Exploring transport perceptions in London: A twitter-based analysis by country of residence

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Abstract: *In an increasingly interconnected world, this study examines how geographical origin influences public sentiment toward transit systems, using social media as a lens. By analyzing a large dataset of tweets related to London's transit system, we explore differences in sentiment between residents and visitors, including temporal patterns, as well as variations among visitors from different continents and countries. The results indicate that residents, who are more familiar with local transit issues, tend to express more negative sentiment than visitors (59.5% of residents vs. 56.8% of non-residents). Among visitors, significant differences emerge: Europeans exhibit the most negative sentiment, with their tweets being 1.7 times more likely to be negative than those of Asian visitors. Central and South Americans also show heightened negativity, while North Americans are only moderately more negative. Regarding temporal distribution, residents exhibit the highest levels of negative sentiment during early morning hours, likely due to commuting stress, while non-residents maintain consistent negativity throughout the day, peaking on weekends as they navigate the city. This highlights distinct temporal patterns in sentiment between these groups. From a continental perspective, North America has the second-highest number of negative tweets; however, it also has one of the lowest shares of complaints. Europeans and Asians primarily express confusion regarding COVID-19 regulations and punctuality issues. These findings underscore the importance of considering geographical and cultural contexts when analyzing public sentiment. They also offer actionable insights for policymakers and transit planners seeking to improve user satisfaction across diverse populations.*

Keywords: *temporal differences, sentiment analysis, transit tweets, residency*

Introduction

The growth of cities has led to an increasing demand for mobility, both among residents and tourists (Lock and Pettit 2020). Public transport plays a key role in this context, as it aims to reduce traffic congestion and lower pollution levels (Chen et al., 2018, Hosseini et al. 2018). The rise in trips, driven by factors such as touristification, has increased congestion in public transport systems, creating a need for public transport agencies to get updated information about their services to detect disruptions and obtain the information needed to provide citizens with a more effective and sustainable service (Ji et al. 2018). In this context, citizens' up-to-date opinions are essential for developing models that effectively address their needs (Osorio-Arjona et al. 2021).

In an increasingly interconnected world, social media platforms such as X (Twitter) have emerged as crucial tools for analyzing public sentiment in real time. As individuals share their thoughts and experiences, transportation frequently emerges as a significant and widely discussed topic. Whether expressing frustration over delayed trains or addressing transit-related concerns to city officials, tweets about public transportation offer valuable insights into collective sentiment. However, the emotions conveyed in these posts extend beyond mere personal opinions; they are deeply influenced by geographical context. Thus, sentiment analysis offers researchers the opportunity to link the opinions of users to geography (Mitchell et al., 2013).

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The concept of Social Media Geographic Information (SMGI) provides a framework for investigating people's concerns, perceptions, and interests in space and time (Campagna 2014), by processing information emerging from discussions among participants. Rooted in behaviourism, SMGI focuses on User Behavioural Analysis and Spatio-Temporal Textual Analysis. The ecological modelling concept is an alternative approach used by Rybarczyk et al. (2018), which posits that a combination of environmental and psychosocial variables can effectively explain physical activity. However, both of these approaches rely on the precise spatial location of posts using geographical coordinates. As this data is currently unavailable and depends on the owners of these platforms, it is necessary to shift the research focus from local spatio-temporal analysis to a multiscale approach involving an extended analysis of user profiles.

This study examines the intersection of geography and sentiments of transportation services, investigating how residents of a given city perceive transit systems differently from visitors. Furthermore, visitors from various countries or continents may exhibit distinct attitudes and sentiment intensities. These findings highlight the complex interplay between geographical context, cultural background, and user perceptions of public transportation systems. Transport planning often overlooks non-resident feelings, so this work includes some social implications that could be useful to plan inclusive strategies for diverse human groups.

Geographical and cultural factors may significantly influence public sentiment. We hypothesize that residents, having greater familiarity with the current state of transit services, are more likely to express highly critical reactions to perceived shortcomings. In contrast, non-residents - primarily visitors - may frame their opinions through the lens of their cultural background and comparisons with transportation systems in other regions or countries. To examine this hypothesis, we pose the following research questions:

- Do residents tend to express more negative sentiments in transport-related tweets than visitors?
- Are visitors from certain continents or countries significantly more negative in their assessments?

The main objective of this research is to explore how nationality shapes spatial perceptions of transport infrastructure. While most studies on transport perceptions focus on aggregated trends or local users, few examine how transnational populations engage with transports systems differently. Specific objectives include exploring the value of social media data as an alternative source that can complement traditional surveys in qualitative studies, and analyzing how transport perceptions can be linked to spatial exclusion (e.g., visitors from countries with robust public transport may influence policy priorities). Particular attention is also given to a detailed explanation of appropriate data processing methods, which are essential for distilling useful information and avoiding data biases.

This study investigates the topic presented using a large sample of tweets related to London's transit system. As one of the largest transit networks in the world, with annual passenger journeys reaching 3.6 billion (Transport for London: Passenger Journeys, by Mode 2024, 2024), London's public transportation system is well known for issues such as overcrowding, particularly during the COVID-19 pandemic. This case study provides a suitable context for analyzing sentiment differences between residents and visitors.

To investigate these dynamics, geocoding was applied to tweet metadata (specifically, user profiles) to identify the domicile of authors, enabling a distinction between residents and non-residents. This methodological approach ensures a comprehensive analysis of how geographical and cultural factors influence public sentiment on transit-related issues.

The structure of this paper is as follows: The State of the Art section provides an overview of existing challenges and approaches in sentiment analysis related to transit systems. The Data and Methodology section details the data collection process and analytical methods employed. Finally, the Results and Discussion section presents key findings and their implications.

State of the art

Research on sentiment analysis and its application to transportation studies has expanded significantly in recent years, driven by the increasing availability of social media data and advancements in natural language processing (NLP) techniques. In recent years, various frameworks have been extensively used, such as Fast.ai – a deep learning library built on PyTorch that enables efficient transfer learning by adapting pre-trained language models to domain-specific tasks on small datasets (Howard and Ruder 2018). Conversely, spaCy employs pre-trained statistical models and rule-based pipelines for essential NLP tasks, including tokenization, part-of-speech tagging, and named entity recognition (Ogbuokiri et al. 2022).

Several key studies provide a foundation for understanding the relationship between sentiment, geography, and transit systems. For instance, Mendez et al. (2019), demonstrated that analyzing social media data, compared to traditional surveys, enables broader geographical coverage and faster identification of transit issues, thereby improving public transport planning. Similarly, Georgiadis et al. (2021) emphasized the value of leveraging social media feedback to address service-related concerns and enhance overall transit quality. Additionally, Díez-Gutiérrez et al. (2024), documented how integrating user-generated data with traditional methodologies enhances data accuracy and granularity, providing policymakers with more comprehensive insights. Rybarczyk et al. (2018) employed exploratory spatial data analysis and spatial regression models to explore the utility of these new data sources for understanding how different travel modes affect the feelings in two major U.S. cities.

Public transport system and accessibility is one of the main parts of the image of city (Stylidis et al. 2021), however it is not as important for tourists that it is for people living in the place. Tourists perceive things differently, without stress or any pressure compared to residents which live and work at a place. Visitors' satisfaction is influenced by various transport related factors. Kourtit et al. (2025), documented how distance to the public transport positively influence visitor satisfaction, conversely distance to central railway station does the opposite. Lower satisfaction was associated with transport related comments in the COVID period. Transport was also an critical aspect for satisfaction of tourists visiting Maritime Greenwich (Hassan and Iankova 2012), where respondents complained about awful traffic congestion, contrary bus journeys were enjoyable. Having London being visited from all over the world, we need to recognize how the transportation is seen by residents as well as tourists.

Social media data requires careful preprocessing to ensure reliability and accuracy. While the dataset primarily consists of content generated by human users expressing their opinions and attitudes, a growing number of bots also contribute to the discourse. Some of these bots serve official functions, such as automated replies or announcements, while others are designed to influence user sentiment. As Mendoza et al. (2024) emphasized, it is essential to filter out such automated accounts to maintain data integrity. Additionally, sentiment analysis can be skewed by influencers - high-profile users who generate hundreds of tweets on various topics - potentially distorting overall sentiment trends (Singh and Gamboir 2023). To mitigate this bias, it is recommended to exclude tweets from these popular users. Influencers can be identified through metadata from their user profiles, particularly their follower count. According to Raje and Singh (2018), the threshold for distinguishing popular users from ordinary users in London typically falls between 55,000 and 65,000 followers. Distinguishing residents and non-residents is an equally important preprocessing task. The approach is dependent on the character and amount of the data. Some researchers uses frequency and temporal approach (Díez-Gutiérrez et al. 2024; Kovacs-Györi et al. 2018).

Sentiment analysis not only captures user perceptions but also provides actionable insights into service satisfaction and dissatisfaction (Luo and He 2021, Saragih and Girsang 2017). By examining sentiment patterns, transit authorities can identify areas requiring improvement, detect recurring issues, and assess the emotional tone of public feedback in real time. This approach serves as a valuable complement to traditional analytical methods, offering a deeper understanding of public attitudes and behavioral trends. Moreover, it enables targeted interventions that address the concerns of both local residents and international visitors, enhancing overall service quality (Haghighi et al. 2018).

Recent advancements in sentiment analysis have been largely driven by the emergence of transformer-based architectures such as BERT, RoBERTa, and their optimized variants, which leverage bidirectional context and self-attention mechanisms to capture intricate contextual relationships in text, significantly enhancing performance (Mann et al. 2023). RoBERTa refines BERT's pretraining methodology by incorporating larger batch sizes, training on more extensive corpora and eliminating the next-sentence prediction objective, thereby improving the robustness (Kajal 2023). These models are frequently fine-tuned for domain-specific applications, making them particularly effective in transportation studies (Aksan and Akdağ 2023). Aspect-based sentiment analysis (ABSA) further enhances precision by dissecting sentiment associated with specific service attributes - such as punctuality or cleanliness – enabling targeted service improvements (Chifu and Fournier 2023).

In parallel, lexicon-based sentiment analysis remains a foundational approach, offering interpretability and robustness by utilizing predefined sentiment lexicons, such as AFINN, SentiWordNet, and the NRC Emotion Lexicon, to assess the polarity and emotional tone of textual data (Alvinika et al. 2022). Frequently, the Bing Liu sentiment lexicon is used, originally created to facilitate opinion mining by extracting and summarizing customer reviews. The lexicon consists of a predefined list of words categorized as positive or negative based on their semantic orientation. Words were compiled using statistical and linguistic heuristics, leveraging large corpora of product reviews to identify sentiment-bearing terms (Bala and Stancu 2023, Hu and Liu 2004). This methodology allows for rapid and reliable sentiment classification, making it particularly valuable in contexts where transparency and simplicity are essential. By aggregating word-level sentiment scores, lexicon-based approaches effectively capture the overall emotional landscape of user feedback. Recent advances in lexicon-based techniques - such as the integration of domain-specific lexicons and context-aware rule-based refinements - have further improved their accuracy and adaptability to diverse datasets. These methods complement more complex machine learning and deep learning models, contributing to a comprehensive sentiment analysis framework that balances accuracy, interpretability, and computational efficiency.

Given the diverse origins of tweets in such datasets, it is essential to examine the demographic and geographic backgrounds of users (Tabbassum et al. 2023). A key aspect of this analysis involves distinguishing whether complaints primarily originate from local residents or tourists, as these groups have differing perspectives on transit services (Tucker et al. 2021). Additionally, identifying which continents contribute the highest levels of negative sentiment and exploring the cultural or experiential factors underlying these patterns (Wang et al. 2023) can offer valuable insights for improving transit systems on a global scale. This focus provides a foundation for analyzing sentiment variations among different user groups in the context of public transportation. Cultural factors and communication norms significantly influence how individuals express themselves on social media. For example, individuals from individualistic cultures, such as those in North America (e.g., the United States), are more likely to emphasize self-expression and openly critique services. In contrast, individuals from collectivist cultures, which are prevalent in many Asian countries, often avoid engaging in discussions that could be perceived as controversial or disruptive to social harmony (Saucier et al. 2015). Understanding these cultural nuances is crucial for accurately interpreting sentiment trends and ensuring that transit-related feedback is contextualized within broader societal frameworks (Blank 2017).

Data and Methodology

This study analyzed tweets referencing London's public transportation authority, the Transport for London (TfL) account, during the COVID-19 pandemic, covering the period from March 2020 to January 2021. The dataset was collected using the Twitter Search API v.1 with filtered search parameters (search keyword and exclusion of retweets). Due to the free API's limitation of providing access only to a seven-day archive, a scheduled routine was implemented to retrieve data on a weekly basis. A basic summary of the dataset is presented in table 1 (left).

Three phases of data processing are distinguished: data preprocessing to refine the dataset, data augmentation to include secondary (usually calculated) data and data analysis (fig. 1).

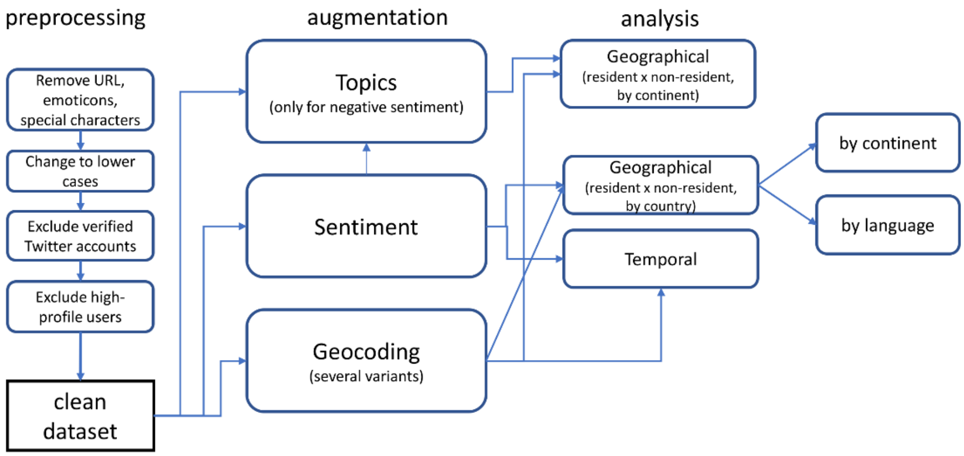

Fig. 1. *Schema of data processing*

Data preprocessing

Standard preprocessing techniques for natural language processing (NLP) were applied to ensure data quality. These included the removal of URLs and emoticons, conversion of all text to lowercase, and filtering out characters outside the basic ASCII table. These steps were essential for standardizing the dataset and minimizing noise in subsequent sentiment analysis.

Popular users were excluded based on two specific criteria:

1) Verified Accounts: At the time of data collection, some accounts were designated as verified by Twitter (indicated by a blue badge), signifying official status or public recognition. Removing these accounts ensured the exclusion of transport providers - who primarily post service announcements - as well as city officials, whose tweets could introduce institutional bias into the sentiment analysis.
2) Number of followers: Tweets from accounts with more than 64,000 followers were removed. This threshold was determined through exploratory data analysis and aligns with the recommendation of Raje and Singh (2018). By implementing this criterion, the study aimed to minimize the influence of high-profile users, allowing for a more representative assessment of public sentiment among regular users.

After filtering out popular users and applying data cleaning procedures, the final dataset more accurately represents the activity of ordinary Twitter (X) users. A summary of the refined dataset is presented in tab. 1 (right).

Tab. 1. *Description of the London TfL dataset*

	original dataset	cleaned dataset
tweets	344062	309515
accounts	99532	97241
tweets per account:		
- median	1	1
- maximum	4246	663
verified accounts	2176	0
followers:		
- median	264	249
- maximum	11372049	63404
tweets per day:		
- median		954
- maximum		7064
non-empty locations	70586	68518

Data augmentation

Sentiment analysis was conducted using the BING lexicon (Hu and Liu 2004). Each tweet was assigned a sentiment score based on the sum of the polarity of recognized entities. The total sentiment score represented the overall polarity of the tweet, reflecting the balance between positive and negative terms. To facilitate interpretation, sentiment scores were categorized into three levels: -1 for entirely negative sentiment, 0 for neutral sentiment, and 1 for positive sentiment. This classification ensured that extreme positive or negative tweets did not disproportionately skew the overall sentiment assessment for specific locations, allowing for a more balanced and representative analysis.

A key component of the data processing was geocoding user locations. To achieve this, a unique list of locations from metadata was generated (n = 21,090), with the number of occurrences serving as a measure of text relevance. The initial step involved cleaning the location data. Various prepositions (at, in, etc.), pronouns (my, etc.), and adverbs (almost, etc.) were identified and removed, extending beyond the standard list of stop words. Additionally, numbers, quotation marks, and humorous or non-informative entries - such as space, Earth, or Milky Way - were excluded. The refined location data were then stored in a new attribute, and the results underwent manual verification to ensure accuracy. Following the cleaning process, geocoding was performed using the Google Geocoding API, which was integrated and executed through RStudio to assign standardized geographical coordinates to user locations.

To enhance the accuracy of geocoded results, additional refinements were applied. A search was conducted for the string “London”, its common abbreviations (e.g., “LDN”), and historical or informal names such as “Londinium”. Furthermore, a comprehensive list of London boroughs was used to identify references to specific areas within Greater London. Beyond London, the dataset was cross-referenced with UK shires, country names worldwide, and official abbreviations of U.S. states to improve geographical classification. Special handling was required for locations recorded with latitude and longitude coordinates (n = 152) and those using UK postcodes (n = 60). To ensure data quality, every location appearing more than five times was manually verified.

Once geocoding was completed, the obtained geographical attributes - including city name, region, state, country, and additional location details - were used to distinguish between residents of London and non-residents. Users were classified as residents if their profile metadata indicated a location within Greater London, while all other recognized geographical locations were categorized as non-residents. Tweets from users without a specified location or with unrecognized geographical entities were excluded. The final localized dataset contained 229,081 tweets from 63,347 users, divided into two subgroups: residents and non-residents.

Data analysis

The differences of sentiment between the two subgroups were tested using two-sample t-tests for comparison of means and by robust tests of equality of means applying Welch and Brown-Forsythe methods of one-way ANOVA (Good 2005).

The temporal distribution of average tweet sentiment was analyzed to identify hourly, daily, and monthly patterns (chronotypes) as well as long-term trends. These insights were crucial for evaluating the stability of sentiment assessment over time. The geographical distribution of tweet sentiment was examined at both the country and continent levels. Differences in sentiment between continents were quantified using odds ratios (Szumilas 2010) to determine the likelihood of negative sentiment varying by region.

To investigate the causes of negativity among continents, the study is focused on public transport issues. Five key categories of complaints were analyzed: Breakdowns, Comfort, Overcrowding, Punctuality, and COVID-related complaints (Osorio-Arjona et al. 2021, Zajac, Horak and Kukuliac 2023). Each category was represented by a set of keywords (examples listed in tab. 2). A tweet was classified into a category if it contained any of the associated terms. Since tweets could reference multiple issues, they were allowed to be assigned to more than one category. This multi-label classification approach provided a comprehensive understanding of the key concerns driving negative sentiment across different regions.

Tab. 2. *Examples of terms describing issues in public transport*

overcrowding	punctuality	breakdown	comfort	covid19
massive	rush	works	ventilation	wearing
sardines	stuck	functioning	hot	masks
can	waiting	label	dirty	masks
cans	delayed	labels	smell	face
canned	delays	panel	suffocated	covid19
fit	slow	panels	air	wear
fitting	frequency	loudspeakers	airpollution	covering
full	waiting	loudspeaker	spat	covered

Results

Differences of sentiment between residents and non-residents

The sentiment distribution between residents and non-residents is illustrated in fig. 2. While the proportion of neutral tweets remains relatively similar for both groups, notable differences emerge in positive and negative sentiment. Positive tweets constitute 28.5% of residents' posts and 31.8% of non-residents' posts. Negative tweets account for 59.5% of residents' tweets and 56.8% of non-residents' tweets.

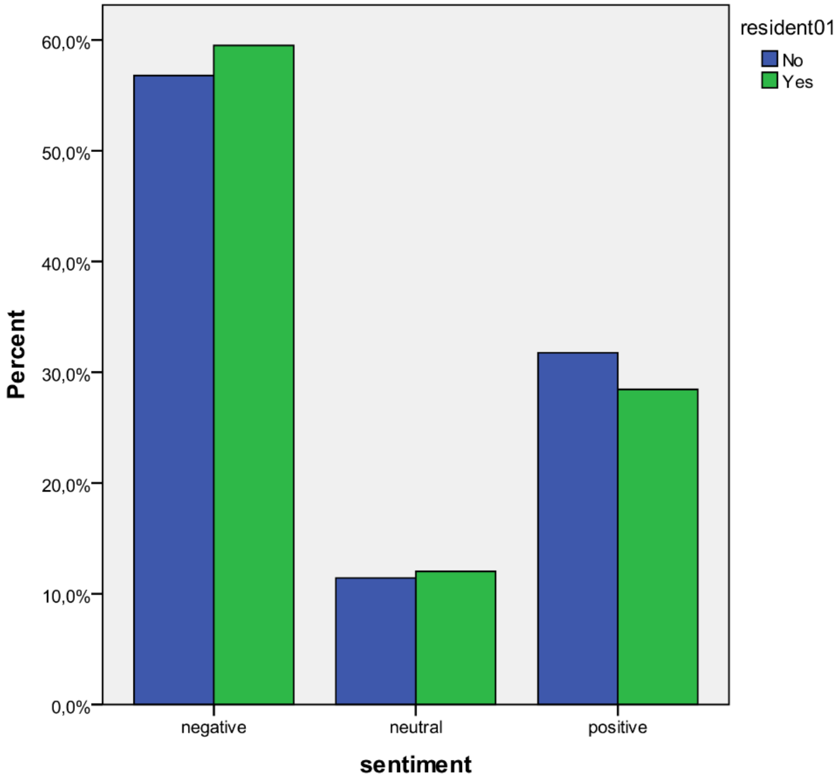

Fig. 2. *Sentiment distribution across resident and non-resident subgroups*

The difference between average sentiment for residents and non-residents are significant according to two-sample t-test for comparison of means as well as robust Welch test for equality of means (both p<0.001, tab. 3). The tests were conducted in SPSS v. 27. The first research question is answered positively – residents tend to express more negative transport-related tweets than non-residents. This finding underscores the impact of user residency on sentiment expression in transit-related discussions within London.

Tab. 3. *Results of tests comparing sentiment means between residents and non-residents*

test	statistic	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
T-test*	13.674	135966	0.000	0.060	0.004
Welch	186.978	135966	<0.001		

*Note: * Levene's Test for equality of variances was employed*

Temporal differences of sentiment between residents and non-residents

To improve our understanding of differences of sentiments between these two groups, their temporal patterns are investigated. The temporal distribution of sentiment reveals distinct patterns in Twitter activity between residents and non-residents of London's TfL, as illustrated in fig. 3. For residents, the highest proportion of negative tweets occurs during the early morning hours (3 AM – 6 AM). This trend likely results from the low volume of posts during this period, where only frustrating transport conditions or negative experiences may prompt users to engage. The influence of early morning stress, combined with commuting preparations, may further contribute to this heightened negativity. Public transport at this time provides an immediate setting for expressing grievances or engaging in ongoing discussions. Between 8 AM and 3 PM, the proportion of negative tweets among residents drops significantly (<10%). This decrease is likely due to commuters being occupied with work, experiencing lighter off-peak traffic, or having limited access to personal devices in certain workplaces.

In contrast, non-residents show a higher proportion of negative tweets between 7 AM and 5 PM - a timeframe when visitors are actively navigating the city and relying on public transport. This group also exhibits slightly greater negativity on weekdays, which may stem from congestion caused by concurrent travel with residents, leading to increased overcrowding and service strain.

The key differences between these groups lie in the timing of peak negative sentiment (fig. 2, right). Residents tend to post negative tweets primarily in the early mornings and evenings, with daytime negativity rising only on weekends. Non-residents express negative sentiment consistently throughout the week, except during late-night and early morning hours. Their peak negativity occurs toward the end of the week and on weekends, mirroring the typical patterns of visitors exploring the city. These findings highlight how user residency and travel habits influence the expression of negative sentiment in transit-related discussions.

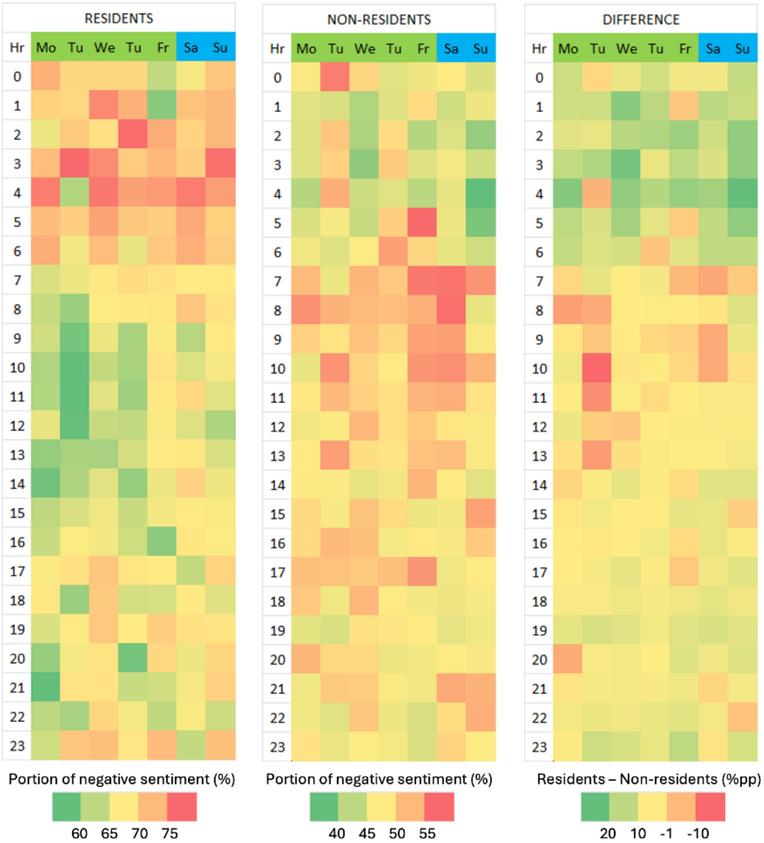

Fig. 3. *Temporal differences in residents and non-residents negative sentiment (from left, residents, non-residents, difference) Note: The difference in percentage points is obtained by subtracting sentiment of non-residents from sentiment of residents.*

Geographical differences in tweeting sentiment

The second research question required to calculate the proportion of negative tweets discussing the situation in London traffic for each country. Countries with less than 30 tweets were excluded from the proportion enumeration. Countries with the highest share of negative tweets include Great Britain, France, and Spain. Surprisingly, also several Latin American and Asian countries, such as Argentina, Brazil, Thailand, and China, exhibited higher rates of negativity, with shares exceeding 50%. Other parts of Europe and North America generally fall into lower negativity categories.

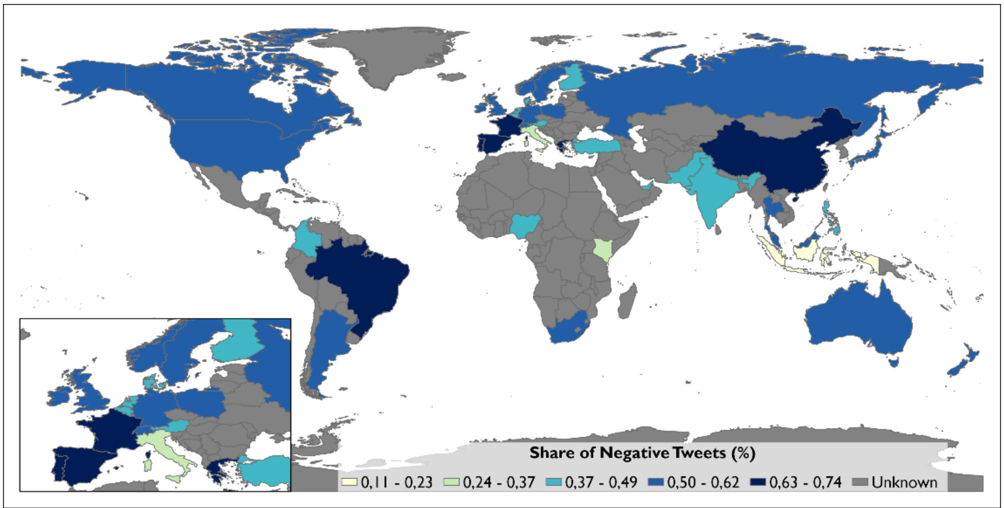

Fig. 4. *Share of negative tweets based on residence of the user*

One potential explanation for these differences is *language proficiency*. It was hypothesized that countries where English is the official language might express more negative sentiment, and this assumption was confirmed through statistical testing. Non-residents from non-English-speaking countries showed an average sentiment of -0.50, while those from English-speaking countries had an average sentiment of -0.64 (T-test, $p<0.001$). It indicates a significant influence of language proficiency to the sentiment of tweets.

Regarding *temporal differences* in sentiment, no clear trend was identified over the given time period. However, some sentiment fluctuations and seasonal differences were observed. A low level of fluctuation in the proportion of negative tweets was noted in the UK, Canada, and Greece, whereas a high level of fluctuation was observed in Switzerland and Malaysia. Seasonal differences were particularly noticeable in Germany, France, and Spain, where negativity significantly decreased during the summer months. This suggests that sentiment during this period may be influenced by an influx of summer tourists in London, who tend to be less critical of the city's transport system.

To explore *global differences*, sentiment results from individual countries were aggregated by continent (see tab. 4). Clear differences emerged, with tweets from European visitors showing 152% odds of being negative, while tweets from Asian or African visitors had less than 90% odds of being negative. Using Asian visitors' tweets as a reference, European visitors' tweets were 1.7 times more likely to be negative. Similarly, Central and South American visitors exhibited significantly higher negativity than Asian visitors (approximately 1.5 times more negative), while North American visitors were only 1.2 times more negative.

Tab. 3. *Sentiment of tweets by continent*

continent	negative	neutral	positive	odds (negative)	share of negative	lower bound	upper bound	odd ratio
Europe	24 963	4 748	11 642	1.523	68.20	67.72	68.67	169.98%
North America	10 979	2 451	8 114	1.039	57.50	56.80	58.20	115.98%
C/South America	175	36	98	1.306	64.10	58.38	69.83	145.76%
Asia	672	155	595	0.896	53.04	50.29	55.79	100.00%
Africa	231	50	203	0.913	53.23	48.51	57.94	101.90%
Oceania	560	128	366	1.134	60.48	57.32	63.63	126.52%

Note: Odds are calculated as the ratio of negative tweets and other tweets. The reference continent: Asia

The smaller difference in sentiment between North American and European visitors may be attributed to several factors. One possible explanation is that North American cities often experience greater suburban sprawl, where car ownership is more common than reliance on public transport (Scherrer and Vernier 2020). As a result, issues like congestion and punctuality in London may seem less significant to North American visitors, who may not be accustomed to a highly efficient public transport system.

Significant differences exist in the polarity of tweets from Europeans compared to North Americans and users from other continents, with the exception of those from Central and South America (see fig. 5). While the average share of negative tweets among European users reaches 68.2%, users from North America exhibit a significantly lower proportion, at 57.5%. Notably, intra-continental differences are also apparent: tweets originating specifically from the United States and Canada contain 64.1% share of the negative tweets. Users from Oceania also demonstrate a distinct sentiment profile, with 60.5% of negative tweets, a pattern surpassed only by Central and South America, which show even higher levels of negativity. In contrast, Africa (53.2%) and Asia (53%) report the lowest shares of negative sentiment, positioning them at the bottom of the global ranking. These variations are likely influenced by differences in public transportation standards across regions. Individuals from areas with underdeveloped public transport systems tend to express more positive sentiment towards London's transport system, whereas visitors from regions with well-functioning transport infrastructure tend to be more critical.

Differences in topics by continents

Finally, we analyzed the topics discussed in negative tweets across different continents. Complaints related to COVID-19 were least prevalent in North America (3.8%), followed by South and Central America (8.6%). In these regions, pandemic restrictions were generally less strict, and enforcement was often inconsistent. As a result, visitors to London may have perceived the local restrictions as reasonable and did not consider them a significant issue. In North America, breakdowns emerged as the dominant concern (22.5%), appearing twice as frequently as any other topic. In contrast, Africa recorded the highest share of COVID-related complaints (16.0%). Comfort was the least-discussed issue in Africa and South America (3.0% and 3.4%), which aligns with expectations given the relatively lower public transport standards in these regions. Similarly, breakdowns were less frequently mentioned in African tweets (4.3%), likely because London's public transport is considerably more reliable compared to many African cities. Overcrowding was the most frequently cited concern among South American visitors (19.7%), indicating a greater sensitivity to passenger density than to issues like punctuality or breakdowns. However, it is somewhat puzzling that punctuality complaints were most prevalent in tweets from Central America and the Caribbean (19.0%), and South America. This unexpected trend remains an open question that could benefit from further investigation.

Fig. 5. *95% confidence intervals for average proportion of negative tweets by continents*

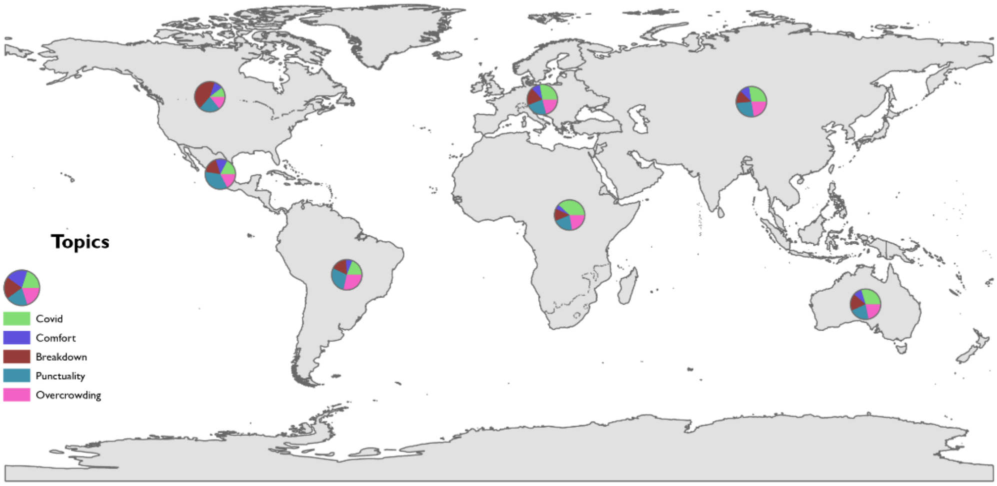

Fig. 6. *Shares of problems discussed on continents*

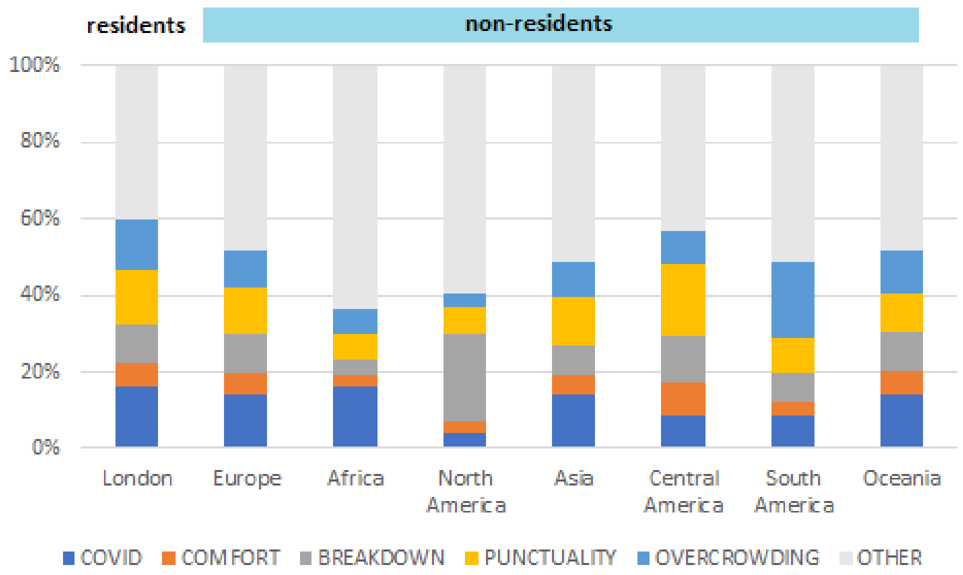

Fig. 7. *Distribution of topics in negative tweets by continent, with London as a baseline*

Discussion

While every city is unique in its characteristics, a universal trait among them is their inherent complexity, influenced by the constant movement of hundreds of thousands or even millions of people (Kovacs-Györi et al. 2018). The cities are populated by both residents and non-residents, each with different purposes and behaviors during their time living in the city. When examining the statistical findings for residents and non-residents of London, notable differences emerge in their online sentiment patterns. Residents of London exhibit a higher share of negativity compared to non-residents in transport-related tweets. This trend may reflect the stresses associated with urban living, such as high living costs, population density, and commuting difficulties. Non-residents, on the other hand, might perceive London more favorably, either due to its cultural appeal or limited exposure to its downsides. Tourists typically avoid problematic or less attractive areas during short-term visits, which may shield them from some of the more frustrating aspects of the city's transport system.

Similar patterns were observed by Stylidis, Cherifi, and Melewar (2021), who found that residents expressed stronger concerns about transportation and the economic environment whereas non-residents were more critical of the social environment and amenities. The “Access” dimension, which includes public transportation, had low significance for non-residents but high significance for residents. Categorizing respondents based on residency and origin was also necessary in the study by Hassan and Iankova (2012), as perceptions, needs, and demands for urban facilities differ according to nationality. Distinguishing between these two groups is fundamental for the development of computational models, as their behavior patterns vary significantly (Chaniotakis et al. 2022). Concerning short-distance transportation, residents prioritize time-saving, while tourists focus more on service quality and convenience (Zhou et al. 2025).

Moreover, English natives may express more negativity, as it is easier for them to articulate their thoughts on social media. In contrast, first-time visitors or individuals from non-English-speaking countries may be less likely to complain on social media after a single bad experience, as such behaviour may not align with cultural norms in societies where public complaints are less common (Saucier et al. 2015). However, experienced travellers, even from cultures where complaining is less typical, may adapt and learn how to navigate these challenges effectively.

A related issue is the difficulty of identifying the appropriate social media account to address complaints, which can deter users from sharing negative feedback. As we know, TfL primarily uses X (formerly Twitter), which is a global platform. However, it is not the most widely used social media site in every region. For example, in Asia, platforms like Weibo are popular, while North America leans more towards platforms like Hive. This could mean that an initial thought of raising a complaint might be abandoned due to the difficulty of finding the right platform to voice concerns. The tendency to write a negative comment may also depend on the length of stay - longer visits increase the time spent in public transport, providing more opportunities to encounter various situations. Among these situations, unpleasant experiences may arise, such as complicated traffic conditions and other transport-related issues.

Additionally, visitors from wealthier countries may be more critical, as they are accustomed to higher standards of public services (Zhou et al. 2025). These differences raise questions about how residence in a city influences sentiment and whether negativity is amplified by direct experience (Stylidis et al. 2021). Furthermore, this disparity suggests the importance of considering geographic and experiential factors in sentiment analysis. The pattern of tweet negativity by countries cannot be easily linked with geographical or economic factors alone. One possible explanation for this is cultural factors, which could play a significant role in shaping how people express their emotions on social media. For example, in some countries, individuals might be more inclined to voice dissatisfaction publicly, leading to a higher share of negative tweets, while in others, social media might be used less frequently for venting frustrations. This variation in attitudes towards public expression of emotions can influence sentiment distribution across different regions.

Another critical factor is social media penetration. Countries with higher internet and social media usage tend to show increased activity and more diverse opinions, which could naturally lead to a larger proportion of negative sentiments being expressed. People in these countries may feel more empowered or comfortable sharing their thoughts online, including frustrations with public transport systems. Finally, global events and media trends can heavily influence sentiment. In some countries, there might be an influx of negative tweets driven by major social or political events that dominate public discussion at the time of data collection (Sasikumar et al. 2023).

The results partially align with our expectations. Wealthier countries, typically characterized by more stable living conditions and greater access to resources, might be expected to show more negativity. However, the data indicates that negativity is not solely determined by economic prosperity. Instead, regional and cultural contexts seem to play a significant role in shaping online sentiment. For example, factors such as political instability, social unrest, or cultural attitudes toward the public expression of dissatisfaction can amplify negative sentiment in both developed and developing nations (Indaco 2020). Regarding the temporal distribution of sentiment, distinct patterns emerge in the Twitter activity of residents and visitors in London. Residents exhibit a peak in negative tweets during the early morning hours (3-6 AM). Between 8 AM and 3 PM, the proportion of negative tweets shared by residents significantly declines (<10%), which aligns with previously observed tweeting rhythms (Zajac et al. 2022). In contrast, non-residents display relatively higher levels of negativity throughout the daytime (7 AM–5 PM). A slight increase in negativity is observed during weekends, which may reflect visitor activities or an increased presence of residents on public transport, potentially leading to system congestion.

The topics discussed in negative tweets show variations across continents. In comparison to London residents, the issue of COVID-19 is similarly discussed worldwide, with the exception of North America. In North American tweets for Tfl, the predominant topic is breakdowns. Interestingly, in South American tweets, overcrowding emerges as the dominant concern. Europe, Oceania, and Asia exhibit similar distributions of topics when compared to London, though punctuality stands out as the primary concern in Asia. This aligns with the expectations, considering the well-known efficiency of public transportation in many Asian countries.

Conclusions

The findings highlight a significant divergence in sentiment toward transit-related tweets between residents and non-residents of London, with residents exhibiting higher levels of negativity. This suggests that daily, direct interaction with public transport challenges plays a substantial role in shaping residents' emotions and perceptions of the system. In contrast, the more positive outlook among non-residents may stem from a limited, often idealized view shaped by tourism or external perceptions. These results underscore the importance of considering experiential factors and geographic proximity when analyzing sentiment. The daily rhythms of sentiment among residents and non-residents were documented by analyzing the level of negativity in their tweets over a 24-hour, seven-day period. London residents exhibited higher levels of negativity in the early morning hours, while non-residents expressed more negativity during daytime hours. This study also identified notable differences in the proportions of topics discussed across continents. Specifically, users from the Americas were less likely to discuss COVID-19 but more frequently expressed concerns about breakdowns and punctuality. The topic distribution in negative tweets from Europe (as expected) and Asia was most similar to London. The most surprising finding came from Africa, where COVID-19 complaints were the most frequently discussed issue, with other topics being rarely mentioned.

The common limitation of all geo-social media (Andrienko et al. 2013) is selective sampling (Rybarczyk et al. 2018). The main limitation of this study lies in the classification of users as residents or non-residents. Location information was available in only 71% of cases, and the accuracy of these location reports varied, with some being vague or even misleading. Additionally, reliance on self-reported location data posed a challenge, as this data could not be independently verified. Geocoding user location data also proved difficult, as many location descriptions required manual intervention. Another limitation lies in the availability of the data. Since July 2022, Twitter data stopped being freely available due to the new policies implemented by Elon Musk on the platform, which showcases the dependence of the availability of the data on the owners of these platforms. Nonetheless, these findings provide valuable insights into public transport usage in London and how it is perceived by both visitors and non-native residents. Generally, it is possible to expect similar significant differences between sentiment of residents and non-residents transport related tweets in other cities.

For future research, we suggest a more detailed investigation of the data samples, including the application of topic modelling analysis to identify the specific issues that people were complaining about. Future studies could also examine whether similar spatio-temporal patterns exist in other major cities or whether London’s unique characteristics contribute to these dynamics. Future lines of investigation could also integrate a deeper integration of GIS-based spatial analysis and could enhance our understanding of how negative sentiment of different nationalities correlates with specific transport nodes, congestion hotspots, or infrastructure deficiencies across different boroughs. Furthermore, incorporating historical sentiment data could reveal how major policy changes, such as fare adjustments or infrastructure projects, influence public attitudes over time. By refining sentiment analysis techniques and linking them with geospatial methodologies, future studies could offer valuable insights for transport planning and urban management in London or other large cities with extensive discussions on social media.

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