# Sentiment and the City: Modeling the Effect of the Urban Environment on Civil Sentiment

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**Abstract**

*Background:* Understanding the interaction between individuals and the urban streetscape is an essential component of sustainable city planning. Numerous studies have characterized the attributes and spatial dynamics of urban environments; however, little is known about the relationship between the built environment and the sentiment of the civil population.

*Objectives:* To assess the extent to which civil sentiment may be influenced by characteristics of the urban environment and how these relationships might change over time.

*Methods:* An analytical framework for characterizing streetscape characteristics and civil sentiment is proposed. Geotagged social media posts and street level imagery are employed to account for individual sentiment and geospatial context. Natural Language Processing (NLP) and computer vision (CV) are then used to infer sentiment and model the urban environment with which individuals interact. An application of the developed framework is conducted using Instagram posts and Google Street View imagery as the basis for characterizing sentiment and urban context respectively. The extent to which elements of urban context correlate with civil sentiment is then assessed.

*Results:* …………………………………………………………….

*Conclusions:* The results of the application indicate that the interaction between individuals and the built environment likely does impact the sentiment of the civil population to varying degrees over time and space. Such analyses can provide urban planners and policymakers with valuable insights on how different planning decision may affect civil sentiment. This opens up a new avenue for research into expanding build environment measurement methods to include perceptions as well as urban environment attributes.

**Keywords**: Urban design; GeoAI; spatial behavior; social media; built environment

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## 1 Introduction

It is increasingly recognized that the relationship between individuals' location and sentiment are important considerations for a variety of decision-making tasks, such as managing urban growth, disaster response, humanitarian assistance, and recovery operations (USGIF, 2021). For instance, in the event of a crisis, knowledge of individuals' sentiment is essential decision support for addressing potential hazards and threats to life and/or supporting infrastructure (Luo et al., 2011; Sadiq et al., 2020). Further, numerous studies indicate that the design, condition, and spatial configuration of urban environment features such as buildings, traffic infrastructure, and parks can elicit a wide range of collective and individual human experiences (Kaklauskas et al., 2021; Batty et al., 2010). Thus, planning agencies are increasingly taking into consideration how individuals experience urban spaces in decisions related to infrastructure design. One example of how these more complex considerations are being jointly conceptualized is the notion of the 'streetscape'. A streetscape in this sense is a synthesis of multiple urban characteristics comprising the environment that individuals experience when moving through urban space (Benabbou and Lee, 2019; Herrera-Yagüe, et al., 2015; Salesses et al., 2013). Developing a better understanding of the extent to which streetscapes may influence individuals' sentiment could therefore provide important insights on urban semantics, better incorporating the needs of the civil population in planning efforts.

Understanding how the characteristics of streetscapes relate to individual sentiment is a crucial component of many decision-making tasks (Ma et al., 2021; Minou et al., 2020; Yuan et al., 2019). However, given the complex spatiotemporal interplay of individual perception, behavior, and geospatial context, quantifying and assessing these relationships can present a challenge. For instance, collecting information on civil sentiment and characteristics of streetscapes via field surveys, voluntary self-reporting, workshops, and interviews can entail a tremendous amount of effort (Jaconsen et al., 2007; Montello et al., 2003; Ben-Akiva and Bierlaire, 1999; Tveit et al., 2018; Choudhry et al., 2015; Hadavi et al., 2015; Ewing et al., 2006). Thus, given the effort associated with such data collection methodologies, their use is typically limited to smaller regions of interest and frequently requires complex research protocols to ensure their applicability over larger geographic areas or time periods (Larkin et al., 2021).

As geospatial data collection technologies such as overhead and street-level sensors, global positioning systems (GPS), and smart phones are yielding an enormous amount of information about the urban environment and its inhabitants, there is great opportunity to utilize these sources of information to study large populations' perceptions and spatial dynamics of cities (Ahn et al., 2022). For example, GPS data collected with a smartphone can shed light on complex spatial dynamics such as those underlying desirability (Salazar Miranda et al., 2021; Malleson et al., 2018), the relationship between physical activity and land cover (Matisziw et al., 2016), and transportation behavior (Williams, 2020). Satellite imagery has been utilized to aid in the assessment and monitoring of safety (Nadai et al., 2016), conflict zones (Kurgan, 2013) and urban heat island effects (Wang et al., 2019). More recently, street-level imagery has been used to better represent the human perspective in a range of contexts such as, urban mobility, street quality, and pedestrian behavior (Biljecki and Ito, 2021; Ye et al., 2019; Zhang et al., 2019; Rzotkiewicz et al., 2018).

Although these relatively new initiatives provide information on a wide range of aspects of urban systems and interplay, the extent to which individual sentiments are linked to the built environment is far less well understood. Few studies attempt to quantify sentiments in urban situations by combining subjective perception data with other geographical data. In this respect, crowd sourced social media data has emerged as a valuable resource (Ilieva and McPhearson, 2018). Location-based social media (LSM) data has been used to support urban analysis such as, assessing accessibility to public places (Hamstead et al., 2022; Marti et al., 2017), spatial interaction (Lovelace et al., 2014), mobility (Luo et al., 2016; Hasan and Ukkusuri, 2014), and disaster management (Murakami et al., 2016). Further, combined with SVIs, the LSM data has been used to reveal insights on inconspicuous urban places (Zhang et al., 2020), urban function (Ye et al., 2020), urban land use (Cao and Qiu, 2018) and cognitive emotion of urban places (Jang and Kim, 2019). Although research in this context has focused on establishing urban environment measurements, the evidence linking these metrics to sentiments remains mixed (Saelens and Handy, 2008).

Therefore, there are several research needs that are important to address. First, with respect to urban planning, the connections between the built environment and the sentiments may offer a way to improve comprehension of urban analyses, such as identifying the traits of crime-free regions, regular travel routes, streetscape preferences, and so forth. However, because the link varies considerably over both place and time, assessing the association for this purpose requires a comprehensive process of collection and analysis of sophisticated spatiotemporal data. Second, in terms of disaster management, the analysis of the built environment that may influence the civil sentiments necessitates an in-depth data collection and analysis effort to better account for monitoring disaster situations. Recent studies have also shown how aspects of the built environment have an impact on urban attitudes, which in turn has an impact on health and wellness (Robinson et al., 2018). How the built environment affects health can be significantly changed by considering sentiments of the built environment, such as how pleasant the place is. To address these issues, a novel analysis framework is presented for coupling imagery and social media data reflecting conditions and sentiment in the urban streetscape. The developed framework is then applied to a case study to illustrate the procedures, decision points, computational considerations, and applicability of the analyses. Finally, discussion and conclusions are provided.

# 2 Background

## *2.1 Impact of urban form on public sentiment*

Urban form and function have long been central to the urban planning process. A variety of spatial features those urban planners have long-sighted to be connected to how pedestrians experience the city is measured (Gehl, 2013; Ewing, 1996; Handy, 1993; Jacobs, 1961; Lynch, 1960). According to Talen (2006), a "compact, pedestrian-friendly, and mixed-use neighborhood" is essential, and that urban attributes design should consider sensory, aesthetic, temporal, and cognitive issues during the early stages of urban planning as well as the urban renewal process (Carmona et al., 2010; Talen and Ellis, 2002). Lynch (1960) identified three components that make up an individual's feelings about the environment: identity, structure, and meaning, with meaning indicating the practical and perceptual value of the location to the individual. Rachel and Stephen

Kaplan's research focused on understanding the impact of nature on people's perceptions and mental health from the standpoint of environmental psychology (Kaplan and Kaplan, 1989). Similarly, Ulrich's research demonstrated that the natural environment could elicit aesthetic and affective responses in people (Ulrich, 1983).

Ewing and Handy (2009) created a number of metrics for urban form that are strongly linked to the civil experience, including visual enclosure, human dimension, and streetscape complexity. While being challenging to quantify at the urban scale, these indicators have been operationalized in numerous research projects to gauge how people feel about the environment (Salazar Miranda et al., 2021). The degree to which streetscape segments are visually delimited by buildings, walls, vegetation, and other vertical components is measured by visual enclosure. Less visibly confined urban areas, according to literature, are regarded to be less preferred for pedestrians (Southworth and Owens, 1993). While streetscape complexity measures the visual richness of a location and is determined by the diversity and quantity of urban features, such as people, bicycles, minibikes, cars, and streetlights, the human dimension assesses the spatial environment attributes, such as sidewalks and their coherence, that match the scale and proportion of an individual. These two actions are inspired by the idea that pedestrian-friendly streets can help create surroundings where people can stroll safely and are also important motivators for pedestrian exploration (Zacharias, 1997b).

## *2.2 Measuring sentiment*

There has been a growing interest in quantifying people's sentiments. Goodchild (2007) proposed the concept of "Citizens as Sensors" in his seminal work, comparing common citizens to environmental sensors capable of observing and collecting a wide range of geographic data. The use of sentiment analysis has been used in a variety of research areas, including walkability (Motieyan et al., 2022; Baobeid et al., 2021), bikability (Ito and Biljecki, 2021; Nagata et al., 2021), safety (Costa et al., 2022; Ogneva-Himmelberger et al., 2020; Naik et al., 2014), and risks (McCluskey and Rausser, 2001), memorability (Isola et al., 2011), greenery (Ma et al., 2021; Uebel et al., 2021), and aesthetics (Fayn et al., 2015), to obtain valuable insights into public opinion on particular areas of interest.. Various methods and tools for collecting and quantifying information about individual sentiment have been proposed. A large experimental literature has focused on in-person assessments or field observations using slides, photographs, or text-based questionnaires as an instrument to investigate people's sentiments (Hadavi et al., 2015; Hartig and Staats, 2005; Kaplan, 1985). These studies generally used a Likert scale as the dependent variable, for instance, inviting subjects to rate the physical setting of a place using 1-5 scale. (Wilson et al., 2012; Michael, 2005; Nasar, 1997).

In recent years, a plethora of crowdsourcing technology such as street view imagery has improved the ability to collect a massive amount of data to represent the physical setting of a place and anticipate sensory responses. Further to that, significant progress has been made on deep learning (DL) algorithms for complex analysis such as text and speech processing (Young et al., 2018), image feature detection and segmentation (LeCun et al., 2015). For instance, the MIT Media Lab's Place Pulse project collected 1.5 million crowd-sourced perceptions for over 110,000 street view imageries from 2010 to 2015, and devised Computer Vision (CV) algorithms to predict up to 74 percent of the overall of perception similarities among image pairs (Dubey et al., 2016). Qiu et al. (2021) integrated crowdsourced survey data, deep learning and ML to evaluate the perceptual evaluation questions. While the data locations showed a diverse range of geospatial contexts, the socio-demographics of Place Pulse image ranking participants are unknown (Larkin et al., 2021).

Individual sentiment can also be inferred from textual content using modeling approaches. Some modeling approaches that have been utilized in this context include lexicon-based techniques, statistical approaches (e.g., machine learning and deep learning approaches), and hybrid techniques that combine the lexicon-based and statistical techniques (Ligthart et al., 2021; Cambria, 2016). Lexicon-based sentiment classification relies on predefined dictionaries like WordNet and SentiWordNet (Baccianella et al., 2010). Bilro et al. (2019) investigated the related concepts in online customer reviews (involvement, emotional states, experience, and brand advocacy) to identify the sentimental drivers of online customer engagement using text mining and lexicon-based sentiment analysis. On the other hand, a variety of machine learning techniques have been used to deal with the task of categorizing civil sentiments. Sentiment analysis based on machine learning approaches, as opposed to lexicon-based approaches, trains the models with sentimental features in the text to enable them to detect sentiments automatically (Xu et al., 2022). The sentiment analysis research efforts have extensively used the K-Nearest Neighbors, Support Vector Machine, Random Forest, and Decision Tree algorithms. In recent years, deep learning (DL) based Natural Language Processing (NLP) models have better performed in sentiment analysis. The Convolutional Neural Network, Long Short-Term Memory, and Bidirectional Encoder Representations from Transformers (BERT) have been used for improved outputs in perception studies (Khan et al., 2022; Duan et al., 2019; Martin et al., 2018).

Six commonly used sentiment markers are, 'safe,' 'lively,' 'bored,' 'affluent,' 'gloomy,' and 'beautiful.' Geotagged postings can be processed using a normalized rating system to reliably classify them by sentiment (Zhang et al., 2018). There are several pre-trained Transformers models that can recognize the context and assign meaning to each word in a sentence, allowing for greater parallelization and shorter training and prediction times (Colón-Ruiz and Cristóbal, 2020). For instance, the Hugging Face API contains several BERT-based pre-trained Transformers models as well as access to create new training models for predicting multilingual sentiment from texts given BERT's ability to create contextually appropriate word embeddings (Colón-Ruiz and Cristóbal, 2020; Devlin et al. 2019). The pretrained models using the transformers NLP algorithm automatically translates each post into a rating system.

Textual content generated by social media networks, primarily microblogging platforms like Twitter and Instagram, is increasingly being used to measure sentiments. According to Batty (2013), what is shared on social media has inherent and intimate personal value. Thus, location-based textual contents obtained from social media data may reflect a connection and shared experience with one's surroundings, with the added benefit of coming directly from citizens themselves (Johnson et al., 2013). For instance, Guerrero et al. (2016) examined how social media posts can be used to learn about how people interact with and perceive urban green spaces, with the goal of informing future sustainable infrastructure planning. Marti et al. (2017) used social media posts and urban cartographies to demonstrate what characteristics may make open public spaces, such as urban plazas, more successful than others. Further research efforts include querying caption verbs from social media postings as the proxy for human activities (Ye at al., 2021), user density data to analyze the time-spatial distribution of urban park users (Chen et al., 2018) and the impact of built environment attributes on social followings (Tang et al., 2022).

## 3 Methods

The proposed analytical framework involves characterizing sentiment and urban context, and then coupling the two to assess their relationship (Figure 2). In the sentiment inference stage, information that can be used to infer individual sentiment is gathered and processed. Social media postings are a rich source of data in this respect since they can contain texture and tone reflective of an individual's sentiment. Many social media posts include indicators of geographic location (latitude and longitude) as well as temporal references (e.g., date/time stamps) that can be used to locate the posting sites in space and time. The contents of each post (e.g., text, emoji's, etc.) can then be analyzed in an attempt to associate them with an appropriate sentiment. Numerous options for accomplishing this exists, such as natural language processing algorithms that have been trained to detect indicators of certain sentiments. Thus, for each posting, the desired output is a point feature representing the location of the post, attributed with a measure of sentiment.

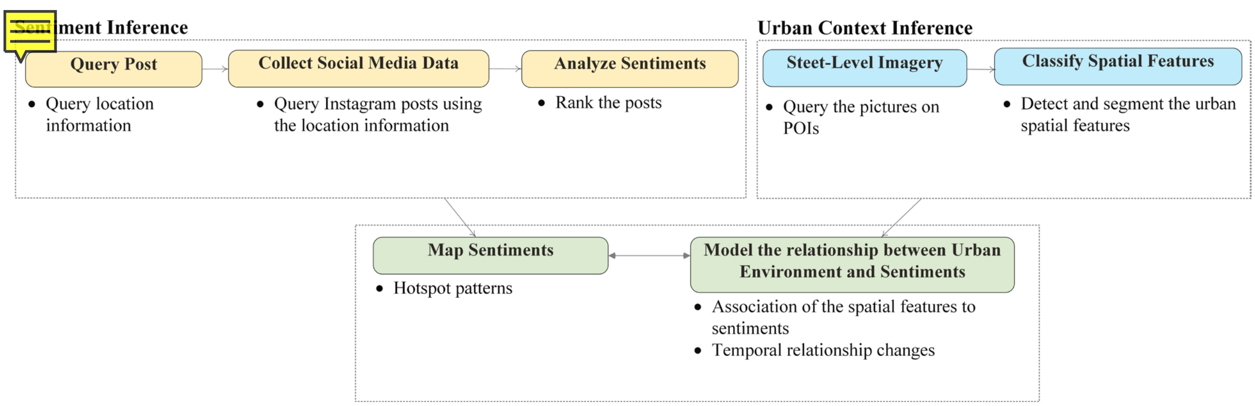


*Figure 2: Analytical Framework of the paper*

In the urban context inference stage, metrics of urban form such as enclosure, human dimension, and complexity in determining sentiment can be derived for locations proximate to sites of social media postings. Computer vision methods such as the PSPNet (Zhao et al., 2017) and Mask R-CNN (He et al., 2017) image detection and semantic segmentation models can be used to classify features such as sky, vegetation, roads, buildings, and sidewalks in each image (Qiu et al., 2021). PSPNet calculates probability values for the objects for each pixel in the image and then categorizes the pixel as belonging to the object with the highest probability. The visual enclosure and human dimension measures can be evaluated using PSPNet. The PSPNet model must first be trained to accurately compute these measures though. Training such a model requires a vast image chip database…. Etc. Whereas one option is to collect and annotate a training dataset specific to a particular region/setting, a more practical option is to use one of the many publicly available image repositories. For example, several that may be suitable for training a model for enclosure and human dimension detection are the ??? , ???, and ??? datasets.

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| **Metrics of Urban Form** | **Urban Features Considered** | **Urban Features Denoted in the CV Models** |
|---|---|---|
| **Visual Enclosure** | Sky | Sky |
| | Wall | Wall |
| | Fence | Fence |
| | Greenery | Tree, grass, field, flower, plant |
| | Building | Building, house, skyscraper |
| Human Dimension | Road | Road |
| | Sidewalk | Sidewalk, bench, path, step |
| Streetscape Complexity | Person | People |
| | Bicycle | Bicycle, bike |
| | Motorcycle | Car, Bus, Truck |
| | Streetlight | Streetlight, pole |
| | Signboard | Signboard |

Once the models are trained, then …

Finally, the sentiment metrics associated with the posting sites can be paired with the measures of urban form to assess the relationship visual enclosure, human dimension, streetscape complexity, and sentiment.

## 4 Case Study

An application to the City of Columbia, MO, USA was examined to demonstrate the analysis framework (Figure 2). Columbia (Figure 3) is a city in the midwestern United States with a population of 126,254 that is home to several major universities/colleges (United States Census Bureau, 2020).

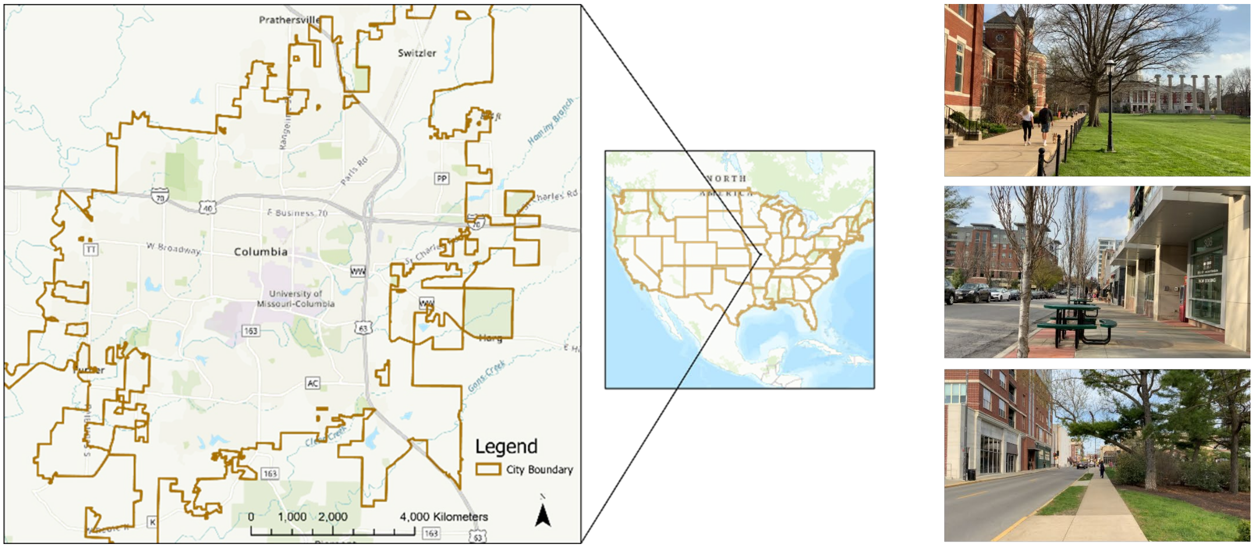



*Figure 3: Study region*

## *4.1 Location-based Social Media Data Acquisition*

In this application, public Instagram posts are used to represent expressions of sentiment toward the city's streetscapes. Previous research initiatives used hashtag-based postings (for example, #Columbiamissouri, #Southboston, #cambridge, and so on) to gather data from Instagram for urban emotion analysis (Kim et al., 2020) and to explore identity-related interpretations in understanding urban identity (Jang and Kim, 2019). While this process has aided in exploring the potential of social media data in urban contexts, some limitations exist. First, many postings lack location information (i.e., latitude/longitude coordinates) which makes associating the posts with a specific geographic location very difficult. Additionally, not all postings may contain expressions of individual sentiment. For example, a large proportion of public posts are often advertisements for goods and/or services. Thus, instead of retrieving Instagram posting using a hashtag-based approach, Instagram postings from known posting sites (i.e., Facebook locations) were sought instead. However, at the time of this research, there was no direct way to query all Instagram posting sites within a city. The only way to search for posting sites was to specify the coordinates of a location within a city and to query posting sites that are nearby, a capability that is provided by the instagraphi Python package (https://github.com/adw0rd/instagrapi). To this end, representative locations throughout the study area were used to query all Instagram posting sites within the study region using the functionalities of the instagraphi Python package (Figure 4b).

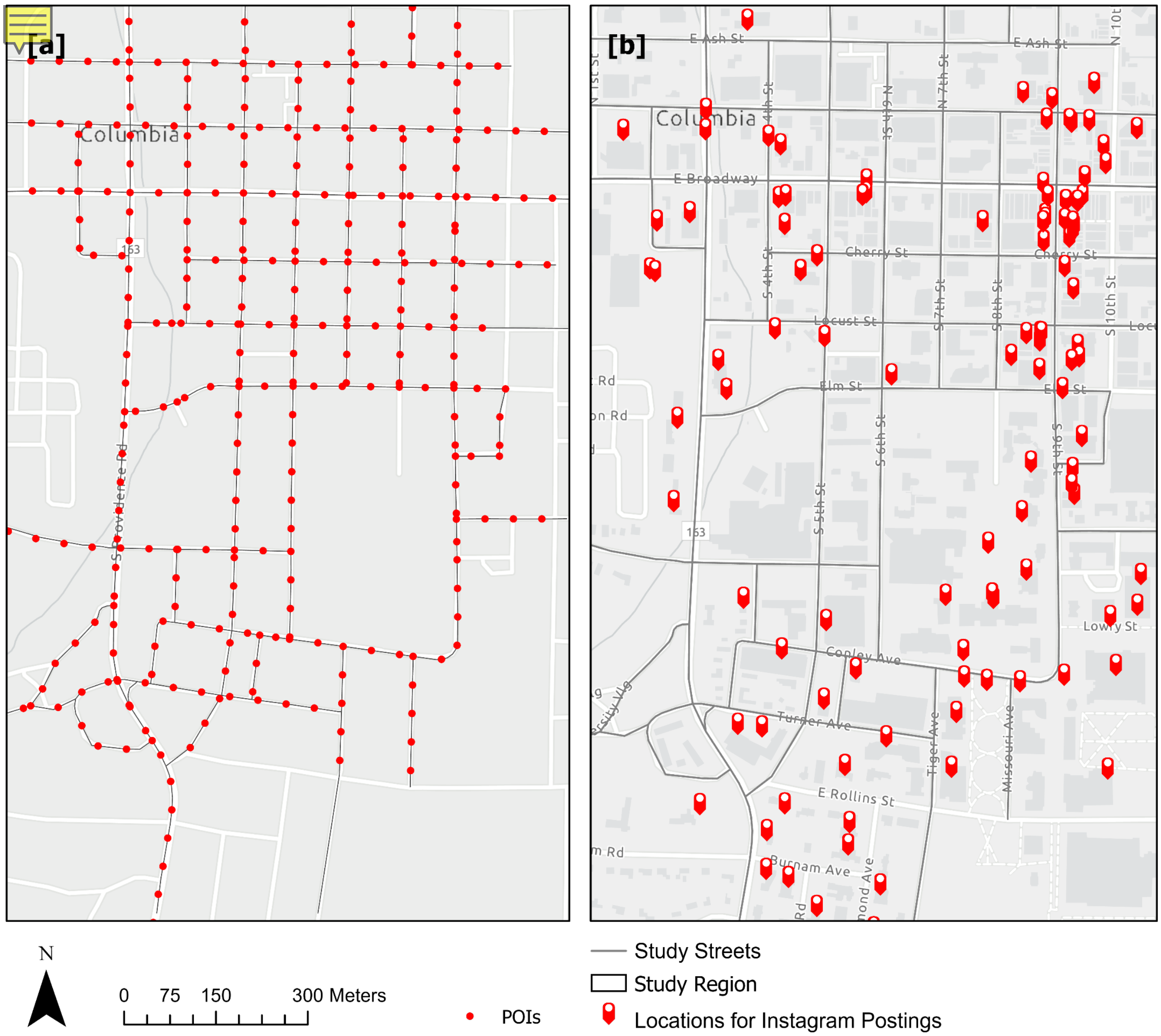



*Figure 4: a) POIs for querying the Instagram locations, b) Instagram posting locations.*

Feature types:

1. Education
2. Food
3. Healthcare
4. Recreation
5. Retail
6. Service

In total 135 unique Instagram posting sites were identified in the study region. Given the set of Instagram posting sites, InstaLoadGram, a third-party data provider, was able to retrieve all public posting associated with those sites. A total of 111 places (out of the primary 135 sites) included the public posts, yielding a total of 63,861 posts spanning a seven-year period (January 1, 2015- October 20, 2021). Several posts lacked a caption, requiring the removal of the empty postings, resulting in 59,918 usable posts for analysis. Figure 5 depicts the number of posts per month over the seven years. In 2015, the number of public posts per month averaged 481 with a peak of 747 in October. From 2016 public posts increased to an average of 850 per month, exhibiting several clear peaks each year in the months of April, August, and October. From late 2019/ early 2020, a sharp decline in postings occurs, corresponding with the onset of the COVID 19 pandemic. By late 2020, the fall peak begins to re-emerge and towards the end of 2021, the fall peak returns to pre-pandemic levels.

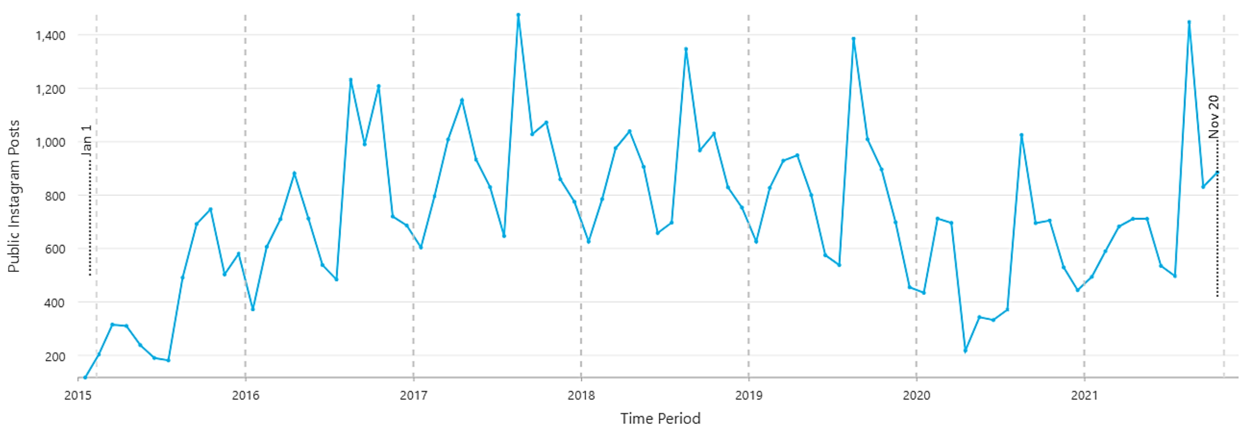



*Figure 5: Monthly Instagram posting frequency over the years 2015-2021.*

## *4.2 Sentiment Analysis*

In order to reliably classify post by sentiment, the geotagged postings were processed using a normalized rating system (Zhang et al., 2018). Several deep learning (DL) models were investigated in this respect. Ultimately, a pre-trained Transformers model, the Hugging Face API a Bidirectional Encoder Representations from Transformers (BERT) based pre-trained Transformers model, on social media data was selected (Colón-Ruiz and Cristóbal, 2020; Devlin et al. 2019). An example of which is depicted in Figure 1 (Hugging Face, 2021). The model "distilbert-base-uncased-finetuned", trained on 8 16 GB V100 for 90 hours using the BERT approach on 11,038 unpublished books and one million human evaluations, automatically translates each post into the binary rating (Negative = 0; Positive = 1) (Sanh et al., 2019).

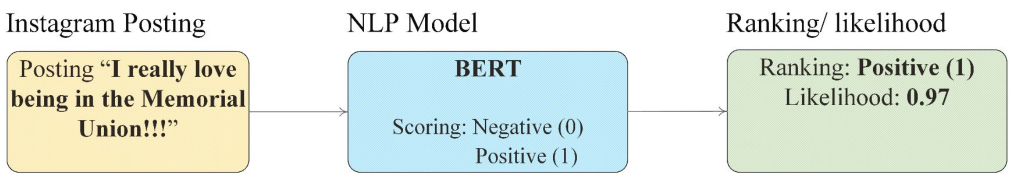



*Figure 5: BERT-based NLP Model*

### *4.3 SVIs Retrieval*

SVIs of georeferenced street segments can be retrieved for spatial feature classification. SVIs provide street-level and profile views of the urban environment and thus represent what individuals navigating the city may encounter. Google Street view is one publicly accessible source of SVIs. The Google Street view database hosts 220 billion Street View images from over 100 countries around the world. The images are captured on a regular basis by driving, pedaling, sailing, and walking around and capturing pictures with special cameras that accumulate pictures in numerous directions at the same time, and only one image date is retained for each location (Google Street View, 2022). The database and can be accessed using the Google API which requires a set of parameters pitch, heading, and location information (latitude and longitude) to identify and retrieve relevant SVIs for a site. Thus, to query the Google API, 341 points of interest (POI) were established at 30-meter intervals along roads in the study region to represent locations traversed by individuals. Each of the POI were then used to retrieve GSV images using Google API (Figure 4 - left panel). Given the sequence in which these locations would be traversed along the roadways was known, four different viewing perspectives were considered for each POI $i \in I$: a) in the direction of the next POI $i+1$, b) 90.0 degrees from POI $i+1$, c) 180.0 degrees from POI $i+1$, and d) 270 .0 degrees from POI $i+1$ as illustrated in Figure 5 (right panel). Whereas the horizontal field of view was kept at 90.0 degrees, the "pitch" of the returned 800x400 pixel images was set to 0.0 degrees. In total, 1,364 images were retrieved for the sampled POIs.

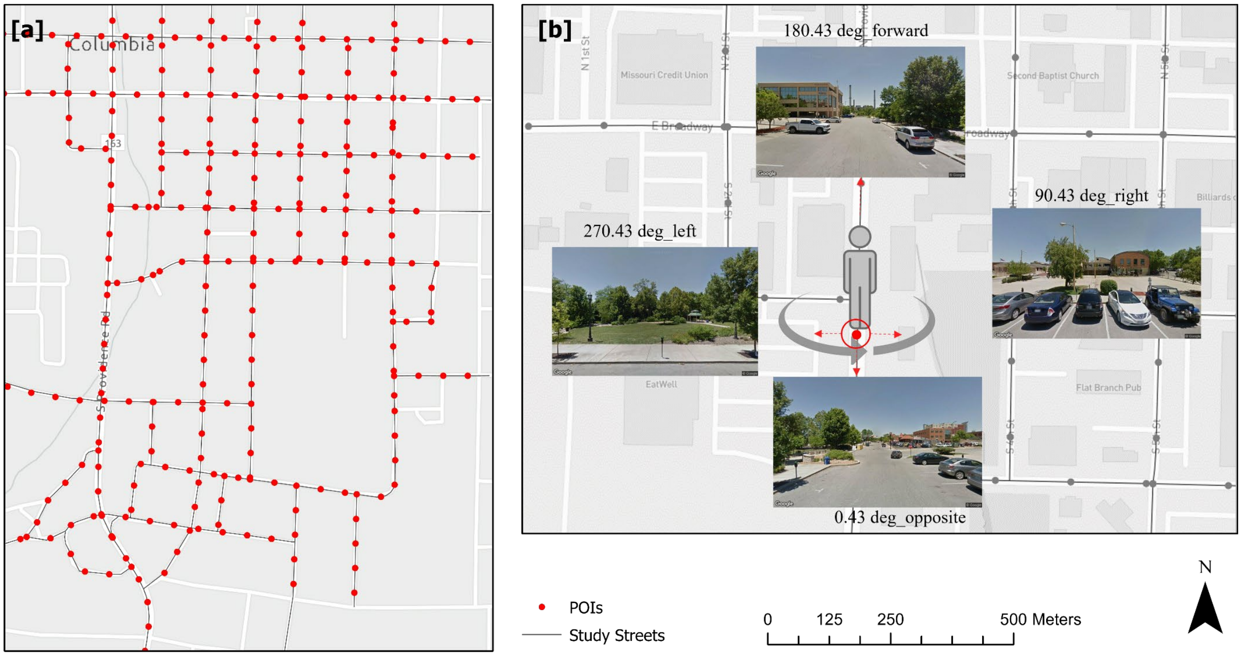



*Figure 6: a) POIs along the street segments, b) SVIs per POI.*

## 4.4 Spatial Feature Classification

PSPNet (Zhao et al., 2017) and Mask R-CNN (He et al., 2017) image detection and semantic segmentation models were used to classify features in each image. The visual enclosure and human dimension measures were evaluated using PSPNet. The 150-category ADE20k dataset was used to train the model. Out of the 150 categories, 12 urban feature categories were focused that capture relevant features of the built environment and combined them to create the metrics. The urban feature categories for groups of similar objects, such as trees and plants, that are added together to produce categorical estimates (Table 2). To represent the level of enclosure that people were likely to experience, the proportion of an image classified as sky, walls, fences, trees, and buildings was used. visual enclosure. The percentage of an image classified as sidewalk or road was used to estimate human scale. The number of people, bicycles, motorbikes, cars, and streetlights present in each image as computed by the Mask R-CNN was used to characterize the level of complexity present in the urban environment. Object estimates for each location are the average estimates derived from all downloaded images at that location.

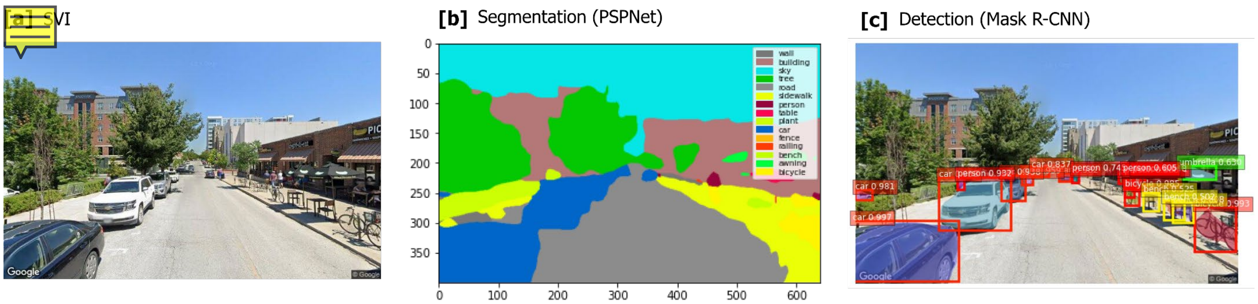



*Figure 7: Spatial Feature Classification*

### 4.5 Spatial Autocorrelation Analysis

Hotspot analysis for preferability mapping

SAR for calculating the correlation between the features and sentiments

One way ANOVA to see the variance in impact of different feature types on the sentiment rankings

## 5 Results and Discussion

### 5.1 Sentiment Mapping

Computations for the sentiment analysis was performed using the Google Colab Pro platform with a system configuration of Nvidia Tesla P100-PCIE GPU and 16GB RAM. Assessing the sentiment associated with each of the 63,861 postings took 35,756 seconds of computational time. Figure 8(a) summarizes the proportion of each sentiment classification at each posting site. At many posting sites, a majority of the posts are classified as very positive. There is quite a bit of variation though in the spatial distribution of negative sentiment, with locations having higher proportions of such sentiment located in the Northwest, Northeast, and Central portions of the study region.

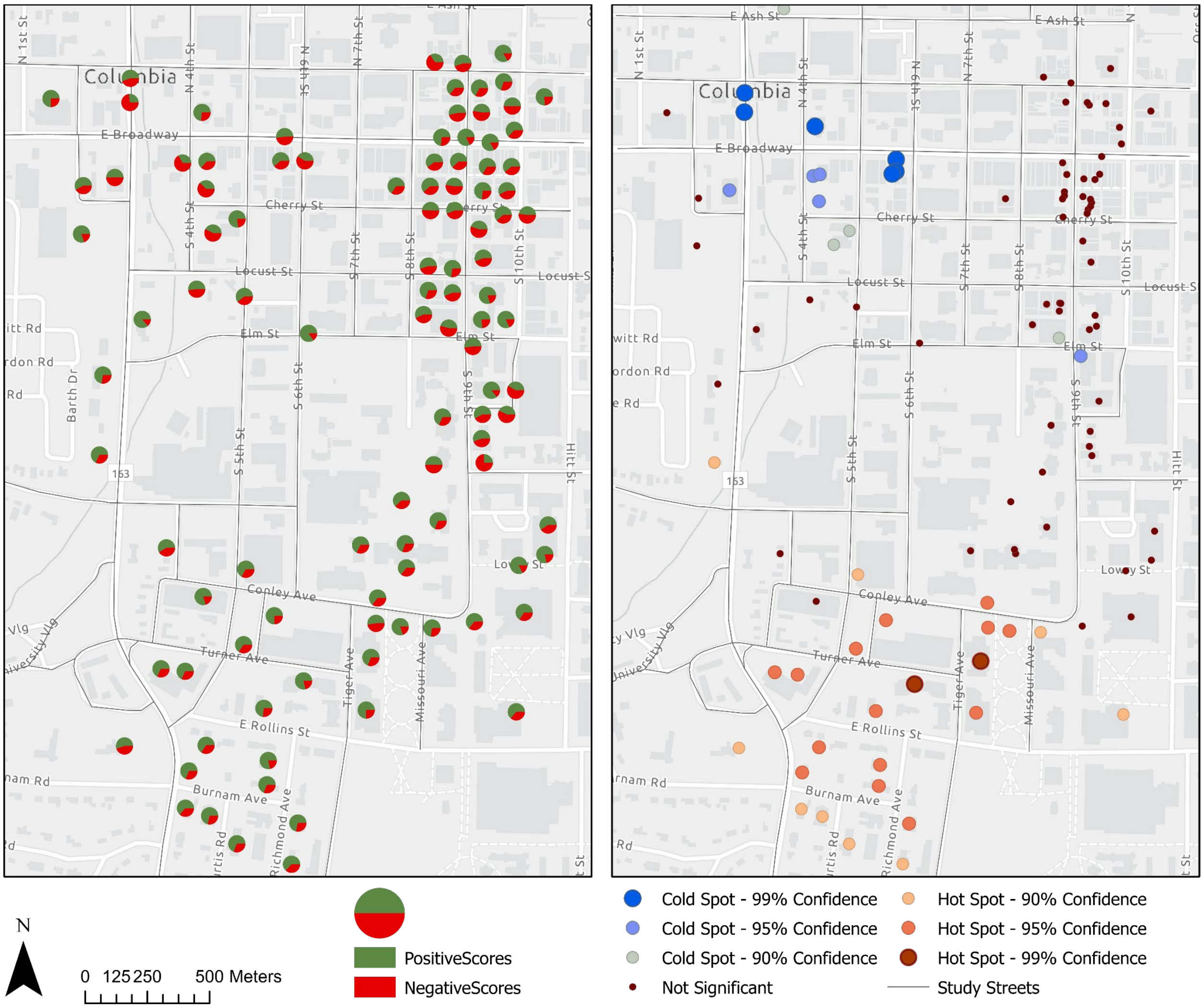
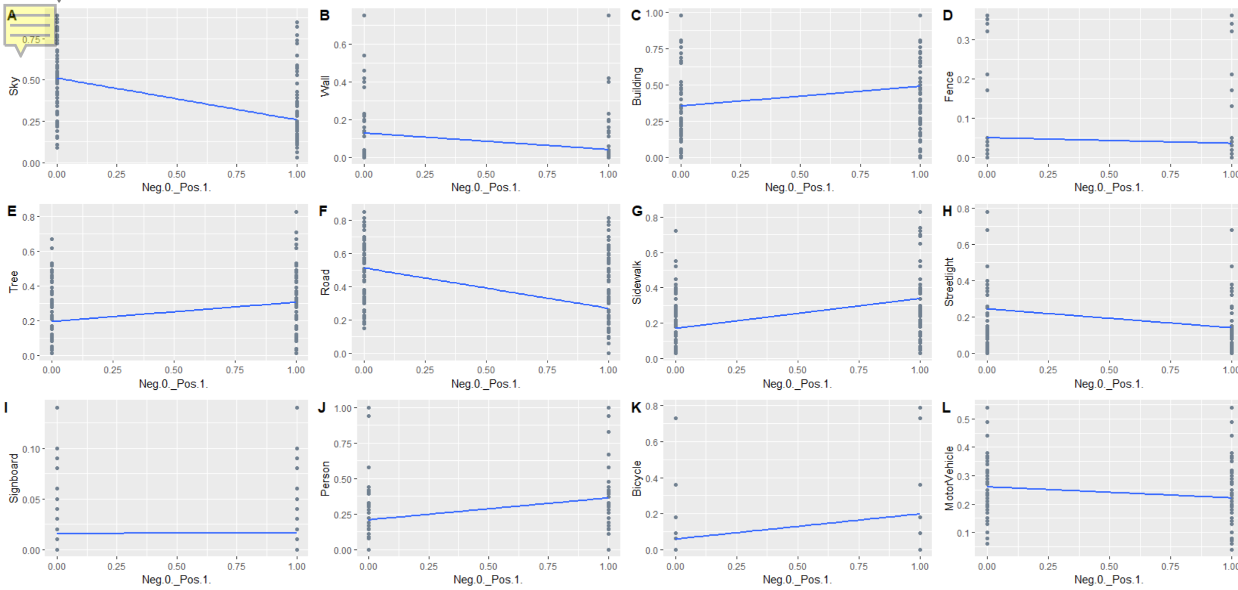


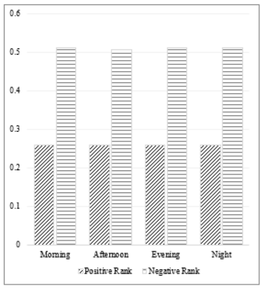

*Figure 8: a) proportion of sentiment ranking on each location, b) Hotspot analysis.*

A Getis-Ord Gi* hotspot analysis (Getis and Ord, 1992) of the proportion of positive postings at each location (Figure 8(b)) reveals the presence of statistically significant spatial autocorrelation at several sites in the study region. In particular, 25 sites in the South portion of the region were found to exhibit statistically significant positive spatial autocorrelation at the 0.90 confidence level or above (14 at the 0.95 confidence level or above, 2 at the 0.99 confidence level or above). Two areas to the North-western region were found to exhibit statistically significant spatial autocorrelation of lower proportion of posts classified as positive at the 0.90 confidence level or above (4 at the 0.95 confidence level, 7 at the 0.99 confidence level or above).

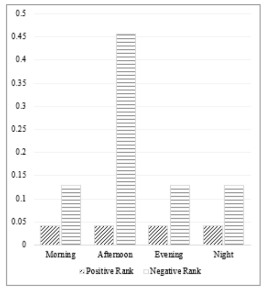
## 5.2 Relationship between the Urban Environment and Sentiments

### 5.2.1 Relationship between metrics of urban form and the sentiments

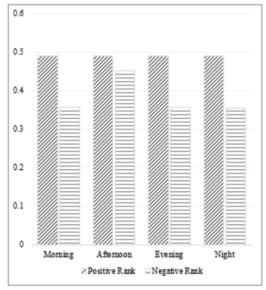




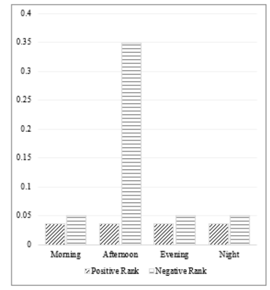

Sky



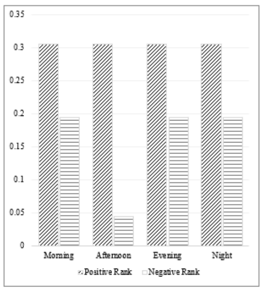

Wall



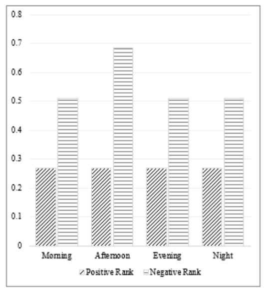

Building



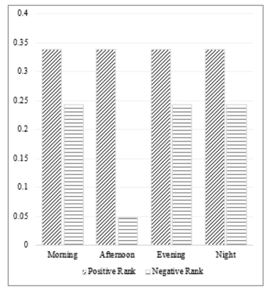

Fence



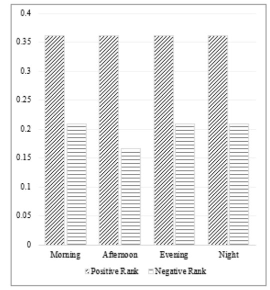

Tree



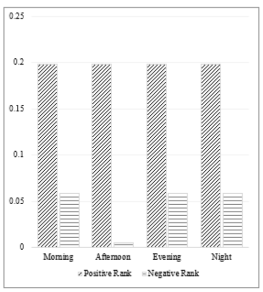

Road



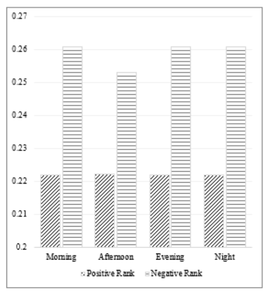

Sidewalk



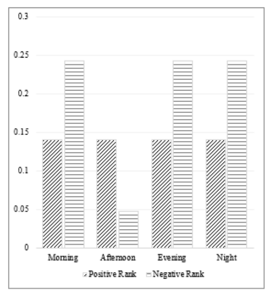

Person



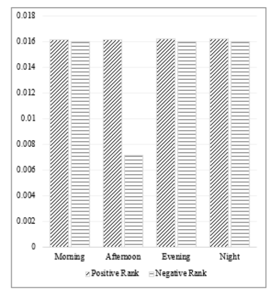

Bicycle




Motor Vehicle




Street Light




Sign Board

### *5.2.2 Relationship changes over time*

Regression analysis results_Urban Features---Sentiment Ranking

**Jan-April 2021**

| **Urban Metrics** | **Urban Features** | ***b*** | ***SE$_b$*** | ***t*** | **Cor. & Sig.** | **Lower Bound** a | **Upper Bound** a | ***β*** |
|---|---|---|---|---|---|---|---|---|
| Results | Intercept | 0.97 | 0.05 | 19.13 | ***p* <.05** | 0.87 | 1.07 | 0.00 |
| Enclosure | Sky | -1.18 | 0.05 | -23.17 | -0.57*** | -1.28 | -1.08 | -0.49 |
| | Wall | -0.35 | 0.08 | -4.34 | -0.41*** | -0.51 | -0.19 | -0.09 |
| | Building | -0.11 | 0.04 | -2.54 | 0.22* | -0.20 | -0.03 | -0.05 |
| | Fence | -0.07 | 0.08 | -0.88 | -0.04 | -0.24 | 0.09 | -0.02 |
| | Tree | 0.19 | 0.05 | 3.77 | 0.26*** | 0.09 | 0.28 | 0.07 |
| Human Scale | Road | -0.17 | 0.05 | -3.37 | -0.48*** | -0.26 | -0.07 | -0.07 |
| | Sidewalk | 0.37 | 0.04 | 9.37 | 0.39*** | 0.29 | 0.45 | 0.18 |
| | Streetlight | -0.47 | 0.05 | -9.05 | -0.12*** | -0.57 | -0.37 | -0.15 |
| | Signboard | 0.76 | 0.37 | 2.07 | -0.03* | 0.04 | 1.49 | 0.03 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Complexity | Person | 0.27 | 0.04 | 6.43 | 0.32*** | 0.19 | 0.35 | 0.12 |
| | Bicycle | 0.24 | 0.03 | 7.08 | 0.26*** | 0.17 | 0.30 | 0.13 |
| | Motor Vehicle | -0.07 | 0.07 | -1.08 | -0.11 | -0.20 | 0.06 | -0.02 |

***$p < .001$, **$p < .01$, *$p < .05$
*F*(12, 2120) = 191.1, $p < .001$ *and represented a large effect* ($R^2_{adj} = 0.52$)
*AIC* = 1344.05, *BIC* = 1423.16
[a] 95% confidence interval

**May- August 2021**

| **Urban Metrics** | **Urban Features** | ***b*** | ***SE<sub></sub>*** | ***t*** | **Cor. & Sig.** | **Lower Bound** [a] | **Upper Bound** [a] | ***β*** |
|---|---|---|---|---|---|---|---|---|
| Results | Intercept | 0.89 | 0.04 | 23.11 | ***p* <.05** | 0.81 | 0.96 | 0.00 |
| Enclosure | Sky | -1.45 | 0.04 | -34.59 | -0.66*** | -1.53 | -1.36 | -0.66 |
| | Wall | 0.10 | 0.06 | 1.81 | -0.41 | -0.01 | 0.21 | 0.03 |
| | Building | -0.18 | 0.04 | -5.06 | 0.33*** | -0.25 | -0.11 | -0.08 |
| | Fence | -0.57 | 0.08 | -7.28 | -0.05*** | -0.73 | -0.42 | -0.11 |
| | Tree | 0.22 | 0.04 | 6.09 | 0.32*** | 0.15 | 0.29 | 0.10 |
| Human Scale | Road | 0.03 | 0.04 | 0.88 | -0.53 | -0.04 | 0.11 | 0.02 |
| | Sidewalk | 0.56 | 0.03 | 18.87 | 0.37*** | 0.50 | 0.62 | 0.29 |
| Complexity | Streetlight | -0.24 | 0.04 | -6.05 | -0.20*** | -0.31 | -0.16 | -0.08 |
| | Signboard | 0.15 | 0.31 | 0.49 | 0.03 | -0.46 | 0.76 | 0.01 |
| | Person | 0.21 | 0.03 | 6.35 | 0.27*** | 0.14 | 0.27 | 0.09 |
| | Bicycle | 0.35 | 0.03 | 10.59 | 0.18*** | 0.28 | 0.41 | 0.17 |
| | Motor Vehicle | 0.14 | 0.06 | 2.57 | -0.10* | 0.03 | 0.25 | 0.04 |

***$p < .001$, **$p < .01$, *$p < .05$
*F*(12, 2067) = 329.7, $p < .001$ *and represented a large effect* ($R^2_{adj} = 0.60$)
*AIC* = 1042.07, *BIC* = 1124.32
[a] 95% confidence interval

**Sep- Dec 2021**

| **Urban Metrics** | **Urban Features** | ***b*** | **$SE_b$** | ***t*** | **Cor. & Sig.** | **Lower Bound** [a] | **Upper Bound** [a] | ***β*** |
|---|---|---|---|---|---|---|---|---|
| Results | Intercept | 0.92 | 0.05 | 20.29 | ***p* <.05** | 0.83 | 1.01 | 0.00 |
| Enclosure | Sky | -1.42 | 0.05 | -29.46 | -0.64*** | -1.51 | -1.32 | -0.60 |
| | Wall | -0.07 | 0.07 | -1.07 | -0.39 | -0.20 | 0.06 | -0.02 |
| | Building | -0.06 | 0.04 | -1.35 | 0.31 | -0.14 | 0.03 | -0.03 |
| | Fence | -0.57 | 0.08 | -6.85 | -0.12*** | -0.73 | -0.40 | -0.12 |
| | Tree | 0.20 | 0.05 | 4.05 | 0.31*** | 0.10 | 0.30 | 0.07 |
| | Road | 0.03 | 0.04 | 0.75 | -0.49* | -0.05 | 0.12 | 0.02 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Human Scale | Sidewalk | 0.44 | 0.04 | 12.04 | 0.39*** | 0.37 | 0.52 | 0.22 |
| Complexity | Streetlight | -0.42 | 0.05 | -9.04 | -0.12*** | -0.51 | -0.33 | -0.14 |
| | Signboard | 0.94 | 0.35 | 2.71 | 0.02** | 0.26 | 1.62 | 0.05 |
| | Person | 0.21 | 0.04 | 5.16 | 0.32*** | 0.13 | 0.29 | 0.09 |
| | Bicycle | 0.32 | 0.03 | 9.63 | 0.23*** | 0.26 | 0.39 | 0.17 |
| | Motor Vehicle | -0.04 | 0.07 | -0.61 | -0.10 | -0.17 | 0.09 | -0.01 |

***$p < .001$, **$p <.01$, *$p <.05$
$F(12, 2648) = 329.7$, $p < .001$ *and represented a large effect* ($R^2_{adj} = 0.58$)
$AIC = 1066.33$, $BIC = 1145.09$
[a] 95% confidence interval

**Jan- April 2020**

| **Urban Metrics** | **Urban Features** | ***b*** | ***SE$_b$*** | ***t*** | **Cor. & Sig.** | **Lower Bound** [a] | **Upper Bound** [a] | ***β*** |
|---|---|---|---|---|---|---|---|---|
| Results | Intercept | 0.93 | 0.06 | 15.62 | ***p* <.05** | 0.82 | 1.05 | 0.00 |
| Enclosure | Sky | -1.19 | 0.05 | -21.84 | -0.48*** | -1.29 | -1.08 | -0.51 |
| | Wall | 0.05 | 0.09 | 0.62 | -0.28 | -0.11 | 0.22 | 0.01 |
| | Building | -0.13 | 0.05 | -2.67 | -0.53** | -0.23 | -0.03 | -0.06 |
| | Fence | -0.62 | 0.10 | -5.94 | -0.02*** | -0.83 | -0.42 | -0.14 |
| | Tree | 0.19 | 0.06 | 3.28 | -0.59** | 0.08 | 0.30 | 0.07 |
| Human Scale | Road | -0.18 | 0.05 | -3.45 | -0.38*** | -0.28 | -0.08 | -0.08 |
| | Sidewalk | 0.43 | 0.05 | 9.45 | -0.23*** | 0.34 | 0.52 | 0.19 |
| Complexity | Streetlight | -0.35 | 0.05 | -7.06 | -0.11 | -0.44 | -0.25 | -0.13 |
| | Signboard | -0.25 | 0.56 | -0.45 | 0.28*** | -1.36 | 0.85 | -0.01 |
| | Person | 0.31 | 0.04 | 7.20 | -0.41*** | 0.22 | 0.39 | 0.15 |
| | Bicycle | 0.30 | 0.05 | 6.56 | -0.35 | 0.21 | 0.39 | 0.17 |
| | Motor Vehicle | 0.07 | 0.08 | 0.80 | -0.54 | -0.10 | 0.23 | 0.02 |

***$p < .001$, **$p <.01$, *$p <.05$
$F(12, 1671) = 142.30$, $p < .001$ *and represented a large effect* ($R^2_{adj} = 0.51$)
$AIC = 1136.84$, $BIC = 1212.60$
[a] 95% confidence interval

**May- August 2020**

| **Urban Metrics** | **Urban Features** | ***b*** | ***SE$_b$*** | ***t*** | **Cor. & Sig.** | **Lower Bound** [a] | **Upper Bound** [a] | ***β*** |
|---|---|---|---|---|---|---|---|---|
| Results | Intercept | 1.00 | 0.06 | 16.30 | ***p* <.05** | 0.88 | 1.12 | 0.00 |
| Enclosure | Sky | -1.34 | 0.06 | -23.93 | -0.42*** | -1.45 | -1.23 | -0.61 |
| | Wall | 0.08 | 0.08 | 0.97 | -0.20 | -0.08 | 0.24 | 0.02 |
| | Building | -0.23 | 0.05 | -4.71 | -0.67*** | -0.33 | -0.14 | -0.08 |
| | Fence | -0.72 | 0.12 | -6.17 | -0.10*** | -0.95 | -0.49 | -0.14 |
| | Tree | 0.20 | 0.05 | 3.96 | -0.58*** | 0.10 | 0.30 | 0.09 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Human Scale | Road | 0.04 | 0.05 | 0.71 | -0.38 | -0.07 | 0.14 | 0.02 |
| | Sidewalk | 0.54 | 0.05 | 11.46 | -0.37*** | 0.45 | 0.64 | 0.24 |
| Complexity | Streetlight | -0.44 | 0.05 | -8.01 | -0.03*** | -0.55 | -0.33 | -0.15 |
| | Signboard | 0.25 | 0.37 | 0.66 | 0.00 | -0.49 | 0.98 | 0.01 |
| | Person | 0.14 | 0.04 | 3.61 | -0.39*** | 0.07 | 0.22 | 0.07 |
| | Bicycle | 0.33 | 0.05 | 6.60 | -0.12*** | 0.23 | 0.43 | 0.15 |
| | Motor Vehicle | -0.10 | 0.08 | -1.29 | -0.53 | -0.26 | 0.05 | -0.03 |

***$p$ < .001, **$p$ <.01, *$p$ <.05
$F(12, 1687) = 137.09$, $p< .001$ *and represented a large effect* ($R^2_{adj} = 0.49$)
*AIC* = 1167.78, *BIC* = 1243.67
[a] 95% confidence interval

**Sep- Dec 2020**

| Urban Metrics | Urban Features | *b* | $SE_b$ | *t* | Cor. & Sig. | Lower Bound [a] | Upper Bound [a] | *β* |
|---|---|---|---|---|---|---|---|---|
| Results | Intercept | 1.18 | 0.06 | 21.11 | ***p* <.05** | 1.07 | 1.29 | 0.00 |
| Enclosure | Sky | -1.35 | 0.05 | -26.81 | -0.30 | -1.45 | -1.25 | -0.58 |
| | Wall | -0.42 | 0.09 | -4.78 | -0.35 | -0.59 | -0.25 | -0.10 |
| | Building | -0.15 | 0.05 | -3.07 | -0.58 | -0.24 | -0.05 | -0.07 |
| | Fence | -0.17 | 0.09 | -1.84 | 0.10 | -0.35 | 0.01 | -0.04 |
| | Tree | -0.07 | 0.05 | -1.30 | -0.48 | -0.17 | 0.04 | 0.02 |
| Human Scale | Road | -0.21 | 0.05 | -3.84 | -0.49 | -0.32 | -0.10 | 0.09 |
| | Sidewalk | 0.37 | 0.05 | 7.44 | -0.30 | 0.27 | 0.46 | 0.15 |
| Complexity | Streetlight | -0.38 | 0.05 | -7.21 | 0.01 | -0.48 | -0.28 | -0.13 |
| | Signboard | 1.39 | 0.35 | 3.92 | 0.07 | 0.69 | 2.08 | 0.08 |
| | Person | 0.21 | 0.04 | 4.80 | -0.37 | 0.13 | 0.30 | 0.09 |
| | Bicycle | 0.16 | 0.04 | 3.63 | -0.28 | 0.07 | 0.24 | 0.07 |
| | Motor Vehicle | -0.15 | 0.07 | -2.26 | -0.52 | -0.28 | -0.02 | -0.04 |

***$p$ < .001, **$p$ <.01, *$p$ <.05
$F(12, 1975) = 154.71$, $p< .001$ *and represented a large effect* ($R^2_{adj} = 0.48$)
*AIC* = 1434.6, *BIC* = 1512.72
[a] 95% confidence interval

**Jan- April 2019**

| Urban Metrics | Urban Features | *b* | $SE_b$ | *t* | Cor. & Sig. | Lower Bound [a] | Upper Bound [a] | *β* |
|---|---|---|---|---|---|---|---|---|
| Results | Intercept | 1.02 | 0.05 | 21.16 | ***p* <.05** | 0.93 | 1.11 | 0.00 |
| Enclosure | Sky | -1.00 | 0.05 | -21.54 | -0.48*** | -1.09 | -0.91 | -0.44 |
| | Wall | -0.22 | 0.07 | -2.99 | -0.16** | -0.36 | -0.07 | -0.05 |
| | Building | -0.03 | 0.04 | -0.81 | -0.53 | -0.12 | 0.05 | -0.02 |
| | Fence | -0.45 | 0.09 | -4.91 | -0.04*** | -0.63 | -0.27 | -0.09 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Tree | 0.16 | 0.05 | 3.48 | -0.56*** | 0.07 | 0.25 | 0.06 |
| Human Scale | Road | -0.22 | 0.05 | -4.78 | -0.44*** | -0.30 | -0.13 | -0.09 |
| | Sidewalk | 0.38 | 0.04 | 10.64 | -0.23*** | 0.31 | 0.45 | 0.17 |
| Complexity | Streetlight | -0.45 | 0.04 | -11.87 | -0.06*** | -0.52 | -0.38 | -0.19 |
| | Signboard | -0.98 | 0.51 | -1.90 | 0.24 | -1.98 | 0.03 | -0.03 |
| | Person | 0.24 | 0.03 | 6.94 | -0.37*** | 0.17 | 0.31 | 0.12 |
| | Bicycle | 0.30 | 0.04 | 8.08 | -0.33*** | 0.22 | 0.37 | 0.17 |
| | Motor Vehicle | -0.32 | 0.06 | -5.01 | -0.49*** | -0.44 | -0.19 | -0.08 |

****p* < .001, ***p* <.01, **p* <.05
*F(*51, 2533) = 43.82, *p*< .001 *and represented a large effect (*$R^2_{adj}$ = 0.52*)*
*AIC* = 1699.31, *BIC* = 1781.21
[a] 95% confidence interval

**May- August 2019**

| **Urban Metrics** | **Urban Features** | ***b*** | ***SE$_b$*** | ***t*** | **Cor. & Sig.** | **Lower Bound** [a] | **Upper Bound** [a] | ***β*** |
|---|---|---|---|---|---|---|---|---|
| Results | Intercept | 0.93 | 0.04 | 20.86 | ***p* <.05** | 0.84 | 1.02 | 0.00 |
| Enclosure | Sky | -1.08 | 0.04 | -25.58 | -0.48 | -1.16 | -1.00 | -0.51 |
| | Wall | 0.06 | 0.06 | 0.97 | -0.17 | -0.06 | 0.18 | 0.02 |
| | Building | -0.01 | 0.04 | -0.35 | -0.59 | -0.10 | 0.07 | -0.01 |
| | Fence | -0.66 | 0.10 | -6.38 | -0.12 | -0.86 | -0.46 | -0.10 |
| | Tree | 0.08 | 0.04 | 1.83 | -0.53 | -0.01 | 0.16 | 0.03 |
| Human Scale | Road | -0.14 | 0.04 | -3.33 | -0.35 | -0.22 | -0.06 | -0.06 |
| | Sidewalk | 0.42 | 0.04 | 11.66 | -0.30 | 0.35 | 0.49 | 0.17 |
| Complexity | Streetlight | -0.32 | 0.04 | -8.14 | -0.03 | -0.39 | -0.24 | -0.13 |
| | Signboard | -1.56 | 0.43 | -3.61 | 0.07 | -2.41 | -0.71 | -0.06 |
| | Person | 0.36 | 0.03 | 12.41 | -0.36 | 0.30 | 0.42 | 0.18 |
| | Bicycle | 0.35 | 0.04 | 9.57 | -0.07 | 0.28 | 0.42 | 0.16 |
| | Motor Vehicle | -0.17 | 0.06 | -2.68 | -0.51 | -0.29 | -0.04 | -0.04 |

****p* < .001, ***p* <.01, **p* <.05
*F(*53, 2467) = 58.13, *p*< .001 *and represented a large effect (*$R^2_{adj}$ = 0.55*)*
*AIC* = 1440.39, *BIC* = 1522.48
[a] 95% confidence interval

**Sep- Dec 2019**

| **Urban Metrics** | **Urban Features** | ***b*** | ***SE$_b$*** | ***t*** | **Cor. & Sig.** | **Lower Bound** [a] | **Upper Bound** [a] | ***β*** |
|---|---|---|---|---|---|---|---|---|
| Results | Intercept | 1.01 | 0.05 | 21.53 | ***p* <.05** | 0.92 | 1.10 | 0.00 |
| | Sky | -1.06 | 0.04 | -24.94 | -0.40 | -1.14 | -0.97 | -0.48 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Enclosure | Wall | -0.04 | 0.06 | -0.65 | -0.32 | -0.17 | 0.09 | -0.01 |
| | Building | -0.19 | 0.04 | -4.61 | -0.52 | -0.26 | -0.11 | -0.08 |
| | Fence | -0.33 | 0.08 | -3.90 | -0.08 | -0.49 | -0.16 | -0.08 |
| | Tree | 0.17 | 0.05 | 3.67 | -0.58 | 0.08 | 0.26 | 0.07 |
| Human Scale | Road | -0.24 | 0.04 | -6.05 | -0.37 | -0.32 | -0.17 | -0.11 |
| | Sidewalk | 0.45 | 0.04 | 11.96 | -0.25 | 0.38 | 0.52 | 0.20 |
| Complexity | Streetlight | -0.35 | 0.04 | -9.16 | -0.05 | -0.43 | -0.28 | -0.15 |
| | Signboard | -0.63 | 0.51 | -1.24 | 0.22 | -1.63 | 0.37 | 0.02 |
| | Person | 0.33 | 0.03 | 9.49 | -0.43 | 0.26 | 0.39 | 0.16 |
| | Bicycle | 0.26 | 0.03 | 7.42 | -0.32 | 0.19 | 0.33 | 0.15 |
| | Motor Vehicle | -0.17 | 0.07 | -2.30 | -0.56 | -0.31 | -0.02 | -0.04 |

***$p < .001$, **$p < .01$, *$p < .05$
*$F(55, 2257) = 35.70$, $p < .001$ and represented a large effect ($R^2_{adj} = 0.52$)*
*AIC* = 1399.99, *BIC* = 1480.34
[a] 95% confidence interval

### *5.2.3 Association of Feature types and Sentiments*

A one-way ANOVA was conducted to find out whether there are differences in impacts of different feature types on positive and negative sentiment rankings are statistically significant. The test indicated that different feature types (Education, Food, Healthcare, Recreation, Retail, Service) were significantly different with regards to the rankings; $F(5, 100) = 8.57$, $p < .05$ (Figure 07b). The result had an overall large effect size, $\omega^2 = 0.26$. Post-Hoc procedures using Tukey adjustments revealed that Education ($M = 68.54$, $SD = 7.65$), Recreation ($M = 67.31$, $SD = 13.22$) and Service ($M = 68.09$, $SD = 15.52$) feature types have significantly ($p < .05$) higher impact on positive rankings than healthcare ($M = 62.55$, $SD = 10.93$) and food ($M = 51.99$, $SD = 10.99$). Assumptions using Shapiro-wilk normality test and Levene test indicated no concerns with normality and homogeneity of variance respectively.

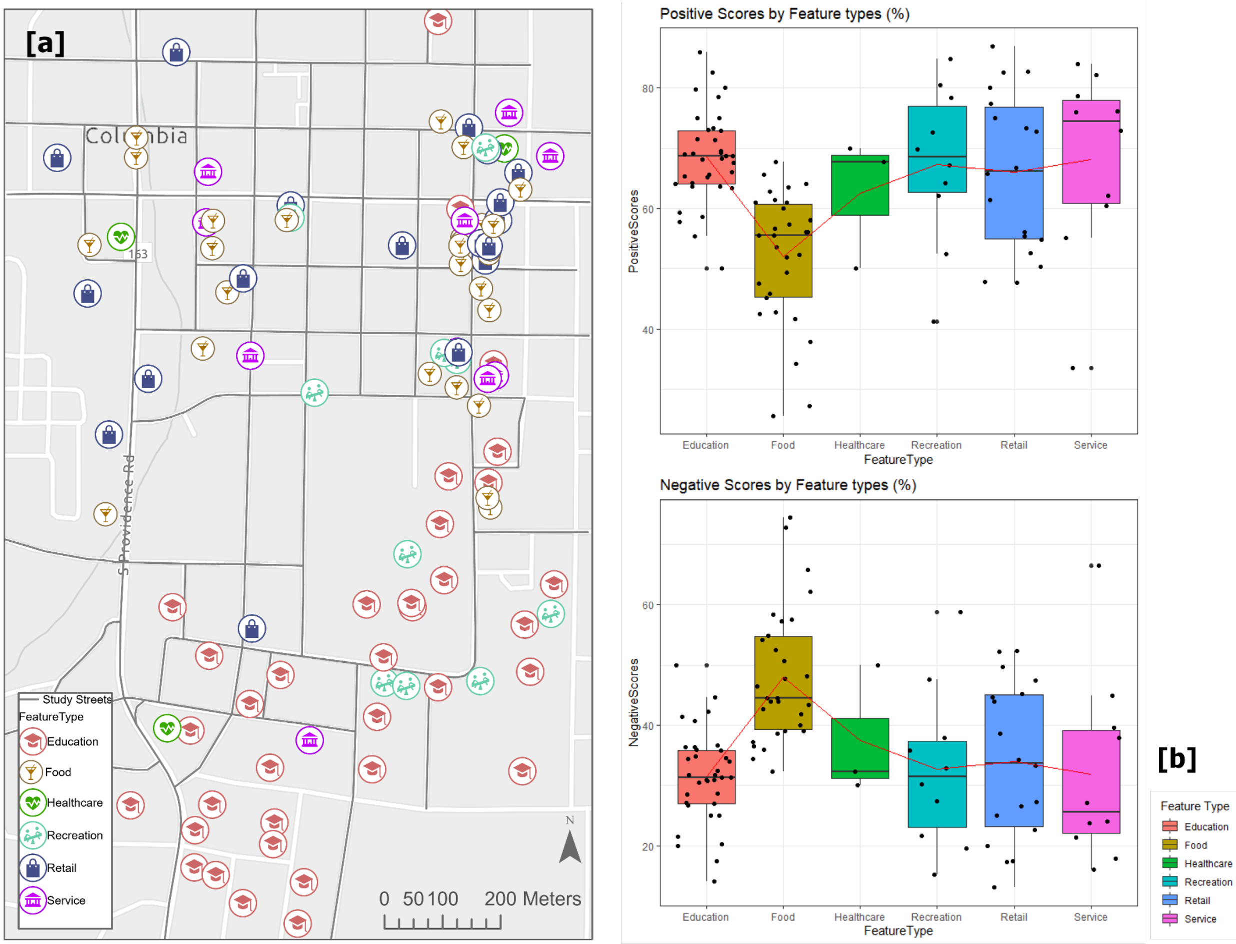



*Figure 07: a) Different feature types, b) variances of different feature types on the sentiment rankings.*

## 6 Discussion

Studies have shown a range of findings due to the variation in the methodologies employed to examine the civil feelings with regard to the built environment. For instance,

The research reported in this article provides evidence that indeed supports many of these relationships. However, this research also highlights that…………

This study examines the relationship between sentiments and built environment in an urban neighborhood setting. Observations of sentiments were crowd-sourced from social media and were then evaluated by NLP model. While other studies have data collection from a limited number of participants for a limited time period, here the ……….. This robust data collection effort was essential to improve the reliability of the sentiment results.

Moreover, each individuals' activity was analyzed for …….. different time periods (Jan-…..) to better understand the extent to which these temporal regimes may affect the relationships between sentiments and built environment.

Results indicate that visual enclosure has a significant positive relationship to human sentiments across all ……….. time periods considered.

## 7 Conclusion

Making urban human settlements more inclusive, safe, and resilient, as well as encouraging healthy lifestyles and well-being at all ages, are critical to long-term urban sustainability. The way people perceive and value places, infrastructures, and events in their daily lives has far-reaching implications for sustainability planning and implementation efforts. To this end, the aim of this research is to provide vital insights into street semantics to promote more informed community planning decisions (what SDG 11 aims to achieve by 2030). The paper details a framework for linking individual sentiment to characteristics of the streetscape. Open-source social media postings and are processed using deep learning methods to infer sentiment and characterize visibility at locations along a transportation system to make these associations possible. The framework is applied to a small case study to illustrate the procedures involved and demonstrate the applicability of the process.

(ii) what aspects of the urban environment relate to the sentiments, and (iii) how these relationships change over time. The first stage of the research involves developing a streetscape preferability mapping based on sentiment ranking. To assess preferability, the study combines collected LSM data with a natural language processing (NLP) algorithm. A positive and negative ranking system on social media postings is used to determine whether individuals like or dislike the specific spaces. In the second stage of the study, a variety of urban attributes that urban planners have long-sighted to be connected to how pedestrians experience the city is measured (Gehl, 2013; Jacobs, 1961; Lynch, 1960). Metrics of urban form including visual enclosure (e.g., sky, trees, buildings etc.), human dimension (e.g., roads and sidewalks), and streetscape complexity (e.g., people, cars, bicycles and so on) are constructed utilizing open-source geospatial datasets, such as Google Street View pictures of urban elements, roadways, and CV methods. In order to assess if the metrics affect sentiments over time, a spatial autocorrelation analysis is performed.

To that end, this study investigates which street segments have more or less enclosure, human scale visibility, or complexity, which can be used to compare with preferred locations.

The paper makes two major contributions to the literature. The first is methodological in the construction of preferability mapping and associations of urban environment attributes. This study extends the exploration by creating a comprehensive framework integrating LSM data, SVI, GIS and ML algorithms to improve the understanding of urban dynamics.

The second contribution of the study is to shine new light on certain urban environment attributes of the urban fabric that can help urban planners and regulatory bodies during the early stages of urban development as well as during urban renewal plans.

There are various decision points, constraints, and extensions to this study that might be worthwhile directions for future research. First, the Google street-level imagery that was utilized in the application of the developed framework was selected for use given that it is publicly available for many locations world-wide, making it an ideal source from the perspective of replicability/applicability of the framework to other regions of interest. However, the Google imagery database at the time of this research is not temporally longitudinal. As such, temporal mismatches between the date/time of sentiment expression and the characteristics of the urban environment can exist. In future applications, the ability to have imagery with good temporal correspondence with sentiment expression is expected to yield better results. Likewise, whereas street-level imagery was utilized in this application as a source of urban characteristics individuals may encounter as they traverse the city, other sources could also be integrated to provide additional geospatial context. For example, data feeds such as crime and accident reports, weather and traffic conditions, power outages, service delays, resource shortages, etc. could provide valuable context to civil sentiment. The use of social media postings as indicators of sentiment also involves a few challenges in that inferring sentiment from postings is not perfect as it is subject to much uncertainty. For instance, the sentiments inferred from the postings may not directly correlate to elements of the streetscape in all cases. Further, inferring the sentiment of many different individuals over time with a trained model alone cannot be expected to provide perfect results as there are many nuances of human communication that are difficult to infer, and comprehensive ground-truth of sentiment isn't typically practical. Regardless, greater attention to model training and ground-truth is expected to improve inference of sentiment.

In the future, real-time social media datasets that incorporate both space and time into analysis, such as Emerging Hot Spot Analysis (EHSA) as a spatiotemporal application of the Getis-Ord Gi* statistical analysis, would be robust and efficient in analyzing urban streetscape. Finally, developing a website-based user-friendly interface for the city residents can be quite beneficial in obtaining real-time responses.

**CRediT authorship contribution statement**

***Jayedi Aman:*** Conceptualization, Methodology, Scripting, Formal analysis, Writing – original draft. ***Timothy C Matisziw:*** Methodology, Software and Scripting, Formal analysis, Writing - original draft, review, and editing.

**Declaration of Competing Interest**

The authors declare that they do not have any known competing commercial interests or personal relations that could emerge to have influenced the tasks discussed in this article.

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