THE UNIVERSITY OF CHICAGO

Understanding What People Need from Visiting Green Spaces During the Pandemic: An Analysis of Visitation Patterns by Integrating Multimodal Data

By

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Abstract

During the pandemic, visiting counts, dwell time, and travel distance to green space significantly declined. Previous studies have not fully explained why this pattern occurred, as they lack the simultaneous inclusion of both objective features and visitor's experience, and do not explicitly distinguish visitation patterns into three categories. To examine how U.S. green space visitation patterns changed during the COVID-19 pandemic, I integrated Google reviews, Street View images, and the Social Vulnerability Index with GPS-based visitation data to examine how experience, environmental features, and socioeconomic status affected green space visitation, and further to identify features that fulfill basic and non-basic needs in different time periods. Machine learning models were used to transform raw data into numerical metrics and capture the non-linear impact of these features on green space visitation. The findings reveal that during the pandemic, basic needs such as green coverage and road are regarded as the most important. Non-basic features, such as water activities and sports, can still attract a smaller proportion of visitors, provided they have access to these green spaces.

Keywords: parks; green spaces; machine learning; image recognition;

1 Introduction

The World Health Organization classified COVID-19 as a pandemic due to the high number of confirmed cases and deaths, creating an unprecedented global health crisis for human beings (WHO, 2023). By the end of 2023, the pandemic has caused over 1 million confirmed deaths across the US (Johns Hopkins University, 2023). To control the spread, key measures like social distancing, quarantine, and public space restrictions were implemented to reduce mobility (Paez, 2020), but raised concerns about people's mental health due to limited access to public spaces (WHO, 2020).

With leisure facilities such as malls, restaurants, and recreational places restricted, green spaces became vital for public health and social benefits, even though some green spaces were fully or partially closed during the early lockdowns (Slater et al., 2020). Early evidence shows that exposure to natural environments promotes faster and more complete recovery from stress, both physiologically and psychologically (Ulrich, 1984; Ulrich et al., 1991). Green spaces play a crucial role in enhancing well-being and health, especially as their usage declined significantly during the pandemic compared with years before the pandemic (Fiorillo & Gorwood, 2020; Moreno et al., 2020; Mouratidis & Yiannakou, 2022). In times of crisis, they offer emotional and mental health benefits and provide safe, open spaces for activity participation (Poortinga et al., 2021; Shoari et al., 2020; Ugolini et al., 2020).

The COVID-19 pandemic impacts greatly on green space's *"contact"* — represented by time spent or frequency of visiting — and *"proximity"*, representing the distance to nearby natural areas (Bratman et al., 2019). Considerable disagreement exists across studies regarding how the pandemic impacts contact (Labib et al., 2022). In areas with severe lockdowns, fear of transmission and restrictions limited outdoor activities, reducing green space contact (Burnett et al., 2021; Heo et al., 2021; Ugolini et al., 2021). However, other studies indicate that contact increased by 69% in Vermont, USA (Grima et al., 2020), 72% in the countryside of the UK (Robinson et al., 2021), and an astounding 291% in Oslo, Norway (Venter et al., 2020) at the beginnining of the pandemic, suggesting factors such as policy variations, enforcement levels, and population density may significantly influence green space visitation.

Regarding proximity, Poortinga (Poortinga et al., 2021) observed that proximity to public outdoor spaces was maintained or enhanced during the pandemic due to reduced mobility, correlating with lower COVID-19 cases in US urban centers. However, Larcher et al. (Larcher et al., 2021) noted that individuals without private terraces or courtyards, often in lower socioeconomic areas, faced longer travel distances to access these spaces during the pandemic (Mell & Whitten, 2021).

Given the pivotal role that green space plays during the pandemic, these mixed findings are troubling. In this study, I use *"dwell time"* as a measure of *"contact"* and *"travel distance"* to indicate *"proximity"*. Additionally, I add a new indicator *"visiting counts"* to reflect the overall frequency and volume of green space visits, capturing comprehensive user engagement and activity within the green space during the pandemic. A framework was developed to analyze how objective environmental features, visitor experience, and the socioeconomic status index influence green space visitation patterns across US green spaces before, during, and after the pandemic. The study makes four specific contributions. First, the analytical framework integrates concepts from urban ecology, structuration theory, social stratification, and the social construction of nature to explore how individual preferences shift during critical periods. Second, utilizing the Dewey Monthly Pattern dataset, this study provides highly accurate measures of green space visitation by detailing average visiting counts, dwell times, and travel distances per green space, sourced from mobile device panels. Third, unlike prior work, this research combines extensive Google Business reviews, Google Street View images, and socioeconomic data, analyzed through a non-linear model with high explanatory power, able to capture the complex dynamics of green space visitation. Last, special attention is given to how different types of needs shift in green space usage throughout the stages of the pandemic, providing insights into what features people really care about by visiting green spaces, whereas no previous studies have set clear boundaries between the two categories.

As a result, the study reveals that basic environmental features significantly impacting visiting counts include trees, walkability, and roads, suggesting that people prioritize accessible and navigable green spaces for routine visitation. Features influencing dwell time include grass, trees, walkability, and the non-basic feature of water activities, indicating that richer, more immersive environments encourage people to linger longer. Travel distance is primarily affected by the presence of roads, sports facilities, and the Housing Type and Transportation domain of the Social Vulnerability Index, implying that accessibility and availability of diverse amenities shape how far people are willing to travel. Together, these patterns highlight that both functional accessibility and experiential quality of green spaces are crucial for promoting their use, especially during times of crisis when physical and psychological needs are intensified.

Future studies will focus on refining more appropriate dataset selection and enhancing model methodologies.

1.1 Hierarchy of Needs in Green Spaces

When considering the basic needs in green spaces according to Maslow's hierarchy of needs (Maslow, 1943), prior studies have extensively examined various features of green spaces that align with basic needs, including walkability (Barnett et al., 2017; Cutts et al., 2009; Fonseca et al., 2022; M. Smith et al., 2017; Van Cauwenberg et al., 2018), green coverage (Gascon et al., 2015), safety (Hong et al., 2018; Maas et al., 2009; Williams et al., 2020), etc. However, there has been limited systematic investigation into features that constitute non-basic needs in green spaces. For instance, Wen (Wen et al., 2018) found that older adults tend to favor green spaces with natural, aesthetic, comprehensible, and diverse landscapes, but the general public's priorities regarding these features remain unclear. Similarly, while blue spaces in green spaces have been shown to offer health benefits (Gascon et al., 2015), public preferences for such features have not been fully explored. In the next two sections, we will first present theoretical support for categorizing non-basic features. Features that cannot be clearly categorized will be addressed in detail in the Discussion section.

1.2 Environmental Features' Impact on Green Spaces Visitation Patterns

It is intuitive that individuals are naturally drawn to green spaces boasting attractive environmental attributes such as abundant greenery, cleanliness, and spacious layouts (McCormack et al., 2010). According to Gibson (1979), these environmental features afford specific opportunities or constraints that influence how individuals interact with the space.

For instance, elements like lush vegetation, well-maintained pathways, and amenities such as benches and playgrounds afford activities like relaxation, socializing, and physical exercise (Ingold, 2021; Kyttä, 2003; Ward Thompson et al., 2010). A green space with clean landscapes and clear skies affords cognitive restoration and stress relief, appealing to those seeking respite from urban pressures (Kaplan, 1995; Ulrich et al., 1991).

Preferences for green spaces, however, vary significantly based on individuals' socio-ecological contexts. Bourdieu's habitus (1977) explains that people's dispositions, shaped by their socialization and accumulated capital (economic, cultural, social), influence how they perceive and utilize these affordances (Grenfell, 2014). Individuals with higher capital may prefer green spaces with sophisticated aesthetic features or specialized recreational facilities that align with their tastes, thereby affecting their visitation patterns (Bourdieu, 1984). Conversely, individuals from marginalized backgrounds may experience a mismatch between their habitus and the symbolic markers embedded in certain green space environments, influencing their preferences and sense of belonging (Rishbeth et al., 2022). While basic infrastructures like lighting are important for all users, individuals from lower socioeconomic backgrounds may particularly value features that signal safety and inclusivity rather than exclusionary or elite aesthetic markers. Importantly, not all non-basic features necessarily align with high socioeconomic status preferences. But we also acknowledge the limitation of such as a binary classification as certain amenities, such as playgrounds or open sports fields, may strongly appeal to users across socioeconomic groups, highlighting the complexity of how environmental features interact with habitus.

During the COVID-19 pandemic, green spaces offering features conducive to social distancing—such as expansive layouts and secluded areas—afforded safer opportunities for outdoor activities, thereby attracting visitors seeking both safety and well-being (Lashua et al., 2021; Volenec et al., 2021). Evidence indicates that these environmental features are more likely to be present in green spaces situated in higher socioeconomic areas (Engelberg et al., 2016; Rigolon, 2016). The pandemic increased existing social disparities, as individuals possessing greater social and cultural capital were better equipped to navigate the evolving green space environments and sustain or even increase their green space visits, whereas those from lower socioeconomic backgrounds encountered heightened barriers to access (K. J. Lee & Scott, 2016; Rishbeth et al., 2022). The pandemic intensified the role of green spaces as essential "third places," (Oldenburg & Brissett, 1982) where individuals sought mental health benefits and social connections amidst isolation, reinforcing the importance of environmental features in supporting resilient communities (King & Dickinson, 2023; Poortinga et al., 2021).

These socio-ecological dynamics suggest that not all green space features hold equal value across different populations, particularly during times of crisis. The environmental elements that most powerfully attract visitors likely reflect underlying disparities in access and preference.Building on this theoretical foundation, this study hypothesizes that basic elements like roads and trees will have a more significant impact on green space visitation, whereas ”luxurious” elements like water bodies will not during times of crisis. Basic features such as roads and trees tend to offer more universal, functional affordances - providing accessibility, shade, and navigability which are essential needs for a wide range of users regardless of socioeconomic background. In contrast, amenities like water bodies, while desirable, may be perceived as non-essential and less immediately supportive of physical and psychological needs during periods of social disruption. This hypothesis will be tested using a random forest model, which is detailed in the Methods section. Socioeconomic status is approximated using the county-level Social Vulnerability Index (SVI), with plans to utilize census-level data in future studies to enhance accuracy. Environmental features are assessed through elements like the presence of water and lamplight derived from Google Images, and general good qualities of green spaces from Google Business Reviews. Future research will incorporate satellite imagery to quantify the percentage of water and tree cover within these green spaces, enabling a more detailed analysis. Further methodological details are discussed in the Data section.

1.3 Understanding User’s Experience

Agency denotes the capacity of individuals to act independently, make choices, and influence their own lives despite structural constraints (Blumer, 1986). Interactionists emphasize the ongoing and co-joint processes of structure and agency, proposing that individuals interact with spaces in ways akin to their interactions with other individuals, characterized by mutuality and the assignment of roles to one another (Cohen, 1989). While socioeconomic structures can shape agency by influencing how spaces like green spaces and green areas are accessed and utilized, they do not deterministically fix the behavior, as human agents retain the potential to restructure their environments and redefine their use (Blumer, 1986; Gieryn, 2002). The rejection of structural determinism (R. W. Smith & Bugni, 2006) is crucial as individuals are not passive recipients of environmental constraints; instead, they actively attribute meanings to spaces, influencing their behaviors and interactions within these contexts to emphasize the dynamic interplay between individual agency and social structure, and further to underscore the importance of personal interpretation and adaptation in understanding how green spaces function and evolve socially, especially during times of crisis such as the COVID-19 pandemic.

General green spaces serve dual roles in this case: they fulfill the daily yet necessary needs of residents (Enssle & Kabisch, 2020; Hunter et al., 2015; Kuo, 2011; Wolch et al., 2014; Zhao et al., 2015), and attract non-local visitors function as tourist destinations

(Hunter et al., 2015; Moreno et al., 2020; Schindler et al., 2022). Frequently the latter possess greater size and spaciousness, a higher variety of facilities, and offers sensory and aesthetic appeal that generate unique experience (Schindler et al., 2022), which share similarities with green spaces in higher socioeconomic regions (Hoffimann et al., 2017). Thus from an interactionist's perspective, individuals actively attribute meanings to environmental features based on their ongoing interactions and experiences. Thus, during the pandemic, positive experiences with certain green space features would strengthen the meaningfulness of these spaces, reinforcing their usage. Similarly, amenities such as sports facilities, perceived as non-basic yet providing opportunities for meaningful social interaction and recreation, would gain importance as individuals actively seek spaces offering richer and safer interactions during periods of crisis.

Previous studies have employed observations and questionnaire surveys to gather information about visitors' personal experiences, behaviors, and perceptions of the green spaces they visit (Li et al., 2020; Palliwoda & Priess, 2021; Priess et al., 2021; Sreetheran, 2017). However, observations and questionnaire surveys typically have limited sample sizes, are constrained by time and space, and may not represent the broader public, thus failing to generalize nationwide (Heikinheimo et al., 2017; Kabisch et al., 2021), while the wording of questions can influence responses (Matovic & Forgas, 2018; Sim et al., 2020). Consequently, the use of social media data has recently been suggested as a new tool for surveying green space visitor numbers and presenting a more holistic picture of what visitors appreciate in specific green space settings and what they may be missing (Arribas-Bel et al., 2015; Y. Chen et al., 2018; Martí et al., 2019). Therefore, Google Business reviews are utilized to analyze direct use value, which refers to actions and experiences of being on site (Ståhle, 2010).

1.4 Methodological Approaches to Studying Green Space Visitation

Existing literature has provided critical methodological foundations for this study. The rapid development of data science has introduced a new approach to studying urban visiting patterns by utilizing a variety of data forms, such as text data, images, and location data (M. Chen et al., 2024; Huai et al., 2022; S. Lee & Son, 2023; Q. Song et al., 2023; C. Yang et al., 2022; Y. Yang et al., 2022). There is still a gap in how to leverage unstructured data, such as social media reviews, to review the complex relationships between visitor's experience and human behavioral patterns. The potential of such data has not been fully exploited, especially in terms of integrating topics to explain visitation patterns (Ma et al., 2023), suggesting the need to include different data forms for a more comprehensive analysis.

Second, most studies rely on traditional statistical methods, such as regression analysis, which can make it challenging to capture the dynamics of multiple factors simultaneously, especially when there are potential interactions, nonlinear effects, and lag effects among variables (Ardic et al., 2020; Bi et al., 2024; Huai et al., 2022; Zhang et al., 2021). As multiple interacting factors shape urban environment and human behaviors, linear analysis can not adequately reveal, particularly when external shocks like the COVID-19 pandemic are involved (Cao & Tao, 2023a). To address this issue, researchers have used machine learning methods to capture nonlinear relationships, but relying on a single type of data such as a structured questionnaire (Q. Song et al., 2023; X. Wu et al., 2024), images (Doan et al., 2025; Komossa et al., 2023; S. Lee & Son, 2023), and review data (Norman & Pickering, 2023). Only a few studies tried combining data forms (Bi et al., 2024; Huai et al., 2022; Ma et al., 2023). This study aim to refine on this approach by exerting non-linear models on unstructured data.

By exploring the non-linear impacts of environmental features and visitor's experience, combined with county-level socioeconomic index, and analyzing the moderating role of external shocks such as COVID-19, this research provides new theoretical and empirical insights into how different urban elements influence visitor behavior together. By incorporating interpretable ML approaches to analyze threshold and nonlinear relationships, the research aims to examine the following hypothesis: basic elements will have a more significant impact on green space visitation during the pandemic.

2 Data and Methods

2.1 Data

As illustrated in Figure 1, we obtained the visiting patterns in green spaces throughout the U.S. from the Dewey Monthly Pattern GPS dataset for the time period of January 2019 to December 2023. More than 240,000 green spaces were extracted from this dataset using the following types of urban modifications: (1) amusement parks and arcades; (2) sightseeing and sightseeing, land, and (3) sightseeing and sightseeing, other, which include not only urban parks, but also natural parks, amusement parks, etc. The dataset aggregates information on visiting patterns to POIs from a panel of mobile devices over a given month, detailing average visiting counts, average dwell time, and average travel distance per green space. Serving as dependent variables, these metrics are calculated monthly and normalized on a state scale to better capture the overarching national trends. To ensure privacy, all personally identifiable information related to phone numbers of each individual place is blocked, and green space names are anonymized, replaced by unique place keys. Figure 2 shows the changing pattern of relevant variables.

Meanwhile, to introduce visitor's experience of green spaces, we collect over 100 million

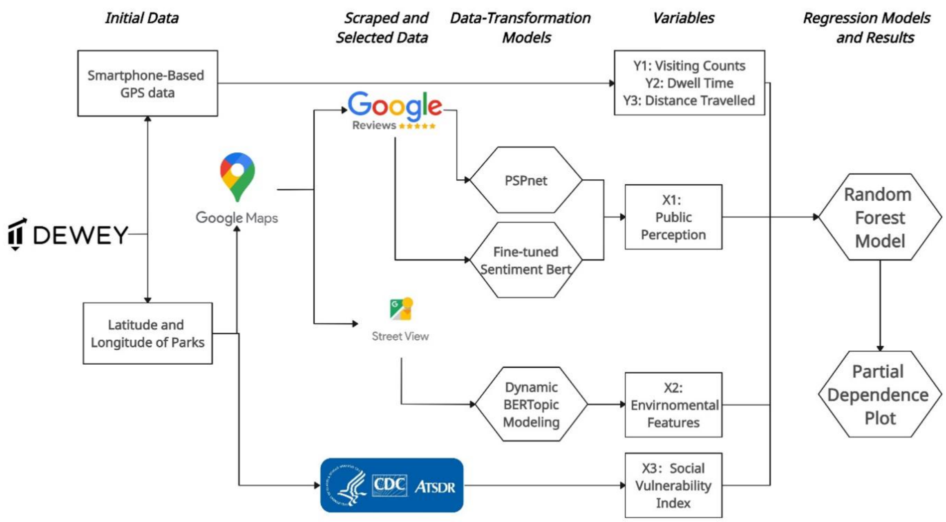


Figure 1: Model's Workflow

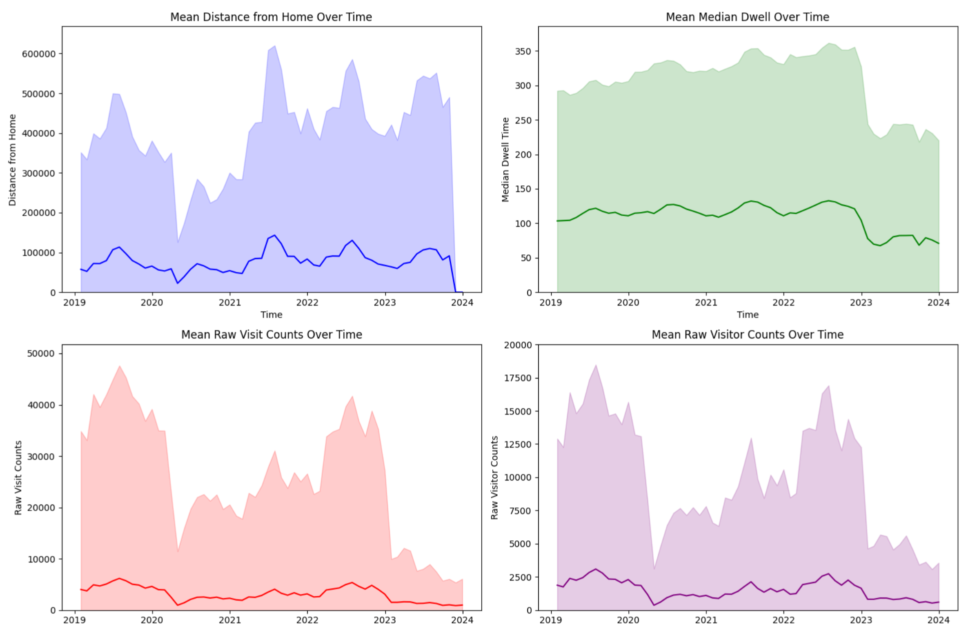


Figure 2: Changing Patterns of Raw Distance Travelled, Raw Dwell Time, Raw Visiting Counts, and Raw Visitor Counts. The line represents the mean value; the shaded area represents the distribution.

Google reviews covering the same period. After filtering out reviews that were too short, incoherent, or in foreign languages, we retained 6,226,016 usable reviews. These reviews were analyzed using Dynamic BERTopic Modeling and sentiment analysis to transform textual data into numerical values, which serve as independent variables. Specific algorithms will be discussed in section 3.2.

Additionally, to obtain objective environmental features, we used the Google Maps API to download Street View images of locations closest to each green space's entrance. Since the exact direction of the green space entrances could not be automatically determined, we collected 360-degree images for each green space's entrance. While it is true that our Street View images were collected near green space entrances and therefore capture only the immediate environment, this limitation is mitigated by the relatively short distance between the Street View capture points and the actual entrances, typically around 10 to 15 meters. Within such a small spatial range, especially in urban and suburban settings, environmental features such as tree cover, road presence, walkability elements, and built structures tend to remain relatively stable and consistent. Thus, although the interior features deeper within larger green spaces may not be fully represented, the environmental characteristics at the entrance level that we measured provide a robust approximation of the accessibility and immediate benefits that are most important to the initial experience and decision making of visitors. These images were processed using a neural network-based semantic segmentation method, allowing us to quantify environmental features by showing the percentage of different types of elements in each image. These variables also serve as independent variables.

Last, we incorporated the county-level Social Vulnerability Index (SVI) dataset to reflect community resilience in preparing for and recovering from public health crises. The SVI consists of four thematic indices according to Figure 3: (1) `RPL_THEME1`: socioeconomic conditions, (2) `RPL_THEME2`: household characteristics, (3) `RPL_THEME3`: Racial/Ethnic Minority Status, (4) `RPL_THEME4`: Housing Type and Transportation, and (5) `RPL_THEMES`: A combination of four thematic scores. These indices can reflect how each subcategory's impact on green space visitation. We used the 2019 version of the Cartographic Boundary Files for Counties to map and join the indices from the SVI dataset to each green space.

In total, 19,013 green spaces simultaneously have valid data across Google reviews, environmental features from images, and SVI indices, approximately 10% of the total. Figure 4 shows the geographical distribution of these green spaces.

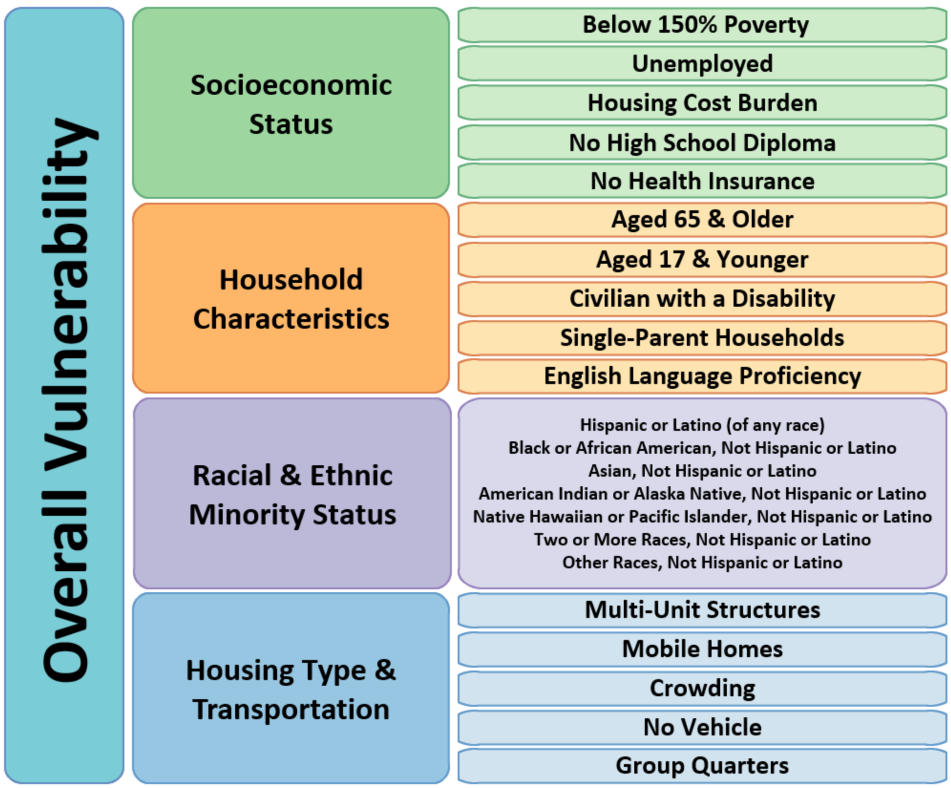


Figure 3: Social Vulnerability Index variables grouped into four themes, source: Social Vuneralbility Index

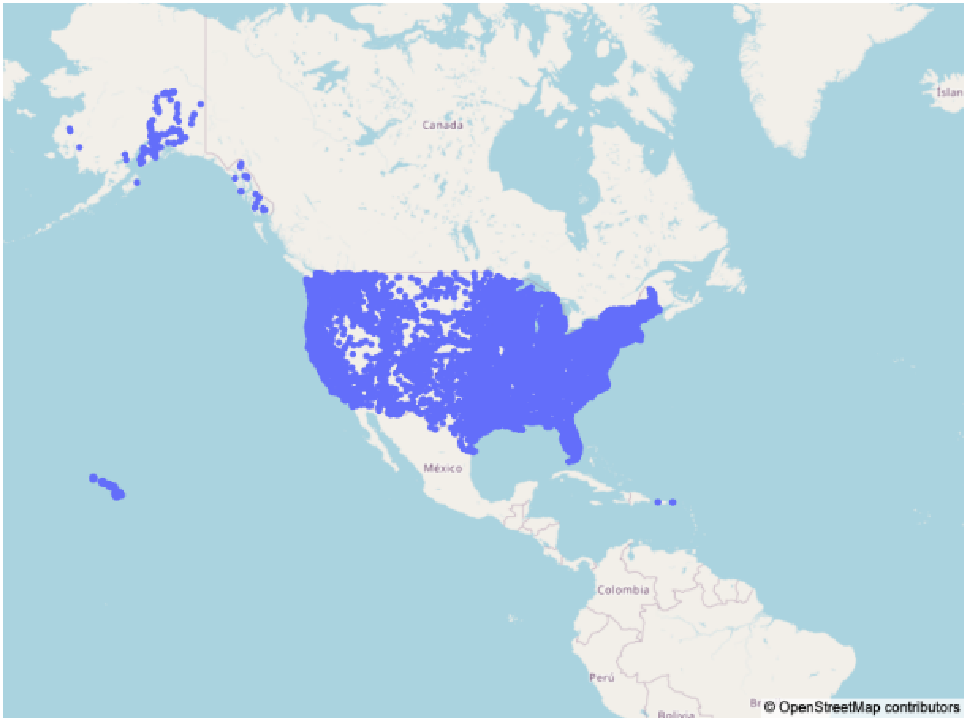


Figure 4: Distribution of parks that have reviews, images, and data of visiting patterns

2.2 Methods

2.2.1 Sentiment Analysis and Topic Modeling for Reviews

Visitor's experience of green spaces significantly influences urban vitality (F. Wu et al., 2023). Drawing from methods used by Lee & Yu (K. Lee & Yu, 2018), who employed sentiment analysis and topic modeling on Google reviews to assess airport service quality, this study also utilizes Google Maps as a source for review data. Using extensive URL engineering, we scraped reviews for green spaces identified in the Dewey Monthly Pattern GPS dataset, using the names and coordinates as keywords. Unlike using the API, which only provides a relative time range (e.g., "3 days ago", "5 years ago"), our URL engineering methods allowed us to capture the exact publication date of each review, enhancing accuracy. For privacy, no usernames or personal information were collected. However, I also acknowledge that this method is against Google's policy; thus, sharing the data is prohibited. Figure 4 shows the distribution of reviews across months, which roughly corresponds to the visiting counts from the Dewey Monthly Pattern dataset. Then we performed sentiment analysis and semi-supervised topic modeling methods on the reviews collected.

A fine-tuned BERT-based sentiment analysis model from Hugging Face is first used to quantify review sentiments. This pre-trained deep learning model effectively captures natural language semantics, assigning sentiment scores ranging from –1 (extremely negative) to 1 (extremely positive). The scores enable us to accurately assess reviewers' emotional tendencies, thereby enhancing our understanding of visitor satisfaction and feedback. Figure 5 illustrates the distribution of sentiment scores.

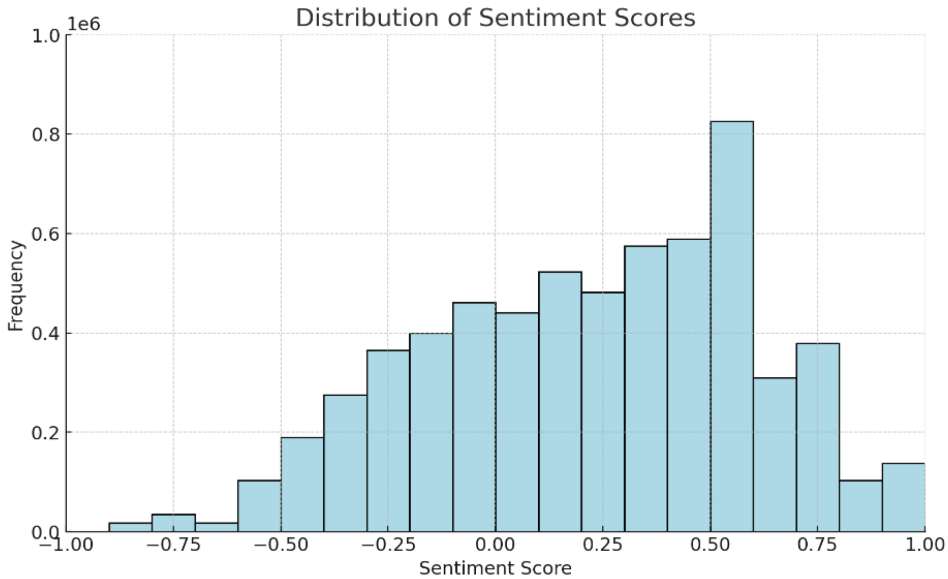


Figure 5: Distribution of sentiment scores

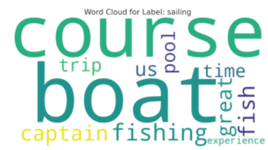
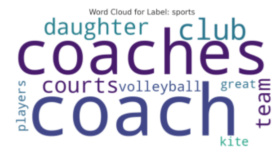
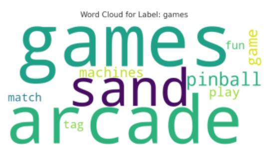
We manually review each word and then name the topic based on the relevance of groups of keywords. According to our results, there are a total of 16 different topics, and 11 of them are of our interest. We have excluded the non-interesed topic to others.

Then we utilized the semi-supervised topic modeling method, BERTopic, to extract significant topics from the textual data. This method offers key advantages: (1) it allows us to guide the creation of topics toward specific, pre-defined themes; (2) we can manually add or remove words to fine-tune topics; and (3) we can adjust the weight of each word within a topic. Unlike traditional unsupervised topic modeling methods, which often fail to cluster large datasets into meaningful categories, BERTopic ensures that the topics and top-weighted words are aligned with our research interests. Reviews that do not fit into relevant topics are labeled as "-1." Appendix 2 details how the model works and how we adjusted topic weights. Table 1 presents word clouds for each topic alongside the distribution of reviews per topic. The majority of reviews focus on the walkability of green spaces, followed by topics on water activities, various sports options, and the presence of friendly people.

The following table shows (1) the theme of each topic, (2) the word cloud of each topic, and (3) the number of reviews for each topic. After performing the BERTopic on the collected text-based reviews, the model will generate a list of words along with their weights. In the word clouds below, each word is a keyword in the BERTopic model and the size of each word represents its weight. We manually review each word and then name the topic based on the relevance of groups of keywords.

<table>
<tr>
<td>Walkability

1,819,109 Reviews</td>
<td>Store and Service

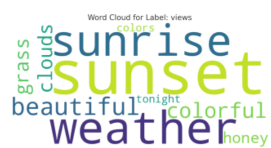
32,776 Reviews</td>
<td>Water Activity

1,332,164 Reviews</td>
<td>Sports

575,626 Reviews</td>
</tr>
<tr>
<td>Games and Entertainment

4,723 Reviews</td>
<td>Party

216,929 Reviews</td>
<td>Unsafety

47,165 Reviews</td>
<td>Good Neighborhood

216,929 Reviews</td>
</tr>
<tr>
<td>Good Green Space

11,589 Reviews</td>
<td>Personal Care

519,624 Reviews</td>
<td>Great View

190,472 Reviews</td>
<td>Others

1,259,000 Reviews</td>
</tr>
</table>

Table 1: The word clouds for each topic and the number of reviews per topic. Their themes are extracted by analyzing the keywords of each topic.

2.2.2 Google Street View Images

Previous studies have shown that environmental features like green spaces and spatial openness impact human visitation (M. Chen et al., 2024; J. Song & Schuett, 2023). Since the 360-degree images primarily capture street entrances, we selected images closest to each POI to ensure accurate representation. Using the POI's geographic coordinates, we retrieved the corresponding street view images and applied the PSPNet model with the ADE20K dataset for image segmentation (Figure 6).

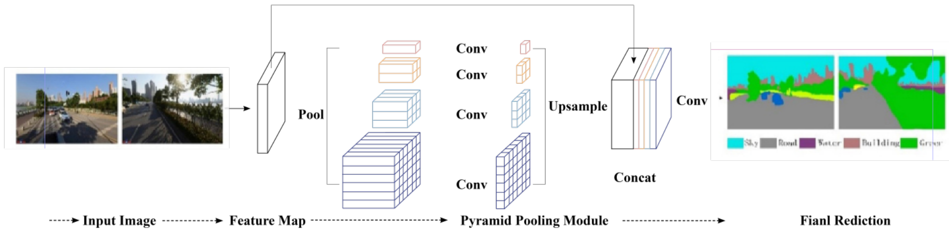


Figure 6: Schematic diagram of PSPNet model.

This process labeled approximately 150 object categories, enabling pixel-level semantic segmentation. We calculated the proportions of various elements to quantify the environmental features. The proportions of environmental features such as sky, tree, and road have been captured in alignment with our research objectives. Figure 8 highlights some of the most observed environmental features and their distribution, according to Figure 7.

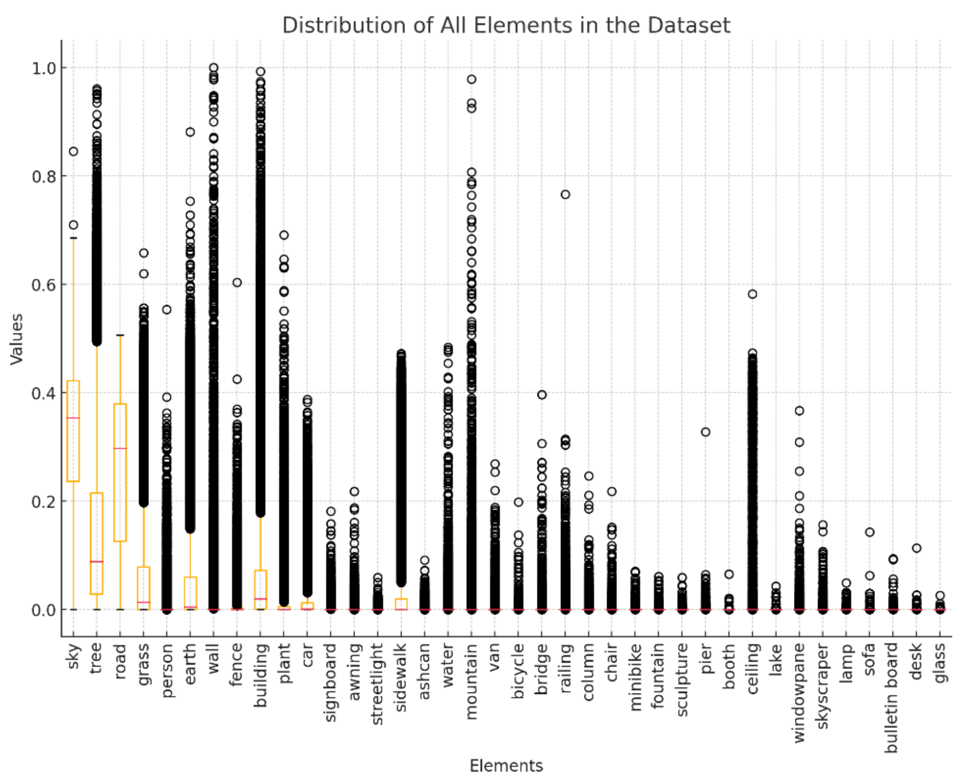


Figure 7: Distribution of environmental features.

2.2.3 Regression Model: Random Forest and Partial Dependence Plot

To explore potential nonlinear relationships between variables, we employed a random forest model. This ensemble learning method effectively captures complex interactions by constructing multiple decision trees and aggregating their results. We chose random forest for its ability to uncover intricate variable relationships. Using visitor's experience, environmental features, and SVI indices as independent variables, we constructed yearly models from March to August for each year from 2019 to 2023. This timeframe is expected to capture the peak pandemic period in 2020 when multiple states enacted statewide lockdowns, allowing us to analyze the non-linear relationships between these variables and visiting counts, dwell time, and travel distance while comparing how these features impact visit behavior in different years. In total, 15 models were built to examine these relationships.

We then used Partial Dependency Plots to understand the influence of independent variables on a target variable independently. PDPs visualize the effect of changes in a single independent variable while controlling for others, helping to identify key turning points or thresholds where variable effects shift. This analysis allowed us to verify nonlinear relationships and optimize the model accordingly (Cao & Tao, 2023b; F. Wu et al., 2023). The PDP visualization offers insights into variable interactions, where the x-axis represents the feature's values, while the y-axis shows the average predicted outcome when that feature is fixed at each value, marginalizing over all other features. In this type of plot, a wider spread on the y-axis indicates that the feature has a stronger influence on the model's predictions, whereas a narrower spread suggests a weaker effect. If the PDP line slopes upward, it means that as the feature increases, the model's predicted outcome tends to increase; if it slopes downward (negative line), higher feature values lead to lower predictions. A flat line indicates that changes in the feature have little or no impact on the model's predictions.

3 Results and Discussions

3.1 Features Serving as Basic Needs in Hypothesis

Table 2 presents the impact of grass coverage, as captured through Google Street View imagery, on visitation patterns using Partial Dependence Plots. The analysis reveals a negative association between grass coverage and visiting counts but a positive association with both dwell time and travel distance. Contrary to our initial assumption that grass is a basic need for green space visitors, it has not had a significant impact over the five-year period analyzed. This reduces its relevance in our study, as the coverage of the y-axis across three different green space visitation patterns is consistently small, indicating minimal variation across years.

Table 2 presents the impact of grass coverage, as captured through Google Street View imagery, on park visitation patterns using Partial Dependence Plots. The analysis reveals a consistent negative association between grass coverage and visiting counts across all five years from 2019 to 2023. This suggests that as the percentage of grass coverage increases, fewer people tend to visit parks, a pattern that remains stable over time, irrelevant of Covid's impact, while becoming counterintuitive. Such result challenges the common assumption that grass represents a basic, universally attractive feature of urban green spaces. While grass coverage may appeal to certain visitors seeking tranquil or aesthetically pleasing environments, it appears to be less relevant in attracting high volumes of visitors.

In contrast, both dwell time and travel distance show positive associations with grass coverage during the same period, indicating that visitors who choose to go to grass-heavy parks are likely to stay longer and travel farther to reach them. The increase in both variables suggests that parks with greater grass coverage serve more specialized purposes, such as quiet leisure, picnicking, or passive recreation, which attract fewer but more dedicated users, even though the topic ”Good Green Space” does not play a major role in our model. Therefore, while grass may enhance the depth of engagement for some users, it does not appear to play a major and universal role in shaping broader visitation dynamics across urban green spaces over time.

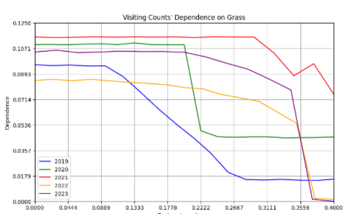
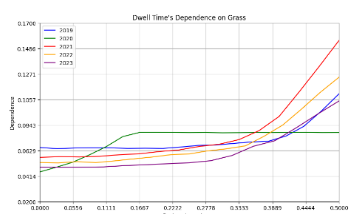
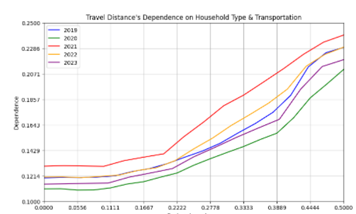
Visiting Counts' Dependence on Grass from Street Views	**Dwell Time's Dependence on Grass from Street Views**	**Travel Distance's Dependence on Grass from Street Views**
		

Table 2: Grass' Impact on Green Space Visitation Patterns

Table 3 shows the positive impact of tree coverage on total visitor counts, particularly during the pandemic, aligning with the category of basic needs. During 2020 and 2021, visitor counts increased sharply and exponentially with higher tree coverage, suggesting that more trees strongly attracted more visitors during times of crisis. In other years, although a positive association between tree coverage and visitor counts persisted, the rate of increase was notably less steep. This pattern stands in contrast to the results for grass coverage: while trees consistently attracted more visitors, greater grass coverage was associated with lower visiting counts. This divergence offers questions on how different types of vegetation are perceived and used in urban green spaces. One possibility is that trees provide not only aesthetic value but also critical functional benefits, such as shade, shelter, and a stronger sense of enclosure, which become especially important during times of heightened stress like the pandemic, providing comfort and a sense of protection. Grass, by contrast, may be perceived as offering fewer immediate physical or psychological comforts, despite its symbolic association with nature. Future research could further investigate how users differentiate between grass-dominated and tree-dominated spaces in terms of perceived safety, comfort, and emotional restoration, particularly under crisis conditions."

However, dwell times showed a threshold effect, increasing up to a point before declining. The pattern may suggest that excessive tree coverage will discourage longer stays, potentially due to reduced walkability within densely green spaces. Meanwhile, this threshold effect is evident both during and outside the pandemic. In contrast, no consistent or significant patterns were observed regarding the impact of tree coverage on travel distance across the years, as the patterns appear to be chaotic.

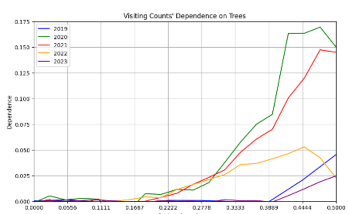
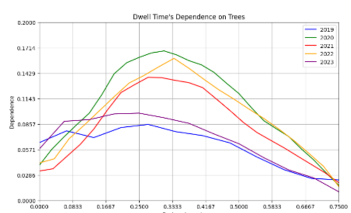
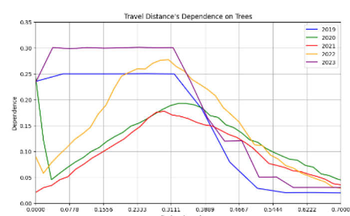
Visiting Counts' Dependence on Tree from Street Views	**Dwell Time's Dependence on Tree from Street Views**	**Travel Distance's Dependence on Tree from Street Views**
		

Table 3: Tree's Impact on Green Space Visitation Patterns

According to Table 4, road connectivity derived from Google Street Views plays an important role as a complementary dimension of walkability, specifically assessing the accessibility of green spaces as part of fulfilling basic needs; this is especially useful in this study as the weight of walkability derived from Google Business Reviews is low. During and after the pandemic, the presence or absence of a road connection to a park significantly influenced visitation counts positively, which suggests that accessibility - not necessarily the quality or size of the road - is a primary determinant of whether people choose to visit a particular green space. Interestingly, the percentage of road coverage as captured in Google Street View images appears to be largely irrelevant, indicating that road width or visual prominence does not significantly shape visitation behavior.

More notably, travel distance shows a strong dependence on road connectivity, especially in 2020 and 2021. This indicates that during the pandemic, when mobility was constrained and preferences shifted toward local and easily accessible spaces, people were more likely to travel farther to reach parks that were better integrated into the road network. This suggests that connectivity may have acted as a proxy for perceived safety, convenience, or familiarity during uncertain times.

An unexpected yet compelling pattern emerges when considering road width: as road width increases, average travel distance to parks decreases. This counterintuitive result may suggest that wider roads, often associated with car-centric infrastructure, do not necessarily facilitate access to more distant green spaces: in fact, they may signal environments that are less pedestrian-friendly, thus deterring longer trips. Alternatively, it may indicate that parks located near wider roads are more likely to serve local populations with dense residential surroundings, reducing the need for long-distance travel. This finding calls for further investigation into the interaction between road typology, perceived accessibility, and transportation mode choices. It also raises the question of whether wider roads represent physical or psychological barriers to green space access in certain neighborhoods.

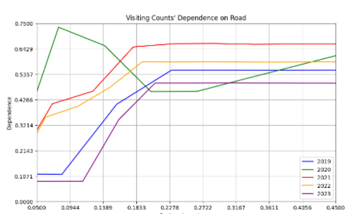
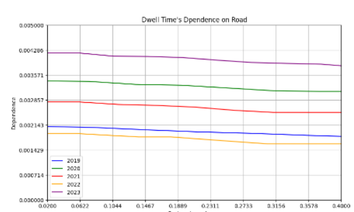
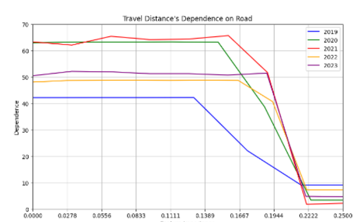
Visiting Counts' Dependence on Road from Street Views	**Dwell Time's Dependence on Road from Street Views**	**Travel Distance's Dependence on Road from Street Views**
		

Table 4: Road's Impact on Green Space Visitation Patterns

3.2 Features Serving as Non-Basic Needs In Hypothesis

Table 5 shows that water activities' impact on visitation counts over time, reflecting their evolving role in green space usage. In 2020, the presence of water activities had a consistently high impact on visitation, suggesting that parks offering such amenities provided a vital source of leisure during the uncertainty of the early pandemic. In 2021, this effect became even more pronounced, with a clear threshold pattern emerging—once water activity offerings surpassed a certain level, visitation counts increased sharply. This threshold effect was notably stronger in 2021 compared to 2019, 2022, and 2023, when the increases were more gradual. One possible explanation is that in 2021, the partial reopening of outdoor venues, including water-based recreation, met a surge in public demand for safe yet engaging outdoor experiences. By contrast, in non-pandemic or post-crisis years, the appeal of water activities may have been more steady, with less dramatic fluctuations. Furthermore, the consistently high number of Google Business Reviews for parks offering boating and fishing reinforces their popularity across all years, suggesting that such features are not only appealing in times of crisis but represent enduring attractions that shape user engagement with green spaces.

The impact of water activities on dwell time displays a distinct temporal variation, with 2020 standing out as an exceptional year. That year, dwell time increased sharply even at the lowest levels of water activity offerings. This suggests that when most facilities were closed or restricted due to public health mandates, any park that remained open with boating or fishing opportunities became a rare and valuable destination: one where visitors chose to stay longer, perhaps compensating for a lack of other recreational options. In contrast, for the years 2019, 2021, 2022, and 2023, dwell time showed a threshold pattern: it increased only after a certain level of water activity presence was reached. This may imply that in more typical years, water activities began to significantly shape visitors' behavior only after such parks gained popularity as reflected through an increase in user-generated reviews. Thus, while water-based features remained important throughout the years, their role in encouraging prolonged park stays during 2020 may reflect both their scarcity and emotional salience amid crisis conditions.

The relationship between water activities and travel distance reveals a counterintuitive and somewhat consistent pattern. In 2020, the height of the pandemic, parks with boating or fishing facilities had a limited impact on how far visitors were willing to travel. This could be due to widespread movement restrictions, risk aversion, or closures of specific facilities, which collectively discouraged long-distance travel even to attractive destinations. Interestingly, in 2019 and 2021, water-based activities appeared to have a much stronger effect on travel distance, with users traveling farther to reach these green spaces. While this aligns with pre-pandemic recreational patterns (2019) and the resurgence of outdoor exploration following restrictions (2021), the discrepancy with 2020 presents an analytical challenge. One possibility is that the structure of the random forest model used to analyze these relationships may have underweighted this interaction due to sparse data or nonlinearities not well captured in tree-based models. This highlights a limitation in interpretability, suggesting the need for future studies to apply more complex models or incorporate qualitative evidence to better explain these surprising shifts. A methodological discussion of this limitation is included in the Discussion section of this paper.

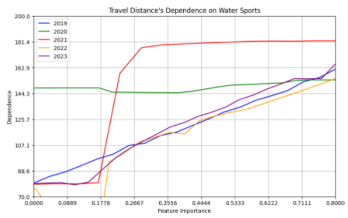
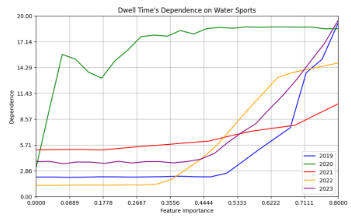
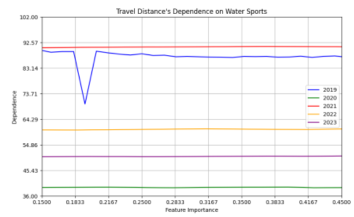
Visiting Counts' Dependence on Water Activity from Street Views	Dwell Time's Dependence on Water Activity from Street Views	Travel Distance's Dependence on Water Activity from Street Views
		

Table 5: Water Activity's Impact on Green Space Visitation Patterns

Reviews related to sports increasingly focus on professional sports, particularly those involving a coach, as highlighted by the emphasis on coach quality in the word cloud presented in Table 1. Overall, during the pandemic, sports had the least impact on visiting counts and dwell times compared to other periods, supporting the hypothesis that sports are a non-basic need. However, the data also reveal that during the pandemic, if sports fields were open and a coach was available, visitors were more willing to travel long distances to access these facilities. Nevertheless, the narrower range of the y-axis for travel distance indicates that only a small proportion of visitors were able to travel long distances during the pandemic, further underscoring the limited impact of sports relative to visiting counts and dwell times (Schlosser et al., 2020).

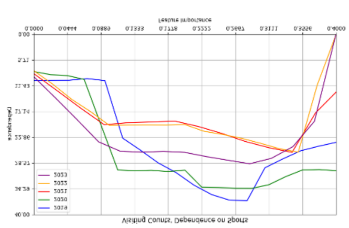
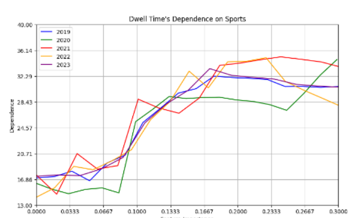
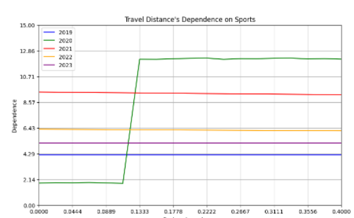
Visiting Counts' Dependence on Sports from Street Views	Dwell Time's Dependence on Sports from Street Views	Travel Distance's Dependence on Sports from Street Views
		

Table 6: Sports' Impact on Green Space Visitation Patterns

The remaining non-basic features in our hypothesis did not significantly impact the model's performance across years and were therefore excluded from the discussion. However, features such as water activities and sports exhibited notable and complex effects on visiting patterns. Contrary to our hypothesis that non-basic features would lose their influence on visiting patterns, the findings indicate variability even within non-basic features. For example, water activities and sports differently affected dwell time and travel distance. This highlights the need for further investigation into not only the role of non-basic features in urban green spaces but also their variability during the pandemic and the factors driving such variation. These findings also suggest the potential need for a refined classification of non-basic features.

3.3 Understanding Inequality's Impact on Green Space Visitation

Among the four categories of the Social Vulnerability Index (socioeconomic conditions, household characteristics, racial/ethnic minority status, and housing type and transportation), only housing type and transportation had a notable impact on visitation patterns, though their influence remained significantly lower than previously examined features. This limited effect may be attributed to the relatively small variation in the Social Vulnerability Index among the green spaces included in the model. Since the model selected green spaces that simultaneously had reviews, Google Street View images, and GPS-based data, it is possible that these green spaces represent similar socioeconomic backgrounds, suggesting the need to check colinearity in the future.

Interestingly, housing type and transportation emerged as the only significant factors among the 4 different SVI indices due to its relatively wider y-axis coverage compared with other indices, but no obvious pattern can be observed. As shown in Table 7, at the beginning of the pandemic (year 2020), indicated by the green line, a slight increase in housing type and transportation was associated with a significant decrease in dwell time in green spaces. However, no variation in visiting counts or travel distance was observed. Given the narrow range of the y-axis from 0 to 0.12, it is also possible that the variation in dwell time was influenced by noise, which will be discussed in the next section on the limitations of the current methodology, particularly the challenges in accurately capturing the effects of socioeconomic status on visitation patterns. Therefore, the Social Vulnerability Index, as a proxy for the socioeconomic status of green spaces, failed to demonstrate a meaningful impact on visitor behavior in this model.

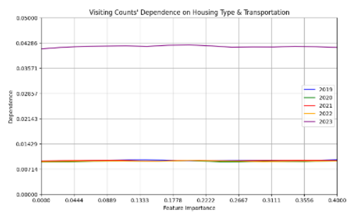
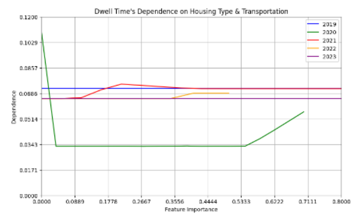
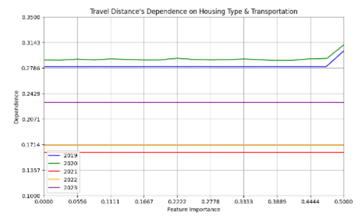
Visiting Counts' Dependence on Housing Type & Transportation from Street Views	**Dwell Time's Dependence on Housing Type & Transportation from Street Views**	**Travel Distance's Dependence on Housing Type & Transportation from Street Views**
		

Table 7: Housing Type & Transportation' Impact on Green Space Visitation Patterns

4 Limitation

This study explores different features' impact on visitation patterns from 2019 to 2023 on a nationwide scale by enriching GPS-based data with images and reviews to satisfy the graduation requirement of the MACSS program at the University of Chicago. However, several issues render the accuracy of this analysis, making it a few steps away from the level of publishment:

(1) Google Street View data captures only green space entry points, which may not represent overall green space characteristics. For example, entry tree coverage may differ from internal coverage. My future work will incorporate satellite imagery and apply the PSPNet model to analyze features such as water, grass, trees, buildings, sports fields, and children's facilities, allowing seasonal variation to be controlled as a confounder.

(2) In this version, I use the Social Vulnerability Index as a proxy for the socioeconomic status of green spaces, a county-level dataset from 2021 that fails to capture temporal changes during the pandemic. Subsequent analyses will utilize quarterly or annual census-level data to improve temporal precision.

(3) Reviews are disproportionately concentrated in prominent green spaces (e.g., Central Green space), potentially reflecting tourist rather than local perspectives. Future studies will distinguish between local and non-local reviewers to enhance validity: for example, one feature in the Google Busines Review marks reviews as "local guide", whose reviews are frequently longer and more meaningful. We can easily use this feature to achieve this purpose.

(4)Random forests and partial dependence plots, while useful exploratory tools, are not considered sufficiently rigorous modeling approaches for academic research in the social sciences. As Professor Michael Bader and his colleagues note, "...the successful use [of machine learning models] in neighborhood research has been more limited. One reason for this is that algorithms designed to select the variables that together best predict an outcome do not, in general, select a subset of distinct variables that are most causally relevant" (Rundle, Bader, & Mooney, 2022). Furthermore, they emphasize that neighborhood predictors are often highly correlated - for example, the percentage of households living in poverty is closely linked to median household income - which can cause naive variable selection methods to produce unstable results, with minor changes in the dataset leading to significantly different selections of variables. Consistent with these concerns, we find that some of our current results are not robust enough to support empirical conclusions such as the result produced by Table 2, highlighting the limitations of using such machine learning approaches in this context.

5 Conclusion

This study has examined the dynamic impacts of environmental features, visitor experiences, and socioeconomic status on green space visitation patterns in the United States before, during, and after the COVID-19 pandemic. By integrating GPS-based visitation data, Google Business reviews, Google Street View images, and county-level socioeconomic vulnerability indices through advanced machine learning methodologies, this research provides nuanced insights into how public usage of urban green spaces evolves under societal disruptions.

Key findings underscore the differential roles of basic and non-basic green space amenities during the pandemic. Essential features such as tree coverage, walkability, and road connectivity emerged as significant determinants of visitation frequency, highlighting their critical role in facilitating routine access during crisis periods. Conversely, non-basic features, including water-based activities and sports amenities, attracted a smaller but distinct group of visitors who exhibited extended dwell times and increased travel distances, suggesting that during times of heightened stress, certain amenities offer particularly meaningful recreational experiences.

Importantly, the study identified clear threshold and nonlinear effects, demonstrating that green space visitation is not merely influenced by the presence of specific features but also by their quantity, quality, and accessibility. Notably, unexpected patterns - such as the inverse relationship between road width and travel distance, and the contrasting roles of grass versus trees - invite further exploration into how people perceive and value urban environmental features differently based on their immediate physical and psychological needs.

The research has both theoretical and practical implications. Theoretically, it expands our understanding of urban ecology and visitor behavior by emphasizing the interplay between structural environmental attributes, experiential preferences, and socioeconomic disparities, especially during crises. Practically, it alerts policymakers and urban planners to existing green inequalities, reinforcing the need to prioritizecertain feartures in urban green space design and management, particularly under conditions of societal disruption.

Future studies should further refine methodologies by incorporating more granular spatial datasets, longitudinal sentiment analysis, and advanced spatial-temporal modeling to deepen our understanding of these complex relationships. Ultimately, enhancing equitable access to multifunctional urban green spaces is crucial not only for fostering community resilience during public health emergencies but also for promoting sustained urban livability and social equity in the long term.

Data and Code Availability Statement

A section of the aggregated data and code can be found here via GitHub. Please email chenanzhi@uchicago.edu to request the full data. However, the original raw data cannot be shared for the following reasons.

Social Vulnerability Index: Images were obtained via web scraping from Google Street View. Redistribution of the raw images is not permitted under Google's Terms of Service. Researchers can access Google Street View imagery directly through their official website or the Google Maps API, subject to Google's licensing agreements.

Google Street View images: Images were obtained via Google Street View and are subject to Google's Terms of Service. Due to licensing restrictions, these images cannot be redistributed or shared. Further information about access and usage policies is available at here.

Google Business Reviews: Review texts were collected through web scraping from Google Business Profiles and are subject to Google's Terms of Service. Redistribution of the original review content is not permitted. For more information, see their website for more details but redistribution of raw review texts is restricted under Google's Terms of Service.

Dewey Monthly Patterns: Foot traffic data was obtained from Advan Research's Monthly Patterns dataset via the Dewey Data platform. Access to this dataset was granted under an academic subscription license, which permits use for research purposes but prohibits redistribution of the raw data. Researchers interested in accessing this dataset can explore subscription options at their official website .

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