Understanding People's Perceptions of Their Liveable Neighbourhoods: A Case Study of East Bristol

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Abstract

Liveable neighbourhoods are urban planning initiatives that aim to improve the quality of residential areas. In this paper, we focus on the East Bristol Liveable Neighbourhood (EBLN) to understand people's perceptions of their neighbourhood's urban reality. We analyse the opinions of citizens collected through the project, by examining their sentiments, the urban subjects they consider, and the language used to express their opinions. The findings of this study offer initial indications to inform urban planning processes and facilitate effective decision-making.

2012 ACM Subject Classification Information systems → Data analytics; Computing methodologies → Visual analytics

Keywords and phrases Urban analytics, liveable neighbourhoods, public participation geographic information system, citizen co-design, spatio-textual data, sentiment analysis, language analysis

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Category Short Paper

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1 Introduction

The term liveability has been used in various studies and at different levels of granularity ranging from individuals, neighbourhoods, and countries. It has also been used in multiple disciplines, such as geography, ecology, and urban planning [9]. Liveable Neighbourhoods (LNs) are fine-grained people-centred urban planning units with the goal of improving overall liveability. LNs aim to integrate various services and facilities in residential areas, aiming to create safe, healthy, inclusive, accessible, and attractive environments [5]. Public engagement in designing changes in their local community to meet local needs, known as co-design, plays a vital role in the development and implementation of LNs.

Understanding people's opinions toward their neighbourhoods is crucial for informed decision-making. Researchers have employed public participation geographic information systems (PPGIS) to examine local views for urban planning and decision-making research [3, 1]. They used PPGIS to collect and analyse public perceptions across diverse landscape types and scales, with examples of application in national park planning [2] and urban planning [4]. All these studies often relied on face-to-face surveys and interviews to collect peoples' opinions [7, 6], and comments were mostly analysed manually with respect to qualitative evaluation. However, these traditional methods are often work-intensive, and limited in sample size. To overcome these limitations, many projects are trying to use online neighbourhood reviews, that allow larger sample sizes and broader geographic coverage.

Table 1 Example of responses in the EBLN dataset.

Sentiment	Positive	Negative
Subjects	Trees and greenery on street, Street trees and planting	Walking, Crossings
Reasons	Pleasant	Not pedestrian friendly, Difficult to cross the street
Suggestions	Slow down traffic	Add crossing, Safer junction for walking and cycling
Comments	The street planters have reduced traffic speed and made the street 'greener'. Something similar could be done in other locations within the project area and in traffic displacement areas outside the project area	Hard to cross here - there is a traffic island slightly above this point but often want to cross lower down and it's hard to do so as the road is busy with two lanes of fast traffic.

These typically combine numeric ratings and textual comments. However, the challenges here are in analysing such a large number of data and efficiently extracting meaningful knowledge [6].

Another group of researchers tried to use geo-tagged social media as a mirror to view public perceptions and opinions of their living environment. For example, social media data have been examined to explore people's sentiments [10], emotions [11], satisfaction [12], and attitudes [8] toward their living area. Despite their significant findings, social media data are generally very noisy and require extensive preprocessing before use.

East Bristol Liveable Neighbourhood (EBLN) project[1] is a pilot study based on online surveys. The project aims to work with people who live, work, study, and travel through East Bristol, UK, to design people-friendly, safe, quiet, and healthy streets. It has been designed in partnership with the community as part of a co-design phase of the project which will help to shape permanent solutions.

With this work, we aim to analyse EBLN data to: (1) Understand citizen sentiment toward their living environment; (2) Investigate citizen choices of urban subjects and their mutual relations; And (3) Analyse citizen comments with respect to their sentiments.

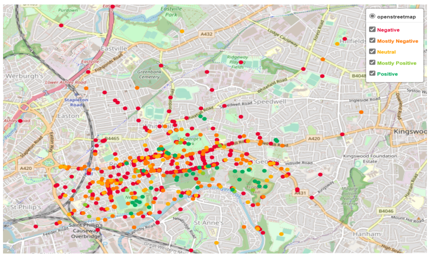
The remainder of this paper is organised as follows. Section 2 introduces the EBLN data. Section 3 provides a detailed discussion of our analysis and results. Finally, Section 4 summarises our conclusions and plans for future work.

2 Data and study area

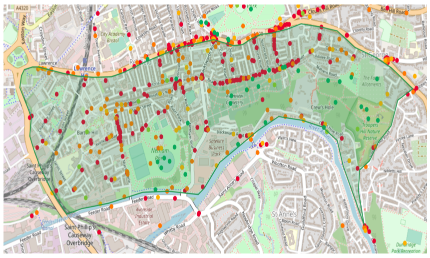
The survey data used in this study were collected between January and March 2022 by Bristol City Council, UK. People living, working, and travelling to or through the survey area (Figure 1b) were asked to express their views using an online interactive map[2]. Respondents could drop a point on the map, and were then asked to:

- Express their feeling by selecting one of five *sentiments*, ranging from negative to positive.
- Optionally, leave a *comment* using a free-text box.
- Optionally, select one or more *subjects* related to the comment, *reasons* for the sentiment expressed, and *suggestions* to improve the area.

[1] `https://eastbristolliveableneighbourhoods.commonplace.is`
[2] `https://eastbristolliveableneighbourhoods.commonplace.is/map/map`

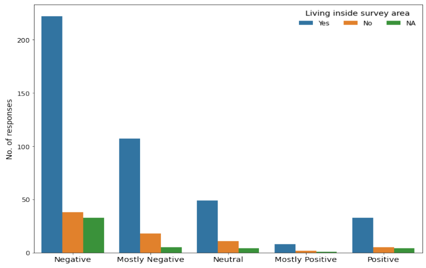


(a) Overall geographic spread of sentiments.

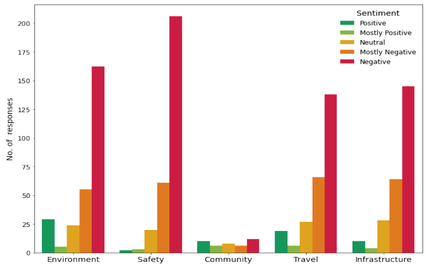


(b) Sentiment spread within the survey area.

Figure 1 Geographical distribution of sentiments within and outside the East Bristol Liveable Neighbourhood survey area.



(a) Respondents' sentiments compared to their living location.



(b) Sentiment distribution for each subject category.

Figure 2 Sentiment analysis based on respondents' living location and subject categories.

An example of responses is shown in Table 1. As Figure 1a shows, some comments refer to locations outside the survey area. Nonetheless, we have decided to include these data points in our analysis, since our final goal is to gain insights into the language citizens use to describe the urban environment around them. The dataset used comprises 540 geo-located, sentiment-based entries, of which 91% contain textual comments and subject labels. In this preliminary study of the EBLN data, we have limited our analysis to the free-text comments along with their corresponding sentiments. We have also focused on understanding the co-occurrence of urban subjects selected within the survey, as well as their relation to respondents' sentiments.

3 Analysis and results

3.1 Geographical spread and frequency of sentiments

Our initial investigation concentrated on analysing the sentiments expressed by the respondents. The primary objective was to investigate the geographical distribution of sentiments, and how they relate to whether the respondents live within the survey area or not. The findings revealed that a substantial portion of the respondents resides within the survey area (Figure 2a), with a noteworthy proportion of the sentiments expressed being characterized as negative. This highlights how PPGIS participants living in a study area are more vested in decisions regarding their community than respondents less connected to the area [1]. Due to the co-design nature of the project, it is not surprising that respondents tended to emphasize the negative aspects of their neighbourhood.

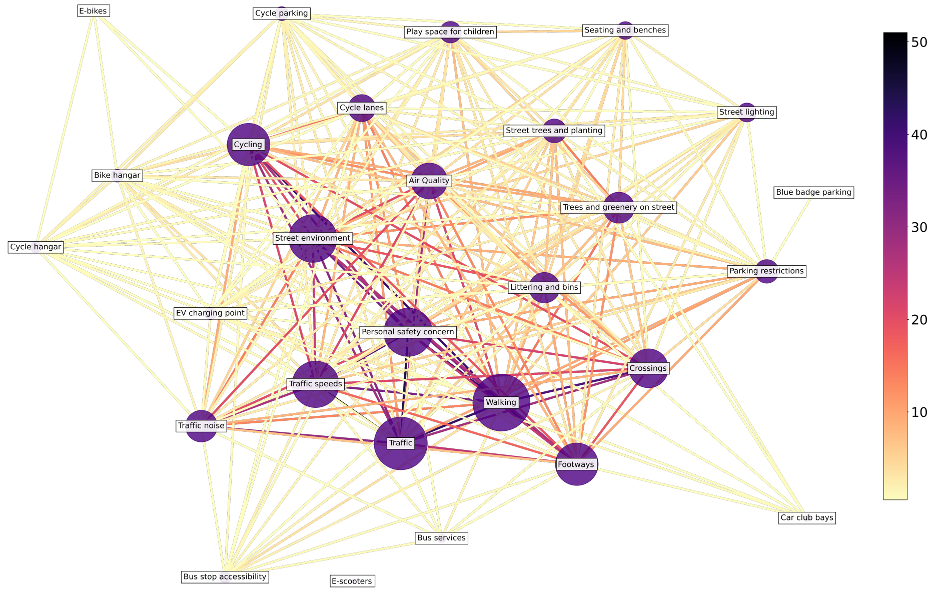


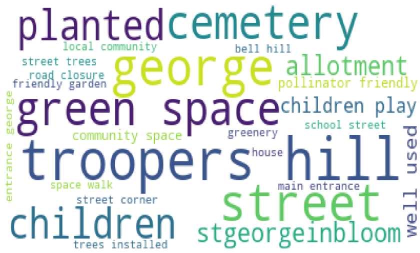
Figure 3 Subjects frequency and co-occurrence. The edge colour scale represents the co-occurrence rate.

The maps in Figure 1 show that most of the negative comments are concentrated along main roads and junctions. Conversely, areas characterized by green spaces tend to display more positive-related comments. Given the aim of the EBLN project is to improve the urban environment of the neighbourhood, it is expected that the majority of comments are pinned to roads. It is worth noticing that further statistical analysis of the data revealed no significant correlation between the sentiments expressed by the respondents and the land cover and type characteristics within the study area.

3.2 Co-occurrence of subjects in the responses

In our analysis, we have identified a total of 28 distinct subjects that the respondents selected to categorize their responses. As Table 1 shows, some comments have multiple subjects associated. The top 3 most selected are: *Walking* (40% of the comments), *Traffic* (34%) and *Personal safety concern* (29%). Figure 3 shows all the subjects selected, as well as their occurrence in the same data entry (edges) and individual frequencies (node sizes) within the dataset. The edge colour represents the occurrence rate of responses containing two node-subjects. The graph shows a clear cluster around *personal safety*, linking together *walking* and *cycling*. Moreover, these two subjects are often selected with *traffic* and *traffic speed* within the same responses, as shown by the darker coloured edges. This is not surprising since both modes of travel commonly occur within the realm of traffic, and they are affected by its dynamics. The frequency of such co-occurrence in the comments highlights the importance of well-designed infrastructure to ensure the safe coexistence of pedestrians, cyclists, and vehicles.

(a) Words associated with **negative** sentiments.



(b) Words associated with **positive** sentiments.

Figure 4 Word cloud: language patterns in the EBLN free-text comments.

3.3 Language and subjects patterns based on sentiments

In the final part of our analysis, we investigated patterns between the response subjects, the language used in the comments and the respondents' feelings. Given the complexity of the subjects' structure, we decided to group all the subjects into five main categories, following the naming convention used by Bristol City Council:

- **Environment**: air quality, traffic noise, street environment, trees and greenery on street, street trees and planting, littering and bins;
- **Safety**: personal safety concern, traffic speeds, traffic, street lighting;
- **Community**: play space for children, seating and benches;
- **Infrastructure**: footways, crossing, cycle lanes, cycle parking, cycle hangar, bike hangar, bus stop accessibility, EV charging point, car club bays, parking restrictions, blue badge parking;
- **Travel**: walking, cycling, bus services, e-scooters, e-bikes.

We analysed the sentiment distribution within the above categories. Figure 2b shows a notable presence of negative statements in the safety and environment categories, while the community category displays a more balanced distribution of sentiments. This aligns with the observations from the word clouds in Figure 4. In the word clouds, we included the *negative* and *mostly negative* labelled responses in the negative group, and the *positive* and *mostly positive* responses in the positive one, while excluding neutral comments. This approach allows us to accentuate the contrast between the words used to express positive and negative opinions. The analysis of the free-text comments in the EBLN data revealed a predominance of negative terms associated with the environment and travel aspects. Conversely, positive words were more linked to community and green areas. It is worth noticing, the word *road* in the negative cluster, and *street* in the positive one. This distinction reflects the perception that roads typically denote larger, traffic-intensive settings, while streets refer to smaller-scale entities. The sentiment contrast between these terms highlights how respondents express their experiences in relation to urban spaces and transportation infrastructure. Finally, we observe that specific road and area names in the word cloud, such as Beaufort Road, Church Road (negative), and Troopers Hill (positive), correspond to the clustering of negative and positive pins on Figure 1b. We can therefore infer that respondents perceive these locations as areas in need of improvement or additional attention.

4 Conclusions and Future Work

In this paper, we have analysed East Bristol Liveable Neighbourhood (EBLN) online review data to understand the aspects of neighbourhoods perceived by people and identify potential problems. EBLN is a trial project and the dataset used in this study comprises 540 geo-located contributions. By analysing this dataset, we found that the majority of the respondents reside within the survey area. They tended to emphasize the negative aspects of their neighbourhood, and identify the names of areas and roads associated with positive and negative sentiments in their comments. We also found that most of the negative comments were linked to main roads and junctions while most of the positive comments were linked to community and green areas. The results of this study provide promising preliminary evidence for urban planning and decision-making. Our analysis approach can be applied to a full-scale project. Given the emergent use of public neighbourhood reviews in recent years, it can also be used for similar projects conducted by other cities such as Glasgow and Bath.

There are a number of directions for future work. First, we can extend our analysis to include the reasons and suggestions given by the contributors. Second, evaluate and apply AI-based Natural Language Processing (NLP) techniques for sentiment and semantic analysis of the free-text comments. This would help urban planners to analyse and deduce sentiment and topics from free-text surveys.

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