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Insights in a City Through the Eyes of Airbnb Reviews: Sensing Urban Characteristics from Homestay Guest Experiences

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Abstract

There is a growing interest in deriving insights about cities from crowdsourced data. We advance the discourse by employing homestay guest experience to sense urban characteristics. We evaluate the relationship between subjective perceptions and objective indicators thanks to rich information in textual reviews that we posit reflect urban qualities. Next, we investigate dominant topics about urban characteristics in Airbnb reviews (transportation, greenery, amenities, safety, and noise) with natural language processing techniques, i.e. a rule-based dependency parsing method designed to extract relevant information. Then, we establish the associations between sentiments and proxies representing the physical patterns of urban areas. The multi-scale results of the experiments in three cities (London, Singapore, and NYC) suggest that reviews on homestay platforms reflect transportation convenience, amenities, sense of safety, and noise pollution. The correlation is stronger at a higher administrative division level, while the perception of people on safety is more sensitive at a more granular scale. Densities of transportation and amenities in nearby districts are more likely to be perceived similarly. Furthermore, the spatial distribution of perceptions is possibly affected by the morphology and development of a city, and the diversity of guests. This study reveals new possibilities for sensing urban characteristics through user-generated information and introduces a new application of accommodation reviews, which may help alleviate gaps in availability of data required for planning.

Keywords: Urban Data Science, Urban Planning, GeoAI, Volunteered Geographic Information, Crowdsourcing

1 Introduction

Reviews on online platforms or social media, such as dining experiences, are a useful textual representation of human perceptions of various aspects of cities (Hu *et al.*, 2019; Jang & Kim, 2019; Olson *et al.*, 2021), in line with the observation of Goodchild (2007) that citizens can observe a great variety of geographic information as *sensors*. Over the past decades, the advancement and popularity of social media, crowdsourcing, and online reviews have tremendously expanded the volume of volunteered geographic information (VGI) and research around it (Hu *et al.*, 2019; Tateosian *et al.*, 2023; Yan *et al.*, 2020). A variety of geotagged social media data has been widely used in urban analysis, including but not limited to socioeconomic and demographic research (Arnaboldi *et al.*, 2017; Cheng & Jin, 2019; Cui *et al.*, 2021; Feng *et al.*, 2022; Fried *et al.*, 2014; Hu *et al.*, 2019; Kiatkawsin *et al.*, 2020; Lansley & Longley, 2016; Liu & Biljecki, 2022; Longley & Adnan, 2015; Quercia *et al.*, 2012), as well as studying urban mobility (Cunliffe *et al.*, 2020; Li *et al.*, 2019; Phillips *et al.*, 2021; Serna *et al.*, 2017). Among different types of geotagged data crowdsourced from various venues such as social media, reviews are unique due to their subjectivity and multifaceted expressions. As reviews relay human perceptions, they may offer a vehicle for studying the relationship between subjective perceptions and objective artefacts in cities.

In this paper, we posit that homestay guest experience such as Airbnb reviews, besides their primary purpose of assessing the accommodation and its host, are rich in information about people's perception on the surrounding urban development. We build on the rich body of knowledge that has taken advantage of the wealth of information available in Airbnb reviews, and expand it for a different purpose -- beyond understanding specific attributes about an Airbnb property (Zhang *et al.*, 2020) to gather the perception and condition of neighbourhoods. Combined with location information that is generally available in such data, we postulate that it has potential to relate the content of reviews to the actual urban development in a city, and to evaluate the relationship between subjective perceptions and objective attributes of developments in urban areas.

A neighbourhood, being a form of basic urban planning unit of a city, is one of the most important features of urban areas. It is increasingly critical to setting planning targets and evaluating social policy (Stone *et al.*, 2015) based on the different scales of neighbourhood units. Just as Lynch (1960) and many subsequent researchers pointed out that human beings are capable of recognizing the physical patterns and activities (Yao *et al.*, 2017; Yuan *et al.*, 2012) of a city, as well as intangible characteristics (Aiello *et al.*, 2016; Quercia *et al.*, 2012; Quercia *et al.*, 2015; Shelton *et al.*, 2015) of different parts of the city, and organizing them as a coherent understanding (Jang & Kim, 2019). Moreover, building on massive qualitative approaches in investigating urban characteristics (Appleyard, 1981; Lynch, 1960), quantitative and systematic methods is increasingly essential to perceive the image of a city.

In this study, we analyse the gap between subjective feedback and objective urban characteristics in urban development. It further supports the evaluation and enhancement of the progress and implementation of urban planning, eventually benefiting citizens' quality of life. Hence, this study aims to answer the research question: To what extent do Airbnb reviews reflect the development of a city? Supporting the research question, we establish two subquestions: What are the main topics of Airbnb reviews that are relevant to urban characteristics? How well do Airbnb reviews describe the urban characteristics on different scales? To answer them, we analysed Airbnb reviews on multiple administrative division levels and evaluate the association between the review sentiments and quantitative proxies for multiple aspects pertaining to urban development. To understand scalability and application, we study multiple cities around the world. The main contributions of this work, besides pushing the frontiers of urban sensing and utilising geotagged user-generated urban data, are to dive into a new perspective in urban textual data analysis, by identifying potential semantic topics of Airbnb reviews regarding urban areas, analysing people's perceptions of the characteristics of cities, and examining the association. To the extent of our knowledge, such a study has not been conducted before, and our work establishes a new research line on understanding the usability of crowdsourcing guest experiences in the function of evaluating cities.

The paper is organized as follows. Section 2 provides a comprehensive literature review on related work to overview existing findings and research gaps of relevance. Section 3 introduces the research methodology and rationale of data source selection. Section 4 describes the results of the analysis, and presents the discussion and limitations in Section 5 . Finally, we summarise this study and raise future research potentials in Section 6.

2 Literature Review

2.1 Subjective perception reflects the space, functions, zoning, and activities of a city

The subjective perception of a city can be organized into a coherent understanding of the city. It reflects various physical aspects that cover space, functions, zoning, and activities of a city. Lynch (1960) proved this approach by conducting interviews and producing a "cognitive map" of Boston. Recently, Filomena *et al.* (2019) endeavoured to reproduce Lynch's (1960) cognitive map using computational methods. Phillips *et al.* (2021) suggested that people develop cognitive maps beyond the neighbourhoods that they reside in, as people usually travel around for various purposes, e.g. work and leisure activities. Despite the importance of these previous studies, online review data, to the best of our knowledge, have not been much examined in this context before, especially on different scales of neighbourhoods of a city.

Although official administrative boundaries of neighbourhoods do not always reflect actual communities (Stone *et al.*, 2015), they provide an unrivalled baseline for real estate market and policy evaluation (Sampson, 2012), which reinforces the boundary of people's cognitive maps. Hence, the recognition of urban characteristics consists of collective representation (Olson *et al.*, 2021) of both official boundaries and people's cognitive maps. Therefore, the investigation of urban characteristics on different administrative division levels is needed to offer extensive insights into understanding how human perceptions reflect the actual development of a city.

The findings of existing research in relevant fields are more focused on structural components, urban mobility, or socioeconomic indicators of a city. Examining the methods to quantify the subjective aspects of the urban environment has been studied across disciplines (Jang & Kim, 2019). For example, Olson *et al.* (2021) generated community boundaries based on Yelp reviews, Serna *et al.* (2017) proved the feasibility of analysing urban mobility with the data on social media, and Dong *et al.* (2019) proved the transferability between crowdsourced data and socioeconomic attributes across geographical locations. However, urban characteristics have yet to be explored in a comprehensive way that encompasses both physical and non-physical aspects of urban areas. Specifically, Airbnb data has yet to be used for sensing urban characteristics.

Effort in exploring new approaches to interpreting a large volume of data has been made to understand the perception of a city. By examining the distribution of geotagged photos on Flickr and Panoramio and creating a perceived image of city, through a computational method, Liu *et al.* (2016) affirmed the elements of developing "the image of the city" proposed by Lynch (1960). Furthermore, researchers have succeeded in reproducing the mental map of cities (Quercia *et al.*, 2013), and utilising georeferenced picture tags to map the attributes of the urban environment (Jang & Kim, 2019), including activities (Quercia *et al.*, 2018), ambience (Redi *et al.*, 2018), and senses (Aiello *et al.*, 2016; Quercia *et al.*, 2015). This line of research further proved that subjective perceptions of human beings can act as sensors to identify the physical patterns and activities of a city.

2.2 Social media and crowdsourced data as tools for reading a city

Geotagged social media has been widely used in urban analysis. Besides the examples provided in the Introduction, real estate listings and social media have been used to assess neighbourhood typology (Delmelle & Nilsson, 2021). Shelton *et al.* (2015) and Jenkins *et al.* (2016) discovered properties of urban areas, focusing on identifying the places that are frequently visited by people using geotagged Twitter data.

Other location-based big data and crowdsourced data also have provided an opportunity for urban and regional research (Hu *et al.*, 2019; Quercia *et al.*, 2012). These sources of data expanded the possibilities for academia to explore both tangible and intangible assets of a city

(Abdul-Rahman *et al.*, 2021; Luo & Tang, 2019; Yao *et al.*, 2017), as these data often contain useful and insightful information that could imply beyond what official datasets and indicators offer. Street view imagery, for example, has been frequently studied to extract urban perception (Biljecki & Ito, 2021; Gong *et al.*, 2019; Zhang *et al.*, 2018a; Zhang *et al.*, 2018b; Zhang *et al.*, 2019). Nevertheless, the capacity to identify dynamic collective identities of a city, using the actual textual expressions of users, has yet to be scaled up more broadly (Olson *et al.*, 2021). We posit that similar data may be used to monitor economic trends along with urbanization in a way that goes beyond what standard official indicators permit. In this paper, we build on the state of the art, and we investigate this hypothesis, which might have promising potential to track the physical patterns and activities of a city.

Airbnb data has been taken advantage of in a variety of urban studies. For example, it has been used to analyse the impact on housing prices (Li & Biljecki, 2019), understand interior design (Liu *et al.*, 2019), and understand urban vibrancy (Chen *et al.*, 2021). Given the extensive information on location and user experience, Airbnb data has the potential in creating an image of the city according to the perceptions of people (Kiatkawsin *et al.*, 2020; Lalicic *et al.*, 2021), as well as in gaining insights for hospitality research (Cheng & Jin, 2019; Thomsen & Jeong, 2020). Given the penetration and diversity of Airbnb around the world, and considering that guests are encouraged to write reviews about their stay after departure, the volume of Airbnb reviews is considerable. In spite, the quality of textual reviews on Airbnb might be compromised due to the pressure of writing a review after staying (Kiatkawsin *et al.*, 2020), and the textual data can be rather unstructured which might impede research.

The literature has employed various approaches for analysing various types of reviews, including those similar to homestay guest experience. However, none is especially suitable for Airbnb reviews. In terms of text reviews, Natural language processing (NLP) techniques are efficient in analysing a large volume of textual data (Kao & Poteet, 2007). Kiatkawsin *et al.* (2020), Hu *et al.* (2019), and Olson *et al.* (2021) discovered latent discussion topics from Airbnb, self-collected reviews, and Yelp respectively by adopting Latent Dirichlet Allocation (LDA) method. According to Mitcheltree *et al.* (2020), LDA has become a common NLP method for aspect extraction and topic modelling in an unsupervised approach (Brody & Elhadad, 2010; Titov & McDonald, 2008), but might not be suitable for analysing Airbnb reviews. The coherence of clustered words is not always plausible, with often unrelated bags of words in a specific aspect (Mimno *et al.*, 2011; Ruan *et al.*, 2017). Although LDA has been widely used on heterogeneous datasets such as newspaper articles (Blei & Laffery, 2007), it has relatively lower performance in extracting aspects of textual data from a more restricted field such as Airbnb. Therefore, we adopt another approach to achieve a desirable result of aspect extraction for this study.

The investigation of Airbnb reviews has been consistently conducted among research entities. Cheng and Jin (2019), Chung and Sarnikar (2021) and Lawani *et al.* (2018) examined Airbnb reviews with prices or marketing strategies. However, existing studies are limited to the assessment of aspects or sentiments of textual data without relating to urban areas. It still lacks a comprehensive investigation on how subjective textual data of Airbnb guest experiences reflect objective aspects of cities. Potential quantitative proxies of such objective urban aspects have yet to be assessed in terms of the relationship with human perceptions in reviews. In this study, we capture the benefits of both aspect extraction and sentiment analysis to generate collaborative advantages in the computational approach, and to gain new and comprehensive insights from this valuable dataset.

3 Methodology

3.1 Analytical approach

Figure 1 illustrates the methodology. After gathering the data (Section 3.2), we explode each Airbnb review into comment sentences, retaining other information including the coordinates of the property, to generate topic-specific sentiment scores (a quantitative value that suggests the general feeling of a piece of text). Sentiment scores are generated by a Python package, Textblob[1], which provides a pre-trained model to score each sentence between -1 (negative perception) and 1 (positive perception), and other tools such tokenisation and lemmatisation (for gaining a better understanding of the meaning of a sentence). We adopted Textblob tools to ensure a consistent workflow.

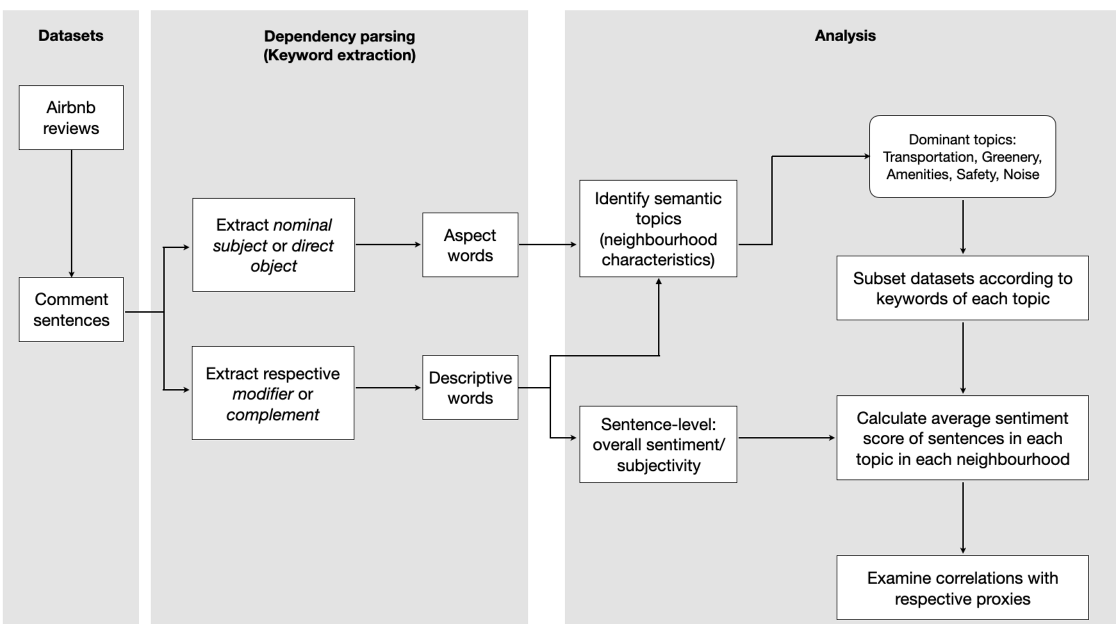

Figure 1. Workflow of the analysis.

[1] https://textblob.readthedocs.io/

Dependency parsing, an NLP technique used to examine the associations of phrases to establish their grammatical structure and relationships, is adopted to extract the nominal subject/direct object-of a sentence as aspect word, as well as the respective modifier/complement that functions as the description of the aspect word. Auxiliary words are excluded from the pipeline, as the subject that they refer to is hard to identify without any context, as similar to other tasks in text mining. Examples of this process are shown in Figure 2.

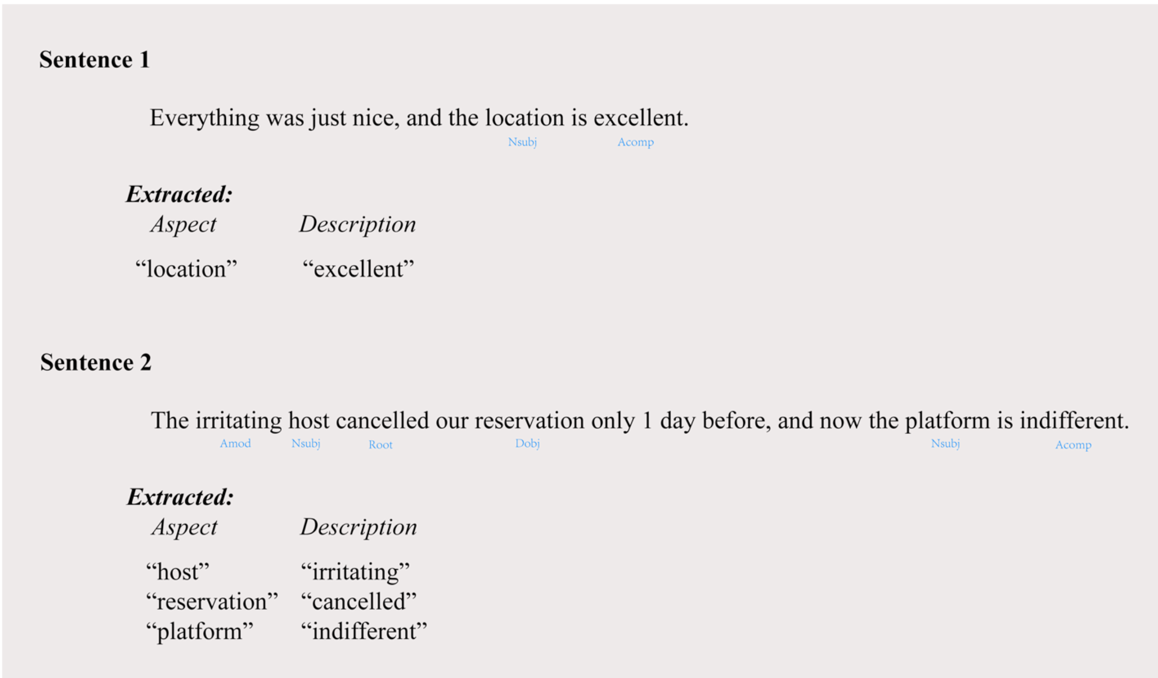

Figure 2. Examples of Dependency Parsing for two sentences with different sentiment and about different aspects.

Based on the extracted pair of words (see Figure 2 for examples), the dominant topics are defined through a process of examining the main semantic topic of each pair of words. The five dominant topics observed are transportation convenience, greenery, amenities, safety, and noise, which serve as the five dimensions of the urban environment that this study focuses on as an instrument of their development and quality. The rationale behind selecting these topics is that the frequent words that appear in Airbnb reviews (as shown in Table 1) can be compartmentalized into these topics. The datasets are further subset according to the keywords of each topic, which are the aspect words or descriptive words extracted. Topic-specific sentiments are further generated through aggregating the average sentiment score in each neighbourhood, where the number of pair of words observations is larger than 3.

Table 1. Frequent words of each topic.

Topic	Frequent Words
Transportation	bus, transport, train, station, location
Greenery	tree, park, garden
Amenities	shop, restaurant, café, market, club
Safety	safety, safe, dangerous
Noise	noise, noisy

The derived perceptions on the dominant semantic topics, namely interested neighbourhood characteristics, reflect the subjective opinions of people towards a neighbourhood. To investigate the relationship between subjective feedback and objective attributes of urban areas, the study conducts a correlation analysis between the topic-specific sentiments and quantitative proxies for each topic. Due to the results of the Shapiro-Wilk Test on the normality of data distribution, Spearman's rank correlation is thus employed since the data does not always sit in a normal distribution, combined with the consideration of the highly skewed datasets. In this case, the raw data are transformed into ranked-based datasets for running the Spearman's correlation. Spatial autocorrelation analysis is also considered to explore whether there exists a high-high or low-low spatial clustering of the sentiment score values as part of the exploratory analysis. The confidence levels to determine the level of significance in this study are 99% ($p<0.01$), 95% ($p<0.05$), and 90% ($p<0.1$). The p-values for insignificant results are not labelled.

3.2 Data

The research uses reviews retrieved from Inside Airbnb. As Airbnb listing data has received much research attention due to its rich information on accommodations and the surrounding environment, and the booming topic of the sharing economy, this dataset has been frequently used in research (Cheng & Jin, 2019; Chung & Sarnikar, 2021; Kiatkawsin *et al.*, 2020), including in some papers mentioned in the literature review. Table 2 shows some excerpts of the review data.

Airbnb reviews can be written in many languages. As the research focuses on the English language, comments in other languages are filtered out. Further, in this study we focus on the period of 2019 to 2021, thus, reviews outside this timeframe are excluded.

Table 2. Examples of Airbnb reviews. Some reviews contain statements that suggest various urban characteristics (examples pertaining to transportation are highlighted in yellow), which we take advantage of in our work to develop a method to sense neighbourhoods.

listing_id	reviewer_id	date	Review
25123	225409357	2020-01-04	Grace is an amazing person, very friendly, receptive, cheerful and always willing to help. The house is excellent and my room was very nice, just like the pictures. The accommodation is well cared for and very clean. It is near the subway station and the market. Thanks for the tips, the hospitality and the kindness, Grace. Highly recommend, grade 10.
36660	57512966	2021-05-03	If I could give this home 10 stars I would. Agri & Roger are so warm & accommodating, I felt like I was amongst family. The garden and the room are an absolute dream. I can't get over how beautiful the garden is, and the room is furnished with lovely floral touches and vintage furniture. Agri & Roger, kindly allowed me to hold a photoshoot in their gardens for my business, and it was the best decision I could have made, it was an absolute dream stay and I will definitely be coming back ❤️
36299	250644756	2019-07-01	Great location to explore Kew Gardens and easy access to London with tube station nearby! Great flat with lovely backyard space. We enjoyed using this as our base for exploring the London area.

Considering the proliferation of Airbnb, listings - and reviews by extension - are available in numerous major cities worldwide, providing great opportunities to conduct a large-scale investigation. The analysis is conducted in three cities at different administrative subdivisions: London (borough and ward), Singapore (planning area and subzone), and New York City (community district and neighbourhood tabulation area). The rationale for selecting these cities is geographical balance and a developed tourism infrastructure catering to a large number of visitors from around the world. Next, English is the official language in all of them, and they have rich open data sources provided by the local government, allowing us to validate the results. Yet, these cities are also different in many aspects, testing our work in diverse settings, e.g. their urban morphology is significantly different (Biljecki & Chow, 2022). In total, there are 114,340 listings and 899,776 reviews, of which 73,364 listings and 459,129 reviews are in London, 4,252 listings and 25,724 reviews are in Singapore, 36,724 listings and 414,923 reviews are in NYC.

Regarding the quantitative proxies of the selected neighbourhood characteristics, we retrieve local administrative boundaries, bus stops, crime data, and road noise pollution data from the authoritative open data resources of the local governments. Street greenery is obtained from Treepedia (Li & Ratti, 2018; Li *et al.*, 2015; Seiferling *et al.*, 2017). The definitions and sources of data are indicated in Table 3. Crime rate and noise data are not available for Singapore, and noise data is not available for NYC. We employ bus stop density, tree density, POI (Point of Interest) density, crime rate, and noise coverage to represent the objective attributes of urban development per the identified topics, namely transportation, greenery, amenities, safety, and noise, respectively. Specifically, we select the POIs according to the keywords that appeared on the topic of amenities. Hence, 16 tag values are selected for retrieving POIs from OpenStreetMap, with most being relevant to eateries and leisure activities. The selection of the dominant topics is based on the words extracted for either aspect or description and manually classified the words into five topics as mentioned.

Table 3. Sources of data.

Data	**Definition**	**Source of Data**		
		London	Singapore	NYC
Listings & Reviews				
Airbnb Listings	Airbnb listings information		Inside Airbnb[2]	
Airbnb guest experiences	Reviews between 2019 and 2021		Inside Airbnb	
Population		London Datastore[3]	LTA DataMall[4]	NYC OpenData[5]
Proxies				

[2] http://insideairbnb.com/get-the-data
[3] https://data.london.gov.uk/dataset
[4] https://datamall.lta.gov.sg/content/datamall/en/static-data.html
[5] https://opendata.cityofnewyork.us/data/

Bus stop density	Number of bus stops normalized by area and population	London Datastore	LTA DataMall	NYC OpenData
Tree density	Number of trees normalized by area and population	Treepedia[6] (Li & Ratti, 2018; Li *et al.*, 2015; Seiferling *et al.*, 2017)		
POI density	Number of selected POIs normalized by area and population (POIs including: retail, kiosk, supermarket, shop, cinema, theatre, bar, biergarten, café, restaurant, marketplace, fast_food, food_court, pub, nightclub, ice-cream)	OpenStreetMap		
Crime rate	Latest crime rate available	London Datastore		NYC OpenData
Noise coverage	Percent coverage of area where road noise L_{aeq16} >= 75 dBA	London Datastore		

4 Results

The key results of the experiments for the three cities suggest that homestay reviews may serve as a moderately reliable instrument for gauging urban development across five dimensions pertaining to the quality of life and wellbeing of residents and visitors. The method exhibits different performances at different levels of aggregations. The results are elaborated in detail in the next sections.

4.1 Spatial Autocorrelation

Spatial autocorrelation (Global Moran's I) measures the spatial distribution of observations, where a significant value indicates the high values or low values are more spatially clustered. Table 4 indicates the results of spatial correlation analysis on sentiment scores of the Airbnb reviews in the three cities. As observed in Table 4, spatial autocorrelation is not significant in Singapore. The results of Global Moran's I in London show the significance for some topics, while the values possess a weak to moderate strength. Interestingly, the values of Global Moran's I are most significant in New York City, and the positive values are comparably higher at the lower administrative division level. Hence, the spatial distribution of high or low sentiment scores would be expected to be more spatially clustered in New York City, especially on the lower administrative division level. This result suggests that nearby analysis objects are likely to be similarly perceived by Airbnb users. Generally, the Global Moran's I values are higher for the topics of transportation and amenities compared to the other three topics.

Table 4. Result of Spatial Autocorrelation – Global Moran's I.

City	**Topic**	**Global Moran's I**

[6] http://senseable.mit.edu/treepedia

London		Borough	Ward
	Transportation	0.3867 *(p<0.01)*	0.2608 *(p<0.01)*
	Greenery	0.0763	0.1047 *(p<0.01)*
	Amenities	0.3577 *(p<0.01)*	0.1369 *(p<0.01)*
	Safety	0.3577 *(p<0.01)*	-0.0015
	Noise	0.1041	-0.0173
Singapore		**Planning area (PA)**	**Subzone**
	Transportation	-0.0004	0.1111 *(p<0.1)*
	Greenery	-0.0546	0.3034
	Amenities	-0.0994	-0.1065
	Safety	-0.0625	-0.1782
	Noise	0.0746 *(p<0.1)*	0.1426
New York City		**Community District (CD)**	**Neighbourhood tabulation area (NTA)**
	Transportation	0.5076 *(p<0.01)*	0.8292 *(p<0.01)*
	Greenery	0.2862 *(p<0.01)*	0.8172 *(p<0.01)*
	Amenities	0.5807 *(p<0.01)*	0.7554 *(p<0.01)*
	Safety	0.1226 *(p<0.1)*	0.7145 *(p<0.01)*
	Noise	-0.0986	0.7351 *(p<0.01)*

4.2 Topic-specific Analysis

In this section, we present the results of correlation analysis in the three cities, for the five dominant topics. Correlation analysis on safety is not performed for Singapore, and the analysis on noise is not performed for Singapore and New York City, due to lack of data for these aspects.

4.2.1 Transportation

The correlation coefficients between average sentiment scores about transportation and bus stop density in three cities are shown in Table 5. The results indicate that the sentiment score about transportation increases as the bus stop density increases in London and Singapore. The coefficients are significantly higher on a higher administrative division level. This finding implies that the monotonic positive association tend to be stronger when the analysis is on a larger scale. The coefficients for New York City are not significant. One possible reason is that New York City is more fine-grided and more walkable comparing with London and Singapore, thus bus stop density is less of a significant factor there.

Table 5. Result of Correlation Analysis – Transportation.

City	Correlation coefficient (Transportation)		Descriptive statistics of sentiment			
			Mean		Standard Deviation	
London	Borough	Ward	Borough	Ward	Borough	Ward
	0.6430 *(p<0.01)*	0.1882 *(p<0.01)*	0.41	0.39	0.04	0.07

Singapore	PA	Subzone	PA	Subzone	PA	Subzone
	0.5094 *($p<0.01$)*	0.2419 *($p<0.01$)*	0.38	0.37	0.12	0.15
New York City	CD	NTA	CD	NTA	CD	NTA
	0.2041	-0.0205	0.41	0.40	0.07	0.07

4.2.2 Greenery

The correlation coefficients between average sentiment scores about greenery and tree density in the three cities are shown in Table 6. Most results are not significant. However, the correlation coefficient is negatively significant for the borough-level analysis in London. There exists a negative correlation between the sentiment score about greenery and the actual tree density. Interestingly, though the coefficients are not statistically significant, most of them are negative.

Figures 3 to 8 present the maps of greenery sentiment and tree density in London, Singapore, and NYC. Tree density is higher in the city centre, namely central London, Singapore's downtown core, and NYC Manhattan, whereas the sentiment score about greenery is relatively lower there. One possible explanation could be that the development in the city centre is comparably denser than that in peripheral areas, diminishing its visibility. Thus, even though the tree density is higher in the city centre, people do not recognize it due to the dense built-up environment.

Table 6. Result of Correlation Analysis – Greenery.

City	**Correlation coefficient (Greenery)**		**Descriptive statistics of sentiment**			
			Mean		Standard Deviation	
London	Borough	Ward	Borough	Ward	Borough	Ward
	-0.3167 *($p<0.1$)*	-0.0740	0.35	0.35	0.05	0.09
Singapore	PA	Subzone	PA	Subzone	PA	Subzone
	0.0882	-0.1125	0.33	0.36	0.15	0.12
New York City	CD	NTA	CD	NTA	CD	NTA
	-0.2006	-0.0253	0.34	0.33	0.10	0.12

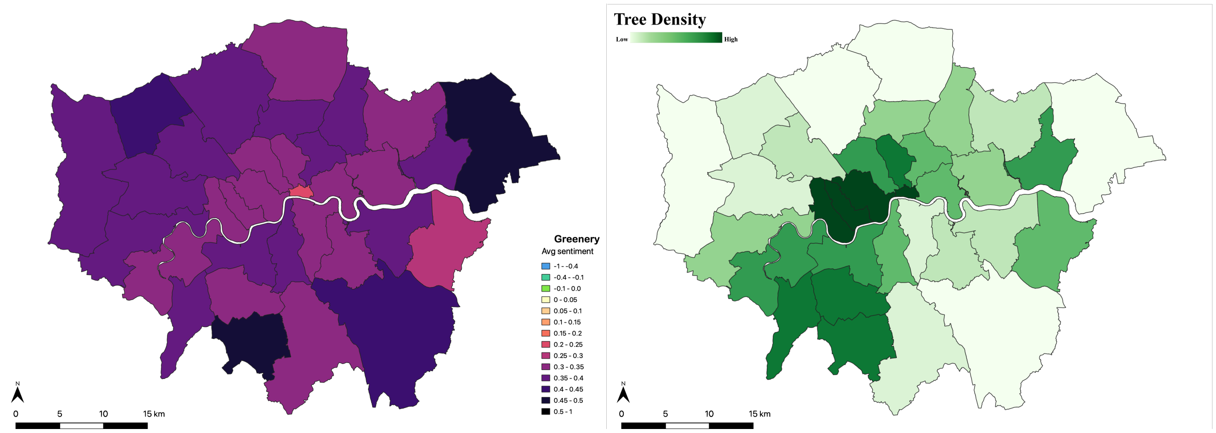

Figure 3. Average sentiment score for greenery vs tree density (borough) in London.

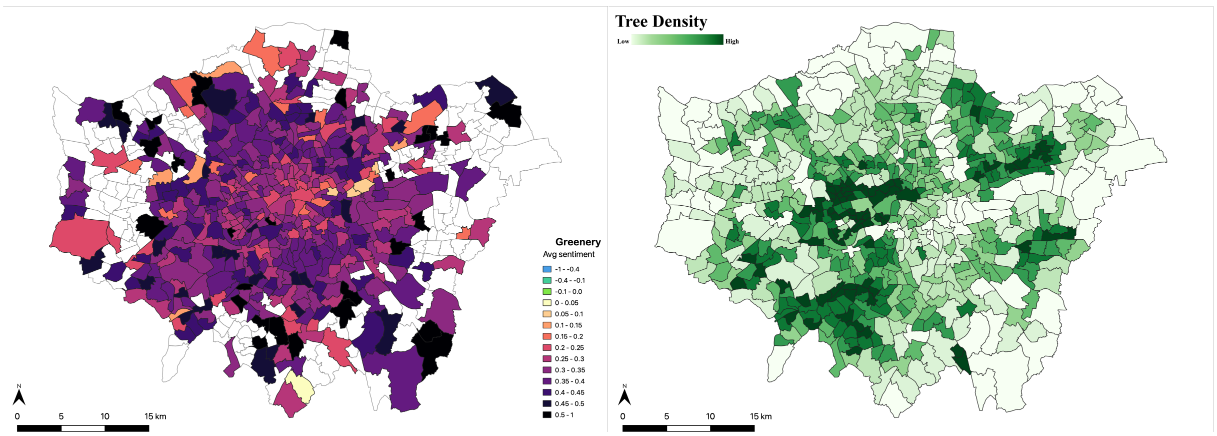

Figure 4. Average sentiment score for greenery vs tree density (ward) in London.

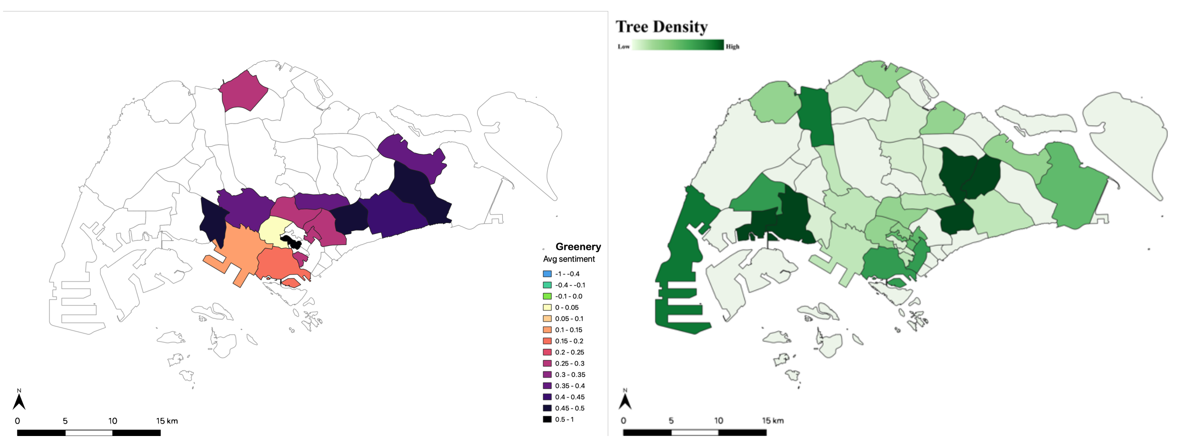

Figure 5. Average sentiment score for greenery vs tree density (planning area) in Singapore.

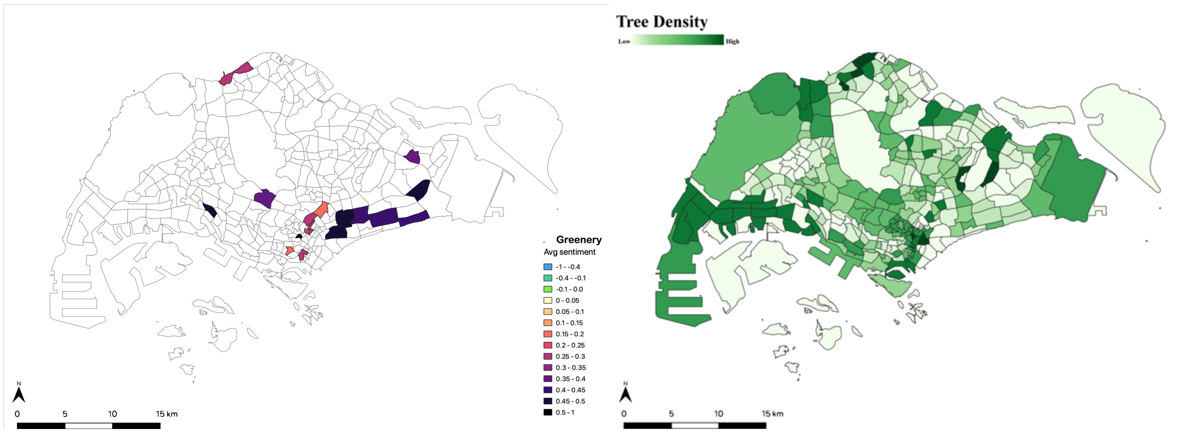

Figure 6. Average sentiment score for greenery vs tree density (subzone) in Singapore.

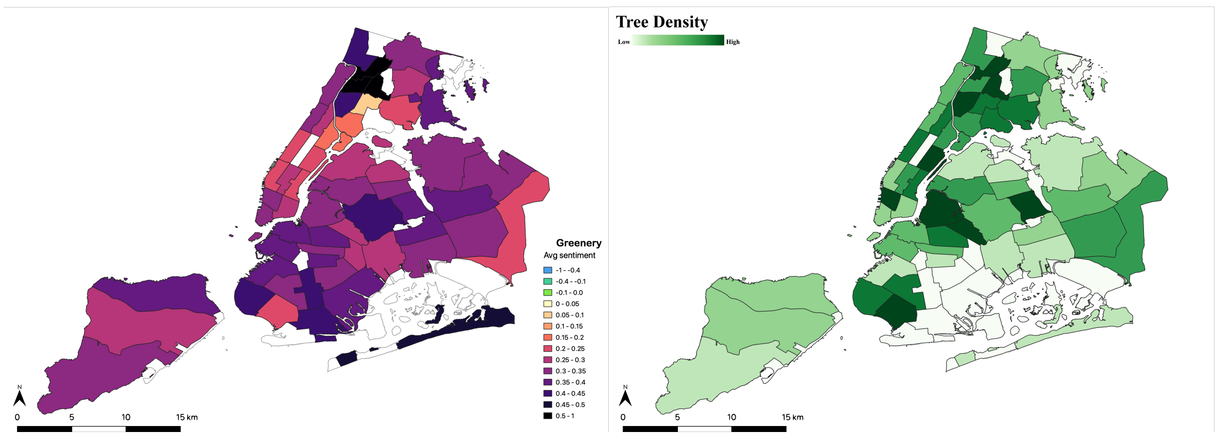

Figure 7. Average sentiment score for greenery vs tree density (community district) in NYC.

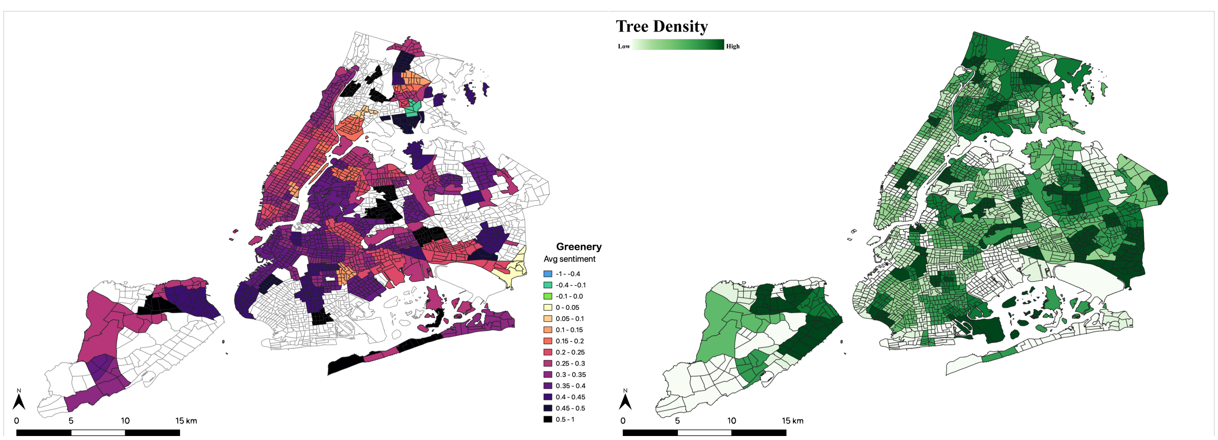

Figure 8. Average sentiment score for greenery vs tree density (neighbourhood tabulation area) in NYC.

4.2.3 Amenities

The correlation coefficients between average sentiment scores about amenities and POI density in three cities are shown in Table 7. The results indicate that guests's perception of amenities is enhanced as the density of POIs increases. The correlation is strongest in New York City, while the correlation can be found weaker in London and Singapore. Additionally, the coefficients are larger at higher administrative division levels. Similar to the analysis on transportation, this finding could infer that the association of amenities tends to be stronger when the analysis is conducted on a larger scale.

Table 7. Result of Correlation Analysis – Amenities.

City	Correlation coefficient (Amenities)		Descriptive statistics of sentiment			
			Mean		Standard Deviation	
London	Borough	Ward	Borough	Ward	Borough	Ward
	0.3486 *($p<0.05$)*	0.2391 *($p<0.01$)*	0.33	0.32	0.04	0.09
Singapore	PA	Subzone	PA	Subzone	PA	Subzone
	0.4853 *($p<0.01$)*	0.2157 *($p<0.05$)*	0.34	0.34	0.07	0.11
New York City	CD	NTA	CD	NTA	CD	NTA
	0.5246 *($p<0.01$)*	0.3561 *($p<0.01$)*	0.35	0.34	0.05	0.07

4.2.4 Safety

The correlation coefficients between average sentiment scores about safety and crime rate in London and New York City are shown in Table 8. The results indicate that when the crime rate is higher, people's perception of safety will be dampened. Although the correlation coefficients show a weak strength, the correlation tends to be stronger on lower administrative division levels, which means the perception of people on safety is more sensitive on a smaller scale.

Table 8. Result of Correlation Analysis – Safety.

City	Correlation coefficient (Safety)		Descriptive statistics of sentiment			
			Mean		Standard Deviation	
London	Borough	Ward	Borough	Ward	Borough	Ward
	-0.1059	-0.1756 *($p<0.01$)*	0.38	0.38	0.03	0.08
New York City	CD	NTA	CD	NTA	CD	NTA
	-0.2186 *($p<0.1$)*	-0.2319 *($p<0.01$)*	0.40	0.40	0.04	0.06

4.2.5 Noise

The correlation coefficients between the average sentiment score about noise and noise coverage in London are shown in Table 9. The correlation coefficient at the borough level is negative with statistical significance, while that at the ward level is not significant. The borough-level correlation is of moderate strength. This means that people's perception of noise is harmed where more area is affected by noise pollution. Interestingly, the average sentiment score about noise is lower compared with the other four topics. One possible explanation could be that people do not mention noise in their reviews if it is not severe. But when the noise becomes a major nuisance, they will likely complain about it in the reviews.

Table 9. Result of Correlation Analysis – Noise

City	Correlation coefficient (Noise)		Descriptive statistics of sentiment			
			Mean		Standard Deviation	
London	Borough	Ward	Borough	Ward	Borough	Ward
	-0.4039 *($p<0.05$)*	-0.0235	0.07	0.08	0.05	0.10

5 Discussion

5.1 General overview

We have performed a series of analyses between the subjective perceptions derived from Airbnb reviews and the objective quantitative proxies of urban development in London, Singapore, and New York City. By overviewing the results, we find that the positivity of Airbnb reviews is representative of a variety of aspects of neighbourhoods relevant in the urban planning context. Therefore, online homestay reviews on Airbnb can be used to infer the characteristics of neighbourhoods.

While developing the method, we identified five contextual aspects that reviews tend to embed: transportation, greenery, amenities, safety, and noise. The experiments indicate that these can be sensed from the reviews, but their performance is mixed.

Unsurprisingly, reviews focus mostly on describing aspects related to the accommodation and the host, and only a minority of them paint a picture of the characteristics of the surrounding context. However, the volume of data is large, often providing a sufficient pool of reviews giving an account beyond the realm of the accommodation and making it possible to infer urban characteristics. The method works well in most cases, but its performance directly depends on the volume of listings and reviews, with neighbourhoods with fewer reviews not providing enough data (which explains why there is no data for some neighbourhoods in our maps in the previous section).

For not all the three cities (as is the case for many others we initially considered for this study), we could not find appropriate proxies for certain aspects (e.g. noise data at high resolution), but that affirms the motivation for our work -- our method might serve as an instrument to approximately infer such data when it is not available. Such datasets are not always available, but they are crucial for urban planning and management, e.g. greenery is instrumental and an omnipresent topic for sustainable urban development (Schraven *et al*., 2021).

Focusing on particular aspects, the topics of transportation and amenities exhibit statistically significant positive correlations between the average sentiment scores and the objective data. This result infers that, at the locations where more bus stops and amenities are built and able to cater for more population, people will have a better impression and perception of these attributes, which will be manifested in reviews. Hence, Airbnb reviews are primarily capable to reflect the physical development of a city, in terms of the convenience of transportation, as well as the density of amenities, especially for eateries and shopping amenities as they are the main components of the topic of amenities in our analysis.

In contrast, there exist significant negative correlations between the subjective and objective data for the topics of safety and noise. Where crime rates are higher, the physical environment is more likely to provide people with an unsafe feeling. Noise pollution is a more tangible issue that people would sense directly, as a higher noise level will affect people's perceptions negatively. Considering these significant correlations, the concern of people over safety and noise issues in the neighbourhoods is reflected negatively in Airbnb documented users' experience, which we take advantage of to sense these aspects at the city-scale and map them.

Greenery has very few outcomes that are of statistical significance, with only that of London's borough-level analysis being negatively significant. This result could be explained by the dense urban development that will fade the existence of urban greens. As in the city centre, trees are more likely to be found along the road, and people may not pay attention to greenery alongside busy streets or will not recollect when leaving a review. On the other hand, in the peripheral areas, as the building density decreases, people may appreciate (and report about) greenery with unblocked views.

Another interesting finding is that people's perception of noise is worse than the other four topics as explained in the previous section. This discrepancy could be because of a potential bias due to the nature of the Airbnb review dataset. Users tend to note in their reviews what they can see on the spot or the most impressive and palpable aspects that are easier to recall. When it comes to noise, it is more likely that people choose to complain about the issue of noise when the environment is significantly noisy and influences their experience.

Furthermore, our multi-scale study is affirmed by the finding that correlations tend to be stronger on higher administrative division levels for transportation, amenities, and noise, while for the case of safety, it tends to be stronger on lower administrative division levels. The possible reason is that the topics of transportation, amenities, and noise pollution are more often evaluated on a larger scale. To explain, human perceptions of these aspects are more sensitive when seeing these characteristics on a more macro level of a city. However, safety is more sensitive on a smaller scale, as human beings are very sensitive to the threats and dangers in a smaller area.

Therefore, if a street block is dark and underdeveloped as in chaos, a person will immediately raise a negative impression of the specific street block.

The results of spatial autocorrelation imply that the positive or negative human perceptions of urban characteristics are spatially clustered. The sentiment scores for transportation and amenities have higher Global Moran's I values. Similar positive or negative perceptions tend to be clustered in adjacent urban districts. This can be explained by the progressive physical development of urban areas. The concentration of urban activities appears along with the expansion of dense central built-up areas (Yang *et al.*, 2012), and physical development grows with the growth of several nodes in urban areas (Makse *et al.*, 1995). Hence, the physical patterns and activities are possibly be found clustered or aggregated in cities due to the progressive physical urban growth. As a result, people's subjective perception of urban characteristics tends to be as spatial clustered as physical development does.

5.2 Limitations

This research has certain limitations, which are largely due to the data. First, Airbnb reviews are very 'touristy'. Although reviews in the most recent 3 years may have more contributions from local residents (i.e. staycations during COVID-19), there is a chance that the input from visitors carries a high weightage among all reviews in the past 3 years. Therefore, the derived perceptions are possibly from the perspective of a visitor, which can be largely different from what a local perceives. Broader coverage of data sources about volunteered geotagged textual information can be examined for future research. For example, reviews on commercial services such as Google Maps can be a good source of data due to its rich information about both location and human perception, covering almost all physical features in a city. Second, users who posted reviews on Airbnb might not represent the entire population who has paid a visit or residents living in the neighbourhood. This is also a major limitation of online review and data on social media as seen in related work (Section 2). The expectations of people on the physical patterns and activities of a city can be greatly varied due to different native living environments, social status, educational background, etc. The same urban area can be perceived quite differently by the diversity of guests that use the large variety of Airbnb accommodation. Hence, any arbitrary generalisation to the entire population should be avoided. Lastly, underground trains and subways are one of the major public transport in all three cities. While in this study, we did not examine its influence, as we only employed density as a quantitative proxy, which is not suitable for measuring train stations.

Another limitation we expose is the NLP computational approach used to generate the aspect-description pair of words. That is because the pipeline we used for dependency parsing is limited to English. Different languages have grammars that are vastly different from each other. Hence, it is hard to expand this approach to other languages. Though, if LDA or other developed topic modelling machines are employed, analysis of other languages is also achievable with the combination of other pre-trained sentiment models. Other than the limitation of dependency parsing and language, the suitability and accuracy of the pre-trained sentiment model is another concern. The pre-trained sentiment model might not be so accurate to analyse such a specific dataset as Airbnb reviews. Instead, training a sentiment model using self-defined labels can be considered to improve the accuracy and performance of a dataset similar to Airbnb reviews.

That said, future work presents ample opportunities to continue research in this topic, which will be supported by continuous advancements in NLP and possible emergence of new services that accumulate reviews that may unearth urban characteristics.

6 Conclusion

We performed a multi-dimensional analysis on Airbnb reviews to sense the urban environment: we considered multiple aspects at multiple scales and in multiple global cities. This study contributes to understanding the usability of textual data of crowdsourcing guest experiences on online platforms in evaluating the character of urban areas, essentially introducing a new application of Airbnb data and a new means to urban sensing. We employed dependency parsing as a tool to extract key information from the text reviews of Airbnb and identified five dominant urban-related topics among the comments that traverse beyond the host and accommodation. We further evaluate the topic-specific correlations between review sentiments and quantitative proxies for urban development in the three cities. Spatial autocorrelation analysis was also conducted to examine the spatial distribution of Airbnb reviews sentiment. On a broader scope, our study contributes to the research in Volunteered Geographic Information (VGI) – it has shed more light on this interesting crowdsourced implicit data source.

The results of our analysis suggest that the subjective text reviews of Airbnb can perceive the objective attributes of physical patterns in urban areas. The five contextual topics of Airbnb reviews are transportation convenience, amenities (leisure, eateries and shopping), urban greenery, safety, and noise pollution. Transportation and amenities are positively reflected by the sentiment of reviews, while safety and noise are reflected in a negative direction. The perception of people will be positive in the area that is more convenient and accessible to public transport and amenities. Human perception will be less positive at the location where there is a sense of lack of safety and noise pollution issues. Nevertheless, it is interesting to find that greenery is negatively associated with people's perception, despite few significant correlations. This could be explained by the impact of the density of the built-up environment which possibly distracts from the existence of urban greenery. Interestingly, noise appears to have a generally worse perception of people compared to the other four topics. Furthermore, the morphology of a city is a potential factor that will influence people's subjective perception of a city. This can be inferred from the results of spatial autocorrelation, as the value of sentiments is more likely to be spatially autocorrelated in a city with a more fine-grid urban fabric such as New York City.

As this study sets a new research line in using crowdsourcing textual data in evaluating urban characteristics, there is substantial potential for developing future research. Future research can continue investigating the relationship between subjective and objective data based on a raster with different cell sizes, instead of administrative districts. Such findings will be more suitable to be conducted for a cross-city analysis, as each city has its special definition that is not able to be applied to other cities. Temporal analysis can be considered as well to investigate the evolvement over time. Finally, the analysis conducted in this study can be expanded to more languages other than English, if a more generalized computational method rather than dependency parsing of the English language is applied. It will lead to more comprehensive and inclusive research in this field.

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