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Exploring public discourse about new cycle lanes and low-traffic neighbourhoods using Twitter/X data☆

Isabella Malet Lambert [a], Wouter Poortinga [a,b], Dimitris Potoglou [c,*], Dimitrios Xenias [a]

[a] School of Psychology, Cardiff University, CF10 3AT Cardiff, UK
[b] Welsh School of Architecture, Cardiff University, CF10 3NB Cardiff, UK
[c] School of Geography and Planning, Cardiff University, CF10 3WA, UK

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ABSTRACT

While sustainable transport initiatives generally enjoy broad public support, new cycle lanes and Low Traffic Neighbourhoods (LTNs) often face strong opposition from local campaign groups, particularly on social media. This study examined public sentiment towards these measures and how it evolved in response to the UK Government's Emergency Active Travel Fund, using social media data from Twitter (now "X"). A total of 36,696 UK-based tweets related to cycle lanes and LTNs were analysed over a four-year period, spanning two years before and two years after the fund's announcement in May 2020 (1 March 2018 to 30 June 2022). Sentiment analysis revealed that while most tweets were positive, negative sentiment increased after the fund was announced. Structural Topic Modelling (STM) identified 13 key discussion topics, including cycle lane design, road user behaviour, and experiences using cycling infrastructure. Notably, discussions rarely addressed broader benefits of active travel, such as climate change mitigation or public health improvements. The findings indicate that new cycling infrastructure is generally well-received, but that public sentiment fluctuates over time. Criticism tends to focus on poorly designed or unsafe infrastructure and concerns around their implementation. This research demonstrates the value of social media analysis to understand the content and dynamics of public opinion on transport infrastructure changes, as well as the use of sentiment analysis and STM in analysing large text datasets.

1. Introduction

In order to increase the number of journeys made by active travel, the UK Government has made several commitments to invest in and develop related infrastructure (e.g., Department for Transport, 2021b). This is due to the capacity of active travel modes to address many growing problems caused by overreliance on cars, such air pollution (Johansson et al., 2017), carbon emissions (Department for Transport, 2020c), and sedentary lifestyles (Jarrett et al., 2012; Saunders et al., 2013). While sustainable transport initiatives generally enjoy broad public support, new cycle lanes and Low Traffic Neighbourhoods (LTNs) often face strong opposition from local campaign groups, particularly on social media (e.g., Hickman et al., 2025). This may give the impression that such measures are less popular than they actually are and can fuel opposition through antagonistic discourses (Gössling et al., 2024). It is therefore important to understand how new active travel infrastructure is received on social media and how these responses evolve over time. In this study, we present the results of a social media analysis of Twitter (now "X") data before and after the provision of new active travel infrastructure, aiming to better understand the content and dynamics of public discourse surrounding their introduction.

The rest of the paper is organised as follows. Section 2 reviews the existing literature on public support for and opposition to active travel measures and discusses how social media can be used to analyse public opinion dynamics. The section concludes with the aims of this research, including a description of the Emergency Active Travel Fund, which forms the use case for this study. Section 3 details the methodology, including the use of Structural Topic Modelling (STM) and sentiment analysis, as well as the overall research design. Section 4 presents the results of the analyses in relation to the study's objectives. Section 5 summarises the key findings, discusses them in the context of the wider literature, and outlines the strengths and limitations of the research.

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* Corresponding author.
E-mail addresses: maletlambertei@cardiff.ac.uk (I.M. Lambert), poortingaw@cardiff.ac.uk (W. Poortinga), potogloud@cardiff.ac.uk (D. Potoglou), xeniasd@cardiff.ac.uk (D. Xenias).

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Finally, Section 6 provides an overall conclusion of the research.

2. Literature review

2.1. Public support and opposition to active travel measures

Understanding public opinions towards government policies to increase active travel, through new cycle infrastructure and other travel demand management measures, such as LTNs, is important because public acceptance is an integral part of any successful policy or infrastructure change (Drews and van den Bergh, 2016). Previous research has identified low public support as a significant barrier to the implementation and success of climate change mitigation policies (Newman and Head, 2015). Studies focusing specifically on policies to reduce car use have similarly found that public acceptance is a key factor in their successful adoption (Gärling, 2007).

Active travel initiatives can face strong opposition from local campaign groups. In some cases, this opposition has led to the removal of newly implemented infrastructure. For example, in Gloucester, UK, a cycle lane funded by the Emergency Active Travel Fund was dismantled just five days after its opening following complaints about increased traffic congestion (Morton, 2020). In Portsmouth, UK, a trial cycle lane was removed after 67 % of survey respondents reported negative impacts on businesses and residents (Portsmouth City Council, 2020). Further across the UK, opposition to new cycle lanes has manifested itself through protests by motorists and residents, as well as petitions organised by businesses (Cantrill, 2020). Similarly, some LTNs that were funded through the Emergency Active Travel Fund have been withdrawn due to protests and petitions (Finn, 2022). Opposition to new cycle lanes and LTNs has also been observed more broadly (Aldred et al., 2019), and has been reported internationally, including in Ireland (Kelly, 2021), Germany (Cantrill, 2020) and the USA (Calvert, 2018), indicating 'bikelash' is a widespread phenomenon.

While opposition to active travel infrastructure may create the impression that it is widely unpopular, research shows that such measures generally enjoy broad support among both local residents and the wider public. For instance, a majority of UK residents favour reallocating road space for active travel (Department for Transport, 2020c), even when this reduces space for cars (Sustrans, 2017). A review by the Department for Transport (2020a) found that only a small minority (7–15 %) strongly oppose such initiatives. Similarly, a recent survey reported that 53 % of respondents supported LTNs (Poortinga et al., 2023). These findings suggest that while (local) opposition may often be vocal and visible, it does not necessarily reflect broader public opinion.

Opposition to new infrastructure is often most intense and vocal at the time of implementation. Research on new energy infrastructures, such as wind turbines (Wilson and Dyke, 2016) and offshore renewable energy developments (Dreyer et al., 2017), suggests that public opinion typically follows a U-shaped curve, with a temporary decline in support at the point of implementation. However, over time, familiarity and extended exposure tend to foster greater acceptance, often resulting in higher support post-implementation than pre-implementation, even after an initial dip (Wilson and Dyke, 2016). Similarly, studies on the introduction of travel demand management measures have found that support often increases after implementation (Schuitema et al., 2010). For example, interviews with residents and business owners conducted before and after the installation of a cycle lane in Sydney, Australia, revealed a positive shift in community perceptions following its introduction (Crane et al., 2016).

However, this trend is not universal. Case studies on road pricing indicate that acceptance does not always improve. Contextual factors, such as the design of the scheme, perceptions of its necessity, and the role of automobility in general influence whether changes are supported or not. Hysing and Isaksson (2015) show that while support for the Stockholm congestion charge increased shortly after the start of the trial, opposition to the Gothenburg congestion charge was effectively mobilised, resulting in a majority voting against its continuation in an advisory referendum. Similarly, Gu et al. (2018) highlight how differences in the design of congestion pricing schemes and how the effects of them are communicated shape levels of acceptance across cities.

It however remains unclear how public responses to new cycling infrastructure and LTNs evolve over time, particularly whether they follow similar patterns observed for green energy infrastructure and travel demand management measures, as limited research has been done in this area. Gaining a better understanding of public attitudes toward cycle lanes and LTNs, and how these shift over time, is particularly important, given that some trial schemes have been removed in response to public opposition only shortly after they were introduced. In such cases, the schemes may not have been in place long enough for attitudes to shift in their favour. Furthermore, as policymakers are often hesitant to pursue initiatives they believe lack public backing, tracking changes in public sentiment is vital for ensuring continued government support and for guiding evidence-based policymaking (Aldred et al., 2019).

2.2. Social media analysis to understand public opinion to active travel measures

Reliable data on public opinion is often not readily available, especially over extended periods, making it difficult to capture evolving attitudes toward active travel interventions. In this context, social media platforms offer a valuable, real-time source of public discourse that is typically accessible to researchers (Dong and Lian, 2021). As a result, the use of social media data to explore social trends and sentiment has grown significantly in recent years (ibid). Social media platforms host a vast amount of openly shared content, particularly around current and controversial topics. Two common approaches to analyse such data are sentiment analysis and Structural Topic Modelling (STM). Sentiment analysis involves evaluating the emotional content of textual data to determine the affective tone, i.e., positive or negative, with which a topic is discussed (Balahur et al., 2014). STM is a Bayesian text analysis method that identifies latent topics within a collection of documents, in this case, tweets, by clustering words based on their probability of occurrence within, and exclusivity to, each topic (Steyvers et al., 2004).

Twitter/X is a microblogging platform designed for sharing experiences and opinions through short public messages, known as 'tweets'. Originally envisioned as a digital town square for public discourse, it has become a valuable tool for public opinion research due to the high volume of concise, time-stamped content it generates. Compared to other media formats (Dong and Lian, 2021), Twitter/X offers particular advantages for social media analysis, at least at the time this research was conducted. These included a large and active user base (Statista, 2022), as well as access to historic tweets. This makes the platform well-suited for large-scale, longitudinal analyses of public sentiment, enabling researchers to track shifts in opinion over time and in response to specific events or policy changes.

Sentiment analysis has been used widely to analyse Twitter/X data across a range of domains, including public attitudes towards vaccines (Narawade and Dandekar, 2023), emerging technologies (Ding et al., 2021), bike sharing schemes (Das et al., 2019; Serna et al., 2019), climate change (Effrosynidis et al., 2022), and transport during the COVID-19 pandemic (Politis et al., 2021). Similarly, STM has been used widely as a method to analyse Twitter/X data in various contexts, including political discourse (Shayegh et al., 2024), vaccine hesitancy (Jiang et al., 2021), public experiences and concerns during the COVID-19 pandemic (Lu and Liu, 2023), attitudes toward climate change policies (Wei et al., 2021), and sustainable consumption (Brzustewicz and Singh, 2021).

In transport research, STM has been applied to investigate attitudes towards autonomous vehicles (Lee and Kolodge, 2020), pedestrian safety (Bardutz and Bigazzi, 2022), and mobility as a service (Leung, 2023). It has also been used to examine the thematic and social elements of conversations surrounding the implementation of new cycling

infrastructure in Canada (Ferster et al., 2021). That study found that early discussions centred on advocacy gradually shifted toward greater acceptance. However, Ferster et al. (2021) primarily relied on discrete time points before and after the intervention, offering limited insight into the dynamic changes that may have occurred over the period of implementation.

In relation to LTNs, research tracking public acceptance and opposition is similarly scarce. To the best of our knowledge, only one study has applied sentiment analysis to tweets concerning LTNs in London (Zhu, 2020). While this study found no significant relationship between the introduction of LTNs and shifts in sentiment, the analysis covered only a brief seven-month period during the early phase of the COVID-19 pandemic. Given the limited body of social media research on LTNs and other active travel measures, and the importance of understanding how public attitudes evolve over time, particularly beyond the immediate post-implementation period, our study addresses a key gap in the literature. Public opinion may shift not only after LTNs are introduced but also when such infrastructure is first proposed (Wolsink, 2007).

Identifying the key topics of discussion surrounding cycle lanes and LTNs, along with the sentiment associated with these topics, can provide insights into the factors that influence public acceptance or opposition. For example, previous research suggests that support for or resistance to such infrastructure may depend on variables such as location and design (Guo et al., 2023; Bland et al., 2024), perceived need and level of disruption (Ferster et al., 2021), and perceived impacts on businesses (Crane et al., 2016; Ferster et al., 2021). However, these factors have not been systematically explored using social media data before. By analysing how specific themes are discussed on social media platforms, such as Twitter/X, this study seeks to contribute a novel perspective on the dynamics of public sentiment and the drivers of support or opposition toward active travel measures.

2.3. The current study

The literature review above shows that, despite growing interest in public responses to active travel measures, there remains a lack of high-quality longitudinal research examining how attitudes to these measures evolve over time, particularly during their implementation. While several studies have examined the introduction of active travel measures (e.g., Zhu, 2020; Ferster et al., 2021), most have focused on single time points or short periods, offering limited insight into the longer-term temporal dynamics of public discourse. Moreover, the potential of social media data to track such shifts at scale remains underutilised.

This study focuses on the Emergency Active Travel Fund; a £250 million fund launched in May 2020 by the UK Government to support local authorities in implementing cycling and walking infrastructure in response to the COVID-19 pandemic. The fund could be used by councils to facilitate social distancing by reallocating road space for active travel, while also advancing the broader active travel agenda beyond the pandemic (Department for Transport, 2020a). By 2021, it had resulted in hundreds of additional school streets, over 100 miles of new segregated cycle lanes, and at least 150 new Low Traffic Neighbourhoods (LTNs) (Department for Transport, 2021a). The Emergency Active Travel Fund is an appropriate use case for this study, as it was a time-bound investment rolled out rapidly across many local authorities in the UK, providing a unique opportunity to make a clear before-and-after comparison in response to the newly introduced infrastructure.

The aim of this study is to explore the content and dynamics of public discourse surrounding the introduction of cycle lanes and LTNs in the UK, using data from the social media platform Twitter/X. Specifically, it examines: (1) the volume of tweets related to cycle lanes and LTNs and how this changes over time; (2) the sentiment of those tweets; and (3) the main discussion topics, including their sentiment profiles and temporal evolution. The analysis spans a four-year period from two years before to two years after the scheme's announcement in spring 2020. Given that both cycle lanes and LTNs were funded under the same programme and have been subject to similar public debates (Ferguson, 2018), with opposition often centred on concerns over road space allocation, congestion, and accessibility (e.g., Hickman et al., 2025), this study examines them in conjunction. By analysing both within the same framework, it demonstrates how the content and dynamics of social media discussion cut across these different travel demand measures.

Beyond its substantive focus, this study also makes several methodological contributions. Firstly, it is the first to apply both sentiment analysis and Structural Topic Modelling (STM) to an extensive dataset of Twitter/X posts about active travel infrastructure in the UK, covering a four-year period that spans both pre- and post-implementation phases. This longitudinal design enables us to capture temporal dynamics in public discourse that shorter or cross-sectional studies cannot observe. Secondly, by integrating sentiment analysis with STM, the study not only identifies the prevailing themes in online discussions but also links these themes to their associated emotional tone, offering important insight into the drivers of support and opposition. Finally, the approach demonstrates how openly available social media data can be leveraged to provide timely, large-scale, and cost-effective public-opinion monitoring, complementing more resource-intensive methods such as surveys or interviews. Together, these methodological advances provide a robust framework for tracking public sentiment toward transport interventions and can be applied to other policy domains where public acceptance is critical.

3. Methods

3.1. Data

The Twitter/X Application Programming Interface (API) was used to extract tweets from Twitter. The API allows for systematic access to both current and historic Twitter/X data through user-defined queries. The identification and screening of relevant tweets required the following parameters: the relevant time period, language, country code and a set of screening criteria.

The study examined a four-year period from 1 March 2018 to 30 June 2022, encompassing two years on either side of the Emergency Active Travel Fund announcement in spring 2020 (Department for Transport, 2020a). Tweets had to be written in English with country code 'GB' (Great Britain). Regarding the set of screening criteria, these included search terms for different versions of terms for cycle lanes and LTNs (see, Table 1), and any tweets, which might have been related to the Emergency Active Travel Fund. Tweets containing the LTN acronym were excluded if they were used in combination with the term airport, as

Table 1
Search terms for Cycle Lanes and Low Traffic Neighbourhoods.

Cycle Lane-related search terms	LTN-related search terms
• "Bike lane" OR • "Bike lanes" OR • "cycle lane" OR • "cycle lanes" OR • "cycle path" OR • "cycle paths" OR • "bike path" OR • "bike paths" OR • "active travel fund" OR • "cycle highway" OR • "cycle highways" OR • "cycle superhighway" OR • "cycle superhighways" OR • "cycling highway" OR • "cycling highways" OR • "cycling superhighway" OR • "cycling superhighways" OR • "cycle route" OR • "cycle routes" OR • "cycling infrastructure"	• "Low traffic neighbourhood" OR • "Low traffic neighbourhoods" OR • "Low traffic neighborhood" OR • "Low traffic neighborhoods" OR • ("LTN" −airport) OR • "LTNs" OR • "Low traffic community" OR • "Low traffic communities" OR • "mini holland" OR • "mini hollands"

the abbreviation is often used to refer to Luton Airport. Also, retweets were excluded to avoid duplication. It is worth noting that before data analysis, additional cleansing of the tweeted text was performed to remove extraneous elements such as symbols (e.g., '@' and '#'), hyperlinks, ampersands (&), punctuation marks, and line breaks. Where an '@' symbol was used to mention a specific Twitter/X account, the account's full name was also removed. The whole procedure was applied, and the relevant tweet data were extracted on 28 July 2022.

3.2. Analytical approach

The Tweets were obtained in JSON format and converted into an R (R Core Team, 2021) dataframe using the 'jsonlite' package (Ooms, 2014). Following data processing and cleansing using the 'tidyverse' package (Wickham et al., 2019), the analysis of the Twitter/X data employed three approaches: (a) Line Graph of tweet number over time, (b) Sentiment Analysis and (c) Structural Topic Modelling (Roberts et al., 2019). These approaches directly corresponded to each of the aims of this study as shown in Fig. 1.

A *Line Graph* of tweets over time was generated by calculating the monthly volume across the four-year study period. This analysis identified how often new cycle lanes and LTNs were discussed and highlighted temporal trends in tweet frequency. The analysis and generation of the line graph was conducted using the R packages 'lubridate' to process the date and time stamp of each tweet (Grolemund and Wickham, 2011) and 'dplyr' (Wickham et al., 2023) to count the Tweets for each time stamp, respectively.

Sentiment Analysis, also named *opinion mining*, is a continuously developing field of study focused on analysing individuals' opinions, sentiments, attitudes, and emotions towards various topics such as policies, services, individuals, issues, and events (Liu, 2012). The field leverages the large volume of opinion-rich data generated on social media applying advanced natural language processing techniques to identify and classify emotional tone (e.g., positive, negative or neutral) in text (Liu, 2012). In this study, Sentiment Analysis was used to determine whether the tweets about cycle lanes and LTNs expressed predominantly positive or negative sentiments. The first step involved counting the number of positive or negative words in each tweet. This analysis was conducted using the 'bing' sentiment lexicon from the R package *tidytext* (Silge and Robinson, 2016), which classified single words (unigrams) as either positive or negative. Positive words were given a score equal to +1 and negative words were given a score of −1. An aggregate positive and negative score was then calculated per tweet ID and their difference resulted into an overall positive or negative sentiment for each tweet. Tweets with an aggregate score of zero – either due to lack of positive or negative words or equal counts of positive and negative words – were excluded from further sentiment analysis.

Structural Topic Modelling was employed to explore thematic patterns within Twitter/X discussions on cycle lanes and Low Traffic Neighbourhoods (LTNs). Structural Topic Modelling is a form of topic modelling that uses unsupervised machine learning to analyse text data (e.g., documents, tweets) and identify underlying topics (Steyvers et al.,

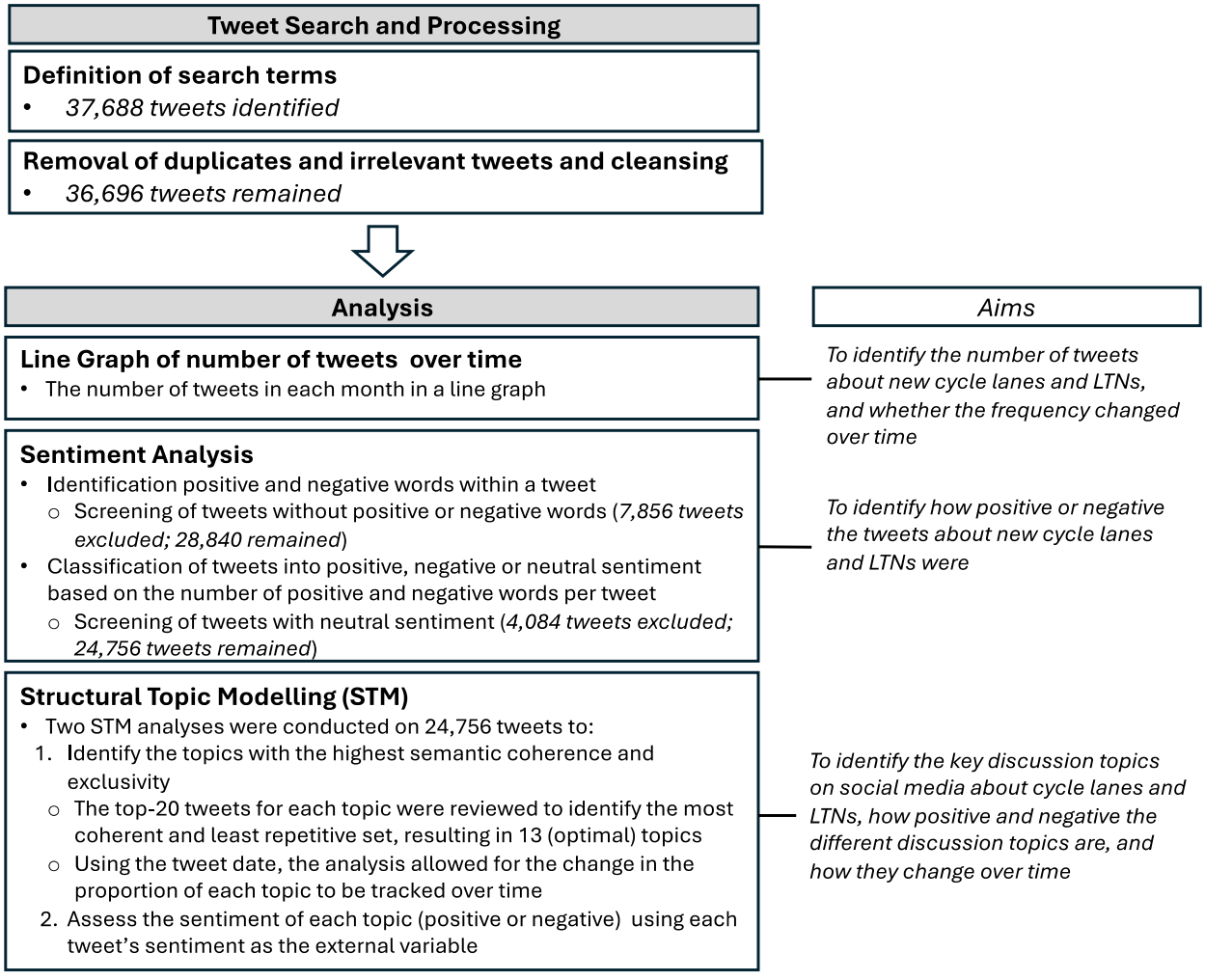


Fig. 1. Research design and analysis in the study.

2004; Roberts et al., 2016). A key advantage of STM over other topic models is its ability to incorporate document-level metadata – such as the date or sentiment of a tweet – into the analysis (Roberts et al., 2019). This allows for the examination of how topic prevalence and content vary across external factors (metadata dimensions). In this study, STM was applied for two main purposes: (1) to identify the key topics of discussion on Twitter/X regarding cycle lanes and LTNs and examine how these topics evolved over time, and (2) to assess the sentiment associated with each topic. To determine the optimal number topics, the SearchK function from the R package *stm* was applied (Roberts et al., 2019). This step involved running multiple STM models with varying numbers of topics (e.g., 5, 10, 15, 20) and selecting the model with the highest semantic coherence and topic exclusivity. For each model run, the top 20 most representative tweets per topic were reviewed to evaluate internal coherence and minimise topic overlap. In this study, two STM models were estimated. The first model used the tweet posting date as external factor (metadata), enabling the analysis of topic prevalence to be tracked over time. The second model focused on the subset tweets that were classified as either positive or negative sentiment through the earlier sentiment analysis. In this second model, sentiment served as the metadata, allowing each topic to be classified as having a positive or negative sentiment.

4. Results

4.1. Number of tweets about new cycle lanes and LTNs

The initial search procedure presented in Section 3.1 yielded 37,688 tweets. After removing duplicate tweeted texts, duplicate tweet IDs (n = 752) and tweets unrelated to cycle lanes, LTNs, the Emergency Active Travel Fund or those referring to Luton Airport or Luton football team (n = 240), a total 36,696 tweets remained for analysis.

Fig. 2 shows the number of tweets per month from 1 March 2018 to 30 June 2022. As expected, the number of tweets increased substantially in June 2020 when the UK Government's Emergency Active Travel Fund was announced and kept increasing over the summer 2020 until they peaked in September 2020. The number of tweets then dropped over the second half of 2020 but remained at a higher level throughout 2021 and 2022 as compared to the March 2018-June 2020 period. Further inspection of Fig. 2 suggests that there were fewer tweets during the winter than the summer months, which may be due to higher levels of cycling in warmer and drier weather. The lowest number of tweets were observed in March 2020, when the first wave of the COVID-19 pandemic gathered pace, and the first national lockdown was announced.

4.2. Sentiment of tweets about new cycle lanes and LTNs

From 1 March 2018 to 30 June 2022, there were 10,465 negative, 14,370 positive, and 12,142 neutral tweets. Fig. 3 shows the percentage of positive and negative tweets over the period, with neutral tweets excluded. There were more positive than negative tweets at almost any time point, except for two short instances in November 2020 and January 2021. Fig. 3 shows an increase in positive tweets up to May 2020, and then a steep decline over the June-November 2020 period. The percentage of positive tweets remained stable after September 2020, if at a lower level than in March 2021 to June 2022.

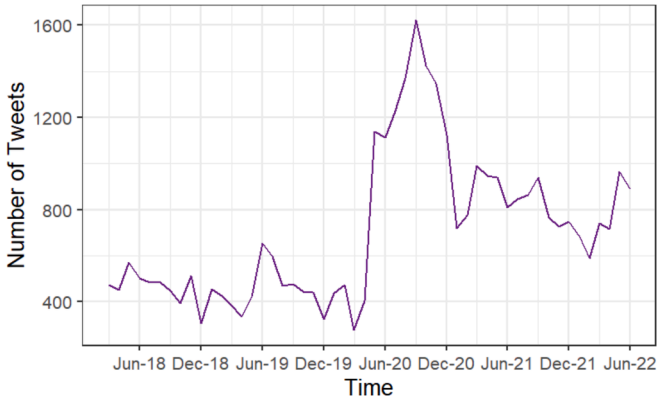


Fig. 2. Number of tweets per month between 1 March 2018 and 30 June 2022.

The pattern for negative tweets is the reverse of the pattern for positive tweets. The percentage of negative tweets declined up to May 2020, after which it increased steeply. The percentages of positive and negative tweets are comparable over the November 2020-January 2021 period, with the percentage of negative tweets being only marginally higher in November 2020 and January 2021. The percentage of negative tweets remained stable for the remaining period, if at a higher level than in the March 2021 to June 2022 period. The percentage of negative tweets was lower than the percentage of positive tweets over the March 2021-June 2022 period.

4.3. Discussion topics on cycle lanes and LTNs

As shown in Table 2, the STM identified 13 discussion topics. Each topic was reviewed to: (a) identify topics with highest consistency in content of the Tweets within a topic and (b) ensure minimal content overlap across topics. The topics that made up the largest part of the discussion were topics relating to use of cycle lanes, the democratic process and the highway code (see Table 2: Topics 5, 7, and 12). The topics making up the smallest share of the discussion were topics relating to concerns and criticisms, community impact and engagement and experiences of cycling environment (Topics 1, 3, and 13). A narrative version of each topic is also shown in the Appendix.

Fig. 4 shows the proportion of the 13 discussion topics for each month from March 2018 to June 2022. The figure shows a clear change in the proportion of many of the topics being discussed in summer 2020, likely as a result of both the Emergency Active Travel Fund and COVID-19 related lockdowns, which may also provide an explanation for the increase in the topic relating to the democratic process around bike lanes (Topic 7), and the decline in topics relating to cyclist and pedestrian behaviour (Topic 11) and the use of cycle lanes (Topic 5) during this period, as lockdown restrictions in the UK may have impacted people interacting with these infrastructures in public spaces. The only other topic which declined over this period was discussion on the highway code (Topic 12). All other topics remained relatively consistent.

Fig. 5 shows how positive or negative the tweets were for each of the 13 topics. Tweets about Community engagement and impacts (Topic 3) were the most positive. Other positive topics include using cycle lanes for leisure purposes (Topic 5), plans for new cycle lanes/upgrades to existing cycle lanes (Topic 4) and highway code (Topic 12). The two most negative topics were about specific individuals or organisations (Topic 6) and driver behaviour (Topic 8). Other negative topics included concerns and criticisms (Topic 13), cycle lane design (Topic 10) and transport hierarchy/modal shift (Topic 2).

5. Discussion

5.1. Summary of results

This study aimed to better understand public discussions around the introduction of cycle lanes and LTNs in the UK, and how these have changed over time. It did so by analysing Twitter/X posts on cycle lanes and LTNs before and after these active travel measures were implemented as part of Emergency Active Travel Fund that was launched in spring 2020. The research shows an increase in the number of tweets about cycle lanes and LTNs, particularly in the summer of 2020. Sentiment analysis shows that discussions are generally positive, but this changes over time. The number of positive tweets increased

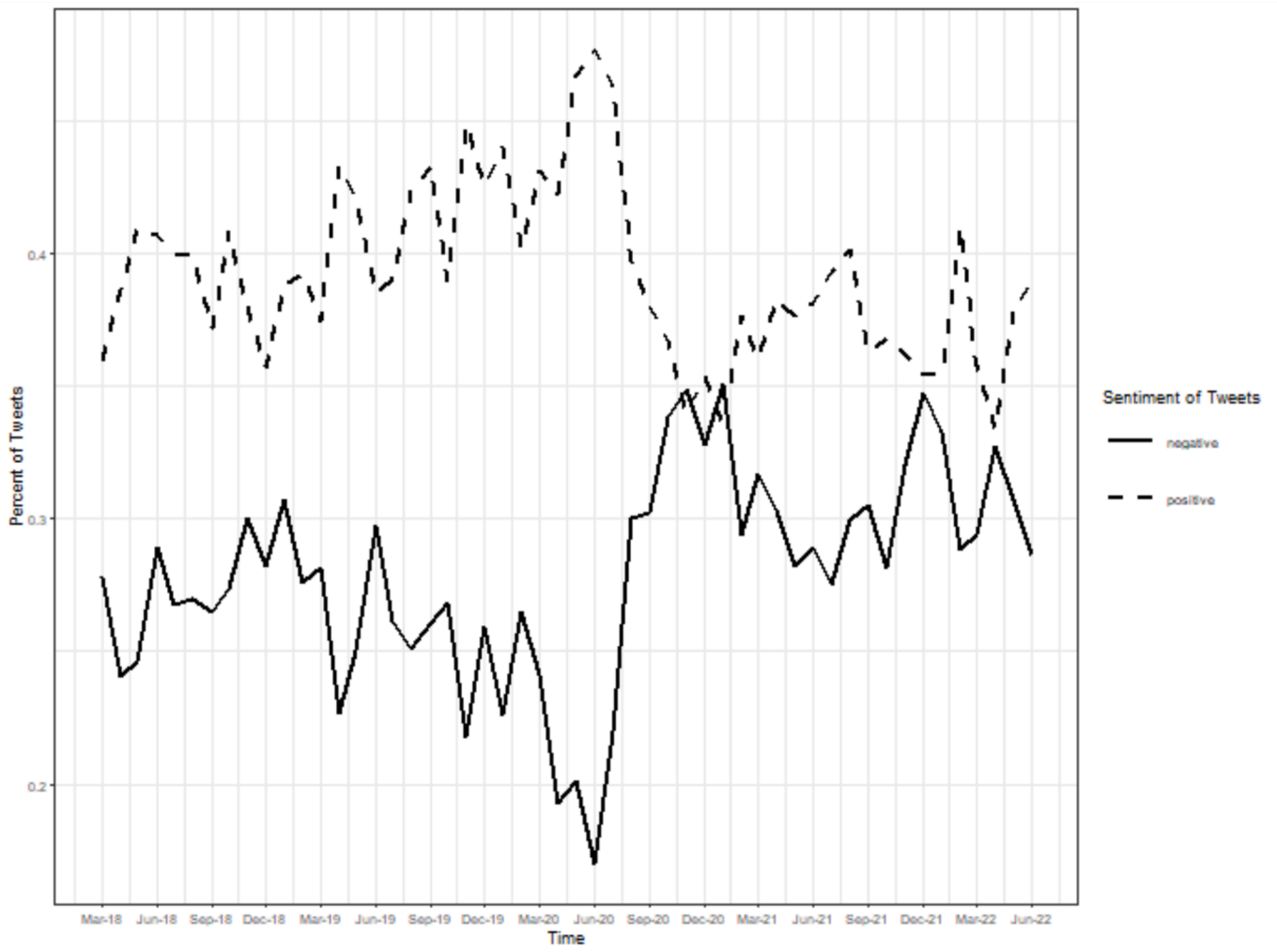


Fig. 3. Proportion of positive and negative tweets over time.

substantially in summer 2020 after the fund was announced, followed by a peak in negative tweets in autumn 2020. There were only two months where there were a higher number of negative tweets than positive, November 2020 and January 2021. For the period between 2021 and 2022, negative tweets remained at a higher level than before the announcement of the Emergency Active Travel Fund.

STM identified 13 different discussion topics, which were broadly categorised into tweets relating to cycle lanes and the cycling environment, behaviour and attitudes, the impacts of cycle lanes, the implementation process, and specific organisations and individuals. The most frequent topics were discussions from people using cycle lanes, and around the democratic process. The least common topics were community impact and engagement, and concerns and criticisms. Most discussion topics fluctuated over time with a large change around summer 2020, shortly after the Emergency Active Travel Fund was announced. Applying the sentiment analysis to the STM topics shows that, despite there being more positive than negative tweets, there were more negative topics than positive ones. The most negative topic related to specific organisations and individuals, and the most positive topic concerned community impacts and engagement.

5.2. Interpretation of results

How can these results be interpreted in relation to the wider literature In line with previous studies (Sustrans, 2017; Morton, 2020; Portsmouth City Council, 2020), the results suggest that, while some opposition exists, the public are generally positive about new cycle lanes and Low Traffic Neighbourhoods (LTNs). However, despite the majority of tweets being positive, the study also identified several negative themes. For example, tweets about cycle lane design (Topic 10) were predominantly negative and made by both cyclists and drivers. The persistence of this topic over time suggests it remains a salient concern for both groups (Sustrans, 2017; Morton, 2020; Portsmouth City Council, 2020; Department for Transport, 2021a). This finding supports similar research which has identified that design is important in acceptance of bike lanes (Vallejo-Borda et al., 2020; Berghoefer and Vollrath, 2022; Guo et al., 2023). Similarly, the topics related to implementation of active travel infrastructure, specifically discussions about individuals and organisations involved in their implementation (Topic 6) and the decision-making process (Topic 7) tended to be negative. Tweets in these topics discussed the lack of public consultation for implementing the infrastructure, and criticised individuals and organisations that were involved. These results suggest that the public may like active travel infrastructure in general but may dislike how they are implemented or designed (Sustrans, 2017; Portsmouth City Council, 2020). This is in line with other research that has highlighted the importance of public involvement (Vecchio et al., 2021) and the role of trust in decision-makers (Ge et al., 2021) in environmental policy. Furthermore, these topics may highlight a 'politicisation' of active travel infrastructure, as political figures and political parties were discussed (Wild et al., 2018).

This research has compared public sentiment before and after the

Table 2
Topics Identified via Structural Topic Modelling.

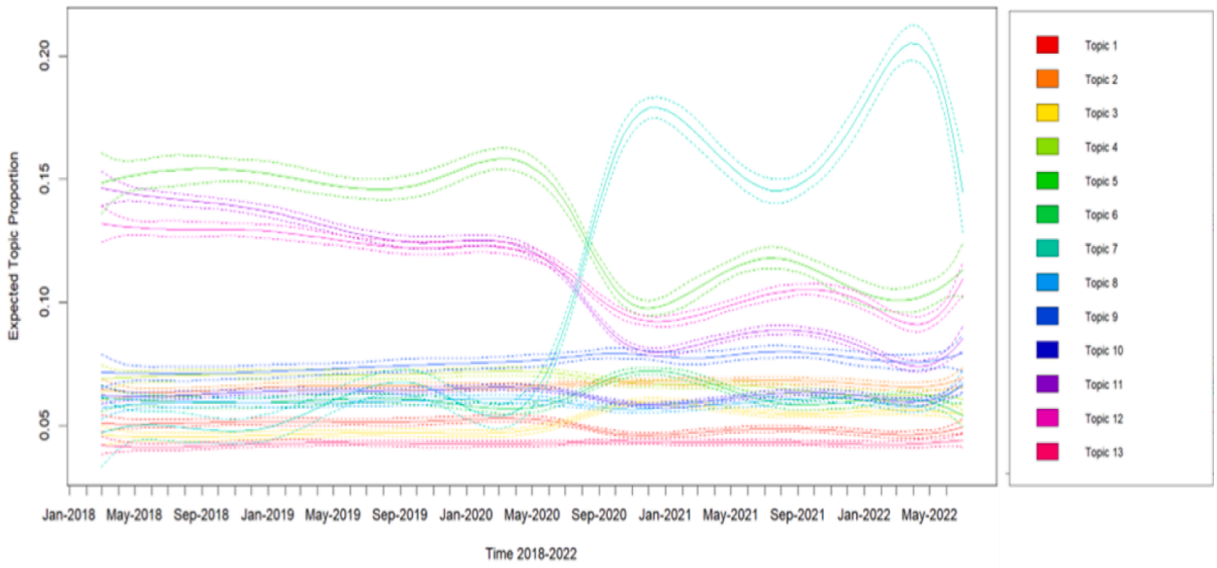
Topic. Label (Est. Proportion)	Key Points / Topic description
1. Experiences of cycling environment (4.9 %)	• Positive or negative experiences of people who used cycle lanes • People enjoying cycle paths, encountering nature on cycle paths, in addition to complaints about glass on cycle lanes and other issues
2. Transport hierarchy, Modal shift (6.8 %)	• 'How to use cycle lanes' or other travel demand management strategies to prevent car use • Tweets alluded to a transport hierarchy, with cars considered the dominant transport mode • Rarely about people who had made a modal shift but more about the cycle lanes encouraging people to make a modal shift in the abstract sense
3. Community impacts and engagement (4.3 %)	• The impacts of LTNs and cycle lanes on residents and communities • The implementation of LTNs and cycle lanes without sufficient consultation • Giving feedback to councils, sharing surveys to provide feedback on LTNs or cycle lanes, and impacts on residents
4. Plans for new cycle lanes, Upgrades to existing cycle lanes (6.7 %)	• Related to plans for the installation of new cycle lanes or upgrades to existing cycle lanes • Sharing announcements that new cycle lanes would be implemented, individuals calling for new cycle lanes to be installed in certain areas, including sharing petitions, or improvements to existing cycle lanes.
5. Using Cycle Lanes (13.0 %)	• Related to tweets from people who were using cycle lanes, either for cycling or for walking and running • Discussed things they had seen on the cycle route or commented on the weather • More likely to be about cycling for fun, rather than for commuting or essential travel purposes
6. Specific individuals and organisations (6.1 %)	• Related to tweets which discussed specific individuals and organisations • Mentioned or frequently criticising Sadiq Khan (Mayor of London) and Transport for London (TfL) and other organisations
7. Democratic Process (12.0 %)	• Related to the democratic process surrounding the implementation of cycle lanes and LTNs • Discussions about lack of consultation and around the outcomes of consultations • Mentioned specific political parties or encouraged people to vote for pro- or anti-cycling councillors. • Mentioned businesses more than any of the other topics.
8. Driver Behaviour (5.9 %)	• This topic related to driver behaviour • Mentioned drivers parking in cycle lanes or specific incidents individuals had seen or experienced • A few mentions of drivers being dangerous or inconsiderate
9. Traffic (7.5 %)	• Tweets discussing the impacts of cycle lanes and LTNs on traffic, including traffic displacement • Also related to road tax and how cycle lanes and LTNs are funded
10. Cycle lane design (6.2 %)	• Discussed poorly designed cycle lanes, with a few mentions of dangerous cycle lanes. • Many design features were discussed where cycle lanes interact with other road users; for example, at bus stops or junctions
11. Cyclist and pedestrian behaviour (10.0 %)	• Often this was a criticism of cyclists running red lights, not using cycle lanes or not having safety equipment such as hi-vis jackets or lights • Also mentions of pedestrians using the cycle lanes instead of the pavement
12. Highway code (11.0 %)	• 'What the Highway Code' says in relation to cyclists and drivers should be doing • 'What is legal for drivers to do' especially on whether drivers could enter painted cycle lanes and overtaking cyclists
13. Concerns and criticisms (4.3 %)	• Often this topic was related to pollution and air quality, the infrastructure money was allocated to, criticisms of the lack of infrastructure in certain areas

implementation of the Emergency Active Travel Fund. Past research on green infrastructure suggests that public opinion tends to become more positive following implementation, after an initial dip in support around the time of announcement and implementation (Wolsink, 2007; Ferster et al., 2021). It however remains unclear whether this U-shaped pattern also applies to cycle lanes and LTNs, as longitudinal studies tracking public opinion on such interventions has so far been lacking. The current study does not find evidence to support the existence of a U-shaped curve in sentiment toward cycle lanes and LTNs. Nor does it align with previous research suggesting an overall shift toward more positive attitudes post-implementation (Crane et al., 2016; Ferster et al., 2021). Although there was an initial rise in positive tweets in summer 2020, this was followed by a marked increase in negative sentiment beginning around September 2020. This suggests the emergence of a backlash against the schemes introduced through the Emergency Active Travel Fund. It should be noted, however, that even after implementation, positive tweets outnumbered negative ones, with the exception of two brief periods.

One possible explanation for this divergence from previous findings is the nature of the interventions themselves. The infrastructure funded by the Emergency Active Travel Fund was explicitly intended to disrupt the existing balance of road use and to reallocate space away from cars (Department for Transport, 2020b). This challenge to the 'status quo' may have intensified public resistance among certain user groups, which may have contributed to the higher volume of negative sentiment observed in this study (Crane et al., 2016; Ferster et al., 2021).

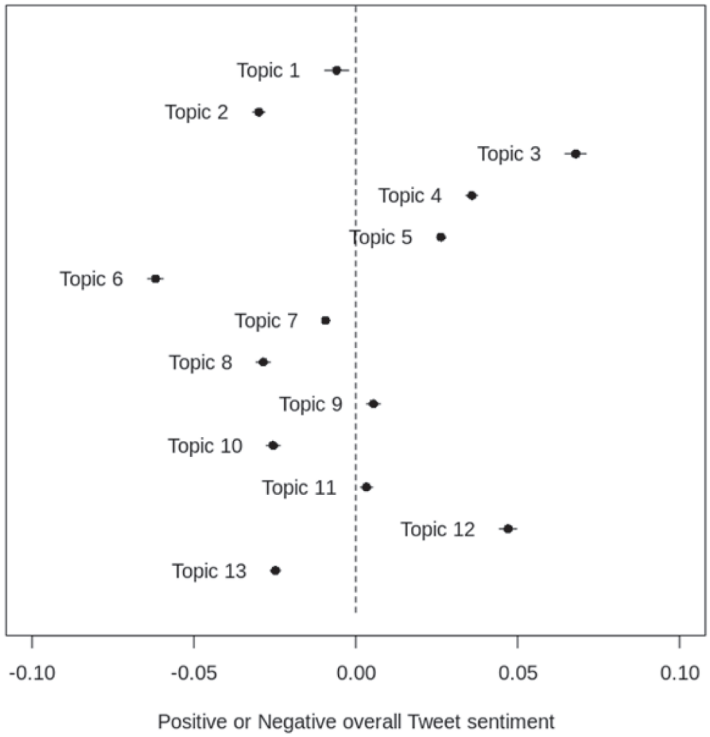
A notable point is that five of the 13 topics identified in the STM do not directly address cycle lanes or LTNs, nor their impacts. Instead, they relate to road user behaviours and attitudes in general, or to public figures, individuals, and organisations involved in implementing the infrastructure. This makes it difficult to determine whether the shift toward more negative tweets around September 2020 reflects changing attitudes toward the cycle lanes and LTNs themselves, or toward these wider topics. This ambiguity may also help explain the discrepancy between the findings of this study and those of previous research (Crane et al., 2016; Ferster et al., 2021). Nevertheless, this study does provide evidence, consistent with existing research, that public opinion is dynamic and subject to change over time (ibid).

Concerns around driver behaviour (Topic 8) were generally related to complaints about drivers parking in designated cycle lanes. Tweets about cyclist and pedestrian behaviour (Topic 11) commonly referred to pedestrians walking in cycle lanes, or cyclists running red lights or not wearing high-visibility clothing. This suggests that public discussions about cycle lanes are not limited to the infrastructure itself but also extend to the behaviour of other road users. While previous research has observed such behaviours among cyclists, pedestrians, and drivers, and explored the reasons behind them (Schleinitz et al., 2019; Bardutz and Bigazzi, 2022), this is the first study to link these behaviours to public discourse about new active travel infrastructure. The results suggest a potential avenue for future research: investigating how rule-breaking behaviours influence perceptions of other road users and of the



Key - Topic 1: Experiences of cycling environment; Topic 2: Transport Hierarchy/Modal shift; Topic 3: Community impacts and engagement; Topic 4: Plans for new cycle lanes/upgrades to existing cycle lanes: Topic 5: Using Cycle Lanes: Topic 6: Specific individuals/organisations; Topic 7: Democratic Process; Topic 8: Driver behaviour; Topic 9: Traffic; Topic 10: Cycle lane design; Topic 11: Cyclist and pedestrian behaviour; Topic 12: Highway code/legal discussion; Topic 13: Concerns and criticisms.

Fig. 4. Proportion of discussion relating to each topic between March 2018 and June 2022.



Topic 1: Experiences of cycling environment
Topic 2: Transport Hierarchy/Modal shift
Topic 3: Community impacts and engagement
Topic 4: Plans for new cycle lanes/upgrades to existing cycle lanes
Topic 5: Using Cycle Lanes
Topic 6: Specific individuals/organisations
Topic 7: Democratic Process
Topic 8: Driver behaviour
Topic 9: Traffic
Topic 10: Cycle lane design
Topic 11: Cyclist and pedestrian behaviour
Topic 12: Highway code/legal discussion
Topic 13: Concerns and criticisms

Fig. 5. Mean sentiment of topics.

infrastructure itself, particularly in relation to safety. The prevalence of these discussions underscores the importance of considering the perspectives of all street space users, not just the intended users of the infrastructure, when planning and implementing active travel measures.

Perhaps surprisingly, discussions rarely addressed the broader benefits of active travel, such as climate change mitigation or public health improvement. While some tweets mentioned climate change, these accounted for only a very small portion of the overall corpus. This could

be because individuals may not directly associate cycling and cycle infrastructure with climate change mitigation, and such benefits may not be the primary motivation for engaging in active travel (Bhandal and Noonan, 2022). Carbon emissions were mentioned more frequently, but primarily in relation to local air quality. In some cases, carbon emissions were even used as an argument against new cycle lanes and LTNs, with tweets suggesting that these measures increase car congestion and, in turn, emissions due to longer journey times. This narrative has also been identified in other research conducted in London (Aldred, 2019). Similarly, health was only occasionally mentioned in tweets about cycle lanes and LTNs. When it was, it was usually discussed in the context of air quality, rather than as a direct benefit of active travel. There were also very few tweets referencing the rising cost of petrol; individuals may not view active travel as a viable option for saving money on fuel. The infrequency of these three topics suggests that Twitter/X discussions around cycle lanes and LTNs tend not to consider the broader 'big picture' rationale for such infrastructure. Instead, the conversation is primarily focused on individual experiences and localised impacts, with limited attention given to wider benefits such as climate change mitigation or long-term cost savings to the NHS through improved public health. This finding aligns with existing research, which has similarly indicated that people may not readily connect active travel schemes to broader societal goals such as climate action (Timmons et al., 2024).

5.3. Policy implications

In addition to the findings of the research, this study also demonstrates that social media analysis can be a useful tool for understanding public opinion about transport policy and infrastructure. This method allows for identification of sentiment before and after the implementation of cycle lanes and LTNs, and also allows the tracking of sentiment over time, which is not available from other methods such as surveys (Adams-Cohen, 2020; El Barachi et al., 2021). Furthermore, this research has shown that this method can be applied retrospectively to collect past sentiment, without the recall bias of interviews or surveys. It also allows for considerably more opinions to be collected than through interviews or surveys with minimal additional resources required (Dong and Lian, 2021; El Barachi et al., 2021). Furthermore, although STM has been applied to Twitter data in several previous studies, this is the first time it has been used to analyse discussions about active travel infrastructure. STM offers a fast and efficient method for examining large datasets over time (Bai et al., 2021; Tamakloe and Park, 2023), and this research demonstrates its value for this topic. In particular, it shows that STM can be used to identify potential reasons underlying attitudes toward cycle lanes and LTNs.

his research has demonstrated the value of Twitter/X data for understanding public opinion, identifying discussion topics, and tracking how these evolve over time. Such insights can help urban planners, policymakers, and other decision-makers make more informed, evidence-based choices in the public interest. However, despite its proven utility (Pew Research Centre, 2019), recent changes to the platform mean that free academic access to its data is no longer supported (Developers, 2023). While paid API access remains available, it is primarily designed for commercial use rather than academic research, and obtaining the volume of tweets that was previously free has become prohibitively expensive (Mehta, 2023). his represents the loss of a valuable, large-scale, and near real-time data source for monitoring public sentiment and discourse. Without affordable access, researchers and policymakers may find it harder to detect emerging controversies, evaluate policy interventions, or understand public responses to infrastructure changes in a timely manner.

5.4. Strengths, limitations and future work

There are some caveats that need to be considered when interpreting the data. Twitter/X users are not representative of the general population (Datareportal, 2023), and that may have an impact on the sentiment and topic of discussions on cycle lanes and LTNs. Furthermore, only tweets from public Twitter/X accounts are able to be accessed using the Twitter/X API, with, only a small percentage of tweets geotagged to include their location (Sloan et al., 2015). As only tweets tagged as being from Great Britain were used in this analysis, any tweets that were not geotagged were excluded. Despite this limitation, Twitter/X has a very high number of users, and therefore a substantial number of tweets remained available for analysis. Furthermore, only a small number of tweets contained location data below the national level, making it difficult to examine spatial variation in more detail. This can be considered a limitation, as responses may well vary by region. Similarly, metadata on individual characteristics, such as age, gender, professional background, or political leaning, is not consistently available on Twitter/X, preventing this line of analysis. These limitations constrained the analyses that could be conducted as part of the study, although they also point to promising future directions for research where such information is available. For example, (Wang et al., 2020) demonstrated the spatiotemporal patterns of public responses to urban flooding through the analysis of data from Weibo, a popular social media platform in China. Such spatiotemporal analyses would also be valuable in relation to active travel measures, such as new bike lanes and LTNS.

In terms of methodology, sentiment analysis may not always correctly reflect the opinions expressed in a tweet (Liu, 2012). As sentiment analysis identifies the individual positive or negative words in a tweet, rather than the tweet as a whole, it is not possible to tell whether the positive or negative words are intended specifically toward cycle lanes or LTNs or another topic discussed in the tweet. Furthermore, as this method of sentiment analysis uses individual words rather than combinations of words, neither sarcasm nor irony can be detected (Liebrecht et al., 2013). Finally, it should be noted that the overall sentiment of tweets tends to be positive (Schöne et al., 2023). This generally tendency toward positive tweets may have influenced the numbers of positive tweets in this analysis. However, sentiment analysis allows for thousands of Tweets to be categorised as positive or negative in a very small space of time and is therefore a useful tool in understanding public opinions.

6. Conclusion

This study aimed to examine public sentiment towards cycle lanes and LTNs, and how this sentiment changed over time. The findings indicated a broadly positive attitude towards cycle lanes and LTNs suggesting public support for continued investment in such infrastructure by the government and local authorities. Additionally, this research highlights the dynamic nature of public opinion and evidences the need for continual monitoring and engagement of public opinion, particularly in response to wider events, infrastructure investment or policy announcements.

This study contributes to understanding how social-media sentiment can reflect public support for interventions aimed at improving urban mobility and wellbeing. Drawing on an extensive dataset of social media posts collected before and after a major investment, the study provides evidence on key discussion topics and their associated sentiment. The study serves as an excellent example of how social-media data, when combined with machine-learning techniques, can enable a form of dynamic 'ex-ante' and 'ex-post' evaluation of public opinion against urban-mobility related investments.

From a policy and decision-making perspective, this study identified key discussion points and associated sentiments that can help urban planners and local authorities to understand where improvements can be made to reduce resistance and enhance public support. Such evidence supports a more democratic, inclusive and cost-effective approach to transport planning. In particular, this research has highlighted that infrastructure design is a significant concern for the public. Ensuring that design accommodate the needs of all street users is therefore an

important factor in gaining and maintaining public support. Furthermore, the limited connection between cycling infrastructure and broader issues such as climate change and public health suggests an opportunity for improving communication strategies. By aligning messaging with these larger societal benefits, policy makers and local authorities may be able to foster greater public support for street space interventions such as cycle lanes and LTNs.

Finally, this research highlights the potential of combining sentiment analysis and STM as practical tools for decision-makers seeking to monitor public-opinion at scale. As cities across the UK continue to invest in active travel infrastructure to address air quality, congestion, climate change and meet Net Zero targets, these methods offer an efficient, real-time approach to capturing and understanding the 'public pulse'. Integrating such data-driven insights into urban transport planning and decision-making can enhance the effectiveness of public acceptance of future interventions.

CRediT authorship contribution statement

Isabella Malet Lambert: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization, Software. **Wouter Poortinga:** Writing – review & editing, Supervision, Methodology, Conceptualization, Funding acquisition, Validation, Writing – original draft. **Dimitris Potoglou:** Writing – review & editing, Supervision, Methodology, Conceptualization, Funding acquisition, Validation, Writing – original draft. **Dimitrios Xenias:** Writing – review & editing, Supervision, Conceptualization, Funding acquisition, Validation, Writing – original draft.

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Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tbs.2025.101128.

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