT,” the overall sentiment is positive, with a compound score of 0.62. Based on keyword heuristics, this tweet references the aspects of technology, traffic, and infrastructure. Thus, each of these aspects was assigned the sentiment valence associated with its topic-specific subtree (i.e., 0.4 for infrastructure and 0 for technology and traffic), while all other aspects were assigned a value of zero.

We applied this method across the entire dataset by assigning sentiment scores at both the tweet level and the level of the seven identified features, allocating a score when a feature was mentioned in a tweet and zero otherwise. This technique captures the polarity and intensity of sentiments associated with each aspect and helps identify the relative impact of various features on public opinion and engagement (Chatterjee et al., 2021).

4.5. Categorisation of topics

To capture the psychological distance embedded in public discourse about SDVs, each tweet in the dataset was initially annotated using an LLM (Mistral AI) classifier. The model was guided by a structured prompt operationalising Construal Level Theory, distinguishing between low-level construals (concrete, specific, proximal), high-level construals (abstract, general, distal), and a none category for tweets lacking sufficient semantic content. Following this automated classification, a stratified sample of 99 tweets (33 per CLT category) was drawn for expert validation. Three domain experts independently labelled this sample using a coding scheme derived from CLT literature, supported by tailored examples and decision rules specific

to SDV discourse. The LLM classifier served as a fourth annotator, providing parallel labels for the same sample.

Inter-annotator agreement was assessed using complementary reliability metrics suitable for nominal, multi-category data. Pairwise Cohen’s κ values among human annotators ranged from 0.86 to 0.89, while Krippendorff’s α across the three human coders was 0.88, indicating excellent agreement. Agreement between the human annotators and the LLM classifier was similarly high ($\kappa = 0.89\text{--}0.94$; $\alpha = 0.90$). These values exceed the reliability thresholds recommended by Krippendorff (2018) and fall within the “almost perfect” range defined by Landis and Koch (1977), demonstrating that the CLT coding scheme is both conceptually robust and consistently applied. On this basis, the validated LLM classifier was used to assign CLT labels to the full dataset of SDV-related tweets. The details on the classification and its validation can be found in Supplementary File S2.4.

4.6. Segmenting the data in market segments

Segmenting AV markets into private, public, and commercial domains is theoretically grounded in institutional and market heterogeneity (Geels, 2004, 2012; Shaheen and Cohen, 2013; Wang *et al.*, 2020). These segments differ systematically in ownership logic, risk tolerance, regulatory exposure, usage context, and value creation mechanisms, shaping distinct key factors, stakeholder incentives, and innovation pathways (Steg, 2005; Hensher, 2008; Fagnant and Kockelman, 2015; Meyer *et al.*, 2017). We could divide the dataset into three segments, namely private cars, public transport, and commercial vehicles. This has been done by keyword search and matching the posts with each of these bag-of-words, as reported in Table 3. Various segment size is also reported in Table 3. The ten most frequent words for each market-segment-related subset, along with their TF-IDF weights, are presented in the Supplementary file (Figure S1). We used an LLM (Mistral AI) to validate and check the accuracy of the keyword-based topic assignments, achieving accuracy scores ranging from 0.723 to 0.824 across the domain-specific subsets, based on a stratified random sample of 996 tweets, as detailed in Section S2.3 of the Supplementary File.

The three segments were not defined as mutually exclusive, since tweets may reference multiple market contexts simultaneously. Tweets containing keywords from more than one segment were included in all relevant categories, enabling segment-wise sentiment analysis even when users expressed contrasting views across contexts within a single post. To increase transparency, we quantified the degree of overlap across segments. For example, 17.3% of

commercial tweets also referenced public transport, 27.8% referenced private cars, and 5.1% referenced all three segments, leaving 60% of commercial tweets exclusive to that segment. Similar proportions were observed for public transport (49% exclusive) and private cars (80% exclusive). In addition, 28,351 tweets (27.7% of the dataset) did not match any segment keywords; these were retained for overall sentiment and emotion analysis but excluded from segment-wise comparisons. Full details, including the overlap table, are reported in the Supplementary File (Section S2.3).

Table 3 Keywords for the subsets

	Keywords for the Subsets	No. of Tweets within
1. Commercial	'commercial', 'truck', 'long haul', 'lorry', 'lorries', 'hgv', 'heavy goods', 'tesla semi', 'waymo via', 'fleet', 'freight', 'tractor', 'food', 'delivery', 'ship', 'boat', 'cargo', 'cruise-control', 'flight', 'aircraft', 'drone', 'last mile', 'supply', 'chain', 'logistic'	17,237
2. Public Transportation	'bus', 'train', 'subway', 'mobility', 'uber', 'taxi', 'robotaxi', 'public transport', 'smart city', 'passenger', 'rail', 'tube', 'transit', 'shuttle', 'dlr', 'tfl', 'station'	17,057
3. Private cars	'car', 'suv', 'tesla', 'polestar', 'private', 'autoindustry', 'automotive'	52,944

4.7. Econometric Model

For overall post engagement two models were tested, Poisson and Negative Binomial Regression models. As the Negative Binomial Regression models performed better (summarised in Supplementary file Table S13), only these results have been reported. We included the following variables as covariates in all models: post age (the number of days between the scraping date and the original posting date, ranging from 4 to 95 days), word count, indicators for whether the tweet contains links, hashtags, mentions, cash tags, or emojis, whether the user is verified, and the user's friend, follower, status, and media counts.

The models exhibited no multicollinearity issues, as indicated by the VIF scores (Table S4 in the Supplementary File). Table S5 summarises the descriptive statistics (tweet counts, means, and standard deviations) for the tweet-level sentiment compound score and the emotion variables in the whole dataset (102,174 tweets) and in the three market-segment subsets (commercial, public transport, and private cars), both overall and across the seven features (Features A–G). Table S6 in the Supplementary File reports the descriptive statistics for the engagement variables—replies, retweets, and likes—which serve as the dependent variables in the models.

4.7.1. Regression results

Table 4 reports the results of the negative binomial regression, with total engagement as the dependent variable and construal level, sentiment, and emotions as the main independent variables. All covariates are included in the model as controls. The model intercept is significant ($\beta = 1.41$, $SE = 0.019$, $p < 0.001$), indicating a non-trivial baseline level of engagement. The results reveal several systematic patterns in how construal level, topic-specific sentiment, and emotional expressions shape public engagement (measured as the sum of replies, retweets, and likes). Analyses of replies, retweets, and likes separately yield additional insights, summarised in Section 4.9 and detailed in Supplementary File S3.1.

CLT_low and CLT_high capture whether tweets are framed at psychologically close or distant levels and how people generally engaged with these levels, while the interaction terms (sentiment $\times$ CLT_low and sentiment $\times$ CLT_high) estimate how sentiment moderates engagement under each framing condition. Contrary to H1a and H2a, CLT_low ($\beta = -0.16$, $SE = 0.011$, $p < 0.001$) and sentiment $\times$ CLT_low ($\beta = -0.19$, $SE = 0.018$, $p < 0.001$) exhibit negative associations with engagement, whereas CLT_high ($\beta = 0.14$, $SE = 0.011$, $p < 0.001$) and sentiment $\times$ CLT_high ($\beta = 0.17$, $SE = 0.011$, $p < 0.001$) show positive associations.. Although these directions diverge from theoretical expectations (H1a and H2a), the pattern is theoretically meaningful: audiences appear less responsive to positive sentiment expressed in highly concrete, identity-relevant framings, while abstract sentiment resonates more strongly in collective or socially shared discourse. Section 4.9 elaborates on these mechanisms.

A similar pattern emerges in several topic-specific sentiment $\times$ construal level interactions. Positive sentiment expressed at low construal levels is negatively associated with engagement for Traffic ($\beta = -0.93$, $SE = 0.182$, $p < 0.01$) and Events ($\beta = -2.27$, $SE = 0.296$, $p < 0.001$), whereas positive sentiment expressed at high construal levels is associated with higher engagement for Safety ($\beta = 0.10$, $SE = 0.033$, $p < 0.01$), Technology ($\beta = 0.23$, $SE = 0.029$, $p < 0.001$), and Traffic ($\beta = 0.23$, $SE = 0.029$, $p < 0.001$). These topics deviate from the expected pattern. For **Technology**, both low-level ($\beta = 0.14$, $SE = 0.053$, $p < 0.01$) and high-level sentiment ($\beta = 0.23$, $SE = 0.029$, $p < 0.001$) are positively associated with engagement, **supporting H1a** in the low-construal condition. In contrast, positive sentiment expressed under high-level framing for **Events** ($\beta = -0.52$, $SE = 0.138$, $p < 0.001$), **Pricing** ($\beta = -1.77$, $SE = 0.203$, $p < 0.001$), and **Infrastructure** ($\beta = -1.52$, $SE = 0.134$, $p < 0.001$) is associated with lower engagement, **consistent with H2a** for these topics.

Several topic-wise sentiment $\times$ construal interactions are non-significant—Safety-low ($\beta = 0.05$, $SE = 0.061$, ns), Employment-low ($\beta = -0.38$, $SE = 0.293$, ns), Employment-high ($\beta = 0.09$, $SE = 0.173$, ns), Pricing-low ($\beta = 0.26$, $SE = 0.304$, ns), and Infrastructure-low ($\beta = -0.20$, $SE = 0.275$, ns). These null effects suggest that sentiment expressed under these framing conditions does not meaningfully shape engagement and may mask opposing patterns that become visible only when disaggregating by market domains as well as by engagement type, as discussed in subsequent sections.

The emotional variables show clear differentiation by arousal level. High-arousal negative emotions Anger ($\beta = 0.80$, $SE = 0.032$, $p < 0.001$) and Fear ($\beta = 0.18$, $SE = 0.016$, $p < 0.001$) exhibit stronger positive associations with engagement than Sadness ($\beta = -0.73$, $SE = 0.023$, $p < 0.001$), a low-arousal negative emotion, **supporting H3a**. Happiness, a low-arousal positive emotion, shows the strongest positive association with engagement ($\beta = 1.79$, $SE = 0.027$, $p < 0.001$), exceeding that of Surprise ($\beta = -0.87$, $SE = 0.020$, $p < 0.001$), a high-arousal positive emotion. This pattern **confirms H4a**.

Table 4 Results of the negative binomial regression model for Post Engagement: whole dataset

<u>target variable: total_eng_count</u> (replyCount + retweetCount + likeCount) Model 4.0 *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$		
Variables	coef.	std. err.
(intercept)	1.41***	0.019
CLT low	-0.16***	0.011
CLT high	0.14***	0.011
Sentiment score x CLT low	-0.19***	0.018
Sentiment score x CLT high	0.17***	0.011
Happy emotion detection score	1.79***	0.027
Angry emotion detection score	0.80***	0.032
Surprise emotion detection score	-0.87***	0.020
Sad emotion detection score	-0.73***	0.023
Fear emotion detection score	0.18***	0.016
Safety sentiment x CLT low	0.05	0.061
Safety sentiment x CLT high	0.10**	0.033
Technology sentiment x CLT low	0.14**	0.053
Technology sentiment x CLT high	0.23***	0.029
Traffic sentiment x CLT low	-0.93***	0.182
Traffic sentiment x CLT high	0.23*	0.099
Employment sentiment x CLT low	-0.38	0.293
Employment sentiment x CLT high	0.09	0.173
Events sentiment x CLT low	-2.27***	0.296
Events sentiment x CLT high	-0.52***	0.138

target variable: total_eng_count (replyCount + retweetCount + likeCount)		
Model 4.0		
*** p < 0.001, ** p < 0.01, * p < 0.05		
Variables	coef.	std. err.
Pricing sentiment x CLT low	0.26	0.304
Pricing sentiment x CLT high	-1.77***	0.203
Infrastructure sentiment x CLT low	-0.20	0.275
Infrastructure sentiment x CLT high	-1.52***	0.134
Post age	0.00***	0.000
Word count	0.03***	0.000
Tweet has link(s)	-0.07***	0.009
Tweet has hashtag(s)	-0.84***	0.009
Tweet has mention(s)	-0.44***	0.008
Tweet has cashtag(s)	0.48***	0.016
Tweet has emoji(s)	1.17***	0.009
User is verified	1.98***	0.015
User friends Count	0.00***	0.000
User followers Count	0.00***	0.000
User statuses Count	0.00***	0.000
User media Count	0.00***	0.000
AIC	648,184	

4.7.2. Segment-wise comparative analysis

To examine segment-wise effects of construal level, topic-wise sentiments, and emotional tone on public engagement, we conducted negative binomial regression analyses across three segments: commercial vehicles, public transport, and private cars. Similar to the baseline model reported in the previous section, the dependent variable was total engagement count, operationalised as the sum of replies, retweets, and likes (the results of the separate engagement measures can be found in the Supplementary File in S3.1). Table 5 presents the detailed coefficients, standard errors (SE), and significance levels.

The model on private cars (Model 4.3) was the only segment-wise model that did not reach overall statistical significance (the column in orange in Table 5). This was unexpected, however, it is theoretically consistent with the identity-relevant nature of private-car discourse, which is known to elicit heterogeneous and sometimes opposing behavioural responses (Tajfel and Turner, 2001; Trope and Liberman, 2010; Turner and Reynolds, 2012). Moreover, prior work shows that replies, retweets, and likes reflect distinct psychological and communicative processes, particularly in identity-laden contexts, making aggregated engagement metrics

sometimes insufficient (Stieglitz and Dang-Xuan, 2013; Bail, 2016). Total engagement aggregates three distinct behaviours (replies, retweets, likes), which in this domain operate in opposite directions in their sentiment and construal-level interactions, confirming that total engagement is not a meaningful behavioural construct for identity-relevant SDV content and underscoring the importance of analysing engagement types separately (these results are shown in Table 6).

For the commercial vehicles (Model 4.1), general engagement with either low ($\beta = 0.37$, $SE = 0.036$, $p < 0.001$) or high ($\beta = 0.12$, $SE = 0.034$, $p < 0.001$) construal level is positively associated with engagement; however, their interactions with sentiment show a similar pattern to that observed in the whole dataset: $\text{sentiment} \times \text{CLT_low}$ ($\beta = -0.24$, $SE = 0.052$, $p < 0.001$) exhibits negative associations with engagement, whereas $\text{sentiment} \times \text{CLT_high}$ ($\beta = 0.30$, $SE = 0.028$, $p < 0.001$) shows positive associations. This effect is strongly embodied in several topic-specific sentiment and their low construal level interactions: Pricing ($\beta = -6.97$, $SE = 2.136$, $p < 0.01$), Events ($\beta = -2.97$, $SE = 0.602$, $p < 0.001$), Infrastructure ($\beta = -2.36$, $SE = 0.802$, $p < 0.01$), whereas positive sentiment expressed at high construal levels is associated with higher engagement for Infrastructure ($\beta = 3.18$, $SE = 0.310$, $p < 0.001$) and Employment ($\beta = 0.71$, $SE = 0.299$, $p < 0.05$). We also observe patterns expected in our hypotheses, such as Employment ($\beta = 1.54$, $SE = 0.578$, $p < 0.01$) and Technology ($\beta = 0.90$, $SE = 0.154$, $p < 0.001$) for low-level construal, and Pricing ($\beta = -0.91$, $SE = 0.436$, $p < 0.05$), Technology ($\beta = -0.77$, $SE = 0.069$, $p < 0.001$), and Safety ($\beta = -0.71$, $SE = 0.093$, $p < 0.001$) for high level construal.

In contrast, public transport shows a general positive engagement with both low (CLT_low : $\beta = 0.24$, $SE = 0.035$, $p < 0.001$, Sentiment_CLT_low : $\beta = 0.64$, $SE = 0.046$, $p < 0.001$) and high (CLT_high : $\beta = 1.26$, $SE = 0.033$, $p < 0.001$, $\text{Sentiment_CLT_high}$: $\beta = 0.37$, $SE = 0.027$, $p < 0.001$) construal-level tweets. Positive sentiment expressed at low construal levels is negatively associated with engagement for Events ($\beta = -4.40$, $SE = 0.976$, $p < 0.001$), but positively associated with engagement, as expected, for Infrastructure ($\beta = 2.42$, $SE = 0.650$, $p < 0.001$), Traffic ($\beta = 1.73$, $SE = 0.526$, $p < 0.01$), and Technology ($\beta = 0.45$, $SE = 0.124$, $p < 0.001$). Positive sentiment expressed at high construal levels is associated with higher engagement for Traffic ($\beta = 1.71$, $SE = 0.218$, $p < 0.001$) and Employment ($\beta = 1.11$, $SE = 0.337$, $p < 0.01$), and is negatively associated with engagement, as expected, for Technology ($\beta = -0.81$, $SE = 0.065$, $p < 0.001$), Infrastructure ($\beta = -0.60$, $SE = 0.238$, $p < 0.05$), and Safety ($\beta = -0.33$, $SE = 0.084$, $p < 0.001$).

For private cars, we observe that both low- and high-construal contexts expressing a topic in more positive (or less negative) terms are negatively associated with engagement

across all engagement types of replies (Model 1.3, *Sentiment_CLT_low*: $\beta = -0.01$, SE = 0.034, ns, *Sentiment_CLT_high*: $\beta = -0.12$, SE = 0.021, $p < 0.001$), retweets (Model 2.3, *Sentiment_CLT_low*: $\beta = -0.52$, SE = 0.032, $p < 0.001$, *Sentiment_CLT_high*: $\beta = -0.08$, SE = 0.020, $p < 0.001$) and likes (Model 3.3, *Sentiment_CLT_low*: $\beta = -0.24$, SE = 0.023, $p < 0.001$, *Sentiment_CLT_high*: $\beta = -0.22$, SE = 0.015, $p < 0.001$). Comparing these values with the other subsets (Tables S15-S17 in the Supplementary file), we can conclude that although **H1b is not supported in general terms**, **H2a is supported** in overall topic sentiments both in the **retweet** (Model 2.3) and **like** (Model 3.3) engagement models, since other segments show positive rather than negative associations with engagement. For the same reason, **H2b is not supported** in overall sentiments with high-construal interactions. The topic-specific sentiments in low construal are positively associated with reply engagement (Model 1.3) for Pricing ($\beta = 1.39$, SE = 0.451, $p < 0.01$), Technology ($\beta = 0.38$, SE = 0.101, $p < 0.001$), and Safety ($\beta = 0.29$, SE = 0.117, $p < 0.05$); with retweet engagement (Model 2.3) for Safety ($\beta = 0.80$, SE = 0.109, $p < 0.001$); and with like engagement (Model 3.3) for Infrastructure ($\beta = 1.22$, SE = 0.336, $p < 0.001$), Safety ($\beta = 1.04$, SE = 0.079, $p < 0.001$), and Technology ($\beta = 0.19$, SE = 0.067, $p < 0.01$). These findings support H1a in these contexts, but **H1b is only supported for Safety in all three engagement types, and Pricing in replies**. In high-construal contexts, topic-specific sentiments negatively associated with reply engagement (Model 1.3) for Technology ($\beta = -0.36$, SE = 0.056, $p < 0.001$); with retweet engagement (Model 2.3) for Employment ($\beta = -1.73$, SE = 0.329, $p < 0.001$) and Pricing ($\beta = -1.21$, SE = 0.358, $p < 0.001$); and with like engagement (Model 3.3) for Employment ($\beta = -1.82$, SE = 0.249, $p < 0.001$), Pricing ($\beta = -1.42$, SE = 0.265, $p < 0.001$), Infrastructure ($\beta = -1.18$, SE = 0.194, $p < 0.001$), and Safety ($\beta = -0.64$, SE = 0.044, $p < 0.001$). These findings support H2a in these contexts, but **H2b is supported for Employment and Pricing in retweets, and for Safety and Pricing in likes engagement**.

High-arousal negative emotions, *anger* and *fear*, demonstrated the strongest positive relationships with engagement for private cars across all three engagement types: replies (Model 1.3, *anger*: $\beta = 0.94$, SE = 0.076, $p < 0.001$; *fear*: $\beta = 0.46$, SE = 0.044, $p < 0.001$), retweets (Model 2.3, *anger*: $\beta = 1.48$, SE = 0.057, $p < 0.001$; *fear*: $\beta = 0.43$, SE = 0.032, $p < 0.001$), and likes (Model 3.3, *anger*: $\beta = 2.31$, SE = 0.047, $p < 0.001$; *fear*: $\beta = 0.53$, SE = 0.024, $p < 0.001$). In comparison, in the public transport segment, fear had more modest positive effect in retweet engagement (Model 2.2, $\beta = 0.15$, SE = 0.059, $p < 0.01$), but had no significant effect in reply ($\beta = -0.03$, SE = 0.071, ns) or like engagements ($\beta = 0.00$, SE = 0.041, ns). These findings provide **support for H3b**.

Low-arousal positive emotion, *happiness*, had the strongest positive effect on engagement for private cars across all three engagement types (replies: $\beta = 0.88$, SE = 0.069, $p < 0.001$, retweets: $\beta = 4.56$, SE = 0.051, $p < 0.001$, and likes: $\beta = 4.70$, SE = 0.042, $p < 0.001$), compared to commercial vehicles (replies: $\beta = -0.39$, SE = 0.114, $p < 0.001$, retweets: $\beta = -0.52$, SE = 0.091, $p < 0.001$, and likes: $\beta = -0.67$, SE = 0.068, $p < 0.001$), and public transport (replies: $\beta = -0.06$, SE = 0.116, ns, retweets: $\beta = -0.52$, SE = 0.103, $p < 0.001$, and likes: $\beta = -0.50$, SE = 0.070, $p < 0.001$). **This supports H4b.**

In summary, H1b was supported for Safety across all engagement types, and Pricing in replies; H2b was supported for Employment and Pricing in retweets, and for Safety and Pricing in likes engagement. H3b and H4b were supported. The findings suggest that emotional and topical resonance vary significantly by transport segment, with private-car-related content yielding the highest engagement in response to both positive and negative high-arousal emotional cues, and in the above-mentioned low- and high-construal topics.

Table 5 Results of the negative binomial regression model for Post Engagement: three market-segment subsets

target variable: total_eng_count (replyCount + retweetCount + likeCount)						
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$						
	Commercial Model 4.1		Public Transport Model 4.2		Private Cars Model 4.3 (NS)	
	coef.	std. err.	coef.	std. err.	coef.	std. err.
(intercept)	1.03***	0.050	0.55***	0.051	2.24***	0.025
CLT low	0.37***	0.036	0.24***	0.035	0.10***	0.014
CLT high	0.12***	0.034	1.26***	0.033	0.98***	0.014
Sentiment score x CLT low	-0.24***	0.052	0.64***	0.046	0.53***	0.022
Sentiment score x CLT high	0.30***	0.028	0.37***	0.027	-0.97***	0.014
Happy emotion detection score	-0.66***	0.066	-0.34***	0.067	13.83***	0.041
Angry emotion detection score	-0.40***	0.076	-0.36***	0.075	6.18***	0.046
Surprise emotion detection score	-0.96***	0.044	-0.58***	0.047	-2.69***	0.028
Sad emotion detection score	-0.86***	0.055	-0.35***	0.057	-1.64***	0.031
Fear emotion detection score	-0.91***	0.036	0.73***	0.038	2.31***	0.021
Safety sentiment x CLT low	0.33	0.176	-0.21	0.137	1.15***	0.074
Safety sentiment x CLT high	-0.71***	0.093	-0.33***	0.084	-2.65***	0.042
Technology sentiment x CLT low	0.90***	0.154	0.45***	0.124	-0.88***	0.063
Technology sentiment x CLT high	-0.77***	0.069	-0.81***	0.065	4.57***	0.037

target variable: total_eng_count (replyCount + retweetCount + likeCount)						
*** p < 0.001, ** p < 0.01, * p < 0.05						
	Commercial Model 4.1		Public Transport Model 4.2		Private Cars Model 4.3 (NS)	
	coef.	std. err.	coef.	std. err.	coef.	std. err.
Traffic sentiment x CLT low	0.42	0.575	1.73**	0.526	0.41	0.213
Traffic sentiment x CLT high	-0.30	0.273	1.71***	0.218	0.24	0.133
Employment sentiment x CLT low	1.54**	0.578	0.45	0.824	-2.73***	0.398
Employment sentiment x CLT high	0.71*	0.299	1.11**	0.337	-2.39***	0.239
Events sentiment x CLT low	-2.97***	0.602	-4.40***	0.976	-6.31***	0.394
Events sentiment x CLT high	-1.66***	0.355	-0.58	0.317	4.18***	0.209
Pricing sentiment x CLT low	-6.97**	2.136	1.15	0.852	-3.63***	0.347
Pricing sentiment x CLT high	-0.91*	0.436	0.32	0.378	-3.33***	0.257
Infrastructure sentiment x CLT low	-2.36**	0.802	2.42***	0.650	0.65*	0.324
Infrastructure sentiment x CLT high	3.18***	0.310	-0.60*	0.238	-3.01***	0.184
Post age	0.00***	0.000	0.00***	0.000	0.00***	0.000
Word count	0.03***	0.001	0.00	0.001	0.00***	0.000
Tweet has link(s)	0.06**	0.023	-0.24***	0.023	2.32***	0.012
Tweet has hashtag(s)	-0.27***	0.021	-0.54***	0.022	-2.48***	0.012
Tweet has mention(s)	0.20***	0.020	0.19***	0.021	0.98***	0.011
Tweet has cashtag(s)	0.74***	0.036	0.96***	0.041	4.23***	0.025
Tweet has emoji(s)	0.21***	0.023	1.50***	0.021	4.78***	0.011
User is verified	2.19***	0.035	2.11***	0.034	3.06***	0.022
User friends Count	0.00***	0.000	0.00***	0.000	0.00***	0.000
User followers Count	0.00***	0.000	0.00***	0.000	0.00***	0.000
User statuses Count	0.00***	0.000	0.00***	0.000	0.00***	0.000
User media Count	0.00***	0.000	0.00***	0.000	0.00***	0.000
AIC	92,485		104,314		738,696	

Table 6 Results of the negative binomial regression model for Private car market-segment by Engagement types

Private Car domain (Model 1.3, 2.3, and 3.3) by Engagement type						
*** p < 0.001, ** p < 0.01, * p < 0.05						
	Model 1.3 target variable: replyCount		Model 2.3 target variable: retweetCount		Model 3.3 target variable: likeCount	
	coef.	std. err.	coef.	std. err.	coef.	std. err.
(intercept)	-1.27***	0.050	0.09*	0.038	1.04***	0.028

Private Car domain (Model 1.3, 2.3, and 3.3) by Engagement type						
*** p < 0.001, ** p < 0.01, * p < 0.05						
	Model 1.3 target variable: replyCount		Model 2.3 target variable: retweetCount		Model 3.3 target variable: likeCount	
	coef.	std. err.	coef.	std. err.	coef.	std. err.
CLT low	-0.01	0.025	0.02	0.021	-0.17***	0.015
CLT high	0.10***	0.024	0.79***	0.020	0.16***	0.015
Sentiment score x CLT low	-0.01	0.034	-0.52***	0.032	-0.24***	0.023
Sentiment score x CLT high	-0.12***	0.021	-0.08***	0.020	-0.22***	0.015
Happy emotion detection score	0.88***	0.069	4.56***	0.051	4.70***	0.042
Angry emotion detection score	0.94***	0.076	1.48***	0.057	2.31***	0.047
Surprise emotion detection score	-0.04	0.054	-1.43***	0.043	-1.15***	0.031
Sad emotion detection score	0.03	0.058	-1.32***	0.048	-0.40***	0.034
Fear emotion detection score	0.46***	0.044	0.43***	0.032	0.53***	0.024
Safety sentiment x CLT low	0.29*	0.117	0.80***	0.109	1.04***	0.079
Safety sentiment x CLT high	0.09	0.062	0.28***	0.057	-0.64***	0.044
Technology sentiment x CLT low	0.38***	0.101	-0.12	0.089	0.19**	0.067
Technology sentiment x CLT high	-0.36***	0.056	0.93***	0.050	2.23***	0.039
Traffic sentiment x CLT low	-0.40	0.336	-0.34	0.297	0.20	0.226
Traffic sentiment x CLT high	0.02	0.195	1.24***	0.175	0.22	0.137
Employment sentiment x CLT low	-1.51	0.773	-2.28**	0.761	-1.50***	0.447
Employment sentiment x CLT high	0.52	0.340	-1.73***	0.329	-1.82***	0.249
Events sentiment x CLT low	-1.25	0.657	-3.40***	0.599	-2.47***	0.420
Events sentiment x CLT high	0.14	0.297	0.05	0.276	0.71***	0.213
Pricing sentiment x CLT low	1.39**	0.451	-0.61	0.506	-1.28***	0.367
Pricing sentiment x CLT high	-0.84	0.364	-1.21***	0.358	-1.42***	0.265
Infrastructure sentiment x CLT low	0.29	0.477	-0.09	0.448	1.22***	0.336
Infrastructure sentiment x CLT high	0.48	0.263	-0.93***	0.262	-1.18***	0.194
Post age	0.00*	0.000	0.00***	0.000	0.00***	0.000
Word count	0.02***	0.001	0.00	0.001	0.03***	0.000
Tweet has link(s)	-0.36***	0.019	-0.45***	0.016	0.18***	0.012
Tweet has hashtag(s)	-0.94***	0.024	-0.48***	0.017	-1.24***	0.013

Private Car domain (Model 1.3, 2.3, and 3.3) by Engagement type						
*** p < 0.001, ** p < 0.01, * p < 0.05						
	Model 1.3 target variable: replyCount		Model 2.3 target variable: retweetCount		Model 3.3 target variable: likeCount	
	coef.	std. err.	coef.	std. err.	coef.	std. err.
Tweet has mention(s)	-0.24***	0.017	-1.83***	0.016	-0.62***	0.012
Tweet has cashtag(s)	0.86***	0.033	0.77***	0.030	1.12***	0.025
Tweet has emoji(s)	0.27***	0.017	1.92***	0.015	1.82***	0.012
User is verified	2.39***	0.026	2.17***	0.024	1.64***	0.022
User friends Count	0.00***	0.000	0.00***	0.000	0.00***	0.000
User followers Count	0.00***	0.000	0.00***	0.000	0.00***	0.000
User statuses Count	0.00***	0.000	0.00***	0.000	0.00***	0.000
User media Count	0.00***	0.000	0.00***	0.000	0.00***	0.000
AIC	115,772		172,622		339,343	

4.8. Robustness check

To assess the robustness of our results, we first experimented with different engagement types and then with other predictive models, to check whether our findings hold across the various engagement types individually, not just overall, and against different predictive models, respectively. While the individual engagement metric results align with the total engagement results, they also offer nuanced insights into the types of engagement users prioritise in different contexts. Our results obtained using various predictive models, such as Poisson regression, XGBoost, Random Forest, and Artificial Neural Networks (ANN), are also aligned with our main results. A summary of these robustness checks is provided in Sections 4.8.1 and 4.8.2, respectively, with the remaining details presented in Section S3 of the supplementary file.

4.8.1. Estimating for individual engagement metrics

To test whether our findings are robust across different forms of user engagement, we re-estimated our models using likes (Model 3.0), retweets (Model 2.0), and replies (Model 1.0) as separate dependent variables. The results are broadly consistent with the total engagement model (Model 4.0), with the like metric showing the closest alignment. Technology-related sentiment in both low and high construal context as well as Traffic-related sentiment in high construal context remains the strongest predictor for both likes and retweets; however, replies reveal a distinct pattern, with users more inclined to engage in discussions related to pricing in low construal, and employment and safety in high construal context. Emotional expressions also exhibit differentiated effects: happy and angry emotions show similar patterns for replies,

retweets, and likes, fear only similar in likes, and either diminished or reversed effects for replies and retweets, where both happiness and anger increase engagement in the private cars context. Additionally, the presence of a link becomes significant only in the retweet model, suggesting that users are more likely to share posts containing external resources, even if such content does not influence liking or replying behaviour. The full model outputs available in Section S3.1 of the supplementary file.

4.8.2. Predictive models

To further evaluate the robustness of our findings, we applied a suite of predictive models—Poisson regression, Random Forest, XGBoost, and Artificial Neural Networks—using the same variables as in the main explanatory model. Across the full dataset, XGBoost achieved the lowest prediction error, revealing that happy is the most predictive emotion and that traffic-related sentiment remains the most influential topic. Partial dependence analyses highlight several non-linear patterns, including decreasing engagement at higher levels of happiness and fear, strong positive effects for anger, and mixed responses to surprise. Topic-level effects also vary: safety exhibits an inverted U-shape, traffic sentiment follows a U-shape, and highly positive employment or infrastructure sentiment reduces engagement. For category-specific subsets, Poisson regression performed best, aligning with the main study’s results. Further methodological details, full model outputs, and all interpretability figures are provided in Section S3.2 of the supplementary file.

4.9. Hypothesis-by-Hypothesis results summary

To integrate our empirical findings with the theoretical model, this section summarises the results for each hypothesis pair (H1a–H4b). We draw on the whole-dataset regression (Section 4.7.1), the segment-wise analyses (Section 4.7.2), as well as the engagement type robustness analysis (Supplementary file Section S3.1) to identify where the hypotheses were supported, partially supported, or contradicted. These outcomes are summarised in Table 7 and further elaborated in Subsections 4.9.1–4.9.5.

Table 7 Summary of results by Hypotheses

Hypothesis	Whole Dataset	Commercial	Public Transport	Private Cars	H*b
H1a (Low-CLT × Sentiment → ↑ Engagement)	4.0: X	4.1: X	4.2: ✓	4.3: –	4.3: –
	1.0: X	1.1: X	1.2: –	1.3: –	1.3: –
	2.0: X	2.1: X	2.2: ✓	2.3: X	2.3: X
	3.0: X	3.1: X	3.2: ✓	3.3: X	3.3: X
H1a (Low-CLT × topic-wise sentiments → ↑ Engagement)	4.0: △ Tech	4.1: △ Employment, Tech	4.2: △ Infrastructure, Traffic, Tech	4.3: –△	4.3: –△ Safety
	1.0: △ Pricing, Tech		1.2: △ Tech	Infrastructure, Safety	1.3: △ Pricing, Safety
	2.0: △ Traffic	1.1: △ Tech	2.2: △ Infrastructure, Tech	1.3: △ Pricing, Tech, Safety	2.3: △ Safety
	3.0: △ Tech	2.1: X		2.3: △ Safety	

		3.1: Δ Employment, Tech	3.2: Δ Infrastructure, Traffic, Tech	3.3: Δ Infrastructure, Safety, Tech	3.3: Δ Safety
H2a (High-CLT $\times$ Sentiment $\rightarrow$ $\downarrow$ Engagement)	4.0: $\times$ 1.0: $\checkmark$ 2.0: $-$ 3.0: $\times$	4.1: $\times$ 1.1: $\checkmark$ 2.1: $\times$ 3.1: $\times$	4.2: $\times$ 1.2: $-$ 2.2: $\times$ 3.2: $\times$	4.3: $-$ 1.3: $\checkmark$ 2.3: $\checkmark$ 3.3: $\checkmark$	4.3: $-$ 1.3: $\checkmark$ 2.3: $\times$ 3.3: $\times$
H2a (High-CLT $\times$ topic-wise sentiments $\rightarrow \downarrow$ Engagement)	4.0: Δ Pricing, Infrastructure, Events 1.0: Δ Tech 2.0: Δ Pricing, Infrastructure, Events 3.0: Δ Pricing, Infrastructure, Events	4.1: Δ Pricing, Tech, Safety 1.1: Δ Safety, Tech 2.1: Δ Events, Safety, Tech 3.1: Δ Events, Pricing, Tech, Safety	4.2: Δ Tech, Infrastructure, Safety 1.2: Δ Tech 2.2: Δ Infrastructure, Tech, Safety 3.2: Δ Tech, Infrastructure, Safety, Events	4.3: $-\Delta$ Employment 1.3: Δ Tech 2.3: Δ Employment., Pricing, Infrastructure 3.3: Δ Employment., Pricing, Infrastructure, Safety	4.3: $-\times$ 1.3: $\times$ 2.3: Δ Employment, Pricing 3.3: Δ Pricing, Safety
H3a (High-arousal negative $\rightarrow \uparrow$ Engagement)	4.0: $\checkmark$ 1.0: Δ Angry 2.0: Δ Angry 3.0: $\checkmark$	4.1: $\times$ 1.1: $\times$ 2.1: $\times$ 3.1: $\times$	4.2: Δ Fear 1.2: $-$ 2.2: Δ Fear 3.2: $\times$	4.3: $-\checkmark$ 1.3: $\checkmark$ 2.3: $\checkmark$ 3.3: $\checkmark$	4.3: $-\checkmark$ 1.3: $\checkmark$ 2.3: $\checkmark$ 3.3: $\checkmark$
H4a (Low-arousal positive $\rightarrow \uparrow$ Engagement)	4.0: $\checkmark$ 1.0: $\checkmark$ 2.0: $\checkmark$ 3.0: $\checkmark$	4.1: $\times$ 1.1: $\times$ 2.1: $\times$ 3.1: $\times$	4.2: $\times$ 1.2: $-$ 2.2: $\times$ 3.2: $\times$	4.3: $-\checkmark$ 1.3: $\checkmark$ 2.3: $\checkmark$ 3.3: $\checkmark$	4.3: $-\checkmark$ 1.3: $\checkmark$ 2.3: $\checkmark$ 3.3: $\checkmark$
Legend: $\checkmark$ Supported; $\times$ Not supported; Δ Partially supported; $-$ Not applicable / not significant					
Engagement Model codes: 4.* total engagement; 1.* reply engagement; 2.* retweet engagement; 3.* like engagement					

4.9.1. Results for H1a/H1b: Sentiments at low construal levels will have a positive relationship with public engagement

The regression models estimate associations between sentiment, construal level, and engagement outcomes. In line with H1a, tweets framed at low construal levels showed a positive association between more positive (or less negative) sentiment and engagement in the Public Transport subset (Model 4.2, $\beta = 0.64$, $SE = 0.046$, $p < 0.001$). This association was not observed in the Whole dataset, Commercial, or Private Cars subsets. Robustness checks of the engagement models confirm that the Public Transport effect was driven by retweets (Model 2.2) and likes (Model 3.2).

Topic-wise analyses revealed support for H1a across technology (Models 4.0, 1.0, and 3.0), pricing (Model 1.0), traffic (Model 2.0) in the whole datasets; employment (Models 4.1, and 3.1) and technology (Models 4.1, 1.1, and 3.1) in the commercial vehicle segment; infrastructure (Models 4.2, 2.2, and 3.2), traffic (Models 4.2, and 3.2), and technology (Models 4.2, 1.2, 2.2, and 3.2) in the public transport domain; infrastructure (Model 3.3), safety (Models 1.3, 2.3, and 3.3), pricing (Model 1.3), and technology (Models 1.3, and 3.3) in the private car subset. H1b was supported for the safety topic in the private cars subset, across replies, retweets, and likes; while pricing in the replies engagement. This indicates that

identity-relevant discourse amplifies engagement specifically when safety is framed positively and concretely.

4.9.2. Results for H2a/H2b: Sentiments at high construal levels will have a negative relationship with public engagement

Across the whole dataset, H2a for tweet-level sentiments and high construal framing was only supported in the reply engagements (Model 1.0), in other models it was either non-significant (Model 2.0) or had the opposite association (Models 4.0, and 3.0). In the segment specific models, commercial vehicles closely reflects the whole dataset H1a support in the reply model (Model 1.1), however it is not significant in the public transport domain (Model 1.2). Private cars is the only subset where H1a is supported in all three engagement type of replies (Model 1.3), retweets (Model 2.3), and likes (Model 3.3), and in case of replies H2b is also supported.

Topic-wise analyses similarly revealed that a more positive sentiment $\times$ high-construal context has negative effects on engagement in the whole dataset for pricing (Models 4.0, 2.0, and 3.0), infrastructure (Models 4.0, 2.0, and 3.0), events (Models 4.0, 2.0, and 3.0), and technology (Model 1.0); in the commercial vehicles H2a were supported for pricing (Models 4.1, and 3.1), technology (Models 1.1-4.1), safety (Models 1.1-4.1), and events (Models 2.1, and 3.1); in the public transport for technology (Models 1.2-4.2), infrastructure (Models 4.2, 2.2, and 3.2), safety (Models 4.2, 2.2, and 3.2), and events (Model 3.2); and in the private car domain for employment (Models 2.3, and 3.3), technology (Model 1.3), pricing (Models 2.3, and 3.3), infrastructure (Models 2.3, and 3.3), and safety (Model 3.3), however H2b was only supported in retweets (Model 2.3) for employment and pricing, and in likes (Model 3.3) for pricing and safety.

4.9.3. Results for H3a/H3b: High-arousal negative emotions will have a positive relationship with public engagement

The whole-dataset regression results strongly supported H3a in total engagement (Model 4.0) and in likes (Model 3.0), but only partially was supported in replies (Model 1.0) and retweets (Model 2.0) through the angry emotion only. Segment-wise analyses revealed partial support for H3a in the public transport context through fear emotions in the total engagement (Model 4.2) and retweets (Model), however in the other two engagement type it was either not supported or not significant. In the commercial context none of the engagement type supported our hypothesis, in fact every emotion had negative effect on post engagements, suggesting users prefer to engage with professional or factual discussions rather than emotion fused ones. In contrast, the private car subset showed full support for both H3a and H3b in every

engagement type. These findings underscore H3b: high-arousal negative emotions are especially potent drivers of engagement in identity-relevant private-car discourse.

4.9.4. Results for H4a/H4b: Low-arousal negative emotions will have a negative relationship with public engagement

The whole-dataset results supported H4a in every engagement type (Models 1.0-4.0). So did the private car segment (Models 1.3-4.3), supporting both H4a and H4b. In the commercial vehicle and public transport segments happiness, a low-arousal positive emotion, showed overwhelmingly negative association with engagement, not supporting H3a in these segments. This aligns with theoretical expectations that low-arousal positive affect promotes affiliative and prosocial engagement behaviours especially in identity-relevant context.

4.9.5. Summary

Across hypotheses, a consistent pattern emerges: identity-relevant private-car discourse behaves differently from commercial-vehicle and public-transport discourse. High-arousal emotions (H3) and low-arousal positive affect (H4) are especially potent in this segment, while sentiment–construal interactions (H1–H2) slightly diverge from theoretical expectations except in identity-laden contexts. These findings highlight the importance of segment-, and engagement-specific modelling and provide a foundation for the theoretical and managerial implications discussed in Section 5.

5. Discussions

5.1. Discussion of the results

The empirical findings reveal a multi-layered engagement system shaped by psychological distance, emotional arousal, topic relevance, and transport-segment identity. Consistent with Construal Level Theory (CLT), psychologically proximal topics such as safety, infrastructure, traffic, and hands-on technology perceptions elicited higher engagement, particularly among private car users. Safety sentiment showed the strongest positive effect across both regression and predictive models, reflecting individuals’ concrete, self-relevant concerns about daily travel and personal well-being (Trope and Liberman, 2010; Wang, Kirmani and Li, 2021; Zhai and Wolff, 2021; Nguyen and Fujita, 2024). Infrastructure sentiment similarly increased engagement, aligning with evidence that tangible, near-term transport issues evoke vivid mental representations and stronger behavioural responses (Thompson Sargoni and Manley, 2023; Schandl, Lermer and Hudecek, 2024). These results reinforce the CLT proposition that reducing psychological distance enhances emotional resonance and motivates public

interaction with SDV content (Haboucha, Ishaq and Shiftan, 2017). Our contribution here is demonstrating that CLT effects are not uniform but segment-dependent, with private car users showing the strongest proximity-driven engagement.

In contrast, high-level, abstract topics such as future technology concepts, long-term infrastructure planning, and distant pricing strategies tended to reduce engagement. These topics are psychologically distant, uncertain, and less personally relevant, which weakens emotional responses and reduces motivation to interact. Negative sentiment on such high-CLT topics further suppressed engagement, suggesting cognitive fatigue or avoidance when content feels too abstract or speculative. Employment sentiment showed no significant effect in the whole dataset, driven by opposing segment-level patterns: positive associations in commercial and public transport contexts but negative associations in private cars. This divergence highlights that topic relevance interacts with transport segment identity, shaping how audiences appraise distant issues. Our contribution is showing that psychological distance is not a fixed property of content but dynamically shaped by audience–segment identity.

The predictive modelling results reinforce and expand upon the theoretical insights drawn from the regression analysis. Among the models tested, XGBoost consistently outperformed others, including Poisson regression, in predictive accuracy, making it the basis for further interpretive analysis. The variable importance rankings revealed happiness as the most influential emotional predictor of total engagement, followed by traffic sentiment. Partial dependence plots (PDPs) provided nuanced perspectives on how these variables affect engagement. Consistent with Construal Level Theory (CLT), the PDPs showed that psychologically proximal topics and concrete emotions evoke stronger behavioural responses. For example, anger exhibited a strictly positive association with engagement, indicating that emotionally intense, possibly injustice-related content prompts public reaction. Similarly, sadness also showed a weak but positive trend, further supporting the idea that emotionally resonant content drives interaction. In contrast, happiness and fear followed inverted U-shaped trends, suggesting diminishing engagement at extreme levels—likely due to message saturation or emotional fatigue. Among topics, safety demonstrated a similar inverted U-shape, reinforcing regression findings that overly positive messaging on safety may reduce engagement. Technology sentiment displayed a rising trend, indicating that too much negativity may dissuade interest, whereas more balanced or positive tones sustain engagement. Traffic showed a U-shaped effect, pointing to polarised reactions, possibly due to its personal impact versus structural blame. Sentiment related to employment and infrastructure showed steep declines in engagement at high levels, supporting the notion that abstract, policy-oriented

topics elicit lower public resonance when framed too positively or optimistically. Finally, pricing showed negligible influence, consistent across both modelling approaches. Our contribution is to demonstrate that machine-learning interpretability tools can reveal non-linear emotional mechanisms that traditional regression models cannot capture.

The segment-wise findings further support CLT's predictions regarding psychological proximity. Private vehicles, strongly tied to personal identity, autonomy, and lifestyle, elicited the highest engagement for safety and infrastructure topics. These topics are appraised as personally relevant, prompting concrete mental representations and heightened emotional involvement (Trope and Liberman, 2010). Public transport and commercial vehicles, perceived as more institutional and distant, showed weaker or negative sentiment–engagement relationships. Interestingly, negative sentiment on distant topics (technology, traffic) reduced engagement more for private cars than for other segments, suggesting that personal relevance does not always buffer adverse effects. Our contribution is showing that identity-relevant domains amplify both positive and negative emotional responses, revealing a bidirectional proximity effect.

The emotional findings strongly support Appraisal Theory (Lazarus, 1991). High-arousal negative emotions (fear, anger) increased engagement across multiple models, particularly in private cars, where safety threats are appraised as personally relevant. Low-arousal negative emotions (sadness) elicited little engagement, consistent with their reflective, non-action-oriented nature. Positive emotions showed the opposite pattern: low-arousal positivity (happiness) produced sustained engagement, especially in private cars, while high-arousal positivity (surprise) had weaker effects. Our contribution is integrating CLT and Appraisal Theory to show that emotional arousal interacts with psychological distance and transport-segment identity to shape engagement.

5.2. Theoretical Contribution

This study advances self-driving vehicle (SDV) related research by examining how emotional and psychological factors influence public engagement on social media across private, public, and commercial transport segments. Prior work has largely relied on surveys grounded in the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Manfreda, Ljubi and Groznik, 2021), Innovation Diffusion Theory (IDT) (Talebian and Mishra, 2018, 2022; Ghasri and Vij, 2021), and trust–risk models (Lee and Mirman, 2018; Wang and Zhao, 2019; Bertrandias *et al.*, 2021; Yoo, Kumagai and Managi, 2024), often overlooking the large-scale, real-time behavioural data available from social

media. By contrast, this study employs social media analytics to reveal how emotional content shapes engagement behaviours (likes, shares, comments).

Existing SDV social media research has focused primarily on sentiment classification and topic identification (Kohl *et al.*, 2017; Ding *et al.*, 2021; Chen *et al.*, 2021; Laurell and Sandström, 2022; Li *et al.*, 2025) but rarely on how emotional content influences engagement. Addressing this gap, our study integrates psychological theories of emotional processing and psychological distance with empirical evidence from engagement patterns, deepening understanding of the mechanisms underpinning technology acceptance across market segments.

We provide empirical support for Construal Level Theory (CLT) (Trope and Liberman, 2010; Haboucha, Ishaq and Shiftan, 2017; Wang, Kirmani and Li, 2021; Zhai and Wolff, 2021; Thompson Sargoni and Manley, 2023; Nguyen and Fujita, 2024; Schandl, Lerner and Hudecek, 2024), showing that psychological proximity amplifies engagement with concrete, personally relevant topics (e.g., safety, pricing, or infrastructure), particularly in a private car context, whereas abstract, distant topics (e.g., technology or employment) elicit lower engagement, especially when sentiment is less positive. We further extend CLT by demonstrating that although psychological proximity amplifies engagement in identity-relevant domains (private cars), public transport and commercial contexts exhibit attenuated or even reversed effects. This refines CLT by showing that proximity is audience-segment dependent rather than solely content-dependent (Trope and Liberman, 2010; Nguyen and Fujita, 2024).

Second, drawing on the Appraisal Theory of Emotion (Lazarus, 1991), we demonstrate that high-arousal negative emotions (fear, anger) drive rapid, automatic responses and immediate engagement, while low-arousal negative emotions (sadness) elicit more reflective processing and lower interaction. Psychological proximity moderates these effects, with private car owners showing stronger reactions to safety threats (Lazarus, 1991; Trope and Liberman, 2010).

We extend affective theories by showing that low-arousal positive emotions (happiness) produce more sustained engagement than high-arousal positive emotions (surprise), supporting the Appraisal Theory of Emotion, which links low-arousal states to appraisals of certainty and control and high-arousal states to novelty and low predictability (Lazarus, 1991; Roseman, 1991; Scherer, 2001; Ellsworth & Scherer, 2003). Finally, by comparing private, public, and commercial transport segments, we refine CLT by demonstrating that distant topics can trigger negative reactions in private car contexts but neutral or positive responses in public and

commercial settings. This highlights psychological distance as a dynamic construct shaped by both content and transport segment, advancing theoretical integration of emotional arousal, proximity, and user engagement in SDV-related discourse.

5.3. Managerial Implications

The findings of this study offer a range of practical implications for transportation managers, communication strategists, and policymakers aiming to create positive public opinion regarding SDVs and increased engagement on SDV-related discourse across varied market segments.

Communication strategies should emphasise psychologically proximal and personally meaningful topics, particularly safety, reliability, and infrastructure, when engaging private car users. These topics align closely with users' daily concerns and self-identity, making them more emotionally resonant and likely to elicit trust, curiosity, and positive engagement. Campaigns that spotlight tangible features such as collision-avoidance systems, lane-keeping assistance, or real-world infrastructure improvements (e.g., smart intersections or dedicated AV lanes) are more likely to generate user interest, stimulate social sharing, and enhance perceived value.

Transportation managers should be acutely aware of the emotional tone embedded in SDV messaging. High-arousal negative emotions such as fear, anger, or anxiety can rapidly drive online engagement (e.g., comments, shares), but they also carry reputational risk if left unmanaged. To mitigate backlash, organisations must respond to public concerns with timely, transparent, and empathetic communication, particularly during incidents or policy changes. Conversely, leveraging low-arousal positive emotions such as happiness, satisfaction, and comfort can promote sustained engagement and long-term affinity with the SDV brand or service. Encouraging user-generated content that showcases pleasant or empowering SDV experiences, such as stress-free commutes or time-saving benefits, can further enhance community building and user advocacy.

The study underscores the importance of segment-specific communication. While private vehicle users respond more strongly to personal safety and autonomy, public transport and commercial vehicle users may be more concerned with systemic outcomes such as efficiency, traffic flow, and technological innovation. Tailoring content to these distinctions is crucial: for example, highlighting reduced traffic congestion or operational cost savings may be more persuasive in public or fleet contexts, whereas overly technical or abstract messaging may alienate private users if not directly linked to their personal needs or concerns.

The emotionally charged and fast-moving nature of social media requires active, real-time monitoring of public sentiment and discourse. Employing tools for sentiment analysis, emotion detection, and topic tracking enables organisations to identify emerging trends, misinformation, or shifts in public opinion. This responsiveness allows communicators to adjust narratives, counteract negative sentiment, and strategically reinforce positive topics before reputational risks escalate.

Engagement can be significantly enhanced through identity-consistent messaging. For private car users, aligning SDV narratives with personal aspirations, such as independence, status, or environmental responsibility, can deepen emotional resonance and increase the likelihood of sharing and endorsement. Positioning SDVs as congruent with users' values and lifestyles transforms passive awareness into active advocacy.

The effectiveness of SDV communication hinges on a nuanced understanding of psychological distance, emotional dynamics, and audience-specific motivations. By strategically aligning messaging with these factors, organisations can foster deeper engagement, build sustained public trust, and ultimately accelerate the diffusion and normalisation of autonomous vehicle technologies.

5.4. Future Scope

While this study offers valuable insights into public engagement with SDV-related content, several limitations warrant attention. Reliance on Twitter data may underrepresent broader public opinion, highlighting the need for multi-platform analyses. Tweets were sampled using AV-related keywords rather than account-based criteria, resulting in a heterogeneous mix of private users, media outlets, firms, and other actors. While this diversity reflects the broader public discourse around AVs, it may limit the precision of managerial implications for specific stakeholder groups. Future research could employ account-level classification or platform triangulation to derive more targeted insights.

The observational design limits causal claims, and our transport mode categories may oversimplify socio-demographic variation; richer demographic and psychographic data could address this. Sentiment and topic models also struggle with sarcasm, irony, and nuanced language, suggesting value in advanced NLP and multimodal approaches. A further limitation is that we do not model the dynamic growth of engagement over time. Posts accumulate replies, retweets, and likes at different rates, and modelling these temporal diffusion patterns could reveal additional behavioural mechanisms. Future work could incorporate temporal or survival-based modelling to capture how engagement evolves after posting.

A related limitation of this study concerns the operationalisation of psychological proximity. While consistent with Construal Level Theory, we conceptualise proximity at the content (tweet) level rather than the audience level; certain audience characteristics (e.g., professional drivers or urban residents) may experience greater proximity to topics associated with commercial or public AV use. Although this does not undermine our theoretical framing, future research could explicitly model audience identity and usage context as moderators to further refine proximity perceptions. Additionally, engagement with earlier posts may shape the emotional tone of subsequent posts, creating potential temporal spillover effects. Because our analysis is not time-series-based, such endogeneity does not arise in the present study; however, examining emotional carryover effects across posts would be a valuable direction for future research.

Finally, cross-cultural differences in psychological distance and emotional response merit further study to inform more effective, locally tailored engagement strategies.

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