Park access affects physical activity:

New evidence from geolocated Twitter data analysis

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Abstract

This study analyzed the association between park access and physical activity in an urban context by extracting tweets from the social media platform Twitter. The results show that areas within a 0.5-mile distance to a park correlate with more physical activity than areas farther than that. Park type might be an essential mediator for the correlation between park size and physical activity. This study suggests that geolocated Twitter data are a viable source of information for researchers inquiring about factors related to urban open space that can contribute to public health.

Keywords: big data, park access, physical activity, urban open space, Twitter

Introduction

Twitter enables researchers to work with a vast amount of spatial and temporal data that include constantly updated information about individual opinions and activities. These data provide an opportunity to develop new ways to understand urban spaces and social phenomena. For instance, researchers used tweets to examine trends in public health, such as healthy food choices (Chen and Yang 2014; Widener and Li 2014) and disease occurrence (Jahanbin and Rahmanian 2020; Nagel et al. 2013). They also used Twitter data in tourism geography by analyzing tourist behaviors and destinations (Garcia-Palomares, Gutierrez, and Minguez 2015; Oliveira and Huertas 2019). Despite the growing amount of research using innovative big data approaches, few studies have used social media to understand urban open space and its effects on human health. Given the massive amount of spatiotemporal information, Twitter data have great potential to complement the information provided by traditional data sources to study urban open space and its influence on health-related behaviors.

Research has shown that the built environment—including open green space, transportation, food outlets, and recreational facilities—can affect physical activity and human health (Handy et al. 2002; Smith et al. 2017). Urban parks and green spaces are critical components of communities and neighbourhoods, affecting residents' quality of life and well-being (Wright Wendel, Zarger, and Mihelcic 2012). The traditional measure of the association between the built environment and health-related activities has been based mainly on survey questionnaires or official statistics. The lack of large quantities of appropriate individual activity data for these approaches has been a shortcoming (Kaczynski and Henderson 2007). With the increasing popularity of social media, it is now possible for researchers to access a vast amount of information about individual spatiotemporal behaviors and understand individuals' interactions with urban open spaces.

The research presented in this paper examines the association of the access to public parks with physical activity—more specifically, active travel behaviors such as walking, jogging, running, and biking—in metropolitan Atlanta in the United States. There are three forms of accessibility —visual, symbolic, and physical (Carr et al. 1992,138, as cited in Carmona et al. 2003). This research mainly focused on physical access, more specifically, the physical proximity to public parks. It should be noted that physical access does not guarantee that the public is able to get into or to use the environment because visibility and symbols (e.g., threatening or inviting) may affect entry into a public space (Carmona et al. 2003). Individual physical activity extracted from geolocated Twitter data in 2017 was linked with the location and size of parklands using GIS land parcel data. This study aims to identify the mechanism by which environmental influences translate into individual choices of physical activities. It contributes to the growing urban design and public health literature on understanding the role of urban open space in promoting physical activity, using a combination of big spatial data and geographic information science-oriented concepts.

Prior research on park access and physical activity

Many studies have analyzed how behavior occurs in relation to built environmental factors. They found consistent positive correlations between physical activity and the built environment, such as access, aesthetics, comfort, and safety (Knapp et al. 2019; Saelens, Sallis, and Frank 2003). Among these studies, the role that parks and recreation settings plays in promoting physical activity has been addressed (Cohen et al. 2016; Kaczynski and Henderson 2007; Schultz et al. 2017). For instance, people who had used parks in the previous month were four times more likely to have engaged in physical activity (Deshpande et al. 2005). Some studies measured the association between park features such as amenities (e.g., sports court, walking trails) or size and physical activity. Others focused on park access, with variables such as park proximity (measured as distance to nearest park) and park density (measured as the presence or number of parks within a certain distance) (Bancroft et al. 2015). The findings for the impacts of park amenities and park size on physical activity are generally positive. For instance, Li et al. (2005) found that recreational open space within 0.5 mile of participants' homes was significantly related to neighbourhood walking activity for older adults. Bedimo-Rung, Mowen, and Cohen (2005) similarly observed that park environmental characteristics, including park features, conditions, access, safety, and aesthetics, could significantly facilitate physical activity.

Studies also found a significant positive association between park access and physical activity when using density and proximity measures (Cohen et al. 2006; Jago, Baranowski, and Harris 2006). It has been emphasized that the presence of parks, trails, and other public recreational facilities helped people reach the recommended 30 minutes per day of moderate-intensity physical activity (U.S. Department of Health and Human Services 2000). Studies have revealed that people who live within walking distance of urban parks are more likely to get the recommended daily physical activity (Giles-Corti et al. 2005). Having access to parks or recreation facilities was positively associated with the physical activity of study participants (Salvo et al. 2017; Zhai et al. 2020). More specifically, the density of parks within 1 mile was significantly associated with moderate to vigorous physical activity (Norman et al. 2006; Young et al. 2014). There was also a positive association between park proximity and neighbourhood walking (Humpel et al. 2004a; Humpel et al. 2004b; Rutt and Coleman 2005; Tappe et al. 2013). Chad et al. (2005) observed that the presence of a public park, walking/hiking/biking trails, or other recreational facilities within a 5-minute walk or drive of the neighbourhood predicted significantly higher physical activity scores. Deshpande et al. (2005) similarly reported that shorter walking times to parks, recreation centers, or biking/walking trails were associated with more regular physical activity. Children between 10 and 12 years old with no nearby parks had significantly lower odds of walking or cycling to destinations at least three times per week (Timperio et al. 2004).

Despite the general findings of the positive relationship, other studies found no significant and even a negative association between park access and physical activity (Duncan et al. 2004; Foster, Hillsdon, and Thorogood 2004; Hall and McAuley 2010; Saelens et al. 2012; Strath et al. 2012). Rutt and Coleman (2005), for instance, found that the number of parks, gyms, and trails within 2.5 miles (4 kilometers) of participants' homes was not related to the number of minutes per week the participants spent engaged in physical activity. Carlson et al. (2012) suggested that the number of parks within a 0.3-mile (500-meter) buffer around each participant's home was not significantly related to moderate or vigorous physical activity. There was no significant association between having any park, walking trail, or other recreational facilities within walking distance and meeting recommended levels of physical activity (Hoehner et al. 2005; King et al. 2005; Li et al. 2005; Lund 2003). Duncan and Mummery (2005) even argued that participants who had the most proximal parkland farther than 0.4 mile (0.6 kilometer) and those who had little convenient proximity were more likely to achieve recommended levels of activity than those who lived closer and had more direct routes to the parkland.

Kaczynski and Henderson (2007) argued that the existing studies provided some evidence about the importance of access to parks in promoting physical activity, but the findings were inconclusive. The mixed results might be partially attributed to the wide range of spatial definitions and measurements adopted by those studies. Ferdinand et al. (2012) reported that the built environment was 18% less likely to be associated with objectively measured than self-reported physical activity. Bancroft et al. (2015) found that studies using smaller buffers indicated a stronger association with physical activity than larger buffers. Studies with objective measures of park proximity tended to have fewer significant findings than studies with perceived measures. Note that there might be potential limitation to only using measure of distance to predict physical activity (Song et al. 2017). As Wilkie et al. (2018) argued it is essential to include measures of quality and quantity because multiple factors impact people's choices of physical activity. In addition, the traditional measure of the association between park access and physical activity based on individual-level survey questionnaires presents some limitations. First is the time-consuming process of collecting a considerable number of individual samples. Second, according to Sallis et al. (2006), most of the research related to parks and recreation involved middle-class, predominantly white adults living in urban and suburban settings. Third, park access studies are based on participants' home locations, which assumes people use the parks near their homes. This assumption overlooks the effects of mobility on physical activity behaviors because people might go to parks close to their workplaces or travel to use more attractive parks (Kaczynski and Henderson 2007; Chen and Yang 2014).

Twitter data have been used in urban space research as a new or an alternative source of information characterizing human behaviors, preferences, and sentiments relating to parks and urban green spaces (Donahue et al. 2018; Roberts 2017; Plunz et al. 2019; Wilkins et al. 2021). A unique feature of Twitter is that its users can share the places where they have conducted a physical activity with geotagged tweets, which contain the site's exact location. Those locations can be used as digital footprints to link people's activities in urban spaces. Indeed, research using geotagged tweets to study people's daily activity patterns in U.S. cities has suggested that the data consistently reveal various daily activities, such as staying at home, going to work, and engaging in leisure and recreational activities (Yin and Chi 2021). Given the history of research examining the impact of urban parks on physical activity, it is of interest to use geotagged tweets in metropolitan cities to analyze the spatial patterns of tweets related to physical activity. More specifically, observing the physical activity conducted in or near urban parks may provide valuable insights into the influence of urban parks on people's physical health.

The new spatial data of Twitter provides some advantages, including an opportunity for researchers to explore larger samples and broader contexts in longer time horizons with no subjective bias related to collection of data on humans. However, it also creates some concerns regarding the data representativeness of larger populations (Sulis et al. 2018). Studies documented that American Twitter users tended to be younger, wealthier, more educated, urban, and non-White compared with the general population (Blank 2016; Pew Research Center 2019). Although Twitter data sets might be limited in representing a full view of urban realities despite their extensiveness, studies have validated the use of Twitter in human mobility studies in urban areas (Plunz et al., 2019). Lenormand et al. (2014) suggested that Twitter, census, and cellphone data offer comparable information about the spatial distribution and mobility of urban residents. Moreover, the results are comparable to the findings from large-scale travel surveys and mobile phone location data that offer limited access for researchers. In addition, geolocated Twitter data enable us to go beyond the home location of participants (as often used in traditional survey methods) to analyze a more dynamic relationship between park access and physical activity patterns.

Methods

Data Collection

This research examined whether spatial variations of physical activity, including walking, jogging, running, and biking, were associated with access to urban parks. It measured the spatial distribution of physical activity by identifying the locations of the tweets whose content included keywords related to physical activity. Park distance and park size constitute two significant elements of park access. The spatial analyst function of ArcGIS (ESRI®) was used to measure park distance by measuring the distance from each tweet's location to the nearest park. The park's size was extracted from park data provided by Planning GIS Open Data of the City of Atlanta (City of Atlanta Department of City Planning 2020).

Atlanta is considered the nation's "most livable city" because it boasts more green space per person than any other major American city (Geotab, n.d.). However, Atlanta's park system ranked 50th among the 100 most popular cities in the United States on the 2017 ParkScore index released by the Trust for Public Land. Its rank rose to 27th in 2022 because of the addition of two major parks—Cook Park and Westside Quarry—and improvement to access. ParkScore evaluates five characteristics of an effective park system: access, acreage, amenity, investment, and equity. With the improvements made, Atlanta currently has 77% of residents living within a 10-minute walk of a park (Trust for Public Land 2022).

Based on the Planning GIS Open Data of the City of Atlanta, there are 373 parks in the city (Fig. 1). The parks are categorized into nine types: regional park, community park, neighborhood park, playlot, nature preserve, green spot, special facility, park in holding, and others (City of Atlanta, n.d.). Among these nine types of parks, a little less than half are green spots (n = 168), which are defined as medians, cul-de-sacs, small green spaces, and building fronts containing small patches of greenery. The green spots are typically small and adopted by neighborhoods and other entities for care and maintenance. The second-largest park type is neighborhood parks (n = 70), which focus on informal recreation and provide residents a local outlet for play and social activities. Neighborhood parks often provide amenities such as playgrounds, basketball courts, and community gardens, but they typically do not have a recreation center on-site. Community parks (n = 43) serve a broader area and a larger population, and they preserve landscapes and open spaces to meet community-based recreational and social needs. Community parks typically have the capacity to house a recreation center or recreational facilities. In addition, there are 38 playlots (small areas providing amenities or green lots for community members to gather), 17 nature preserves (land set aside for preserving natural resources, historic landscapes, and open spaces and providing visual aesthetics/buffering), 11 large-scale regional parks (parks that can accommodate large or small events), 6 special facilities (parks and recreation facilities oriented toward single or unique purposes), 16 parks in holding, and 4 others (no classification). This study focused on four types of parks—green spots, neighborhood parks, community parks, and playlots—because those parks constitute around 85% of all parks in Atlanta.

Fig 1. (a) Locations of parks in Atlanta (highlighted in green) and the distribution of physical activity–related tweets collected between Jan. 1 and Dec. 31, 2017 (shown in blue dots). (b) Spatial distribution of the nine types of parks in Atlanta.

The study extracted 147,821 tweets considered related to physical activity within the city boundary from Jan. 1 through Dec. 31, 2017. Because the research focused on active travel behaviors such as walking, running, and biking, the tweets were selected by using keywords such as 'run,' 'bike,' 'walk,' 'jog,' and accommodated for possible modifications such as 'ran' and 'biking,' as well as variations in upper/lower cases such as 'BIKE' and 'Bike.' Note that use of those keywords in tweets, however, did not guarantee relevance to physical activities because the keywords can be used in different contexts. In response, a naïve Bayes classifier was trained to determine whether the tweet content was about physical activity. The classifier is a machine-learning module developed in the TextBlob library (Loria 2018), a natural language processing (NLP) toolbox for processing textual data. Because the classifier is based on a supervised machine-learning model, the first step is to provide a labeled training dataset. In that step, 3,000 out of the 147,821 tweets were randomly selected, and then each tweet was labeled with a value of 1 if it was related to physical activity. A value of 0 was assigned to any tweet not related to physical activity. The research used the 80/20 split rule to train and evaluate the classifier, whereby 2,400 tweets were used for training, and the remaining 600 tweets were treated as testing data to measure the performance of the trained classifier. The accuracy of the classifier was 95.25%, with a precision value of 94.44%, a recall value of 90.84%, and an F1-score value of 92.61%.

Using the developed classifier to evaluate the whole Twitter data collection, 10,841 tweets were identified as physical activity related. All the parks in Atlanta are in an area with a longitude from –84.56 to –84.29 and a latitude from 33.65 to 33.90. Because the study considered the tweets within this area only, 4,371 tweets were selected at the end. Given the 95.25% accuracy of the classifier, at least 4,163 out of 4,371 tweets should be deemed physical activity related.

Data Analysis

The study considered two essential factors when investigating how park access was associated with people's participation in physical activities—park distance and park size. For each factor, it also considered how park types might impact the correlation with physical activity.

Park Distance

A simple descriptive statistic was adopted to test the correlation between the number of tweets related to physical activity and distances to parks. Using GIS, the study built a dataset measuring the straight-line distance from each tweet's location to the boundaries of its nearest park (the distance from the boundaries of a park was set as 0 if the tweet was within the park). It then used a one-way analysis of variance (ANOVA) to measure the correlation between park types and physical activity at different distance buffers. The number of physical activity–related tweets was examined located within the buffers of 0.5 mile (approximate walking time of 10 minutes), 1 mile (20 minutes), 1.5 miles (30 minutes), 2 miles (40 minutes), 2.5 miles (50 minutes), and 3 miles (1 hour) for each park type. The study adopted the use of larger buffers because physical activities, such as running and biking, usually cover a longer travel distance. The tweets might have been re-enumerated if they were located within the same buffers of different parks. ANOVA was conducted to measure the correlation between the distances of the tweets to the parks and the park types (Table 1).

Park Size

Park size is another factor considered in the study when examining the impact of park access on people's participation in physical activities. The research collected information about park size from data published by the City of Atlanta Department of City Planning (2000) (Table 2). Linear regression was adopted to measure the association between park size and the number of physical activity–related tweets. The model was formulated as follows:

$$\#tweets = \beta_0 + \beta_1 \times parksize + error \qquad (1)$$

The research considered park size as an independent variable and the number of tweets within a given distance buffer as the dependent variable. In this model, β_0 was an intercept, and β_1 was a dimensional parameter. The dataset was the number of tweets around each park within the distance buffer of 0.5 mile, 1 mile, 1.5 miles, 2 miles, 2.5 miles, and 3 miles. The distance was measured from a tweet's location to the boundary of its closest park within the distance buffer (The distance was set as 0 if the tweet was in a park). In each buffer, the study tested the correlation between tweet numbers and park size (all parks) and the correlation for each park type (Table 3).

Results

Correlation Between Park Distance and Physical Activity

Of the 4,371 physical activity–related tweets, 72.2% (3,157 tweets) were located within a 0.5-mile distance (10-minute walk) to parks. Of all those tweets, 546 tweets were made in parks. There was a significant drop in the number of physical activity–related tweets sent farther than 0.5 mile from the parks (Fig. 2). Within the distance between 0.3 and 0.4 mile to a park, the number of tweets was the highest compared with other distance intervals—803, or 18.4% of all tweets. This result indicated that an area within 0.5 mile of a park was more likely to be associated with physical activities.

Fig 2. The number of physical activity–related tweets within certain distances to the parks.

In terms of the impact of park type on physical activity, there were no statistical differences (p-value > 0.05) in physical activity among different park types when the distance to parks was less than 2.0 miles (40-minute walk) (Table 1). However, when the distance to a park was more than 2.5 miles (50-minute walk), playlots tended to be associated with more physical activities than other park types (p-value < 0.05). Indeed, playlots had the highest mean value of the numbers of physical activity–related tweets at all distance buffers among the four park types. Neighborhood parks and green spots had a similar correlation with physical activities when the distance was greater than 2.0 miles. In contrast, community parks were the least correlated with physical activities.

Correlation Between Park Size and Physical Activity

When looking into the correlation between physical activity and park size for each park type, park size was not significantly associated with physical activity (Tables 2 and 3). The only exception was playlots. Park sizes positively correlated with physical activity within the 0.5-mile distance (10-minute walk) to playlots. When the correlation by omitting park types was tested, park size appeared to be modestly associated with physical activity. At a distance between 2.0 and 3.0 miles to the parks, smaller parks were associated with more physical activity than larger ones (β_1 was negative). However, the low R^2 suggested that the model fitted the data poorly. In other words, park size was not a significant feature for predicting physical activity, even though the correlation was statistically significant.

Discussion

The study used geotagged Twitter data to investigate how active travel behaviors such as walking, running, and biking are correlated with park distance, park size, and park type. The findings contribute to the knowledge of the effects of park access on physical activity and provide evidence for urban planners and designers to consider sufficient park access in promoting public health and equity.

Park Distance

The results of this study correspond to those of previous research—increased park access facilitates physical activity. Distance is considered an essential component of park access because park distance is correlated with other aspects of park use, such as the frequency and duration of park visitations and the types of activities undertaken in the parks (Rossi et al. 2015). The results showed that a buffer distance of 0.5 mile or less tended to be associated with most physical activity–related tweets, while a distance farther than 0.5 mile showed weaker correlations. The 0.5-mile distance is considered a 10-minute walk, the median value for people's daily walking distance (Yang and Diez-Roux 2012). Cohen et al. (2007) found that 64% of observed park users lived within 0.5 mile of a park. Only 19% of the residents living less than 0.5 mile away from a park were infrequent park visitors, compared with 38% of those living 1 mile or more. They also observed that residents living within 0.5 mile of a park reported leisurely exercising more than five times as often as those living more than 1 mile or more. Kaczynski et al. (2008) observed that parks used for physical activity had a mean distance of 0.59 mile from study participants' homes, while parks that were not used for physical activity were 0.62 mile on average from participants' homes. These studies provide evidence suggesting a 0.5-mile distance to a park might be a threshold value beyond which parks would be less associated with physical activity. Empirically derived travel thresholds have implications in city planning, considering effective and reasonable park distance to facilitate physical activity for different neighborhoods and people's workplaces. City planners and designers could use these findings to improve service-area analysis by understanding the distances that residents are willing to travel to parks to engage in physical activities. The travel thresholds could also help identify areas that need increased access to urban parks and address social and environmental inequalities arising from differentiated park access (Rossi et al. 2015).

Some scholars suggest that distance decay effects might interact with the sociodemographic characteristics of potential park users (race/ethnicity, age, sex, income) and psychometric factors (perceptions, values, attitudes) (Rossi et al. 2015; McCormack et al. 2006). For instance, Boone et al. (2009) found that whites had access to more park acres than African Americans despite African Americans being more likely to live within walking distance of a park (0.25 mile). Likewise, younger people are more willing to travel a long distance to visit parks than the older population (Rossi et al. 2015). The method adopted in the study, however, was not able to infer Twitter users' demographic information and thus involved uncertainty at the individual level, which prevents further investigation about the types of people who would engage in physical activity in urban open spaces (Roberts 2017; Yin, Chi, and Van Hook 2018). Other factors such as road connectivity, walkability, and traffic safety might also influence physical activity by affecting residents' perception of park distance and actual travel time. Future research could build on the method and results of this study to develop a more nuanced model to understand the threshold value of the reasonable park distance that best promotes physical activity—controlling for sociodemographic variations and other factors that could affect objective and perceived travel distance to a park.

Park Size

The study echoed previous studies suggesting park size was not a significant predictor of physical activity (Kaczynski et al. 2008). Some studies suggested that a larger open and green space area predicted more walking activities (Li et al. 2005; Brown et al. 2014; Zhang and Zhou 2018). However, as Brown et al. (2014) argued, park type might influence the relationship between park size and park benefits, including physical benefits (exercise/fitness). The study investigated all the park types in the City of Atlanta and compared their association with active travel behaviors, including walking, jogging, running, and biking. Playlots appeared to be associated with more of these behaviors than other park types. The mean size of playlots was 0.58 acre compared with 20.86 acres for community parks and 5.90 acres for neighborhood parks (Table 2). The relatively small playlots might contribute to the results showing that smaller parks predicted more physical activity than the larger parks. However, when considering each park type, the results showed a positive correlation between the size of playlots and physical activity. The correlation was significant within a 0.5-mile distance.

Some researchers emphasized the importance of building small parks proximate to residents' homes (Zhang and Zhou 2018; Grow et al., 2008). They observed that smaller parks with easy access and good management had a relatively high visitation intensity (number of check-in visits per unit of park area) compared with larger parks that served as regional destinations (Zhang and Zhou 2018). On the contrary, Schipperijin et al. (2010) argued that residents who had no personal factors that reduced their mobility tended to use larger urban green spaces at a reasonable distance more often than they used a nearby smaller park. The discussion of whether large or small parks are more beneficial to cities has been extended to comparing their ecosystem services. For instance, Lin et al. (2011) suggested that more small green areas performed better at carbon savings (resulting from the cooling effects of green spaces) than fewer large green areas of the same sum of size. Other scholars, however, found a positive correlation between park size and cooling effects (Almeida et al. 2018; Jaganmohan et al. 2016). Researchers acknowledged that factors such as the characteristics and shape of green space also affected the ecosystem performance of the urban parks (Lin et al. 2011; Jaganmohan et al. 2016). Thus, whether large or small parks would be more beneficial to the cities remains inconclusive.

The study suggested park size was not significantly associated with physical activity such as walking, running, and biking. Instead, park types or park characteristics appeared to be a more important predictor. Other research similarly noted that in parks of the same size, parks with more attributes attracted more visitors for physical activity (Kaczynski et al. 2008; Giles-Corti et al. 2005). Research has indicated that parks of different sizes provided various benefits (health, environmental, psychological, and social), and some parks were unique in providing certain benefits regardless of their sizes (Brown et al. 2014). Thus, it might be crucial for urban planners and designers to provide large parks and small parks that possess attributes that meet the recreational and environmental needs of city residents.

Park Type

The results of the study suggested that park type was a significant predictor of residents' willingness to engage in physical activity in and around a park. Playlots appeared to correlate with more physical activity than other park types. The differences were significant when the distance to a park was greater than 2.5 miles, indicating that people were willing to walk, run, or bike a longer distance to visit a playlot. Researchers have suggested that the characteristics of a park or the different services it offers may facilitate shorter or longer travel (Golicnik and Thompson 2010; Rossi et al. 2015). The typical playlots in the study area include walking paths/trails, playgrounds, picnic tables, large grassy areas, and shade trees. Some playlots have unique features like a 'free little library' (a book box mounted on a wooden plank), a creek running through the park, a community garden, or a natural habit area (Fig. 3). Most of the playlots in the study are in neighbourhoods and provide on-street parking instead of designated parking areas.

Fig 3. Ardmore Park is categorized as a playlot. It is 1.75 acres and features a shaded playground and a walking trail (Photo by author, ca. 2022.)

The qualitative studies of park use and physical activity suggest that access to various facilities in parks support active and passive recreational activities (McCormack et al. 2010). Walking paths attract people who undertake recreational walking, running, and dog walking activities. Picnic tables and seating promote socializing. Facilities that support children's play, such as playgrounds, are crucial in encouraging park use. Tester and Baker (2009) observed that playfield renovations undergone in two San Francisco parks significantly increased the average number of visitors per observation among most age groups. Moreover, playgrounds on regularly walked routes tended to be used more often than elsewhere (Ferre et al. 2006; McCormack et al. 2010).

In addition, the distance traveled to parks might affect visit duration and physical activity behaviors (McCormack et al. 2006; Spinney and Millward 2013). More specifically, people who live closer to a park tend to visit more often but for shorter periods than those who live farther away (Rossi et al. 2015). They also seemed to undertake activities that be only partly related to park design, such as daily exercise routine and dog walking. Those who travel farther to visit a park might spend longer time in the park and undertake active recreational activities or socializing (Rossi et al. 2015). Playlots are usually located near residents, and their amenities support the parks' more frequent and regular use.

This study found that community parks tended to be the least correlated with physical activities compared with the other three park types (green spots, playlots, and neighborhood parks). Other research similarly suggested that the most significant percentages of low-intensity/sedentary physical activity (such as resting/sitting, very slow walking/strolling, standing, yoga/stretching) were associated with community parks (Brown et al. 2014). However, this result did not necessarily imply that community parks offer fewer benefits than other park types. Instead, community parks had the most diverse benefits when other aspects of user needs were taken into consideration, such as environmental (e.g., enjoying nature), psychological (e.g., escaping stress), and social (e.g., connecting with other people) (Brown et al. 2014).

In the study, community parks typically featured playgrounds and various sports facilities such as soccer fields, basketball courts, tennis courts, and baseball fields. Some include swimming pools, golf courses, splash pads, and walking trails (Fig. 4). They usually provide designated areas for parking. Community parks serve a larger geographic area (2 to 3 miles in diameter) than other park types. People traveling a long distance to a park tended to be non-frequent visitors who traveled by car, often accompanied by friends or families, and visited the park mainly on weekends. The sports facilities also appeared to attract a younger population, who usually visit the park less frequently, but for longer, mainly on weekends (Wright Wendel, Zarger, and Mihelcic 2012; Rossi et al. 2015). It might explain why playlots attract more active travel behaviors such as walking, running, and biking than other park types. They are proximate to users and are typically visited frequently by visitors who travel in non-vehicle modes for everyday activities such as exercise routines, dog walking, and children's play. Community parks, on the contrary, were more likely to be visited by people who drove a farther distance to conduct active recreational activities and to socialize.

Fig 4. Frankie Allen Park is categorized as a community park. It has baseball fields, tennis courts, a small playground, and large picnic areas (Photo by author, ca. 2022.)

The results raise attention to how different types of parks might meet residents' recreational demands in different ways. They do not necessarily indicate which park type would better promote physical activity because different park types generate various benefits to the residents and fulfill the needs of diverse sociodemographic groups. It should also be noted that physical activity is only one of the many positive effects offered by urban parks in promoting human health. Urban parks contribute to other health benefits including stress recovery, psychological well-being, cognitive ability, and social cohesion (Holland et al. 2018). Nevertheless, it is helpful to see how playlots that are small but with easy access, appropriate amenities, and reasonable proximity to neighbourhoods are essential for promoting an active lifestyle for nearby residents. Grow et al. (2008) observed the strong association between frequent active use of recreation sites with proximity to home and active transport to recreation sites for children and adolescents. Parents tended to drive their children to team sports and other structured activities (such as what community parks usually provide), which may be farther from home. Active transport such as walking and biking increased accessibility to parks when parents were unavailable or unwilling to provide car transport. Their findings support building more small parks that are accessible via active transport. The study concurred with the recommendation and highlighted playlots as a vital park type to the city residents. Building more playlots and improving the quality of existing ones, especially in underprivileged neighbourhoods, could significantly enhance the equity of park access and encourage physical activity for residents.

Limitations

The research implies that data from social media services like Twitter could be used more often for urban space studies to understand the link between park access and physical activity. Geotagged tweets could serve as a proxy for the spatial distribution of people participating in physical activity, enabling measurement and mapping of the association with access to urban green spaces. However, there are limitations to consider when using social media data for research. First, the data are not fully representative of the whole population and might overrepresent young adults, African Americans, and others who use Twitter at a higher rate (Smith and Brenner 2012; Widener and Li 2014). As Arribas-Bel (2014) suggested, the representability and quality issues of these new data sources should be carefully considered for use in data analysis. Especially the vulnerable groups who are of the most public health concerns, such as seniors, low-income population, children/adolescents, have been underrepresented in Twitter users. Second, the analyses of physical activity–related tweets might be limited because of their inability to pick up nuanced or ambiguous meanings in content. Some tweets might not necessarily include the keywords used in the study to indicate the physical activity being conducted. Third, owing to recent changes in Twitter's geocoding policy starting in the latter half of 2019, precise location tagging is turned off by default, which might significantly reduce the number of geotagged tweets and cover even fewer groups of the Twitter user population (Hu and Wang 2020). Although the data collection is from 2017 and was not affected by the policy change, the reduced number of geotagged tweets raises concerns about future studies using geotagged tweets to measure park access and physical activity. Instead of using geo-locations in tweets to determine the locations of activity, identifying activity relating to specific places from the tweet content might be a research direction to explore.

The study points to a convincing relationship between increased physical activity and better park access despite the limitations described. The methods adopted in this research provide a new way to understand the impact of urban parks in promoting physical activity such as walking, running, and biking by using social media data on a large geographic scale. The results are significant because the information is helpful for urban green space planning and related decision-making. Specifically, knowing how access to a park affects physical activity can help planners and designers determine the distance, size, and types of parks that are most beneficial for neighbourhoods and for city dwellers.

Conclusions

The increasing prevalence of social media provides new means for collecting information about physical activity patterns of individuals. This study examined how park access was associated with people's choices in physical activity by extracting user-generated content tagged with spatiotemporal information from the social media platform Twitter. The use of tweets overcame some of the barriers of traditional data collection methods and facilitated an exploration of individual activity that is geographically accurate and time sensitive (Chen and Yang 2014; Zhang and Zhou 2018).

This study suggests that proximity to a park (within 0.5 mile) was significantly correlated with more people engaging in physical activities such as walking, jogging, running, and biking. It also found that park size was not a significant predictor of physical activity. Instead, park type affected park use and choices of physical activities. A playlot was the type of park associated with most of these physical activities. The findings suggest that urban planners and designers should consider the threshold value for adequate park distances to encourage physical activity when developing equitable urban open space systems that support community health. Playlots, even small ones, should be integrated into the network of urban parks, especially for disadvantaged communities that might lack access to larger community or neighbourhood parks. Installation of children’s play equipment, walking trails, and social gathering facilities in new park design or park retrofit efforts would encourage more active park use.

Future work should seek to integrate social media data with contextual data (such as road connectivity) of the geographic areas under study. More research is also needed to validate social media data as an indicator of physical activity in the urban context by using traditional survey-based or observation data across a wide range of park types. To better understand the association between urban open space and human health, the study recommends that researchers consider how traditional data collection methods and new social media data may complement each other to improve the overall quality and validity of data collection.

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Table 1. Number of tweets by types of parks in Atlanta

Distance from Parks (miles)	All	Community Parks	Neighborhood Parks	Playlots	Green Spots	Difference (p)
0.5	37 (5)	36 (19)	27 (6)	54 (19)	37(6)	0.486
1.0	171 (14)	121 (37)	169 (30)	183 (40)	182 (21)	0.573
1.5	335 (24)	244 (64)	328 (49)	449 (76)	336 (32)	0.196
2.0	548 (33)	448 (92)	532 (68)	760 (109)	533 (45)	0.105
2.5	816 (42)	683 (115)	824 (85)	1135 (132)	775 (58)	0.035*
3.0	1096 (48)	903 (132)	1107 (98)	1436 (146)	1063 (66)	0.040*

Notes: The number refers to the mean of the number of relevant tweets in the corresponding park's type. Standard errors are in parentheses. Difference refers to whether each variable was statistically significant across the four types of parks, as calculated by the one-way ANOVA.
*$p \leq 0.05$.

Table 2. Sizes of different park types

Park Type	Number of Parks	Mean of Acreage	Standard Error of Acreage
Community Park	43	20.86	2.85
Neighborhood Park	70	5.90	0.70
Playlot	38	0.58	0.09
Green Spot	168	1.03	0.08

Table 3. Results of the linear regression model for relationship between park size and tweets

All Parks	β_0	β_1	R^2	p
0.5 mile	39 (5)	–0.6 (0.5)	0.004	0.251
1.0 mile	182 (16)	–2.2 (1.4)	0.007	0.124
1.5 miles	356 (26)	–4.5 (2.3)	0.012	0.056†
2.0 miles	580 (37)	–6.9 (3.3)	0.019	0.038*
2.5 miles	858 (47)	–9.0 (4.2)	0.014	0.033*
3.0 miles	1144 (53)	–10.4 (4.8)	0.015	0.030*

Community Park	β_0	β_1	R^2	p
0.5 mile	56 (28)	–0.9 (1.0)	0.021	0.351
1.0 mile	140 (56)	–0.9 (2.0)	0.004	0.659
1.5 miles	306 (97)	–3.0 (3.5)	0.017	0.399
2.0 miles	606 (136)	–7.6 (4.9)	0.055	0.128
2.5 miles	897 (170)	–10.2 (6.1)	0.064	0.101
3.0 miles	1104 (196)	–9.6 (7.0)	0.043	0.180

Neighborhood Park	β_0	β_1	R^2	p
0.5 mile	26 (10)	0.1 (1.0)	0.0002	0.892
1.0 mile	205 (48)	–5.2 (5.1)	0.015	0.319
1.5 miles	393 (77)	–9.2 (8.4)	0.017	0.277
2.0 miles	585 (108)	–7.5 (11.7)	0.006	0.525
2.5 miles	908 (133)	–11.9 (14.5)	0.010	0.416
3.0 miles	1204 (154)	–13.7 (16.8)	0.010	0.415

Playlot	β_0	β_1	R^2	p
0.5 mile	–13 (35)	72.9 (31.7)	0.128	0.027*
1.0 mile	108 (75)	80.9 (68.4)	0.037	0.245
1.5 miles	378 (146)	76.4 (133.1)	0.010	0.570
2.0 miles	718(211)	45.0 (192.5)	0.002	0.817
2.5 miles	1105 (255)	31.2 (232.9)	0.0005	0.894
3.0 miles	1370 (282)	69.9 (257.8)	0.002	0.787

Green Spot	β_0	β_1	R^2	p
0.5 mile	38 (7)	–3.4 (6.3)	0.002	0.590
1.0 mile	188 (22)	–12.8 (20.3)	0.002	0.529

1.5 miles	339 (35)	–8.6 (31.8)	0.0004	0.786
2.0 miles	539 (48)	–15.8 (44.2)	0.0008	0.721
2.5 miles	789 (62)	–37.1 (56.8)	0.003	0.515
3.0 miles	1078 (71)	–37.2 (65.0)	0.002	0.567

Notes: The linear regression model is tweets = $\beta_0 + \beta_1 \times$ park size. The linear regression model used park size as the independent variable. $^{\dagger}p \leq 0.10$; $*p \leq 0.05$.