DIGITAL PERCEPTIONS:

COMPARING THE PERCEPTIONAL DIFFERENCE BETWEEN PUBLIC SPACES AND POPS (PRIVATELY OWNED PUBLIC SPACES) THROUGH ONLINE REVIEWS

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Yucheng Zhang

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Stephan Schmidt

This Thesis is Approved by:

Yucheng Zhang

Stephan Schmidt

Faculty Advisor

ABSTRACT

This study explores the potential of an automated process in assessing the perceived quality of public spaces using Natural Language Processing (NLP) algorithms and online reviews. Over 1900 reviews were analyzed, revealing significant differences in perceptions influenced by factors such as user groups, amenities, space management, and visibility. This study found that public plazas are more welcoming and inclusive but lacking in safety and maintenance, while POPS are viewed as uninviting due to inappropriate physical design and rude personnel. In response, the study recommends policy remedies, such as stronger community relations, better design strategies, and improved information dissemination channels. While the use of the automated social media analysis method provides advantages in terms of time and labor input, improvements in accuracy require additional skill sets and data/labor input. Researchers and policymakers should still balance efficiency and accuracy while using novel methods as there is no one-size-fits-all solution to any urban issue.

BIOGRAPHICAL SKETCH

Yucheng Zhang is an undergraduate student in the Urban and Regional Studies program at Cornell University. Born and raised in Shenzhen, China, Yucheng is interested in technology-assisted, data-driven analytic methods in the field of urban planning. During Yucheng's undergraduate studies, he received training in both empirical planning practices and computer science, which allowed him to utilize cutting-edge, computational quantitative methods to understand and address urban issues. Yucheng is receiving his degree of Bachelor of Science with honors from Cornell University in May 2023.

"However deep his gratitude, how can he ever

Repay a debt that will bind him always."

\- *The Wanderer*

To

my parents

in recognition of their love

And to the city where I have fond memories.

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LIST OF ABBREVIATIONS

API	Application Program Interface
LDA	Latent Dirichlet Allocation
NLP	Natural Language Processing
NYC	New York City
NYC DCP	New York City Department of City Planning
NYC DOT	New York City Department of Transportation
POPS	Privately Owned Public Space

PREFACE

Unsupervised learning techniques have made significant breakthroughs and greatly supported the development of data-driven analytic tools like Natural Language Processing, Deep Learning, and Machine Learning. In the field of computer science, these state-of-the-art methods have demonstrated their potential to greatly improve the efficiency and effectiveness in multiple decision-making scenarios. However, the application of digital tools in urban planning is still in its nascent stages.

The provision of high-quality living spaces often comes with weighty financial burden of constructing and maintaining these spaces. This thesis raises this long-haunted question for local governments and aims to provide an in-depth analysis, utilizing the newly developed NLP techniques.

INTRODUCTION

Public spaces can be defined as spaces that are publicly owned and managed, and can be utilized freely by any individual. Streets, playgrounds, plazas, and their accompanying facilities are all forms of public spaces (Ramlee et al. 2015), and they play an increasingly vital role in cities by providing citizens with a place for outdoor recreation and social interactions (Donahue et al. 2018; Madanipour 1999). Urban public spaces are also crucial gathering places for community building, engagement, and expression. Serving as the identity and pride of one's community, public space in communities promotes social interaction and contributes to residents' mental health (Francis et al. 2012). In addition, the lockdown of the COVID-19 pandemic has given the public a renewed appreciation of public spaces, as plazas and parks have become a place where existing and new social interactions could safely flourish (Honey-Rosés et al. 2021).

Economically speaking, public spaces are public goods that can be used by any person free of charge without diminishing their availability to others. Therefore, to ensure the equity and availability of public spaces, they are traditionally provided and maintained by the government or other public entities. However, the quality and accessibility of public spaces are highly dependent on available funding and the neighborhood's socio-economic profile (Bakar, Malek, and Mansor 2016). Since the public provision and maintenance of these places require significant resources, local governments have to make tough decisions between investing in public spaces and other competing priorities. Additionally, low-income neighborhoods often have less access to public spaces due to the lack of funding, political power, and community engagement to advocate for high-quality spaces. These factors leads to the disparities in both the quality and the spatial distribution of public spaces.

The concept of Privately Owned Public Spaces (POPS), or spaces that are privately owned but accessible to the public, was initially introduced in New York City's 1961 Zoning Regulation to offer more open public spaces and greenery in the densest areas of the city. In these mostly privately owned parcels, property developers take the construction and maintenance responsibility of the POPS in exchange for zoning bonuses. Since the 1960s, the emergence of POPS has stimulated wide-ranging discussion on their quality and accessibility, garnering both praise and concern. The argument was that the private sector can offer public spaces with unique design features and amenities in the most densely populated area without incurring significant financial burdens. Furthermore, private developers who take the obligation to construct and maintain POPS can receive benefits such as loosened building and zoning regulations, which allow and incentivize them to have more aesthetically pleasing or profitable building designs. Consequently, the concept of POPS has diffused beyond New York City and has been adopted by many cities around the world as a mutually beneficial agreement between the government and private developers. To date, various metropolitan areas have started their own POPS program to provide more public space in their most densely populated urban areas. These examples include Seattle City in North America; Greater Santiago in South America; Aachen City in Europe; Bangkok City, Hong Kong, Taipei City, Tokyo Metropolis in Asia, and Metropolitan Melbourne in Oceania (Dimmer et al. 2013).

However, studies revealed that POPS are more exclusive and hostile but receive less maintenance than their publicly owned counterparts, and are often designed and altered by the developer's interests rather than the need of the public (Miller 2007; Németh and Schmidt 2007; 2011; Schmidt, Nemeth, and Botsford 2011). As a result, POPS become the subject of ongoing debates, with scholars questioning their roles in the city in relation to conventional public spaces.

Previous studies have proved the existence of qualitative differences between publicly and privately owned spaces. Specifically, Nemeth and Schmidt (2011) have developed an observational, objective index based on the spaces' features and management approaches to compare the difference between public and private spaces. Based on an observational analysis of 62 public spaces and 89 POPS, they found that POPS scored significantly different from public spaces with the additional presence of features that discouraged use. However, do users' perceptions of these spaces match the results of previous observational studies? To answer this question, this study will use automated natural language processing (NLP) algorithms to analyze online user-generated reviews and examine the differences in the public perceptions of and degree of satisfaction with both public and private spaces. The rest of this paper will be organized as follows: The first part will provide a comprehensive overview of precedent literature on public space evaluation. This part will discuss the methods and results of previous studies, as well as the advantages and limitations of each method. Then, the second part will describe the proposed methodology of this research. The third part will demonstrate the results. Lastly, the fourth part will discuss the limitations of the proposed method, together with implications for both future researchers and practitioners on the topic of public spaces.

BACKGROUND AND LITERATURE REVIEW

1. Reviewing the empirical studies: Do POPS qualify for high-quality urban public space?

Urban planners, scholars, and local governments have long been concerned with the quality of urban places. Historically, the success of urban spaces was often measured by how effectively they fulfill their social, civic, and leisure functions (Banerjee 2001). However, the emergence of new types of public spaces and zoning reforms challenges previous interest and emphasis on the functionality of public spaces. Scholars argue that contemporary public spaces should focus more on supporting existing social life, emphasizing the importance of adequately balancing accessibility and opportunity rather than merely serving as the only commerce and social center in the area (Mehta 2014). With the shift in focus, modern public spaces are now trying to find a balancing point between effectiveness and opportunity, as well as between public freedom and individual safety (Németh and Schmidt 2007). All-purpose open spaces can provide more improvisation opportunities but lack the aesthetic appeal of well-designed spaces. On the other hand, the emphasis on security and control will limit the accessibility and inclusiveness of the space.

Clearly, there is no perfect recipe for building a successful public space. POPS as an emerging type of public space that has been extensively studied by scholars, has its own flaws. Privatization of public spaces generally exerts a restrictive force on the availability, accessibility, and inclusiveness of the space through both micro and large-scale physical designs, spatial distribution, and management. Jeremy Németh examined the magnitude of control in 163 bonus spaces at 93 buildings in New York City during working hours from Feb. 2007 to April 2007. Based on a quantitative index of the degree of behavioral control, Németh found that private management intentionally excludes certain groups of individuals and creates disruptions to users through security measures (Németh and Schmidt 2007; Németh 2009). In 2010, Jeremy Németh and Stephen Schmidt employed the same observation-based index in 151 publicly and privately owned public spaces in NYC. They found that privately owned spaces are statistically significantly more restrictive compared to traditional public spaces (Németh and Schmidt 2011). This quality gap between POPS and traditional public spaces was called to attention and induced continuous reforms in the design and operational standards. While these reforms have created more physically usable spaces with the introduction of required amenities and signages, most of the POPS are still perceptually daunting due to the restrictions posed by controlling designs and exclusive management according to an examination of 123 NYC POPS by Stephen Schmidt in 2011 (Schmidt, Nemeth, and Botsford 2011).

Discussions on the quality of POPS in NYC, however, are mostly based on the one index developed by Jeremy Németh and Stephen Schmidt in 2007 (Németh and Schmidt 2007). Even though the index aimed at creating an unbiased, objective, and qualitative measurement of controls in POPS, the scoring rubric still does not directly represent people's perceptions of the space. This limitation exists in other observation-based methods. First, the effect of observable indicators is defined by scholars, professionals, and critics. The speculated effects may fail to capture the actual overall perception of visitors with different backgrounds, cultures, and personal preferences. Empirical methods, such as interviews, surveys, and focus groups can provide direct and rich information about their experiences in public spaces, but the presence and actions of the researcher will influence the subjects' responses. Furthermore, empirical methods are labor and cost-intensive when examining large numbers of sites over a long period. While multiple independent observations can minimize the effect of randomness, significant logistical challenges exist for research conducted at multiple sites over a long time span. Few studies have incorporated multiple variables like time of the day, weather, and date into their study due to the resource-consuming nature of the observational methods.

2. Automated methods: adaption of crowd-sourced data and NLP in public space evaluation

To address these challenges, researchers adopt technology-assisted automated methods to optimize their data collection and analysis process. Crowd-sourced data are voluntarily contributed by individuals through portals from smart devices to online platforms (Niu and Silva 2020). These crowd-sourced datasets include social media data, community-based websites, and collaborative map services. Taking advantage of the prevalence of online communities, user-generated content has become a rich source of user perceptions (Holsapple, Hsiao, and Pakath 2014). Compared to traditional empirical methods, crowd-sourced data have considerable strengths in providing a more comprehensive picture of user opinions. First, self-reporting contents are direct representations of individuals' unbiased perceptions compared to conjectural scores based on observational measurements. Secondly, crowd-sourced data often contain additional metadata that provides information about the location, date, time, and weather of the original data. This allows researchers to trace past data and perform multivariate analysis considering the aforementioned variables. The collection and analysis of online crowd-sourced data is, therefore, a more cost-effective and comprehensive method than traditional methods (Sim and Miller 2019).

The interpretation and utilization of user-generated data present challenges for researchers despite the volume and richness of the information available. Most of the user-generated data are text-heavy and unstructured, meaning that they cannot be applied to any pre-defined data model for data analysis (Gandomi and Haider 2015). Researchers faced challenges when attempting to extract underlying information from human languages using early sets of complex, hard-coded, and qualitative rules. These attempts were highly ineffective in interpreting human language due to the lexical ambiguity and lingual dependencies inherent in text-based datasets. To solve the inefficiencies in the supervised data analysis process that was based on rule sets, automated, unsupervised natural language processing was developed to understand and analyze large amounts of text-based data. In the 2010s, the increasing computational power and the abundance of datasets on the internet have led to significant improvements in NLP. Progress characterized by the adoption of neural network models has enabled NLP algorithms to efficiently summarize contextual meaning, identify subjective sentiments, and uncover major themes from vast text-based datasets (Goldberg 2016). In addition, the availability of publicly available trained language models has made it possible for researchers who are not specialized in computer science to analyze efficiently and effectively analyze large-scale data.

The revolution in NLP models during the 2010s has sparked interest among researchers in exploring the potential of these models for analyzing urban datasets. Urban researchers have applied the NLP algorithm to a wide range of datasets, including social media platforms such as Twitter, Foursquare, TripAdvisor, and Facebook, as well as datasets collected through more traditional methods such as interview transcripts and focus groups (Cai 2021). With regard to the topic of this research - public space assessment, researchers often use locative social media comments as a proxy of people's perceptions and activity patterns within the study sites. In 2020, Fernandez et al. collected 11,419 TripAdvisor reviews on Bryant Park and categorized them into five topics based on user experiences in the public space (Fernandez et al. 2022). Donahue et al. analyzed the spatiotemporal distribution of 1388 tweets on 1581 parks in the Twin Cities, MN to capture the overall park visit pattern in the area. They proved social media can serve as a reliable proxy by comparing their result to survey-based estimation (Donahue et al. 2018). Ruixue Liu and Jing Xiao analyzed 11,272 reviews to investigate user satisfaction with 79 parks in Shenzhen, China. They utilized sentiment analysis to measure visitors' satisfaction levels and linked the identified emotions to various park elements (R. Liu and Xiao 2020). Overall, these works demonstrated the potential of using NLP and user-generated content from social media platforms as a cost-effective and accurate method for assessing public spaces.

While the aforementioned researchers laid the foundation for the adaptation of NLP in the field of urban studies, to the best of the author's knowledge, there are few studies that have applied this method to POPS. This study attempts to investigate whether POPS offers the same utility to city residents as traditional publicly administrated spaces by examining users' perceptions of the public space elements ranging from specific amenities to the overall atmosphere. Compared to existing research of POPS that evaluates the spaces through interviews and site visits, this study proposes a non-intrusive, quantitative method for understanding the public's satisfaction with the two kinds of public spaces: parse the readily accessible comments the visitors left online using Natural Language Processing (NLP) algorithms. Taking advantage of the state-of-the-art analytic technique, this study will address two questions: 1) Which difference exists in the public perception of and degree of satisfaction with both public and private space? 2) What spatial elements contribute to explaining these differences? Understanding the perceptions of POPS and their comparison to publicly owned public spaces can shed light on how to improve the quality and accessibility of urban public spaces.

METHODOLOGY

This section presents an overview of the study site, the data collection method, and the analytical methods employed in this study. Given that most of the POPS in the sample are privately owned plazas and street-front spaces, only public plazas are selected as samples of publicly owned spaces to control confounding variables and to ensure comparability between the two ownership types. 1944 comment entries with locational information and text were collected in October 2022. To derive the results, the author first applied sentiment analysis and keyword extraction to the collected comments. The extracted results of keywords and their corresponding sentiment scores were then classified into five categories that measure different aspects of the perceived quality of the space. Finally, the author compared the results of the two types of spaces and derives the final findings.

1. Study sites

Shown in Figure 1 and Figure 2, this study selects 23 public neighborhood plazas and 171 privately owned public spaces in New York City (NYC) as the study sites. Table 6 and Table 7 in the appendix provide a full list of the study sites. The 23 public neighborhood plazas are filtered from the NYC Plaza Program, which is funded, designed, and constructed by the New York City Department of Transportation (NYC DOT). The plazas within the program are designed to fulfill community members' recreational and social demands, offering a range of amenities such as tables and chairs, art installations, and program stages. NYC DOT also partners with local community groups and commits to the public plazas' conceptual design, and operation. (NYC DOT n.d.) The local partners are also responsible for the maintenance and management of the plazas. This includes tasks such as sweeping and snow removal, maintenance of greeneries and amenities, and ensuring appropriate visitor usage. According to the NYC DOT's website, as of Dec. 2022, the NYC Plaza Program has opened 77 public plazas citywide.

In NYC, privately owned public spaces (POPS), are public spaces that are owned and maintained by private owners with approval and monitoring from the New York City Department of City Planning (NYC DCP). As of 2020, there are more than 590 POPS at 392 buildings, with most of them being open to the public as plazas and arcades. The design of the POPS must comply with the Zoning Resolution Section 37-70 for public plazas, which set forth provisions on the amenities, design elements, and accessibility of the POPS (New York City Zoning Resolution §37 2018).

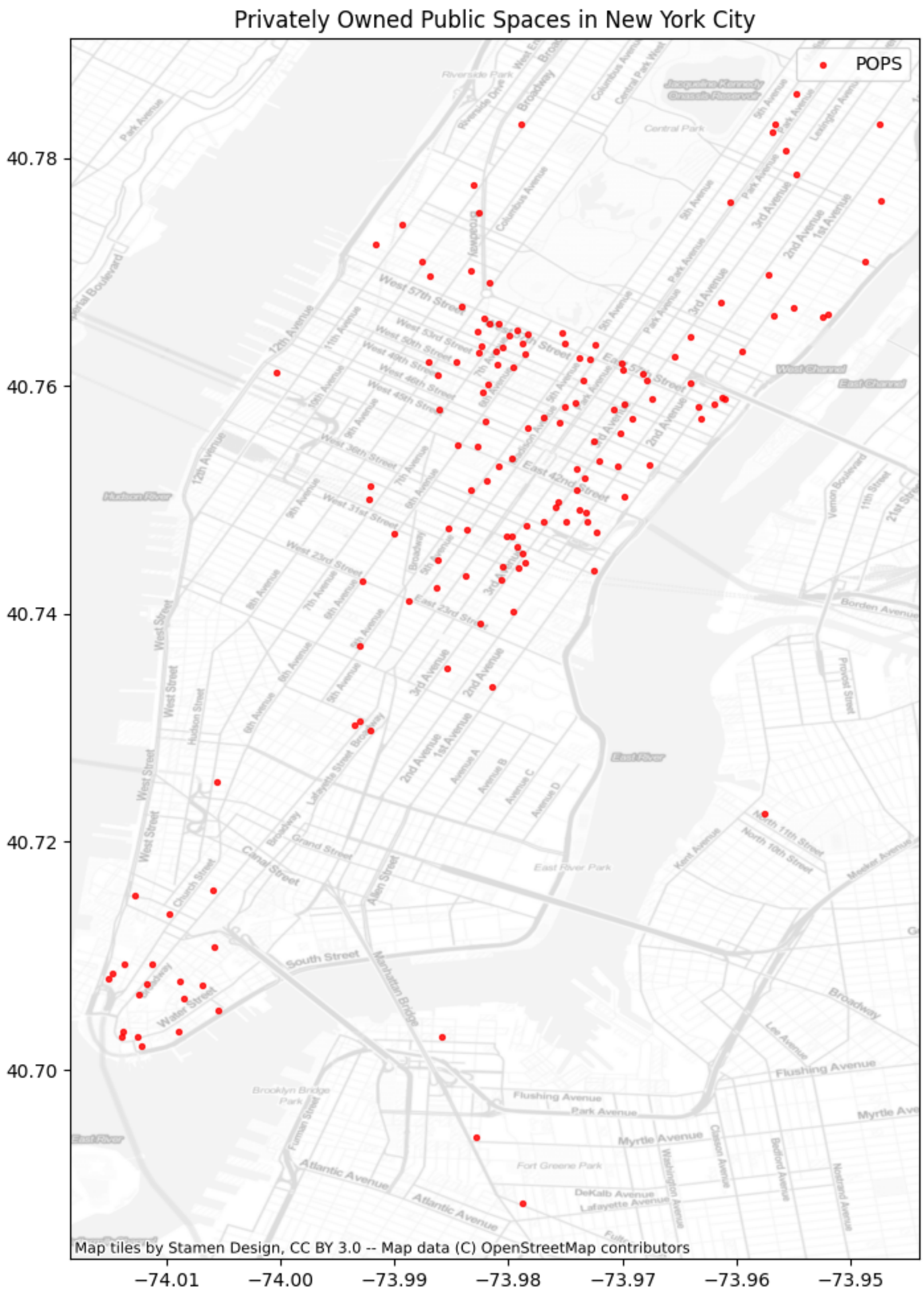

Figure 1. Location of POPS in NYC

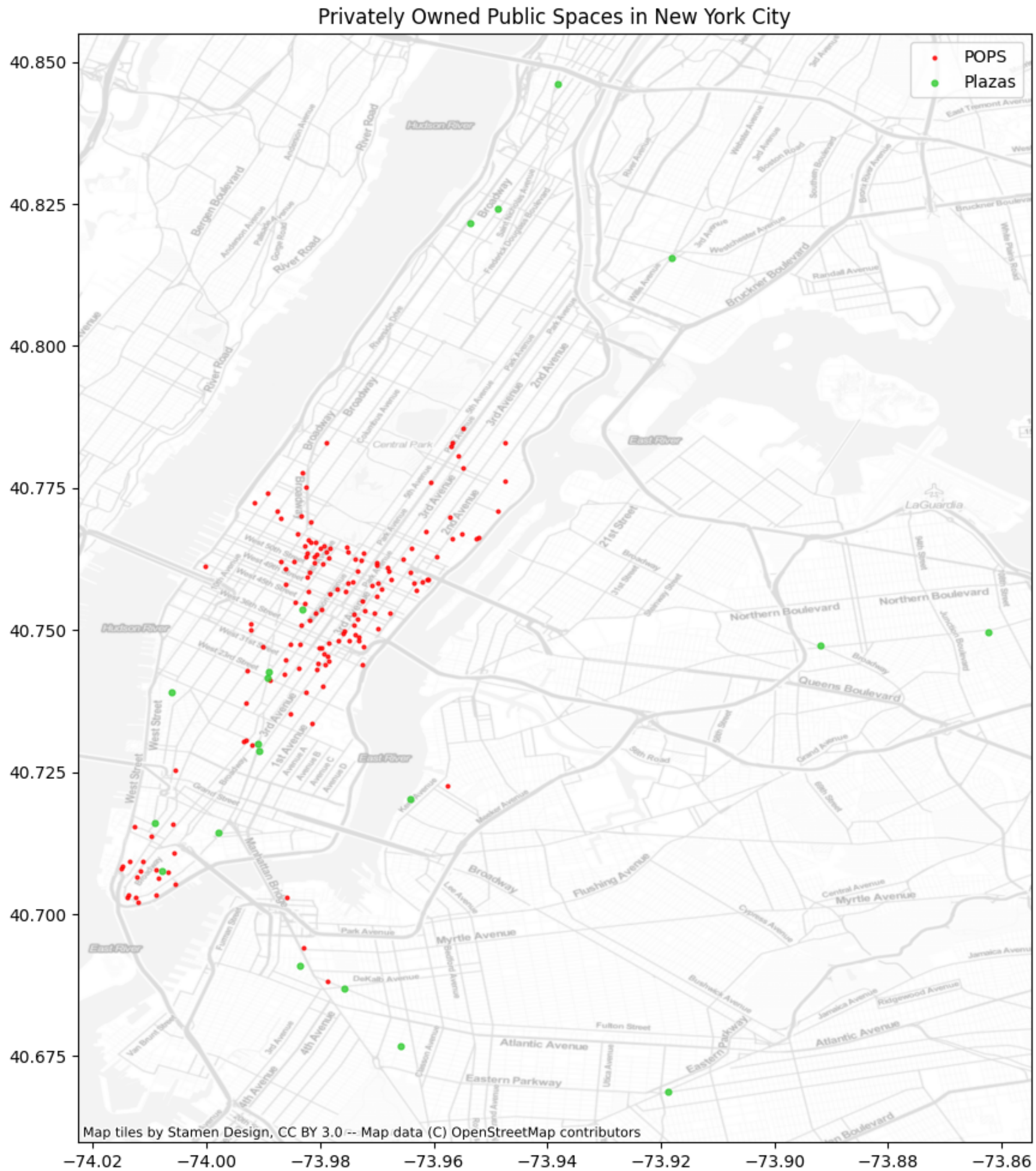

Figure 2. Location of selected public and private spaces in NYC

2. Data Collection

Comments on public plazas and POPS were collected from two separate platforms using Python web scraping scripts. Google Maps is used as the data source for collecting comments on public plazas. Launched in 2005, Google Maps is a widely used web mapping service that is recognized as one of the largest crowdsourced mapping services in the world. With over one billion monthly active users, the platform hosts an extensive collection of locations with their basic information, reviews, ratings, and photos (Google n.d.).

Although Google Maps does not offer an application program interface (API) for querying comments, this study used Python and Selenium to automate the process of collecting reviews. The data collection methodology queried the 23 selected plaza names to create a data frame as a collection of the collected comments. Each entry in the data frame includes the comment text, the relative date with respect to the retrieval date, and the rating. After filtering out empty and non-text comments, a total of 1484 reviews were collected from Google Maps. As shown in Figure 3, the dataset contains reviews over a time span of 10 years, from 2012 to 2022. About 73.7% of the reviews (1093 reviews) are in English, and the remaining 26.3% (391 comments) are translated into English using the Google Translate service. A sample entry collected from Google Maps is presented below in Table 1. “Relative date” provides an approximate date of the comment’s submission time, with a format of “[number] days/weeks/months/years ago”. The “Rating” ranges from 1 to 5, with 1 as the lowest rating and 5 as the highest rating.

Table 1. A sample entry for Google Maps comments

Location	**Text**	**Relative Date**	**Retrieval Time**	**Rating**
Bryan Park	I was there briefly for an event. The "park" is only a triangle separating two major roadways. It is clean but the Parks Dept. needs to plug five small rat holes seen in one area.	“A year ago”	10/30/2022 11:02:06 AM	3

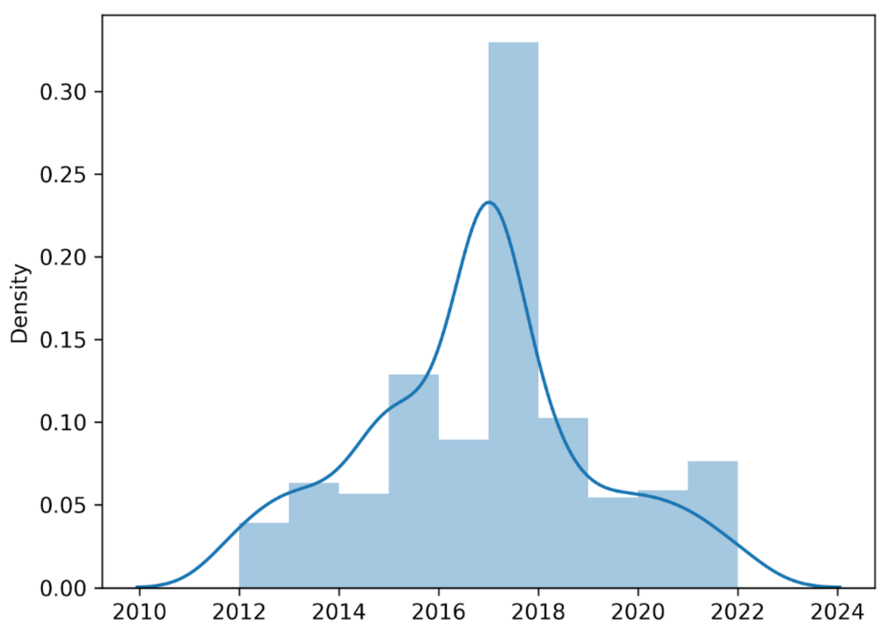

Figure 3. Time distribution of comments from Google Maps

Comments on POPS were collected from “Privately Owned Public Space in New York City” (https://apops.mas.org/), a website maintained by “Advocates for Privately Owned Public Space” and “The Municipal Art Society of New York”. The website provides a digital space for city residents and other stakeholders to submit comments, profiles, and photographs of POPS in NYC. The data collection process using Python gathered 458 comments in total, with a coverage of 10 years from October 2012 to September 2022. Each comment entry includes the location of the POPS, the date, and the comment text, as shown in Table 2.

Table 2. A sample entry for POPS comments

Location	**Text**	**Time**
590 Madison Avenue	It is closed until further notice. I have already filed a 311 complaint on it.	12.21.20

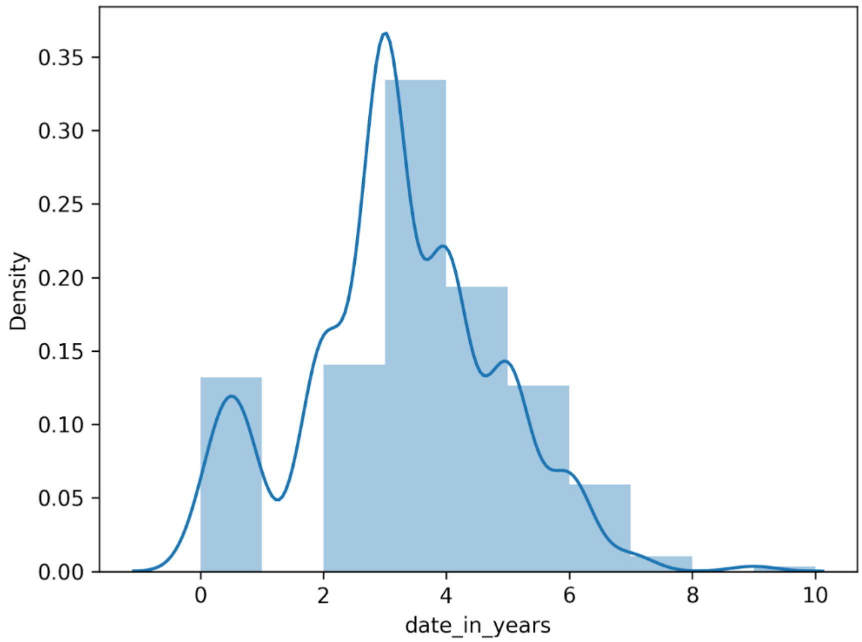

Figure 4. Time distribution of comments of POPS

3. Data Processing and analysis

To understand the underlying perceptions within the comments, this study uses the following natural language processing (NLP) methods to parse online comments: Sentiment analysis, keyword extraction, and topic classification. Sentiment analysis separates positive and negative reviews based on the polarity of the sentences - whether users associate the given space with positive or negative emotion. Keyword extraction analyzes the frequency of meaningful nouns and adjectives in the comments, as well as the association between nouns and adjectives. Topic classification separates the annotated comments and word sets into different categories to reveal the specific theme within the comments.

3.1 Sentiment Analysis

Sentiment analysis provides a basic overview of the perceptional and satisfaction difference between public and private spaces by separating reviews into positive and negative ones for consequential word-level analysis. This study uses the Python library *spaCy* and a pre-trained English pipeline model to conduct an automated calculation of the sentiment scores. For each comment, the algorithm calculates a polarity score ranging from -1 (strongly negative) to 1 (strongly positive) to measure visitors' attitudes. In addition, to validate the accuracy of sentiment analysis, the study examines the relationship between sentiment scores and ratings of the place. The result in Figure 5 indicates that there is a moderative positive correlation between the sentiment scores and ratings (r-squared = 0.408, non-correlation p-value = 0.00). Given that higher ratings imply higher satisfaction and more positive perceptions, the study considers the sentiment score as a robust indicator of the perceptions of visitors towards public spaces.

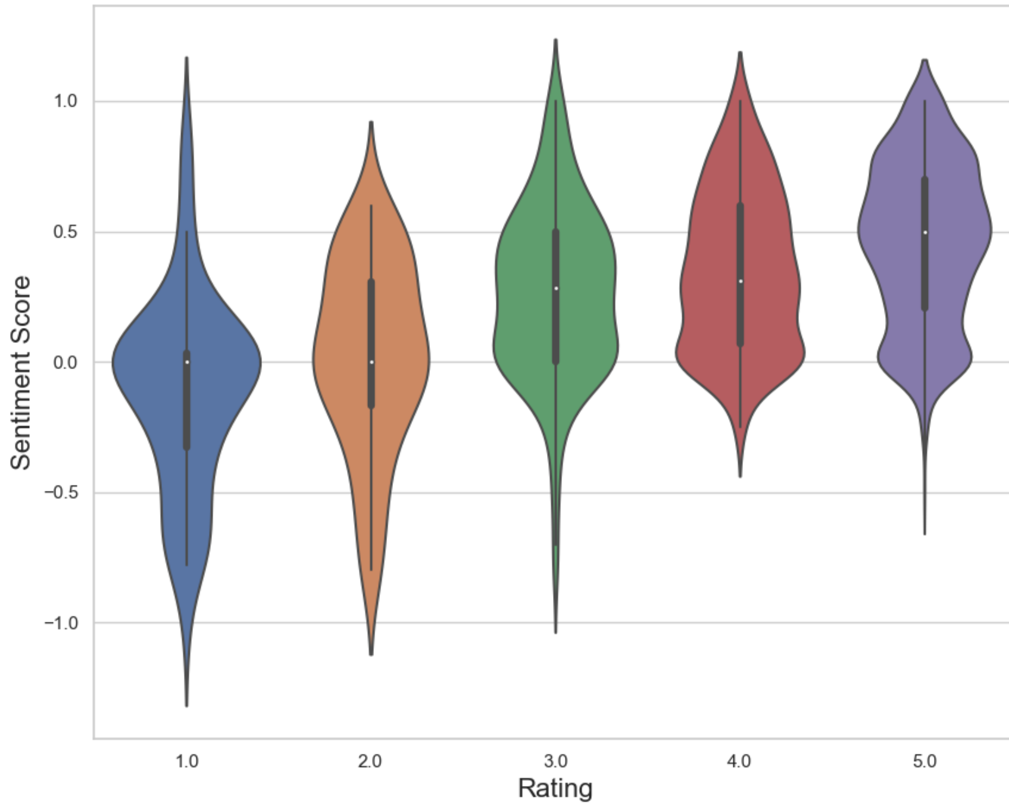

Figure 5. Relationship between ratings and sentiment score from Google Maps reviews

3.2 Keyword Extraction

Keyword extraction, consisting of frequency analysis and association analysis, identifies the co-occurring frequency of words in the comments. This technique helps understand the relationship between different elements in the public space and the sentiment of visitors toward them. When a word appears more frequently, it indicates its greater influence as a feather within the space. A higher co-occurring frequency suggests a strong relationship between the given feature and the sentiment expressed in the descriptive word.

This NLP pipeline is used to process each review in the dataset. First, segmentation and tokenization separate review paragraphs into labeled words. The second step, stemming normalizes words into their base form, for example, converting “walking” to “walk”. Third, lemmatization groups inflected words into their base form, or “Lemma”. For example, grouping beautifully, beauty, and beautiful to their common root. The final step, POS tagging, identifies the grammatical functions of the words, such as whether they are nouns, verbs, stop words, etc., as well as their relationship to other words.

Frequency analysis is a powerful technique in identifying the most frequently occurring words in a corpus of text, mostly takes advantage of the stemming, POS tagging, and lemmatization process. POS tagging filters out occurring words with little or no lexical meanings in the sentence, i.e. articles, pronouns, and conjunctions. Stemming and Lemmatization process group similar words in different forms. Once processed, the occurrences for each word family are then counted using Python. Words with high mention frequency are believed to have a greater impact on the users’ sentiments, according to B. Liu (2015).

Word association analysis helps to reveal relationships between nouns used to describe public space elements, such as “bench” and “tree”, and adjectives that describe satisfaction and emotion such as “dirty” and “disgusting”. This analysis relies on the dependency relationship between words and noun chunks to associate users’ attitudes with certain public space elements. (Matthew and Montani 2017). Specifically, each word in a sentence either describes another word or is being described by another word(s). This relationship is visualized as a dependency tree in Figure 6, where each arc represents a dependency relationship between two words. When processing text with the dependency parsing linguistic feature, each annotated word token is assigned a sequence of the word’s immediate syntactic children or a list of words describing the annotated word. This sequence can be used to generate a list of word pairs. Table 3 presents a sample list of word pairs generated using this method.

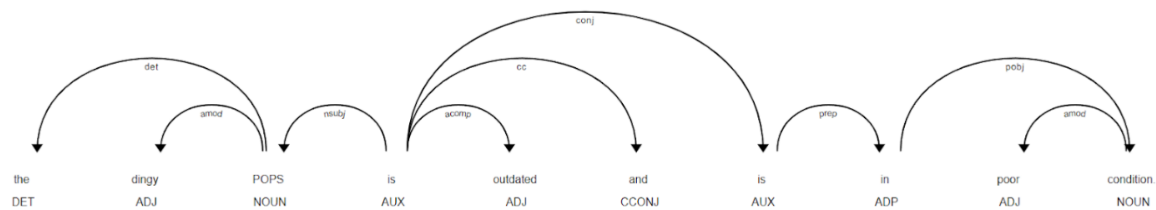

Figure 6. Sample dependency relationship of a POPS comment

Table 3. Sample result of word association analysis

text	**dep**	**head_text**	**head_pos**	**children**
the	det	POPS	NOUN	[]
dingy	amod	POPS	NOUN	[]
POPS	**nsubj**	**is**	**AUX**	**[the, dingy]**
is	**ROOT**	**is**	**AUX**	**[POPS, outdated, and, is, .]**
outdated	acomp	is	AUX	[]
and	cc	is	AUX	[]
is	conj	is	AUX	[in]
in	prep	is	AUX	[condition]
poor	amod	condition	NOUN	[]
condition	**pobj**	**in**	**ADP**	**[poor]**
.	punct	is	AUX	[]

SpaCy also has the ability to identify and separate sentences into noun chunks, which are basic phrases consisting of a noun and other words describing the noun (Matthew and Montani 2017). Table 4 shows a list of noun chunks in the comment corpus, which identified that the place is being described as "dingy", and the condition is "poor" in the sample comment entry.

Table 4. Sample result of noun chunk analysis

Text	**root_text**	**root_dep**	**root_head_text**
the dingy POPS	POPS	nsubj	is
poor condition	condition	pobj	in

3.3 Topic Classification

Topic classification divides comments and the extracted keywords within the comments into different perceptual categories. However, commonly used fully-automated, unsupervised topic modeling techniques, for example, Latent Dirichlet Allocation (LDA), was not suitable for this study due to the limited sample size and the algorithm's inability to capture the specific dimensions of public space quality. Instead of employing the unsupervised algorithm, this study chose to build upon existing public space evaluation frameworks and semi-automatically categorize keywords based on their co-occurrence relationships. The resulting categories were drew from previous research on public space quality, which identified key dimensions including surroundings, accessibility, facilities, amenities, aesthetics and attractions, incivilities, safety, usage/activities, covers policies, and biodiversity (Knobel, Dadvand, and Maneja-Zaragoza 2019). After aligning the available categories with the keyword extraction outcome, the study ultimately assesses the perceptions of public spaces based on five categories: “Visual Quality”, “Amenity”, “Accessibility”, “Comfort”, and “Safety”.

The category “Visual Quality” refers to the user’s perception of the landscapes both within and outside the public space. Dynamic characteristics, for example, the cleanliness of the space, also fall within this category. “Amenity” refers to users’ perception of the presence and condition of the amenities within the public space. “Accessibility” measures the extent to which users are able to utilize the public space. For example, a plaza with ongoing construction or entirely closed is considered less accessible. Features like signages and visible sign rules also count into this category as they either enhance or control the visitor’s ability to use the public space (Németh and Schmidt 2007). “Comfort” is a rather intricate category that measures inclusiveness and general impression. This category reflects feelings projected from park amenities, other park users, and park personnel. The presence of other visitors can create a vibrant and welcoming atmosphere, while the overemphasis on security guards and cameras can make the public space uneasy to stay in (Németh and Schmidt 2007). Lastly, “Safety” measures the perceived level of safety within the public space and considers factors such as the presence of undesired visitors from the perspective of other park users and graffiti, which often evoke the feeling of unsafety among public space users.

Based on the keywords’ literal meaning, their dependency relationship, and their association with other keywords, each keyword is manually classified into one of the five categories. By examining the occurrence of words in different topics, the study identifies the perceptional differences between public plazas and POPS.

RESULTS

1. Sentiment Analysis

The sentiment analysis results suggest that POPS receive more negative comments compared to public spaces, as Figure 7 indicates below. Out of the 1485 Public Spaces comment entries, 1208 comments (87.5%) are categorized as positive and 278 comments (12.5%) are categorized as negative. For the 459 POPS comments, 173 (37.7%) comments are categorized as positive, and 286 (62.3%) comments are categorized as negative. Below are some examples of positive comments:

> "*This place is getting fixed and its a lot nicer now. Seems more safe. Nice place to relax.*" (Public Plaza, Bryan Park Plaza)

> "*Excellent place to share with friends, couple and alone outdoors surrounded by buildings and skyscrapers of the city of New York*"
> (Public Plaza, Flatiron Public Plaza)

> "*This POPS is spacious and well maintained, with only a couple minor issues. Extensive seating is available - in addition to the 10 required tables with chairs, benches ring the central circle of the space, and a separate path semi-secluded behind plantings on the eastern side of the space provides for more secluded seating. With the exception of the grass on the central mound (which given the time of year of this visit, may have been a victim of the winter), the greenery is well maintained, with a large variety in terms of the plants present in planters. Signage is clearly posted with correct hours.*"(POPS, 10 East 29th Street)

> "*The recessed cavities on the east side are now accessible and are well lit at night*"
> (POPS, 135 West 52nd Street)

And examples of negative comments:

> "*Lack of logical design, the planters around it are untended and eroding into the sewer and the concrete/metal boxes are eye sores. The small fences made of piping were never improved or even removed from the plastic that initially covered*"
> (Public Plaza, Cooper Square Plaza)

> "*Place is dirty and messy. They put chairs and tables for you to sit and eat ...but who wants to eat there when the 7 train keeps passing by every few minutes and lifting up dust everywhere. Place is hectic cars honking all the time, you can't sit there and relax.*" (Public Plaza, Corona Plaza)

> "*This place is filthy. It used to be better maintained. What happened?*"
> (POPS, 835 Sixth Avenue)

> "*Terrible! Been closer for years with a never ending construction project. Now being treated as a junk yard*" (POPS, 325 Fifth Avenue)

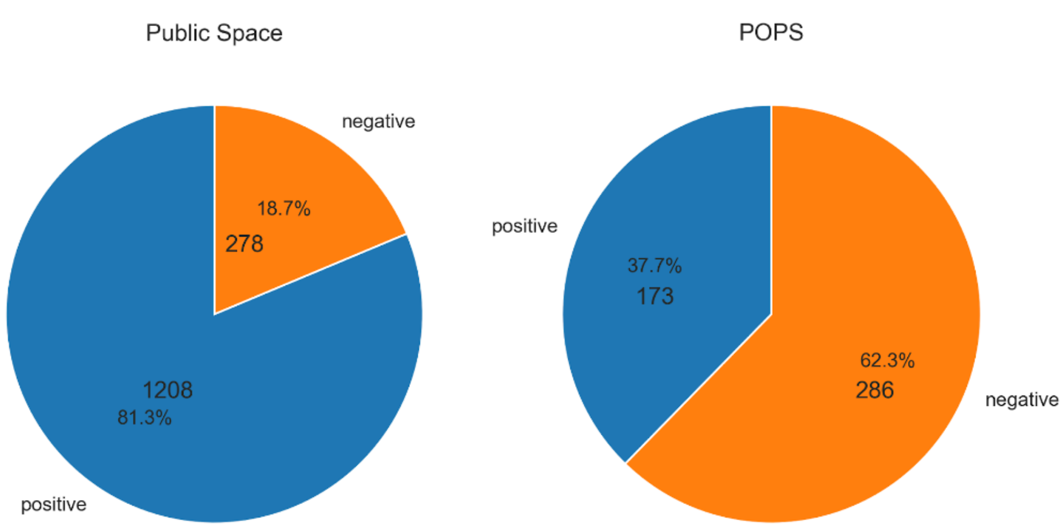

Figure 7. Distribution of classified sentiment

2. Feature Extraction and Topic Classification

Single Word Frequency Analysis extracts the nouns and adjectives that are associated with semantic positive or negative meanings. Feature extraction and topic classification examine the grammatical meanings of the words and phrases. This process identifies the key elements that contribute to a certain kind of perception and thus reveals the relationship between public space elements and users' perceptions. Table 5 below summarizes the sentiment analysis results by category and type of space. Table 8 in the appendix provides a more detailed table for the topic classification results.

Table 5. Summary Table for Sentiment Analysis, break down by category

Type	Category	Pos/Neg	Count	Pct. in Cat.	Pct. of Tot.
Plaza	Visual Quality	Positive	145	77.1%	12.0%
		Negative	43	22.9%	15.5%
	Amenity	Positive	220	92.1%	3.6%
		Negative	19	7.9%	6.8%
	Accessibility	Positive	99	90%	8.2%
		Negative	11	10%	4.0%
	Comfort	Positive	190	74.2%	15.7%
		Negative	66	25.8%	23.7%
	Safety	Positive	166	98.2%	13.7%
		Negative	3	1.8%	1.1%

Type	Category	Pos/Neg	Count	Pct. in Cat.	Pct. of Tot.[1]
POPS	Visual Quality	Positive	71	86.6%	41.0%
		Negative	11	13.4%	3.8%
	Amenity	Positive	87	41.0%	50.3%
		Negative	125	59.0%	43.7%
	Accessibility	Positive	31	14.9%	17.9%
		Negative	177	85.1%	61.9%
	Comfort	Positive	6	9.7%	3.5%
		Negative	56	90.3%	19.6%
	Safety	Positive	8	100%	4.6%
		Negative	N/A	0%	0%

2.1 Visual quality

Visual quality is the most influential feature of positive comments, as visitors mention their pleasure found in high-quality physical features most frequently. Artistic installations, for example, fountains, sculptures, and statues are features often positively commented on. Additionally, the view outside the space is also highly valued by visitors due to the high openness and connectivity of the public spaces. These external visual features include landmarks, connecting streets and neighborhoods, and the city skyline. The finding on visual components' importance aligns with both studies using observational methodologies and studies that have utilized social media data to understand user satisfaction (R. Liu and Xiao 2020). Typical comments about landscape visual quality include:

> "***Great view*** *to some iconic landmarks of NYC, such as the Flatiron and the Empire State Building.*" (Public Plaza, Flatiron Public Plaza)

[1] Reviews of POPS are much longer than those of public plazas, and often containing multiple aspects of the park. Thus, the total percentage adds up more than 100%.

> "*The most striking and unique feature of the POPS is a mural, which spans across one side of the POPS and depicts a* ***beautiful landscape***." (POPS, 150 East 34th Street)

The overall design is equally important as the presence of visual elements in increasing the visual appeal to POPS users. 10 of the 173 positive POPS reviews deliberately mentioned the space is well-designed. Dirt and the presence of trash contribute the most to negative perceptions of public spaces' visual quality. However, the wording difference revealed a slight disparity between the two types of spaces. Reviews of public plazas emphasize that inappropriate behaviors of visitors create dirtiness, while reviews of POPS stressed the lack of trash cans in the area.

2.2 Amenity

Amenity is another significant common factor, highlighted in both positive and negative comments. The most critical amenity is seating, with 175 (14.5%) positive reviews on public plazas and 61 (35.3%) positive reviews on POPS mentioning the existence of some form of seating facility. On the other hand, negative amenities reviews mostly focus on uncomfortable, limited, and unshaded seating areas. POPS users paid more attention to the absence of the required amenities while public plaza users are more focused on the general maintenance of existing facilities. 32 negative POPS reviews included the keyword "require", often associated with the phrase "no required amenities". 20 public plaza users mentioned that the public space is equipped with adequate amenities to fulfill their "needs", and 11 negative public plaza reviews mentioned the term "need", mostly stating that the facilities need to be "cleaned", "maintained", or "improved".

“The "park" is only a triangle separating two major roadways. It is clean but the Parks Dept. ***needs*** *to plug five small rat holes seen in one area.”* (Public Plaza, Bryan Park)

“A few years ago when this building was doing some facade work they removed the ***benches*** *"temporarily". This POPS has been stripped of the* ***required amenities****. There is no plaque, no artwork, no seating, no water fountain, no ornamental water feature, no bicycle parking, and no litter receptacle other than the usual overflowing city garbage can on the corner.”* (POPS, 108 Fifth Avenue)

Comparing the general maintenance situation, POPS reviews have a significantly higher percentage of positive comments. 16 (9.2%) POPS reviews emphasizes the place as “well-maintained while only 25 (2.0%) public plaza reviews categorize the place as “newly renovated” or in good condition.

2.3 Accessibility

The issue of accessibility is a common theme in negative comments. Construction, especially long-duration construction is cited as a significant hindrance to users’ access to the parks. In addition, construction disrupts the visual enjoyment of the space and creates undesired noise and odors, which have a negative impact on visitors’ satisfaction. However, visitors, especially regulars from adjacent neighborhoods, are often optimistic about construction as long as the duration is reasonable, due to their belief in utilizing the renovated space in the near future. Compared to public parks, neighborhood plazas and POPS in this study tend to have more regular visitors from adjacent neighborhoods than tourists (Fernandez et al. 2022). These regular visitors have expressed a more optimistic view toward construction compared to non-residents as construction brings renovations of amenities and improvements in visual features in the foreseeable future. Comments on construction include:

> "*This used to be a nice park. But it's been under* ***construction*** *for at least 7 years. What is going on ??? I gave it 3 stars because it's almost done now. But that was ridiculous....*"(Public Plaza, Cooper Square Plaza)

> "*This space has been closed for construction in the building for well over a year. When construction gates are open, you can see that the vast majority of the space is not being used for* ***construction*** *purposes.*" (POPS, 135 West 52nd Street)

Lack of proper signage is a unique problem in POPS, as this can limit users' ability to discover and properly utilize the public space. Due to the vague regulations specifying the admissible business occupations of POPS, these privately owned spaces are often walled by planters or even fully enclosed with barriers and can be interpreted as no different from private spaces (Schmidt, Nemeth, and Botsford 2011). Without the existence of signages, users may have difficulty distinguishing between private spaces and POPS, and may not feel comfortable or welcome entering the space.

> *"There is no POPS* ***sign****. It looks like a private enclosed food court"* (POPS, 7 Hanover Square)

> "*The Plaza is not particularly welcoming. In fact, I struggled to find it. I asked the bellhop at Trump Palace about it, and he didn't know it existed. After walking around, I realized it was located in the back of the building and gated in, with two openings. there were two clear* ***signs*** *that stated this was a public space, however it*

seemed secluded and unlikely many people would accidentally stumble upon it and walk in."

POPS may also employ inappropriate signage or subjective rules that can limit user access to the space (Németh and Schmidt 2011).

"This one also has 'Private Property No Trespassing' ***signs****"*

(POPS, 728 Second Avenue)

2.4 Comfort and Safety

Other park visitors play an important role in determining the perceived **comfort** level and **safety** in public spaces. In terms of visitor volume, public plazas had more mentions of "crowded" in the comments compared to terms like "quiet" and "tranquil". POPS, however, received a similar amount of comments suggesting the place as crowded or vacant.

"Crowded" public plazas can be attributed to the adjacency to local transit hubs and community spaces. The high pedestrian volume brings vitality to the community and creates a sense of safety through the concept of "eyes on the street". Public plaza users consistently state that appropriate social interactions with other park users create a relaxed and comfortable atmosphere, in which they describe people they interact with as "beautiful", "friendly", "helpful" and "polite". The presence of certain kinds of park visitors, such as families with children, also improves the public space's perceived safety. Public space users are more likely to choose a perceptually safe location to spend time with their family and friends, and their presence in the space reinforces the perception of safety, creating a positive cycle. Many comments have expressed this desire: 102 public space users included the keyword “kid/child” in association with “safe” and “friendly”. 46 users emphasized the place’s suitability for spending time with their family and friends.

However, when a public space becomes too crowded, it can negatively impact the perceived safety and comfort of space users. Most of the comments associate crowds with negative feelings, often evoking feelings of unease and danger. Crowds also increase maintenance costs and bring in undesired visitors like drunkards, homeless people, and addicts into the community. 13 comments mentioned the presence of “homeless” people in the public plaza, and 11 comments mentioned drunk people. Other adjectives associated with negative perceptions of other public space users include “disgusting”, “noisy”, “sketchy”, and “inappropriate”.

> *“Too crowded, **unsafe**. A lot of **drunk men** on the park, not a safe place for children's, a lot of garbage on the streets”* (Public Plaza, Corona Plaza)

Discussion around perceived safety and comfort in POPS are far more polarizing compared with their public counterparts. On the one hand, the well-maintained area with stricter surveillance and rules repeals undesired visitors, which makes the public space safer and more enjoyable. Lighting, as a key amenity contributing to the perceived safety in POPS, is positively rated. 8 comments mention that natural light during the daytime and well-lit areas in the nighttime not only creates a pleasant atmosphere but also make the public area feel safer. On the other hand, the presence of security and management personnel tends to have negative consequences on the POPS users by imposing unreasonable rules and even rejecting their usage of the space. “Security” and “guard”, contrary to their semantics, only occur in negative comments. 19 negative POPS comments included the word “security” and 10 comments included “guard”, claiming that the presence of security chiefs, security guards, or security cameras either indirectly provokes an atmosphere of tension or directly insults the visitors.

> *“845 First Avenue has a large courtyard that appears to be a POPS, next to the driveway, with a sign that reads “Private Property” and security guards who* ***intimidate*** *people from sitting there.”* (POPS, 845 First Avenue)

> *“I was harassed by* ***security*** *for putting my feet up on a chair while reading a book in this park. Is this really the kind of policing POPS* ***security*** *is for.”* (POPS, 825 Eighth Avenue)

> *“The* ***security*** *was menacing and mean. Said I could not sit or eat a sandwich. Told me to go outside to eat in the cold.”* (POPS, 622 Third Avenue)

Hostile architecture, such as spikes on planters, individual benches with armrests, and security cameras, is intended to deter undesired public space users, also has a negative impact on the perceived comfort and safety of the public space (Rosenberger 2020). Hostile architecture can create a sense of unwelcoming by implying the potential presence of undesired visitors in the public space.

> *“If the Atrium at 875 is a public space and open to persons with disabilities, then why did you install ANTI-HOMELESS SPIKES?”* (POPS, 875 Third Avenue)

> *“Spikes affixed to the ledges of the flowerbeds make it impossible to sit on them.”*(POPS, 132 East 35th Street)

"Seating is impeded by spikes." (POPS, 300 East 59th Street)

DISCUSSION

1. Comparing Public Spaces and POPS from a Bigger Image

Based on the findings in the previous section, this study concludes that the difference in the physical design, management style, and ownership results between public spaces and POPS results in the perceptional disparities between the two types of spaces. These perceptional differences in visual quality, accessibility, comfort, and safety corroborate those of other observational studies (Schmidt, Nemeth, and Botsford 2011).

First, this study found that visual quality and amenities are equally important in public plazas and POPS. Both types of public spaces are positively rated for their inner designs and exterior views. Negative comments mainly focused on the cleanliness of the space, which is a maintenance issue rather than a physical design problem. Seating was found to be the most important amenity in both types of spaces, increasing the liveliness of the space by providing opportunities for improvised activities like reading, socialization, people-watching, and relaxing (Mehta and Bosson 2021). Visitors are mostly satisfied with the maintenance of the public spaces, but overall public plazas receive less cleaning compared to their private counterparts, which can create unpleasant environments through garbage and smells. Maintenance situations were found polarized in POPS. Most POPS are well maintained by the property owner to brand their accompanying properties and commercial areas. Others were completely abandoned, under construction, or used for other purposes. Accessibility issues were found to be more severe in POPS than in public plazas. While ongoing construction was the only factor limiting visitors' access to public plazas, POPS can deny visitors entrance and limit their utilization of the space by proposing closing hours and rules, posting security guards, implementing physical barriers, and removing moveable amenities like chairs and benches. Additionally, POPS can also be hard to locate and identify. Without the presence of visible signs and other public space amenities, people are likely to treat the POPS as passageways or private spaces and only pass through them (Kayden 2000).

The two types of spaces have distinct user profiles. With more mentions of terms like “family” and “friends”, public plazas seem to be more often utilized by community members, families, and tourists. Public plazas also reside more homeless people and undesirables which makes the place perceptually unsafe and unsettling. POPS, on the other hand, with the presence of additional rules and security measures, tend to be utilized mostly by office workers as observed 30 years ago, if the space is not completely vacant (Loukaitou-Sideris 1993). The (imagined) line of sight from the man and women in suits passing by and working in the adjacent building, and even the empty, vacant space itself makes the POPS feel unwelcoming and uncomfortable, as said by a visitor of Grace Plaza in October 2018. In addition, private property owners may also use hostile designs and security measures to directly regulate visitors’ behavior, further contributing to the negative perception of POPS. Even though people know that POPS are actually safer than public plazas, the “hard controls” imposed on visitors through security measures make visitors feel insecure and threatened.

2. Policy Suggestions

This study uses positive review contents as a proxy for the physical quality of the space and finds that the conditions of most POPS meet or exceed those of public plazas. However, POPS received significantly lower ratings and are less utilized compared to the public plazas, even though they are more densely populated within NYC. This is evidenced by the lower percentage of positive reviews, lower number of reviews, and content of reviews describing POPS in NYC. We argue this could be attributed to a) the limited public knowledge of and exposure to POPS, and b) the unwelcoming atmosphere generated by security personnel. Below, this study suggests some potential approaches to improving the quality of public space for local authorities, urban planners, and community members.

Public plazas can benefit from various strategies to alleviate the identified issue of overcrowding and undesired visitors, including community policing, environmental design strategies, and non-invasive technologies. Community policing programs are proven to be effective in suppressing low-level arrests without increasing crime, thereby lowering unlawful behaviors in the community (Beck, Antonelli, and Piñeros 2022). In addition, community policing promotes a positive relationship between public space users and officers through required community engagement training and routine resident interactions. Compared to the security personnel in POPS, publicly funded police are not dedicated to the public space and are trained more uniformly. This will allow community police to exert less controlling effects on visitors and thus have fewer negative impacts on the perceived comfort and safety level of the public space (Németh 2009). Additionally, community policing strengthens the relationship between the local authorities and community members. For instance, community affairs programs implemented by NYPD equip volunteers with skills to effectively identify and report incidences (Community Affairs Bureau n.d.). Trained volunteers from community affairs programs can help inspect and maintain the comforts of the public space without introducing additional uneasiness. Similarly, local volunteers can also contribute to the inspection program by effectively reporting the cleanliness, perceived safety, and structural conditions of the public space to both NYC DOT and local partners. Since most users of public plazas are local community members, community cooperation can be particularly effective with less effort. The relatively stable user community made it easy to recruit local volunteers and build relationships between local authority officials and users. However, any strategy to increase surveillance in the space is still an expedient measure that should be implemented with care and close examination to ensure they don't sacrifice the privacy of public space users.

In addition to community policing, design strategies can help shape public plazas as inclusive, safe, and welcoming places. The promotion of exposure and visibility can help citizens identify the place as a public plaza, while the natural lighting and line of sight contribute to perceived safety (City of Vancouver and Places for People, n.d.). Movable seatings and tables, lighting facilities, and other architectural trellises can help the public plaza stand out as a community space that supports all kinds of activities in any weather condition and time of day. These design strategies can also contribute to a sense of belonging and pride among local community members, who will be more likely to utilize the space with care.

Non-invasive technology like Wi-Fi sensors, can effectively monitor the crowdedness within public plazas and mitigate it accordingly through consequential analysis and management. With the real-time crowdedness data, plaza visitors can be informed and advised to avoid a public plaza when it gets crowded. Wi-Fi sensors can detect the presence of mobile devices and estimate the crowdedness in the public space anonymously and without visual presence, without triggering visitors' feelings of being monitored. Additionally, Wi-Fi sensors can provide services like fast, free public Wi-Fi, emergency phone calls, and device charging ports to enhance park users' experience within the public plazas. The city of New York and CityBridge have already installed over 2000 Wi-Fi kiosks in NYC and proved the program as a well-maintained, self-funded, and beneficial project that fills the technology gap across different communities (Intersection n.d.). Wi-Fi sensors can thus be a cost-effective addition to public plazas that both promote the effective usage of public space and provides a better visiting experience for plaza users. However, it is also important to consider the potential downsides of using Wi-Fi sensors in public plazas. Free Wi-Fi and charging stations can attract homeless visitors and lead to inappropriate behaviors like playing loud music or harassing other space users. A study by Amsellem in 2021 found that LinkNYC kiosks have raised complaints regarding users watching pornography, playing loud music, and threatening users' privacy (Amsellem 2021).

Regarding the lack of public knowledge and exposure to POPS, this study found that POPS received significantly less amount of public recognition, based on the number of reviews and mentions on the internet. Few or none of the POPS are marked on Google Maps, making people difficult to locate and utilize public spaces.[2] This is despite the fact that NYC DCP already made available and maintains a dataset about the POPS in NYC covering

[2] By searching "Privately Owned Public Space, New York" on Google Maps, the only result directs user to 43-51 Park Place, which, ironically, is categorized as a "Garden" and have a picture of under construction as of July, 2022.

information on their location, construction condition, hours of access, and required amenities, together with an interactive map (NYC Capital Planning Explorer n.d.; NYC DCP 2022). However, the dataset and its accompanying map, created in 2019, only received 1187 views as of February 2023. To address this issue, city governments are encouraged to cooperate with advocacy groups to provide information about POPS using digital platforms. Existing examples include community-sourced websites like "Privately Owned Public Space in New York City" (https://apops.mas.org/). Other possible digital platforms include mobile apps, cooperation with other map service providers, and social media accounts. These platforms are more accessible and receive more attention than government websites, thus being more effective in transmitting information to the public. Once the public is aware of the existence and locations of POPS, visitors can become an oversight mechanism for these spaces. Their presence in the space can help create a more welcoming atmosphere for other potential space users and educates the security personnel on the visitors' rights to utilize the POPS. Visitors' utilization of the space can monitor the presence of signages and required amenities. Educated visitors may even become autonomous volunteers that supervise and improve the perceived quality of the space.

3. Limitations

The use of online reviews as a proxy of visitors' perception of public spaces has the potential as a low-cost, time-efficient, and unobtrusive proxy for understanding the perceptional differences between publicly owned spaces and privately owned spaces. However, this method has its limitations and biases. One major limitation of this study is the biased information input. First, since all comments are voluntary responses, the comments may only represent the users who are willing to share their opinions online. While not all public space users have access to the online platform, the dataset may over-represent the opinions of the park users who are more active on social media. Additionally, this study relies on automated NLP tools to collect and classify users' opinions, which may introduce measurement errors such as misclassifications. To address these limitations, future research should validate the methodology with empirical studies such as interviews, surveys, and other qualitative measurements. These validation methods can also provide additional demographic information to the study.

Since this study collects comments from two different data sources, the disparities in user groups and their knowledge level in public spaces are expected to be confounding variables that could have affected the results. Public plaza reviews are collected from Google Maps and received far more comments from the community-based POPS website, despite the number of POPS being much higher than public plazas. Public plaza reviews were collected from Google Maps, while POPS reviews were collected from a community-based website. The difficulty in accessing the POPS website acts as a threshold that only selectively keeps in the more knowledgeable users. As a result, POPS users, often with a better sense of the public space tend to leave longer and more sophisticated reviews of the space. This study also observed that more knowledgeable users are also more likely to criticize a public space. Among the users, public plaza users left more comments on general impressions while POPS users are inclined to point out specific elements that have an effect on visitors' perceptional feelings. This difference in user groups could have influenced the perceived differences in visitors' perceptions between publicly and privately owned spaces, as this study did not develop a method to address the aforementioned confounding variables.

The limited number of reviews on each public space is another limitation of the data source. To make the outcome statistically significant, this study groups the comments by the type of public spaces to increase the sample size. However, Public spaces receive uneven levels of recognition and utilization. Popular public spaces that received more comments and therefore are over-represented in the dataset. These two biases in the data source make the outcome not an accurate representation of the real-world situation.

With regard to the applicability of the methodology, the NLP-based analysis method still requires specific skill sets in computer science and may not be scalable. Social media data analysis methodology involves using specialized techniques to collect, clean, and analyze data from online platforms, and thus it may not be accessible to all researchers. Moreover, compared to field research methods like observations and surveys, social media data analysis requires significant expertise in programming as well as time and effort to train a team of researchers.

This study uses a pre-trained language model in interpreting public space users' perceptions, which is a powerful, time-efficient, yet general-purpose approach to analyzing social media data. However, pre-trained models may not be able to fully capture the specific context-related characteristics in the urban planning domain. The pre-trained model used in this study does not have domain-specific knowledge of public spaces, and thus may not accurately understand the relationship between space characteristics and user perceptions. Future studies are suggested to use a fine-tuned language model to improve accuracy and contextual understanding. Fine-tuning is the training process of a pre-trained model using a context-specific dataset to improve the model's performance on a certain task. Within the scope of this study, a set of labeled comments with sentimental information, important public space features, and revealed perceptions can be used as the training dataset to optimize the language model. The fine-tuned model is expected to interpret the sentiments and perceptions of public spaces more accurately with supplementary context-specific information. However, it is important to note that fine-tuning requires additional expertise and effort, which may not be feasible for researchers with limited resources.

CONCLUSION

This study presents a method to understand the perceptional differences between public plazas and POPS by using online reviews. Drawing from over 1900 reviews, the study concludes that perceptional differences exist in public plazas and POPS as the result of the disparity in park user groups, amenities, space management, and visibility. Public plazas are generally more welcoming and inclusive but lack perceptional safety with the presence of undesired visitors. POPS are more uninviting because of the rude personnel and the lack of amenities to signify their existence. This result corroborates other empirical studies on POPS in NYC. The study's findings also suggest several possible policy remedies to address the identified issues. Public plazas can benefit from stronger community relations, better design strategies, and technology-assisted management. POPS can improve its accessibility through better information dissemination channels. However, it is worth noting that each recommendation has its own limitations and potential drawbacks. There is no panacea to improve the perceived quality of public spaces, and policymakers should take a case-by-case basis approach to address the issues in the perceived quality of public spaces.

The use of social media data in public space study offers several advantages over empirical methods. Social media data analysis is more efficient in terms of labor and time input and is effective in capturing the general image of the result when dealing with large datasets. However, researchers still have to balance accuracy and labor input for more in-depth analyses. Similar to other adoptions of AI in the planning field, technology has greatly enhanced researchers' ability to understand the world. But at the end of the day, it is ultimately up to planners to interpret and apply this information in a way that aligns with broader social and ethical considerations.

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APPENDIX

Table 6. List of study sites: public plazas

Data Source: NYC DOT, geocoded by the author

Address	**Latitude**	**Longitude**
Astor Place Plaza	40.72991	-73.991
Albee Square	40.69092	-73.9835
Bogardus Plaza	40.71594	-74.0091
Bryan Park	40.7536	-73.9832
Cooper Square Plaza	40.72872	-73.9908
Corona Plaza	40.74972	-73.8623
Diversity Plaza	40.74732	-73.8918
Doyers Street	40.71435	-73.9979
Flatiron Public Plaza	40.74152	-73.9892
Fowler Square	40.68695	-73.9757
Gansevoort Plaza	40.73917	-74.0062
James Forten Playground	40.67671	-73.9657
Johnny Hartman Plaza	40.82416	-73.9486
Louise Nevelson Plaza	40.70763	-74.0079
Montefiore Square	40.82169	-73.9535
North 5th Street Pier and Park	40.72023	-73.9641
Plaza de Las Americas	40.84609	-73.9381
Roberto Clemente Plaza	40.81561	-73.9182
Madison Worth Square Plazas	40.74272	-73.9891
Zion Triangle	40.66867	-73.9187

Table 7. List of study sites: POPS

Data Source: “POPS in NYC”, geocoded by author

Address	Latitude	Longitude
200 East 64th Street	40.76431	-73.964
50 East 89th Street	40.78229	-73.9569
835 Sixth Avenue	40.74702	-73.99
325 Fifth Avenue	40.74749	-73.9853
845 First Avenue	40.76302	-73.9595
639 West 59th Street	40.77246	-73.9917
343 Gold Street	40.69411	-73.9829
111 Murray Street	40.71535	-74.0128
153 East 53rd Street | Citigroup Center	40.75836	-73.9698
180 Maiden Lane	40.70527	-74.0055
90 Washington Street	40.70802	-74.015
25 Kent Avenue	40.72251	-73.9576
590 Madison Avenue	40.76234	-73.9729
560 Third Avenue | Murray Hill Mews	40.74809	-73.9769
52 Broadway	40.70658	-74.0123
10 East 29th Street	40.74478	-73.9862
172 Madison Avenue	40.74743	-73.9836
240 East 27th Street	40.74022	-73.9796
1991 Broadway | Bel Canto	40.7752	-73.9826
445 Fifth Avenue	40.75164	-73.9819
1 Central Park West	40.76903	-73.9816
222 East 39th Street	40.74813	-73.975
300 East 74th Street	40.76982	-73.9572
401 East 34th Street | Rivergate	40.74384	-73.9725
425 East 58th Street	40.75888	-73.961
410 East 58th Street	40.75842	-73.962
300 East 59th Street	40.76029	-73.9641
353 East 17th Street | Gilman Hall	40.73365	-73.9814
767 Fifth Avenue	40.76359	-73.9724
1 New York Plaza	40.70213	-74.0122
36 Central Park South	40.76462	-73.9753
185 East 85th Street	40.77863	-73.9548

45 East 89th Street	40.78296	-73.9567
118 West 57th Street | Le Parker Meridien	40.7645	-73.9784
1000 Tenth Avenue	40.7697	-73.9869
125 Broad Street | 2 New York Plaza	40.70286	-74.0125
60 Wall Street	40.70623	-74.0084
475 Park Avenue South	40.76198	-73.9701
240 East 47th Street	40.75291	-73.9704
825 Third Avenue	40.75587	-73.9701
43-51 Park Place	40.71371	-74.0097
728 Second Avenue	40.74813	-73.9731
900 Park Avenue	40.77613	-73.9606
1 Wall Street	40.70749	-74.0116
41 Madison Avenue	40.74233	-73.9863
1114 Sixth Avenue	40.75472	-73.9828
135 West 52nd Street	40.76193	-73.9809
108 Fifth Avenue	40.73725	-73.9931
825 Eighth Avenue	40.76214	-73.987
515 East 79th Street	40.77096	-73.9488
1285 Sixth Avenue	40.7429	-73.9928
1755 Broadway	40.76593	-73.9821
1301 Sixth Avenue	40.76169	-73.9796
1345 Sixth Avenue	40.76278	-73.9785
125 West 55th Street	40.76374	-73.9788
146 West 57th Street | Metropolitan Tower	40.76487	-73.9793
1325 Sixth Avenue	47.61091	-122.334
230 West 55th Street	40.7648	-73.9827
825 Seventh Avenue	40.76303	-73.9811
1700 Broadway	40.76352	-73.9823
810 Seventh Avenue	40.76288	-73.9826
151 West 54th Street	40.76344	-73.9805
156 West 56th Street	40.76449	-73.9799
888 Seventh Avenue	40.76549	-73.9809
211 West 56th Street	40.76551	-73.9817
575 Fifth Avenue	40.75632	-73.9783
75 West End Avenue	40.77417	-73.9893
725 Fifth Avenue / Trump Tower	40.76243	-73.9738

115 East 57th Street	40.76147	-73.97
875 Third Avenue	40.75719	-73.9692
201 East 17th Street	40.7352	-73.9854
1 Battery Park Plaza	40.70338	-74.0138
420 Fifth Avenue	40.75086	-73.9833
26 Astor Place	40.72977	-73.9921
5 East 22nd Street	40.74116	-73.9888
246 Spring Street	40.7253	-74.0055
200 East 69th Street	40.76734	-73.9614
330 East 39th Street	40.74719	-73.9723
230 Ashland Place	40.68827	-73.9787
8 Spruce St | Beekman Plaza	40.71073	-74.0058
1 Liberty Plaza | Zuccotti Park	40.70926	-74.0113
60 East 8th Street	40.73059	-73.993
300 Mercer Street	40.7303	-73.9935
2 Gold Street	40.70747	-74.0068
622 Third Avenue	40.74978	-73.9757
55 Water Street	40.70332	-74.0089
6 East 43rd Street	40.7537	-73.9797
For Sale: One Chase Manhattan Plaza.	40.70776	-74.0089
100 United Nations Plaza | 871 United Nations Plaza	40.75305	-73.9677
55 East 52nd Street	40.75853	-73.9742
123 Washington Street	40.70926	-74.0136
360 East 57th Street	40.75822	-73.9634
1095 Sixth Avenue	40.7548	-73.9844
12 East 49th Street	40.75723	-73.977
115 East 87th Street	40.78071	-73.9557
105 Duane Street	40.71578	-74.0059
40 Rector Street	40.70843	-74.0147
9 West 57th Street	40.76379	-73.9751
1251 Sixth Avenue	40.7601	-73.9818
17 State Street	40.70289	-74.0139
235 East 40th Street	40.74915	-73.9738
200 Water Street	40.70291	-73.9858
245 East 40th Street	40.74886	-73.9732
600 Third Avenue	40.74932	-73.9759

1633 Broadway | Paramount	40.76209	-73.9846
400 East 70th Street	40.76614	-73.9568
524 East 72nd Street	40.76602	-73.9525
201 East 42nd Street	40.75084	-73.974
322 West 57th Street	40.767	-73.9841
200 West 79th Street	40.78293	-73.9789
2 Pennsylvania Plaza	40.75007	-73.9922
407 Park Avenue South	40.74337	-73.9837
525 East 72nd Street	40.7663	-73.952
166 East 34th Street	40.74535	-73.9787
535 Madison Avenue	40.76045	-73.9735
685 Third Avenue	40.75189	-73.9734
650 West 42nd Street	40.76117	-74.0003
3 United Nations Plaza	40.75025	-73.9698
40 East 94th Street	40.78562	-73.9548
1515 Broadway	40.75798	-73.986
200 East 33rd Street	40.74455	-73.9786
200 East 32nd Street	40.74399	-73.9791
200 East 24th Street	40.73917	-73.9825
155 East 31st Street	40.74413	-73.9805
155 East 29th Street	40.74301	-73.9806
150 East 34th Street	40.74591	-73.9793
141 East 48th Street	40.75514	-73.9725
140 East 45th Street	40.75271	-73.974
137 East 36th Street	40.7478	-73.9784
132 East 35th Street	40.74681	-73.9797
115 East 34th Street	40.74687	-73.9802
150 East 58th Street	40.76112	-73.9682
418 East 59th Street	40.75901	-73.9613
200 East 61st Street	40.76259	-73.9654
489 Fifth Avenue	40.75298	-73.9808
950 Third Avenue	40.7605	-73.9679
422 East 72nd Street	40.76692	-73.955
455 East 86th Street	40.77625	-73.9473
201 West 70th Street	40.77762	-73.9831
1221 Sixth Avenue | McGraw-Hill	40.75943	-73.9822

280 Park Avenue	40.75674	-73.9756
400 East 56th Street	40.75711	-73.9631
30 West 61st Street	40.77012	-73.9833
919 Third Avenue	40.75892	-73.9675
200 West 60th Street	40.77097	-73.9876
235 West 48th Street	40.76092	-73.9862
301 East 94th Street	40.783	-73.9475
457 Madison Avenue	40.75822	-73.975
747 Third Avenue	40.75348	-73.9721
599 Lexington Avenue	40.75796	-73.9708
1166 Sixth Avenue	40.75686	-73.982
1 Pennsylvania Plaza	40.75119	-73.9921

Table 8. Summary table for sentiment analysis, break down by category

Type	Category	Pos/Neg	Base Text	Freq.	Associated set
Plaza	Visual Quality	Positive	Beautiful	104	[people, decoration, place, flower, monument, street, views, art, sunset, sculpture]
			water	22	[nature, waterfront, feature, walk, sit, by, view]
			art	19	
	Amenity	Positive	sit/rest	106	
			bench/chair/seat	69	
			need	20	[find, everything, have]
			new	19	[renovated, enjoy, painted, modern, sidewalk]
			maintenance	6	
	Accessibility	Positive	food	80	[places, near, stand, around, sit, enjoy, street, purchase]
			close[3]	19	[safe, market, restaurant, neighborhood, street, shop]
	Comfort	Positive	relax	71	

[3] Interestingly, the keyword "closed" have different connotations in positive and negative reviews. In positive reviews, "close" is the root word for the phrase "close to". The adjacency to other attractions or city services adds to the exposure and accessibility of the public space. In negative reviews, "close" is associated with the inability to access the place due to regulations or construction.

			people	62	[beautiful, interesting, friendly, best, love, bizarre, watch, helpful, polite, chat]
			clean	57	
	Safety	Positive	Kid/ Child	102	[safe, friendly, socialize, meet, family]
			family/friend	46	[share, bring, time, visit, eat, go, talk, hangout, local]
			safe	18	

Type	**Category**	**Pos/Neg**	**Base Text**	**Freq.**	**Associated set**
Plaza	Visual Quality	Negative	Dirty	22	
			small	14	
			garbage	7	
	Amenity	Negative	need	11	[improvement, clean, security, rat]
			bench	8	[uncomfortable, limited, more, enough, shade]
	Accessibility	Negative	construction	11	
	Comfort	Negative	People	46	[homeless** (13), drunk** (11), transient, sketchy, many, disgusting, selling, noisy, inappropriate, full, crowd]
			crowded	14	
			bad	6	[smell, garbage, nonaccessible, hood]

Type	Category	Pos/Neg	Base Text	Freq.	Associated set
	safety	Negative	dangerous	2	
			scary	1	
Type	**Category**	**Pos/Neg**	**Base Text**	**Freq.**	**Associated set**
POPS	Visual Quality	Positive	view	17	[city, allow, immersive, provide]
			plant	17	[planters, planting]
			fountain	10	[waterfall, landscaping]
			nice	10	[impressive vestibule, flowerbed, weather, design, garden, aesthetic]
			design	10	
			clean	7	
	Amenity	Positive	seating/ chair/ bench	61	[moveable chair, fixed marble bench, tables,
			maintain	16	[well maintained]
			amenity	10	
	Accessibility	Positive	use	16	[great, quality, frequently, chairs, different, well, worthwhile]
			sign	8	[posted, illuminated, clear, have, adding, well]
			access	7	[ADA, seamless, public, ramp]
	Comfort	Positive	Inviting	6	

Type	Category	Pos/Neg	Base Text	Freq.	Associated set
	Safety	Positive	light	8	[well lit, nature, pleasant, night]
POPS	Visual Quality	Negative	trash	11	[sidewalke, no, trash bin, trash can]
	Amenity	Negative	Seating/Bench	65	[no, lack, separate, uncomfortable, restrict, removed, backless, minimal, blocking, unusable]
			require	32	[no require amenities, not functional, signs, removed, drinking fountain,
			amenity	28	
	Accessibility	negative	close*	63	[private, legal, remain, construction, fully, years, currently, enclosed, frequently, inaccessible]
			construction	51	
			sign	42	
			rule	21	
	Comfort	negative	people	27	[homeless** (10), rarely, preventing, selfish, watched by, stop, passing, exclusionary, restrict, keep out
			security	19	[security chief, security guard, measure, camera]
			guard	10	