Examining Inequality in Park Quality for Promoting Health Across 35 Global Cities

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ABSTRACT

Urban parks provide significant health benefits by offering spaces and facilities for various recreational and leisure activities. However, the capacity of specific park spaces (e.g., children's playgrounds, lakes) and elements (e.g., benches, sports equipment) to foster health remains underexamined. Traditional studies have focused on parks' size, greenery, and accessibility, often overlooking their ability to facilitate specific health-promoting activities. To address this gap, we propose a taxonomy consisting of six categories of health-promoting activities in parks: physical, mind-body, nature appreciation, environmental, social, and cultural. We estimate the capacity of parks in 35 global cities to promote health by establishing a lexicon linking park spaces and elements with specific health-promoting activities from our taxonomy. Using this lexicon, we collected data on elements and spaces in all parks in 35 cities from OpenStreetMap. Our analysis covers 23,477 parks with a total of 827,038 elements and spaces. By first comparing similarly sized parks across cities, we found that North American parks offer more spaces for physical activities, while European parks focus more on nature appreciation. Second, by scoring parks based on both elements and spaces, we investigated the variability in their health-promoting potential. We found the most uniform provision across parks for physical activities and the highest disparities regarding social activities. Additionally, parks offering a variety of activities are usually located in city centers, while offerings diminish in parks towards the suburbs. Lastly, we identified significant inequalities in park standards across cities, regardless of their continental location: Tokyo and Paris offer the most uniform park standards, while Copenhagen and Rio de Janeiro exhibit the most pronounced disparities. Our study provides insights for making urban parks more equitable, engaging, and health-promoting.

1 Introduction

As the world's population continues to gravitate towards urban areas[1,2], cities are faced with the immense task of creating and maintaining green spaces to foster public health[3–5]. Urban green spaces are shown to enhance various health aspects, including physical, mental, and social[6–13]. Among specific benefits, having access to parks lowers rates of morbidity[14], reduces social isolation[15], decreases stress levels[16], and contributes to overall well-being[17]. Health benefits of parks are especially relevant to socioeconomically deprived[6,14] and elderly populations[18–20].

Park developers seeking cost-effective ways to promote health[21–24] have placed strong emphasis on physical activity[25–28]. This is not surprising, given that physical inactivity has been identified as a major health issue in Western countries[29] leading to record levels of obesity in the United States[30]. There are also worrying levels of child obesity in Chinese mega cities[31]. However, beyond physical activities, even mere exposure to the natural environment and its appreciation has been shown beneficial for health[32]. For instance, research by Olszewska-Guizzo et al.[33] highlights how the visual characteristics of green spaces can elicit positive emotional responses and brain activities akin to stress reduction, yet such aesthetic considerations have seldom been prioritized in park design[34]. Social interactions, too, are critical for overall health and well-being[35], leading in some countries to the adoption of the practice of social prescribing[36]. Parks can complement other urban environments in providing engaging social as well as cultural experiences[37], with literature indicating potential strategies for park management to facilitate these experiences[38].

Despite these various activities through which parks can promote health, previous work linking urban greenery with health has mainly considered parks as mere green boxes, e.g., looking at the size and type of green space in them or at their distance

Project website: https://social-dynamics.net/healthy-parks
Replication Repository: https://github.com/LinusDietz/Health-Promoting-Parks-Replication

from concentrated human habitation[39–41], and did not dive deeper into the specific activities afforded by those parks. Example factors identified to drive park visitations, in general, include the area, number of food establishments, and the presence of natural vegetation and fields[42]. Other works have focused on the surroundings of parks, such as accessibility and the socioeconomic environment, factors which were then used to estimate the park usage through location-based social network check-in data[43]. Overall, the attributes to understand park usage in prior work are quite broad and disregard the amount of and specific facilities[42–45]. In summary, prior research on the connection between parks and health largely overlooked the range of potential health-promoting activities these spaces can offer. Additionally, studies focusing on park usage patterns have only examined a limited selection of facilities without adequately connecting these facilities to the usage and health-promoting activities.

To address this gap and provide a detailed understanding of park quality with respect to various activities that people can do in them, we collected data on park elements and spaces in parks across 35 cities worldwide. The raw counts reveal design priorities for park activities on different continents, while the park health scores indicate a trend where parks closer to city centers offer a wider range of facilities. Additionally, we identified the successes and failures of various cities in providing high-quality parks, highlighting those that offer more uniformly distributed park facilities compared to others that show significant disparities in facility provision.

2 Results

We first present the lexicon of health-promoting park facilities that we operationalized with OpenStreetMap (OSM). We then focus on 35 large cities listed in Table 3, selected to cover various parts of the world and to have good Internet connectivity and OSM data availability, allowing for robust analyses. Afterward, we present the results of scoring parks in those cities based on their facilities, highlighting the globally outstanding parks we uncover for each activity category. We conclude with an inequality analysis of parks both within and across cities.

2.1 Lexicon of Health-Promoting Park Facilities

We aimed at identifying health benefits associated with specific activities performed in parks and measuring park facilities' support for these activities. To achieve this, we implemented a three-step method (detailed in Methods Section 4.3): *1)* identifying activities in parks, *2)* confirming health benefits of these activities, and *3)* gathering park facility data and connecting it with health-promoting activities.

Step 1: Identifying Activities in Parks.

We convened an expert panel to identify common park activities, which they organized into six main categories, constituting a taxonomy of activities in parks (described in Methods Section 4.3, *Expert Panel*):

Physical activities: moving your body and sports, like walking, hiking, biking, swimming, and group fitness classes;

Mind-body activities: practices that combine movement, breathing, and meditation for relaxation and well-being. Examples include yoga, meditation, and tai chi;

Nature-appreciation activities: enjoying nature, with activities like bird watching, camping, picnicking, and nature journaling;

Environmental activities: gardening and park conservation, such as planting trees and flowers or participating in conservation efforts;

Social activities: coming together with others, like attending outdoor events, playing sports, and volunteering; and

Cultural activities: celebrating community diversity and heritage through activities like cultural festivals, art exhibits, music performances, storytelling, and workshops.

The categories of this taxonomy sometimes overlap. For instance, gardening falls under both environmental and nature-appreciation, and team sports, though physical, also have a social aspect. The expert panel agreed that, while there are overlaps, the taxonomy is accurate and valuable, comprehensively covering a broad range of park activities.

Step 2: Confirming Health Benefits of these Activities.

A literature review (detailed in Methods Section 4.3, *Scoping Review*) was done to link these park activities to health benefits. After identifying 114 research studies as relevant, we annotated each study with the activity category and the specific health benefit this study evidenced. We found that engaging in activities within urban parks provides a range of health benefits, impacting physical, mental, and social well-being (Table 1).

Most research has focused on the benefits of *physical activity* in parks. Out of 79 studies on the health benefits of exercising, 46 underscored positive outcomes like weight loss[62–64], cardiovascular improvements[91,93], metabolic activity[70,71]. Additionally, these activities demonstrated positive effects on mental health (16 articles), well-being (7 articles), and social health (6 articles).

The second most studied category is *nature-appreciation*, with 68 articles. These activities significantly boost mental health (34 articles), primarily in reducing stress[7,49] and anxiety[104,107] and preventing depression[54,55,57,58,104–106]. They also contribute to physical health (14 articles) and overall well-being (12 articles).

Table 1. Activities in urban parks linked to health benefits. Specific health benefits evidenced in the respective articles are grouped by health aspects.

Activity Category	Health Aspect	Specific Health Benefit
Physical	Cognitive health	dementia prevention[46]
	General health	longevity[19,47]
	Mental health	stress reduction[48–52], depression prevention[52–59], anxiety reduction[56], various[60], mood improvement[61]
	Physical health	weight reduction[47,62–68], increase of physical activity[28,49,51,55,57,69–90], blood pressure reduction[58], diabetes prevention[47,91], various[60], increase of leisure activities[92], hypertension[47], cardiovascular health improvements[66,91,93–95], bone development[66]
	Social health	various[60,96], social cohesion[55,58,97,98]
	Well-being	increase restorative capacity[99], enhanced social interactions[100], quality of life[46,57,79,86,95]
Nature-appreciation	Cognitive health	attention fatigue reduction[20]
	General health	lower morbidity[101]
	Mental health	positive emotions[33,102], depression prevention[54,55,57,58,103–106], anxiety reduction[104,105,107,108], suicide prevention[109,110], mood improvement[20,61,106,111], relaxation[33], mindfulness[33], calmness[108], stress reduction[7,16,17,20,49,104,105,111–114]
	Physical health	mood improvement[111], improved ghq-12 scores[115], blood pressure reduction[58,111,116], antenatal health[117], respiratory health[118], increase of physical activity[49,55,57,88,115,119,120], blood oxygen saturation[111]
	Social health	increased social capital[121], social loneliness reduction[122], various[96], social cohesion[55,58]
	Well-being	stress reduction[17,104,111], quality of life[17,57,103,104,123–125], blood pressure reduction[111], increase restorative capacity[126]
Environmental	Cognitive health	restorative effect against cognitive failures[127]
	General health	lower morbidity[101]
	Mental health	stress reduction[16,128], anxiety reduction[129,130], improved sleep[129,130], depression prevention[103,130]
	Physical health	cardiovascular health improvements[131], inflammation reduction[127], respiratory health[131], access to healthy produce[132], immune system improvement[133], increase of physical activity[71,134], improved sleep[129]
	Social health	access to healthy produce[132], social cohesion[128,132]
	Well-being	nutritional diversity[135], quality of life[103,129,136,137], improved sleep[129], increase restorative capacity[138]
Social	Cognitive health	dementia prevention[46], restorative effect against cognitive failures[127]
	General health	longevity[19]
	Mental health	mood improvement[139], depression prevention[52,53], various[140], improved mental health inventory (mhi-5) scores[141], stress reduction[52,128]
	Physical health	access to healthy produce[132], various[140], inflammation reduction[127], increase of physical activity[86,90]
	Social health	social cohesion[97,98,128,132,139,142], various[96], access to healthy produce[132], increased social capital[143], social loneliness reduction[15], improve sense of social belonging[144–146]
	Well-being	increase restorative capacity[138], quality of life[46,86,147], enhanced social interactions[100]
Cultural	Cognitive health	dementia prevention[46]
	General health	various[148]
	Physical health	increase of physical activity[149]
	Well-being	quality of life[46,147,149]
Mind-body	Mental health	stress reduction[112], anxiety reduction[56], depression prevention[56,59]
	Physical health	increase of physical activity[90]
	Well-being	quality of life[150]

In our review, we found that *social* and *environmental activities* received less attention in conjunction with urban parks, with only 33 and 28 articles covering them, respectively. Despite this, both contribute to all identified health aspects. Social activities enhance social and mental health, fostering a sense of belonging[144–146] and improving mood[139]. Environmental activities, such as gardening, offer diverse benefits, including cognitive restoration[127] and improved general health[101].

Finally, *cultural* and *mind-body activities* are relatively under-researched regarding their health benefits in the context of urban parks. Cultural activities often fell outside the scope of our review, which required a connection to urban parks, while more general cultural activities were studied. However, their health benefits are likely underreported given the presence of cultural facilities in parks (e.g., historic monuments or arts venues). Yoga and other mind-body exercises have not been studied as much in the context of parks, highlighting a potential gap in the scientific literature that warrants future exploration.

Step 3: Gathering Park Facility Data and Connecting it with Health-promoting Activities.

Using OSM, a collaborative mapping platform, we collected all parks in the 35 cities and curated all map objects within the outlines of these parks. This established a large collection of park facility data, which are either designated spaces, such as a forest or pond, or elements such as a bench or an individual tree. Each element and space is described by tags, which we used to assign them to one of the activity categories. To scale this approach, we employed a large language model (LLM)-based

Table 2. Lexicon of *elements* and *spaces* for health-promoting activities in parks. We show the 10 most frequent tags per activity category. The full lexicon of 1441 elements and spaces is available in the replication package.

Activity Category	Elements	Spaces
Cultural	information=board, tourism=artwork, historic=memorial, artwork_type=sculpture, artwork_type=statue, board_type=history, historic=monument, memorial=plaque, memorial=war_memorial, memorial=bench	tourism=artwork, tourism=attraction, religion=christian, leisure=bandstand, historic=memorial, denomination=anglican, building=church, historic=building, tourism=museum, amenity=theatre
Environmental	waste=trash, produce=plum, amenity=recycling, fruit=apple, produce=damson, leisure=garden, man_made=beehive, produce=apple, amenity=watering_place, man_made=monitoring_station	leisure=garden, landuse=flowerbed, landuse=allotments, building=greenhouse, landuse=orchard, landuse=farmland, building=farm_auxiliary, landuse=farmyard, garden:type=community, garden:type=residential
Nature-appreciation	natural=tree, amenity=fountain, tourism=viewpoint, board_type=nature, tourism=picnic_site, amenity=shelter, natural=shrub, attraction=animal, board_type=wildlife, waterway=weir	natural=wood, natural=water, natural=scrub, water=pond, natural=heath, landuse=forest, heath=bracken, natural=grassland, natural=wetland, amenity=shelter
Physical	amenity=bicycle_parking, highway=crossing, amenity=drinking_water, leisure=fitness_station, barrier=cycle_barrier, sport=fitness, leisure=pitch, sport=orienteering, orienteering=marker, leisure=playground	leisure=pitch, leisure=playground, sport=soccer, sport=tennis, highway=footway, golf=bunker, sport=basketball, highway=pedestrian, area:highway=footway, golf=tee
Social	amenity=bench, tourism=information, leisure=picnic_table, amenity=cafe, board_type=notice, amenity=telephone, amenity=fast_food, playground=playhouse, amenity=restaurant, advertising=board	amenity=cafe, building=pavilion, building=retail, amenity=community_centre, leisure=outdoor_seating, amenity=school, amenity=restaurant, building=kiosk, amenity=kindergarten, building=terrace

classifier, which we validated using an expert-derived gold standard dataset (Section 4.4, *Using Large Language Models for Annotation*). We display the top 10 most frequent tags for each activity category in Table 2 and publish all 1441 entries of the lexicon in the replication package. As there were no OSM tags that supported *mind-body activities* (see Section 4.4, *Operationalization of the Taxonomy*), this category was not considered in the rest of this study, but could be considered by future work if behavioral data on this activity category would be available.

The collected OSM tags allow to categorize different elements and spaces in parks, giving us a detailed insight into their potential use and linked health benefits. This new way of examining urban parks allowed us to compare parks within and across different cities based on their health-promoting potential.

2.2 Park Health Scores

To quantify a park's health-promoting potential, we measured how well it can support each of the health-promoting activities from our taxonomy. To do so, we scored each park based on the presence of the gathered facilities (OSM elements and spaces) that were associated with each specific activity relative to the park's size. In the end, we combined the counts of elements and areas covered by spaces into one overall score for each health activity category (Section 4.5).

The main outcome of our study is the scoring of 23,477 parks across 35 cities in five continents based on their potential for health-promoting activities. Each park's score captures its health-promoting offering relative to an average park of the same size in the city. As an illustrative example, Figure 1 shows scores for nature appreciation and physical activities in London parks. The park health scores of all 35 cities are visualized in an interactive online map at `https://social-dynamics.net/healthy-parks/visualization/`.

Quantitative Validation Through Geolocated Flickr Images

As our primary validation of the park health activity scores, we verified whether activities seen in millions of individual Flickr images in parks closely matched the potential activities derived from OSM data. We used a global dataset of geotagged photos from Flickr, providing an alternative way to evaluate park usage[42]. We measured Flickr park activity using both user-generated tags and automatic tags generated from computer vision algorithms that label objects within the images. By semantically mapping the Flickr tags using sentence embeddings to OSM tags, we transferred our activity taxonomy to the domain of Flickr

Figure 1. Visualization of the park health scores in London, UK. On the left, scores for nature appreciation are shown, and on the right, scores for physical activities. The diverging color palette uses green for high nature appreciation scores, red for high physical health scores, white for average park offerings, and black for low scores. The web interface allows browsing individual park scores in each of the study's cities: `https://social-dynamics.net/healthy-parks/visualization/`.

tags (Methods Section 4.7). Matching the tags allowed us to characterize parks based on the visual content within the photos and calculate activity scores similar to those computed from OSM.

To determine how well the OSM and Flickr scores aligned across different activity categories, we used the Pearson Correlation Coefficent (PCC) (Table 3). Overall, the correlation coefficients suggest that the amount of images that people share on Flickr shows the greatest agreement with the facilities present in parks on OSM for cultural attractions ($\mu = 0.53$), with a PCC ranging from 0.30 in Amsterdam up to 0.75 in Philadelphia; followed by social activities ($\mu = 0.39$), ranging from 0.15 in Buenos Aires up to 0.72 in Chicago; and environmental activities ($\mu = 0.39$), ranging from 0.01 in Copenhagen, up to 0.93 in Stockholm. The correlation is lowest for nature-appreciation ($\mu = 0.33$), ranging from -0.04 in Madrid up to 0.72 in Perth, and physical activities ($\mu = 0.30$), ranging from -0.04 in Buenos Aires up to 0.47 in Seattle. These results are influenced by the socio-cultural nature of Flickr[151] and motivations for tagging photos[152]. The average correlation across 35 cities worldwide demonstrates that the OSM scores are in line with the photographed uses of our parks. We found an average PCC of 0.39, with a fairly low standard deviation of 0.07. The strongest links between OSM and Flickr activity scores were seen in Washington DC ($\mu = 0.52$) and Perth ($\mu = 0.50$). Conversely, the weakest correlations, at 0.30, were found in Amsterdam, Hong Kong, and Vienna. Despite the fact that we translated tags from local languages into English, a pattern emerged: cities where English is predominantly spoken tended to have stronger correlations between the two data sources. We suspect this might be attributable to a range of factors, including that the OSM and Flickr data, primarily lacking from non-English-speaking countries, could lead to both, limited usage of two platforms and reduced data quality in those regions.

Qualitative Validation of Globally Outstanding Parks

As a second way to validate our methods, we identified the most outstanding parks in terms of the health benefits they offer. We found that urban parks that score high in a specific category, such as social or cultural, are internationally renowned for facilities in that specific category, as evidenced by their Wikipedia pages. To do so, we picked out and evaluated the parks with the highest scores in each of the five categories (Table 4). The full list of the top parks for each city and category is shown in Table 8 in the Appendix. These parks are renowned globally as natural, cultural, sports, and social landmarks in their cities, famous for the facilities they offer. To initially validate the associations of those parks with their activity categories, we ascertained whether the parks' Wikipedia pages would discuss the facilities supporting activities in those categories.

In the *physical* category, top parks serve as sports centers. Australia's Centennial Parklands and Paris's Bois de Boulogne offer a variety of sports facilities, such as fields for tennis, soccer, polo, and race courses. Rio's Flamengo Park is known for beach sports, and Tokyo's Wakasu Seaside Park, a 2020 Olympics venue, provides ample space for sports, such as golf.

Nature-appreciation parks, like Madrid's La Dehesa de la Villa and Taipei's Guandu Nature Park, are valued for their lush vegetation and wildlife. Tokyo's Ueno Park and Montreal's Parc Angrignon are celebrated for their dense greenery and biodiversity.

For *environmental* activities, parks with extensive botanical gardens stand out. The Washington Park Arboretum in Seattle and Kita-no-maru Park in Tokyo focus on plant preservation and include unique gardens. Hagley Park in Christchurch and Bronx Park in New York feature premier botanical gardens, while Madrid's Retiro Park offers a green oasis with community gardening spaces.

Table 3. Correlation between OSM park health scores and Flickr activity scores. The values showcase the connection of available facilities and photographed usage of parks. The results are based on all parks with at least 250 Flickr images within their boundaries.

City	Parks	Mean PCC	Individual Activity Categories PCC				
			Physical	Nature-appreciation	Environmental	Social	Cultural
Amsterdam	25	0.32	0.24	0.36	0.2	0.49	0.29
Auckland	33	0.46	0.38	0.39	0.43	0.47	0.63
Berlin	77	0.34	0.22	0.14	0.53	0.39	0.42
Boston	50	0.4	0.27	0.43	0.36	0.35	0.58
Buenos Aires	54	0.36	-0.04	0.34	0.92	0.15	0.41
Chicago	69	0.41	0.2	0.45	0.35	0.45	0.6
Christchurch	16	0.49	0.27	0.52	0.21	0.72	0.71
Copenhagen	19	0.33	0.31	0.31	0.01	0.22	0.8
Hong Kong	80	0.3	0.38	0.21	0.36	0.21	0.32
Houston	28	0.46	0.36	0.48	0.15	0.61	0.68
London	304	0.44	0.45	0.4	0.32	0.45	0.55
Madrid	42	0.32	0.08	-0.04	0.19	0.66	0.72
Melbourne	59	0.49	0.45	0.63	0.44	0.64	0.29
Montreal	55	0.43	0.31	0.27	0.44	0.49	0.64
Moscow	65	0.34	0.33	0.2	0.34	0.21	0.6
New York	210	0.42	0.41	0.21	0.58	0.45	0.47
Paris	108	0.39	0.42	0.28	0.3	0.39	0.55
Perth	23	0.5	0.18	0.71	0.3	0.68	0.61
Philadelphia	39	0.46	0.43	0.2	0.63	0.32	0.75
Rio de Janeiro	19	0.36	0.26	0.6	0.23	0.41	0.33
Rome	41	0.31	0.43	0.35	0.08	0.16	0.52
San Diego	47	0.44	0.27	0.38	0.61	0.48	0.44
San Francisco	98	0.31	0.17	0.19	0.42	0.32	0.46
Seattle	76	0.38	0.47	0.36	0.09	0.4	0.6
Seoul	52	0.35	0.34	0.36	0.43	0.23	0.38
Singapore	73	0.36	0.14	0.07	0.61	0.39	0.6
St Petersburg	28	0.34	0.17	0.22	0.38	0.39	0.56
Stockholm	50	0.47	0.45	0.32	0.93	0.23	0.42
Sydney	99	0.31	0.42	0.39	0.22	0.14	0.36
Taipeh	107	0.34	0.16	0.22	0.48	0.26	0.56
Tokyo	208	0.31	0.19	0.24	0.37	0.32	0.42
Toronto	111	0.34	0.31	0.3	0.17	0.39	0.51
Vancouver	62	0.44	0.33	0.37	0.33	0.5	0.67
Vienna	40	0.3	0.18	0.08	0.57	0.19	0.5
Washington DC	61	0.52	0.4	0.52	0.56	0.56	0.56
Mean (sd)	72.23 (60.07)	0.39 (0.07)	0.29 (0.12)	0.33 (0.16)	0.39 (0.21)	0.39 (0.16)	0.53 (0.13)

In the *social* sphere, parks with diverse entertainment and social spaces excel. Hong Kong's Inspiration Lake offers leisure activities, while Toronto Island Park features amenities for social gatherings. Ueno Park in Tokyo is also a popular spot for its cafés and social spaces, showcasing parks as essential places for community and leisure.

In the *cultural* category of Table 4, we spotlighted parks rich in history and culture. Tokyo's Ueno Park, spotlighted for the third time, is filled with historic sites like the Kan'ei-ji Temple, along with the Tokyo National Museum. Seattle Center is a cultural hub with museums and the Seattle Opera. The National Mall in Washington DC is packed with museums and monuments. Seoul's Gyeongbokgung Palace Park hosts the ancient royal palace and museums. The Garden at the Saint Petersburg State Forestry University is known for its educational and historic significance.

Finally, in the *overall* category, which represents the mean value of the five other categories, we identified parks that stand out in their respective cities for their comprehensive offerings across all dimensions. These are typically large parks of outstanding significance, receiving the utmost attention from their municipal maintainers (e.g., Bois de Boulogne in Paris and, once more, Ueno Park in Tokyo).

To further confirm our method's effectiveness in identifying leading parks for various categories, we conducted online

Table 4. Top five parks globally for each health-promoting activity category as well as an overall score. We have linked each park to its Wikipedia entry or municipal webpage.

Activity Category	City	Park	Score
Physical	Sydney	Centennial Park	6.90
	Paris	Bois de Boulogne	6.83
	Taipeh	Da'an Forest Park (大安森林公園)	6.47
	Tokyo	Wakasu Seaside Park (若洲海浜公園)	6.08
	Rio De Janeiro	Aterro do Flamengo	5.71
Nature-appreciation	Madrid	Dehesa de la Villa	6.59
	Tokyo	Ueno Park (上野恩賜公園)	6.35
	Taipeh	Guandu Nature Park (關渡自然公園)	6.23
	Rio De Janeiro	Quinta da Boa Vista	6.14
	Montreal	Parc Angrignon	5.64
Environmental	Seattle	Washington Park Arboretum	4.95
	Tokyo	Kita-no-maru Park (北の丸公園)	4.19
	Christchurch	Hagley Park North	3.84
	New York	Bronx Park	3.70
	Madrid	Retiro Park	3.36
Social	Moscow	Timiryazevskiy Park (Тимирязевский парк)	4.82
	Hong Kong	Inspiration Lake Recreation Centre (迪欣湖活動中心)	4.79
	Toronto	Toronto Island Park	4.32
	Madrid	Finca Vista Alegre	4.18
	Tokyo	Ueno Park (上野恩賜公園)	4.08
Cultural	Tokyo	Ueno Park (上野恩賜公園)	8.20
	Seattle	Seattle Center	4.61
	Washington DC	National Mall	4.24
	Seoul	Gyeongbokgung Palace Park (경복궁)	4.19
	St Petersburg	Garden of Saint Petersburg State Forestry University (парк Лесотехнической академии)	4.15
Overall	Paris	Bois de Boulogne	3.82
	Tokyo	Ueno Park (上野恩賜公園)	3.74
	Washington DC	National Mall	3.74
	Christchurch	Hagley Park North	3.62
	Paris	Bois de Vincennes	3.57

searches using queries structured as: "`[city name] parks for [activity category] activities`" (e.g., *"Tokyo parks for cultural activities"*). Consistently, articles about the parks our method pinpointed appeared within the top ten search results for each category (e.g., *"Ueno Park: A Seasonal Guide to Tokyo's Cultural Haven"*).

Average Park Offerings

By comparing the offerings in parks across different continents, we reveal varying priorities in urban planning and park design for supporting health-promoting activities. Figure 2 shows the expected number of elements and the size of spaces for individual activity categories in a fictional, *"statistically average"* 8-hectare park for cities in the different continents. We chose this size as it represents a medium-sized neighborhood park and is also the mean park size in our study. The values are computed using the parameters of the linear regression models that we used to score the parks for each city (see details in Section 4.5, *Transforming Counts into Health Scores*). Since we fit individual linear models for each city, our health scores for individual parks in different cities are incomparable, however, the statistical model we used allowed for the comparison of the baseline parks falling on the *"average park line"* across different cities (cf. Figure 7).

Figure 2 reveals that nature-appreciation and physical spaces are most common. When it comes to elements, nature-appreciation is again the most frequent category, followed by social and environmental categories. Cultural elements and spaces are the least frequent ones. In the Appendix, Figure 8, we showcase the same data subdivided by cities.

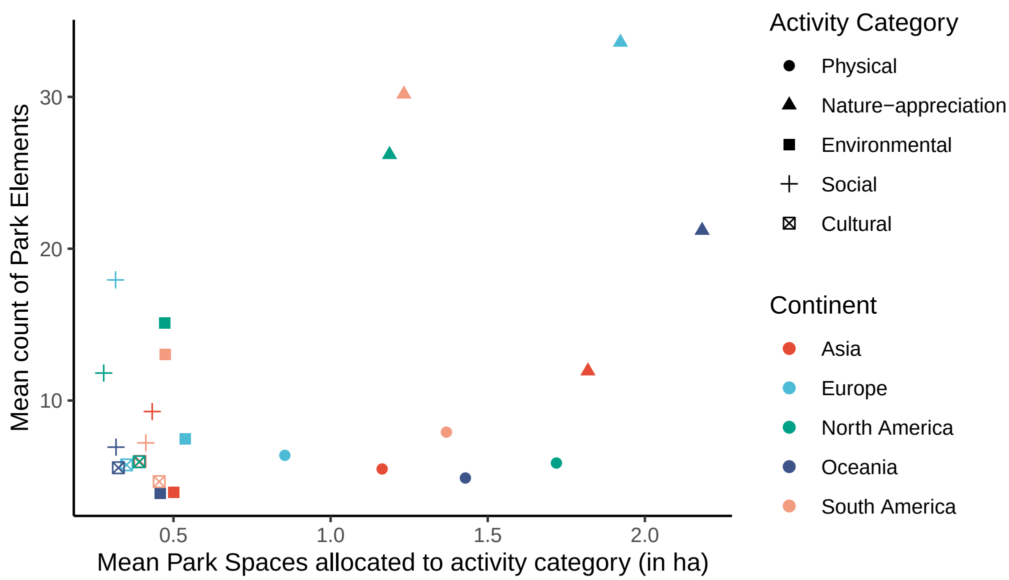

Figure 2. Total area of park spaces (horizontal axis) versus the count of elements (vertical axis) in an 8-hectare park for each activity, broken down by continents. Nature-appreciation and physical activity spaces are the most common, with elements for nature-appreciation also outnumbering other activity categories. Cultural elements and spaces are the least frequent.

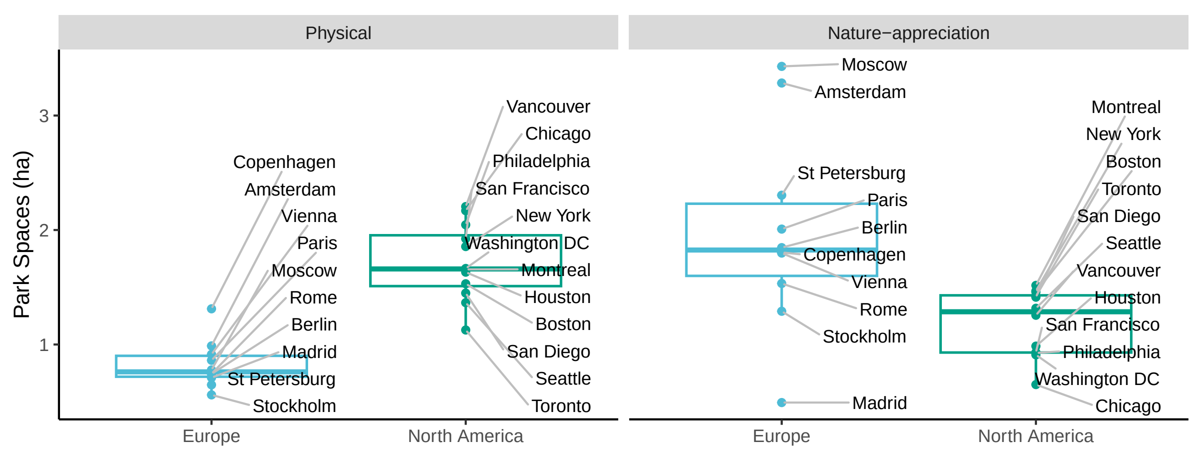

Figure 3. Park spaces in an average 8 ha park dedicated to nature-appreciation & physical activities in North America and Europe. North American cities offer more spaces for physical activities, whereas European cities devote more space to nature-appreciation. Standard box plot with Q1, median, Q3; whiskers at 1.5× interquartile range.

European parks offer most spaces for nature appreciation, and North-American for physical activities. The most notable difference revealed by the average park offering analysis is between European and North American cities in the physical and nature-appreciation categories, as shown in Figure 3. European urban parks are primarily dedicated to nature appreciation, while North American parks allocate a larger proportion of spaces to physical activities. This highlights the priorities in urban planning across regions and reveals the different roles parks play in various cultures.

2.3 Inequality of Park Scores Within and Across Cities

Centralization of Park Quality Within Cities

Turning our attention to the locations of parks that are great for doing health-promoting activities, we found that parks in the city center tend to score higher not only in cultural and social activities but also in physical and nature-appreciation activities.

Table 5. Park health scores by quartiles determined using the distance to the city center. Q1 are the inner city parks, and Q4 are the parks that are most distant to the city center. On the left, we show the mean health scores for each quartile; on the right, we show the p-values for each null hypothesis $H_0 : Q_i = Q_j$ stating that the mean scores for two subsequent quartiles i and j are equal. All null hypotheses can be refuted with high significance levels ($p < 0.001, ***$), with the exception of the difference between Q3 and Q4 in the environmental category, where the significance is $p = 0.003, **$.

	Mean Health Scores				p-values of H_0		
Activity Category	Q1	Q2	Q3	Q4	Q1 = Q2	Q2 = Q3	Q3 = Q4
Physical	0.382	0.297	0.160	0.068	0.000	0.000	0.000
Nature-appreciation	0.107	-0.211	-0.497	-0.580	0.000	0.000	0.000
Environmental	0.020	-0.076	-0.156	-0.186	0.000	0.000	0.003
Social	0.289	0.137	-0.004	-0.088	0.000	0.000	0.000
Cultural	0.260	0.096	0.010	-0.022	0.000	0.000	0.001

Specifically, we categorized all parks into four quartiles based on their proximity to the city center, from the innermost 25% (Q1) to the outermost 25% (Q4) (Figure 4). This analysis revealed a clear trend: the closer a park is to the city center, the higher its score in health-promoting activities.

Interestingly, the most significant discrepancies were observed in *nature-appreciation* scores, challenging the assumption that suburban areas, due to less crowding, would have more natural spaces (Table 5). This phenomenon, described as the "Savannah Trap" by Montgomery[153], highlights a common oversight in suburban planning where urban planners regularly fail to create biodiverse spaces in the suburbs, instead inadvertently creating monotonous, savannah-like expanses between residential blocks. Our findings, detailed further in Section A.3 in the Appendix, were consistent across cities on every continent, with only two exceptions in South America (Buenos Aires and Rio de Janeiro, where the urban topology is influenced by the sea), demonstrating the widespread applicability of these trends.

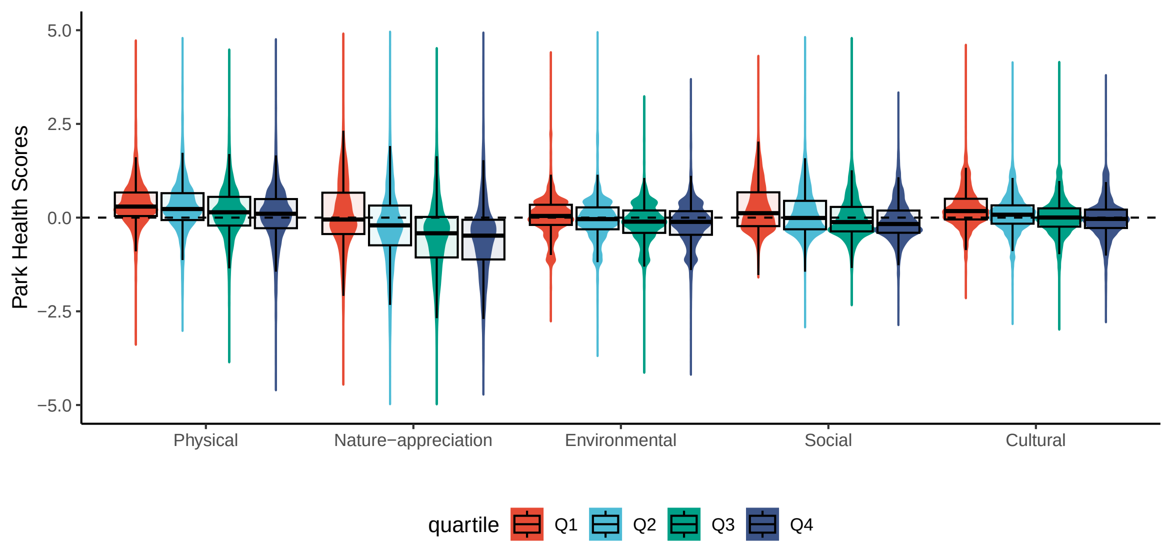

Figure 4. Park health scores by quartiles of the distance to the city center. Q1 are the inner city parks, and Q4 are the parks that are most distant from the city center. The scores decrease monotonously with each quartile further away from the city center, meaning that the farther a park is to the city center, the lower is its score in health-promoting activities. The effect is strongest for nature-appreciation and is least prominent for environmental activities. Standard box plot with Q1, median, Q3; whiskers at 1.5× interquartile range.

Disparities in the Offered Activities Across Cities

Following our examination of how park scores differ within cities, we quantified the disparities in park health scores across different cities. To that end, we used an inequality metric (refer to Equation 3 in Methods Section 4.6), which ranges from 0 (indicating uniform distribution of facilities) to 1 (indicating absolute disparity).

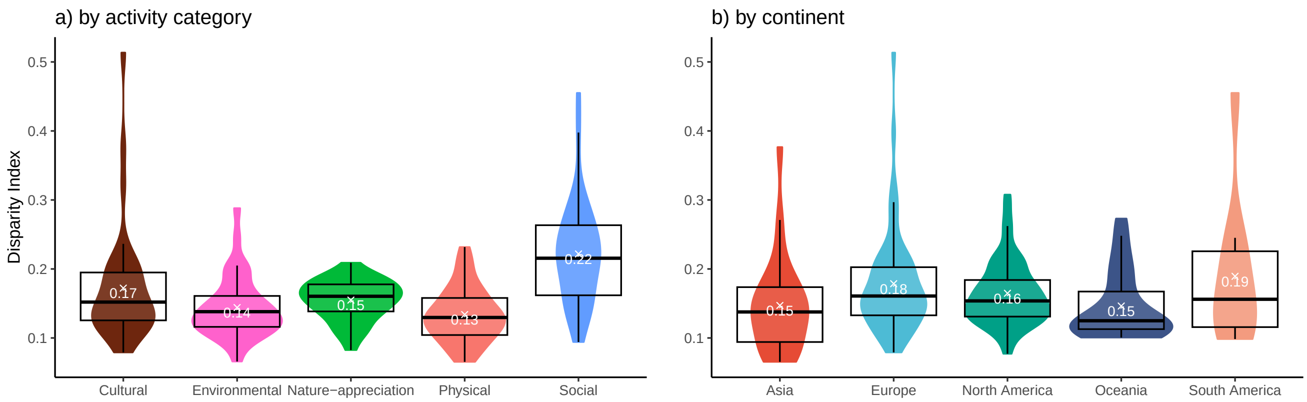

Figure 5. Disparities in Park Health Scores by activity categories (left) and continents (right). While the disparities of the cities converge to a relatively uniform level between 0.15 and 0.19 across all continents, different activities exhibit varying levels of disparities. Physical facilities have the most uniform provision, whereas social facilities show the largest disparities. Standard box plot with Q1, median, Q3; whiskers at 1.5× interquartile range. The white cross indicates the mean value.

The box plots in Figure 5 aggregate the disparity scores by continent and activity category. The individual values are tabulated in Table 6. Generally, we found low disparities, with an average score of 0.165 across all categories and cities. Disparities were notably low in *physical activities* ($\mu = 0.135, \sigma = 0.039$), suggesting a consistent distribution of physical activity facilities across parks. Conversely, *Social activities* exhibited the highest disparity ($\mu = 0.222, \sigma = 0.073$), indicating significant variation in social amenities among parks within cities. *Nature-appreciation activities* displayed a slightly higher average disparity ($\mu = 0.157$) than physical activities but with the least variation ($\sigma = 0.032$), indicating a relatively consistent focus on nature-appreciation facilities across the cities studied.

We hypothesize that equitable distribution of amenities and facilities supporting different activity categories is generally beneficial from a societal fairness perspective. Interestingly, the disparities of the cities converge to a relatively uniform level between 0.15 and 0.19 across all continents (Figure 5b). This indicates that there is no clear divide between the different regions of the world when it comes to fairness aspects of park quality. We use Table 6 to investigate this phenomenon on a city level.

Cities Providing a Range of Activities. Tokyo, Paris, Auckland, Buenos Aires, and Hong Kong were found to have the most equitable provision of park offerings across our five health categories. Tokyo and Paris stood out, with five and four categories, respectively, being below one standard deviation from the mean disparity. These minimal disparities in park facilities may result from centralized park management and legislation promoting community involvement in Paris[154], and equitable public service provision in Tokyo[155].

Cities Focused on Specific Activities. At the other end of the spectrum in Table 6, Moscow, St. Petersburg, Stockholm, Rio de Janeiro, and Copenhagen exhibit pronounced disparities in park facilities. Stockholm has the highest individual disparity score in the cultural dimension (0.514), indicating a considerable centralization of cultural facilities in only a few parks in the Swedish capital. Copenhagen's inequality in park facilities is especially high in the cultural and social dimensions, particularly in central districts, raising concerns that the city's transformation in recent decades has overly catered to the affluent[156]. In Rio de Janeiro, disparities were observed across social, environmental, and cultural activities, aligning with existing research on health inequalities[157] and reflecting the city's deep-rooted socioeconomic segregation[158].

3 Discussion

Urban parks offer a variety of health benefits that extend beyond the typical physical and mental advantages usually highlighted. By discriminating six types of activities people do in parks, we created a detailed taxonomy of park activities and their associated health benefits as found in the medical literature. Our efforts to provide a balanced review unveiled a clear bias towards physical and nature-appreciation activities in the literature. We used this taxonomy to evaluate parks globally based on their support for five of the six activity categories (data to evaluate the mind-body category was unavailable on OSM). By providing individual scores for each activity, we were able to give useful insights about the parks. This allows citizens to identify parks that best suit their preferences and needs, while city authorities can determine which parts of the city may be

Table 6. Comparison of disparity scores across cities by activity category. The mean value over all activity categories determines the table order. Lower values signify a more uniform offering of activity type across a city, whereas higher values indicate a greater disparity in that offering. Values lower or higher than 1 standard deviation from the mean value a marked in gray and bold, respectively.

City	Mean Score	Inequality of each activity category's offering in a city.				
		Physical	Nature-appreciation	Environmental	Social	Cultural
Tokyo	0.089	0.065	0.082	0.066	0.146	0.084
Paris	0.097	0.104	0.101	0.087	0.114	0.079
Auckland	0.121	0.103	0.117	0.105	0.154	0.126
Buenos Aires	0.125	0.172	0.107	0.098	0.137	0.108
Hong Kong	0.125	0.079	0.134	**0.197**	0.094	0.12
Vienna	0.135	0.13	0.144	0.107	0.17	0.125
New York	0.138	0.113	0.137	0.131	0.177	0.129
Rome	0.138	0.122	0.16	0.116	0.153	0.141
Christchurch	0.138	0.104	0.113	0.101	0.273	0.101
San Francisco	0.14	0.09	0.152	0.116	0.212	0.132
Berlin	0.143	0.131	0.14	0.138	0.152	0.154
Chicago	0.153	0.077	0.178	**0.205**	0.151	0.153
San Diego	0.153	0.129	0.169	0.124	0.214	0.128
Melbourne	0.155	0.122	0.167	0.124	0.248	0.114
Montreal	0.156	0.126	0.178	0.142	0.215	0.118
Singapore	0.157	0.166	0.14	0.119	0.227	0.133
Perth	0.157	0.132	**0.19**	0.125	0.21	0.128
Madrid	0.16	0.104	0.163	0.168	0.197	0.167
Sydney	0.16	0.11	0.119	0.153	0.226	0.191
London	0.163	0.134	0.154	0.138	0.23	0.158
Vancouver	0.165	0.102	0.144	0.153	0.216	0.208
Toronto	0.169	0.129	0.178	0.124	0.24	0.172
Houston	0.173	0.139	**0.188**	0.141	0.218	0.18
Taipeh	0.174	0.082	0.156	0.116	0.138	**0.377**
Philadelphia	0.175	0.158	0.174	0.122	**0.308**	0.116
Seattle	0.179	0.132	0.161	0.141	0.265	0.195
Boston	0.186	0.158	0.183	0.147	0.292	0.152
Washington DC	0.191	0.154	0.16	0.173	0.262	0.205
Seoul	0.191	**0.177**	0.184	0.174	0.271	0.152
Amsterdam	0.197	0.161	**0.187**	0.153	0.267	0.217
Moscow	**0.205**	**0.232**	0.161	**0.205**	0.236	0.194
St Petersburg	**0.213**	**0.21**	0.166	**0.288**	0.201	0.199
Stockholm	**0.247**	**0.189**	0.132	0.105	**0.297**	**0.514**
Rio De Janeiro	**0.254**	0.141	**0.193**	**0.245**	**0.455**	0.236
Copenhagen	**0.266**	**0.209**	**0.209**	**0.195**	**0.398**	**0.321**
Mean (sd)	0.165 (0.039)	0.134 (0.039)	0.155 (0.029)	0.144 (0.045)	0.222 (0.074)	0.172 (0.085)

lacking in parks with specific facilities.

Despite all the positive aspects of parks, disparities in access to urban greens is a prevalent theme in academic literature[5,159–163]. Our city-level results also reveal disparities in park facilities, with a clear geographic trend: parks located in the heart of the city are better equipped for health-promoting activities than those on the outskirts. This pattern holds true across all types of activities, even ones that intuitively would be more available in less populated areas (i.e., outskirts), like nature appreciation or environmental activities. This finding aligns with the work of other researchers, such as Wolch et al., who conclude (mostly based on Western studies) that the distribution of parks in a city disproportionately benefits affluent communities[159]. Furthermore, it has been shown that the urbanization of the past two decades has resulted in considerable greening in the downtown areas of cities, whereas the suburbs have not seen the same level of investment[161]. Our results show, additionally to the diminished access to parks in the suburbs described in the literature[159,161], that the quality of these parks is lacking compared to the city center parks. This is a call to action for urban planners to shift their focus to improving these suburban parks. Remarkably, the greatest contributions could be made by creating more natural spaces that support nature-appreciation activities, followed by social activities.

We also investigated overall disparities of facilities across cities. Here, the findings are generally positive in the sense that the overall disparity scores were relatively low and did not display a pronounced geographic variability on a global scale as in previous studies[162,164,165]. This finding can be summarized in a way that while absolute access to greenery has been shown to have quite a high level of inequality, the relative inequality regarding access to health-promoting activities in parks is less severe. Interestingly, the five cities showing the greatest disparities in offerings of activity types are spread across four different continents, indicating that overall disparity in the quality of parks is a prevalent issue worldwide. This finding suggests that just urban planning is not a matter of financial resources, but a question of municipal decision-making and community involvement[154,166,167]. A positive trend can be observed in Asia and Oceania, which have the most equitable provision of park facilities. We found that physical activities were the most evenly distributed, indicating that they receive more attention from urban planners[25,28]. This is in line with the focus of medical literature on the health benefits of physical activity in our literature review (cf. Section 4.3). On the other hand, dedicated social activities showed the highest inequality, indicating a clear need for improvement in these areas in the respective cities[168]. We hope that, based on these insights, urban planners will recognize the need to look beyond physical activities and put more emphasis on improving parks in other ways so to benefit all the citizens (e.g., elderly, who might not be able to engage in physical activities).

While creating high-quality urban green areas might be a balancing act with potential negative effects such as gentrification arising[159], our research can serve as a roadmap for urban planners about which parks to improve with which kind of specific facilities. The ongoing urbanization will not provide them with an easy task, and the obesity crisis coupled with increasing costs of living in cities puts planners into a dilemma: should the available space be used for housing, parks, or other services[169]? Irrespective of such considerations, improving the existing parks with more facilities for health-promoting activities will be foundational for public health[3,22], especially in the outskirts of the cities. This needs to be accompanied by efforts to make parks and their facilities accessible for everyone[170].

In the broader context of urban health, our research adds to earlier studies that explored the environmental benefits of urban green spaces, such as cooling effects[171,172] and reduced air pollution[173,174]. Our focus on activities provides an opportunity to merge these findings, for example, in the form of recommendations for the best times to enjoy activities in certain parks when the environmental conditions are adequate to do so.

Limitations and Future Directions

The first limitation of our work was that activities not requiring specialized facilities could not be accurately considered using our method. While there are approaches to understanding the relationship between open spaces in parks and their usage[175], we have refrained from speculating about such usage to avoid any cultural bias in our park evaluations. This meant we had to remove mind-body activities like yoga from our main analysis, as they often do not need designated areas in city parks. Similarly, our data does not typically account for temporary cultural events like music festivals held in parks.

The quality of parks was measured using map data from OSM, under the assumption that if facilities and spaces that support certain activities are present, they will be utilized for those purposes. However, as acknowledged in the previous limitation, not all activities are directly linked to specific facilities, and the intensity of use cannot be determined using OSM cartographic data alone. This gives rise to instantiating our activity taxonomy (Table 1) using a different data source, which could more accurately reflect actual usage. We demonstrated that the OSM park scores are closely linked to activities captured in Flickr photos, but other data could also be used to approximate park usage. For instance, detailed mobile traffic data could offer intriguing insights into how parks are used[43,176,177].

Our scores for each city's parks are adjusted to reflect the unique circumstances of that city, making direct comparisons between different cities' park scores impermissible. This property prevents some comparative analyses but also avoids comparing vastly different situations as each city has its own cultural, historical, climate, and geographical factors that promote or hinder having high-quality parks. By individually scoring each city, we tailor our ratings to the specific needs of each city, helping urban planners address the most urgent improvements in their city.

We focused on urban parks, excluding other urban green spaces like gardens, street trees, and green roofs, which also promote urban health. The choice of parks was because they offer a wider range of activities compared to the more specialized functions of, e.g., gardens—primarily dedicated to the appreciation of nature—and street trees, which enhance walkability. Parks indeed have a premier role in urban life due to their public accessibility[178], and the commission of their facilities usually falls under the influence of the city administration, meaning our findings about any shortcomings could lead to actionable improvements.

By analyzing snapshots of the OSM database, we captured the state of park amenities and facilities in fall 2023. Like all urban spaces, parks are in constant flux, which raises the question of how parks have evolved over time[5]. This is particularly relevant in the context of the COVID-19 pandemic, when many cities had to reconsider their public health strategies, possibly leading to significant changes in park facilities[163,179]. By examining historical data from OSM, we could use our methodology to track these changes in park facilities. However, a key challenge would be differentiating between actual changes in park development and potential temporal variations in OSM data quality.

Our study primarily examined park facilities that encourage health-promoting activities. However, we did not investigate how these facilities are actually utilized. Therefore, a key area for future research could be analyzing how park quality directly affects people's health. Although it would be unrealistic to gather medical data worldwide to determine the health impact of individual parks, more targeted studies might be possible in certain areas. For example, prescription data that are available for some countries, such as England, could be used to estimate various medical conditions[180, 181]. It would also be worthwhile to further investigate the causal relationships between the temporal changes of parks resulting in better health (e.g., fewer prescriptions).

4 Methods

4.1 Data

OpenStreetMap (OSM) is a globally encompassing geographic information database based on crowdsourced contributions. While accessible through a map interface at `https://openstreetmap.org`, its primary value lies in its data being an indispensable source for third-party mapping, navigation applications[182, 183], and diverse scientific analyses, such as urban planning[184, 185], geospatial analyses[186, 187], and disaster management[188, 189]. With its permissive licensing, the project has nurtured a vast ecosystem of contributors, from individuals to corporations engaged in the geographic information sector. As a result, OSM has achieved comprehensive worldwide coverage, with near-perfect mapping quality across the western world[190], while retaining remarkable detail in the global south[188].

For this study, we utilized an OSM data dump obtained from `https://geofabrik.de` in fall 2023. OSM uses three data structures to describe map objects — *nodes, ways,* and *relations*. Furthermore, OSM employs a tagging system with key-value pairs to categorize and describe all these map objects. Each map object is typically associated with multiple tags, i.e., key-value pairs, that provide insights into its main purpose, used primarily for rendering the object on the map. However, these tags can encompass various additional information, such as opening hours, inscriptions, and data source references.

To avoid the complexities of the OSM data model[191], for our tasks, it was sufficient to focus on two key map objects related to parks: *park elements* and *park spaces*. *Park elements* are 0-dimensional points representing objects like benches, individual trees, and statues. These *elements* are stored as "nodes" in the OSM data model. On the other hand, *park spaces* refer to areas within the parks, such as meadows, lakes, and forests. In the OSM database, these *areas* can be modeled as "ways" or "relations", but for the purpose of this study, we treat all areas equally.

Flickr (`https://flickr.com`) has established itself as one of the most prominent platforms for sharing photography. Since its inception in 2004, the platform has gained considerable popularity, accumulating billions of images. Notably, many of these images have been precisely geo-located, thanks to the utilization of the (phone) camera's GPS module.

We utilized a substantial dataset comprising geo-located images posted between 2004 and 2015. This extensive dataset offered us a valuable secondary perspective on activities taking place within the parks of the world. By intersecting these images with the park outlines from OSM, we identified 10,788,686 pictures captured within the boundaries of parks in our study cities. To extract the depicted content from these images, we used user-assigned tags in conjunction with automatically-generated computer vision labels[192, 193]. These labels enabled us to gather information about the various facilities and activities within the parks.

4.2 Study Area

Our research focuses on 35 cities listed in Table 6 selected using three criteria to make our analysis broad yet robust.

First, we chose to look at big cities worldwide with at least 650,000 people. This size was selected because it includes many of the largest cities, including most of the large capitals in Europe and other densely populated areas across the globe where parks are crucial for people's well-being[9, 194]. It also helped keep our study focused and understandable without including too many smaller cities. However, to ensure better representation in Oceania, we made an exception for Christchurch in New Zealand, which we included, although it is less populous than our cutoff. This first criterion allowed us to examine parks in cities from various parts of the world, each affected by its own climate, history, and cultural background.

Second, we only looked at cities in countries where at least 80% of the population has access to the Internet[195]. This ensured we had enough online data (like tags on OSM or photos on Flickr) for our study. Since there is no detailed global data on Internet use in cities specifically, we used the country's overall access to the Internet as our guide. This way, we set a basic standard, knowing that people in cities, especially in developing countries, usually have better access to the Internet than those in rural areas. We decided on this threshold upon our preliminary empirical analyses, finding that in many cities in Africa and South America, where fewer people have Internet, there was not enough digital information for our data-intensive approach.

Third, we chose cities where, on average, parks have at least one-eighth of their area tagged with health-related tags on OSM. Because we relied heavily on OSM for our analyses, this rule helped us focus on cities with sufficient information on the platform for our study. We settled on this one-eighth rule after observing that this was the threshold where the lack of manual tagging prevented us from obtaining sufficient information for our task. Mainly, this meant we could not include cities where the predominantly automatic tagging of areas in OSM through earth observation was not accompanied by manual tagging of OSM contributors. This was mainly the case in China, where OSM mapping is deemed illegal[196].

4.3 Identifying Health-promoting Activities in Urban Greenery

We used an expert panel to identify and categorize activities and discovered their health benefits through a scoping literature review.

Expert Panel

First, we assembled a list of activities that people engage in at urban parks. This was accomplished with the help of an expert panel composed of three co-authors of this paper. To collect relevant papers, we used two specific queries of Google Scholar: "(urban) AND (parks OR greenery) AND usage" and "(activities in urban) AND (parks OR greenery)". From this process, we collected the top 50 scholarly articles for each search phrase. This resulted in 91 unique papers.

We carefully examined each article, making a note of all the activities mentioned. This gave us a wide range of activities that varied in their level of detail. For instance, both broad activity terms like *leisure activities* or *recreation* as well as more specific activity categories like *physical* and *social activities* were frequently mentioned. We also noted down plenty of individual activities like *walking*, *performing street theatre*, *fishing*, and *playing all kinds of different sports*. There were instances where we inferred activities from the mention of specific facilities. For example, the mention of playgrounds was noted as *"playing"*, boat rentals as *"boating"*, and fitness facilities as *"exercising"*. Afterward, we held a meeting to categorize these activities. We especially focused on the potential health benefits of each activity and tried to find the similar levels of detail for each category. For instance, *leisure activities* or *recreation* were seen as too broad categories, while distinguishing between *physical* and *social activities* was considered appropriate. In the end, six categories emerged: physical, mind-body, nature-appreciation, environmental, social, and cultural activities (Section 2.1, *Step 1: Identifying Activities in Parks.*).

Scoping Review

Next, our goal was to collate and map health-prompting activities in parks discussed in prior studies. Considering between a systematic and scoping type of review, the scoping review was a better fit for our task because we only needed to map activities discussed in the literature, and we did not need to focus on the types and quality of data collected in those studies, which is a task for systematic reviews. Specifically, we turned to using the well-established PRISMA method[197], which is designed to facilitate transparent reporting of reviews, and it has been designed primarily for reviews of studies that evaluate the effects of health interventions, irrespective of the design and strength of effects found in the included studies.

The overarching research question was: *"Which are the health benefits of activities in urban greenery?"* Our focus on urban greenery instead of only parks was to ensure both the *comprehensiveness* and *generality* of the taxonomy, as future studies might look beyond urban parks. We used the WHO's definition of urban greenery to determine the scope of our survey: *"[. . .] urban green space is defined as all urban land covered by vegetation of any kind. This covers vegetation on private and public grounds, irrespective of size and function, and can also include small water bodies such as ponds, lakes, or streams ("blue spaces")*[2]."

As we were interested in the intersection of urban greenery and medical studies, we performed a set of queries on PubMed and SpringerLink to identify papers that linked the usage of urban greenery with health benefits. An article was deemed relevant if the results evidenced that one or more activities typically done in public urban green spaces had a health benefit. To obtain a comprehensive overview of each activity category, we used a total of 6 queries. Upon our preliminary experiments, we employed a collection of keywords for our queries that included both those commonly encountered in the initial set of studies and those formulated by our experts. This approach enabled us to discover a diverse range of papers relevant to each category of activity. The queries were:

Physical activities: (urban greenery) AND (health) AND (sports OR exercise)

Nature-appreciation activities: (urban greenery) AND (health) AND (nature) AND (exposure)

Environmental activities: (urban greenery) AND (health) AND (garden OR planting OR conservation)

Social activities: (urban greenery) AND (health) AND (social OR social cohesion OR social capital OR social contacts)

Cultural activities: (urban greenery) AND (health) AND (culture) OR (cultural ecosystem)

Mind-body activities: (urban greenery) AND (health) AND (mindfulness OR meditation OR yoga OR tai chi OR breathing techniques)

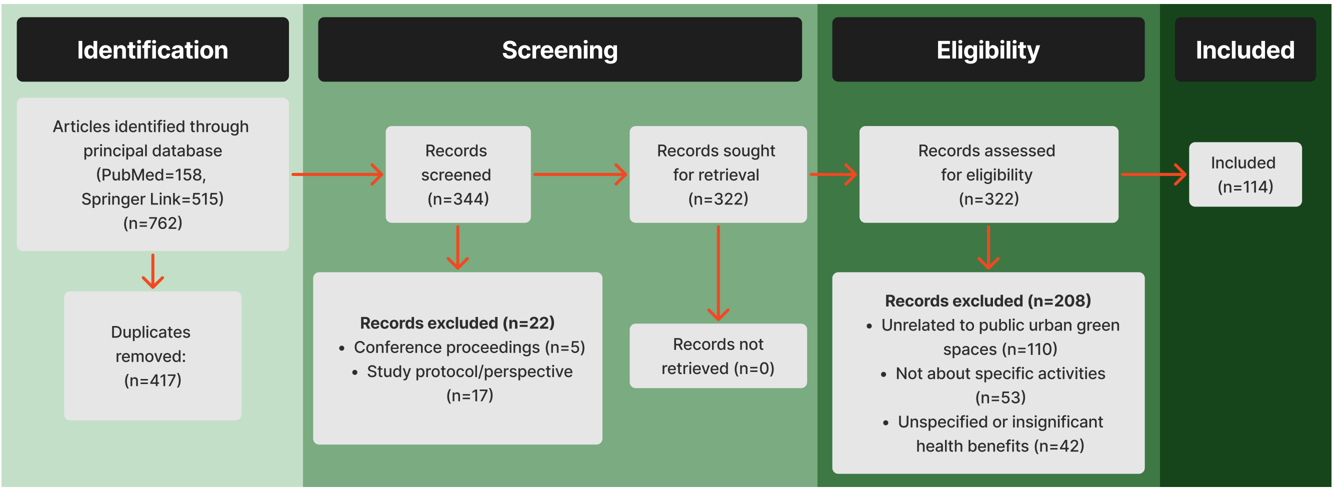

Figure 6. Our PRISMA Statement: Process of identification, screening, and determining eligibility for articles in our literature survey.

Following the PRISMA statement depicted in Figure 6, out of the initially *identified* 762 articles, 417 were duplicates, leaving us with 344 unique articles. Next, we *screened* these articles and discarded 5 conference proceedings and 17 articles that were perspectives or study protocols, successfully retrieving the remaining 322 articles. In the *Eligibility* step, we determined whether these articles were relevant to our search. We found that 114 articles were relevant, while 208 were not. Most articles were excluded because they were not about urban green spaces or because there was no significant link between the activities and health benefits. When analyzing the *included* articles, we recorded each activity category alongside the general health aspects and specific health benefits the article evidenced (Table 1).

4.4 Annotating Park OSM Tags with Activities Using LLM Classifiers

To associate different park elements and spaces with health-promoting activities, we annotated OSM tags describing those elements and spaces with activities. This turned out to be a challenging task. OSM is a collaborative platform with some governance and guidelines[178] for tagging, but the flexible tagging system offers the crowdsourcing contributors substantial freedom in their tasks. Consequently, the data can be disorganized, requiring intense preprocessing and tidying up. Each map object, such as park elements and spaces, can be marked with an unlimited number of tags, offering in-depth descriptions. This results in a large variety of tags — specifically, we noted more than 30,000 unique key-value pairs describing park elements and spaces. Given that our main interest is in the primary aspect of the *park elements* and *spaces*, we performed a data cleaning step, detailed in the Appendix, Section B.2, where we eliminated irrelevant meta information of the items. This step lets us concentrate exclusively on the key aspects linked to health-promoting activities, making the labeling task more manageable and pertinent to our study.

Using Large Language Models for Annotation

Even for domain experts, it was challenging to unequivocally link these tags to health-related activities. For example, a bench could be associated with various health benefits — socializing, enjoying nature, or resting from physical activity. Choosing one activity over another depended largely on personal experiences[198], as many tags could be linked to multiple activities. Given the vast number of items and the specialized nature of the task, we opted for an LLM classifier as an alternative to expert annotation or crowdsourcing.

Using LLMs as classifiers comes with several benefits. They offer a more objective and consistent way to annotate that can be applied to a large number of necessary annotations in a short time and at low costs. In some instances, these classifiers have even been found to perform better than crowdworkers[199]. This is particularly true as crowdworkers might themselves use available machine learning models for performing tasks[200]. Furthermore, research suggests that the quality of annotation achieved with LLM classifiers could be on par with domain experts[201]. Therefore, we chose to establish a benchmark in our domain to evaluate the feasibility of using LLM annotations in mapping OSM tags to health-promoting activities. To do so, we had three of our experts manually annotate a set of 100 most frequent tags, and then we chose the final labels with majority voting. We then used this expert-labeled dataset to assess the accuracy of the labels generated by different LLM classifiers. The details of the LLM annotation benchmark can be found in the Appendix, Section B.3. The outcome indicated that GPT-4, set at a temperature of 0.9, yielded the best annotation performance of an F_1 score of 0.77.

Operationalization of the Taxonomy
Using the taxonomy with six categories of health-promoting activities in Table 1, and GPT-4 as the best-performing annotation model, we ran the annotation of OSM tags describing *park elements* and *park spaces*. These tags were then labeled with one of the health-promoting activities, or *"none"* if they didn't support a particular activity. By doing so, we gained insights into which type of health-promoting activities each *park element* and *park space* potentially facilitate, which in turn led to a comprehensive and precise understanding of the health-promoting activities in parks and their potential contributions to public health (Table 2). Note that the mind-body activities category was discarded in this step since none of the OSM tags found in parks were primarily mapped to this category.

4.5 Computing Park Health Scores by Aggregating OSM Tags
The core method to characterize parks in terms of their potential for health-promoting activities is based on counting the respective *park elements* and *spaces*. These counts are then combined to give each park an overall score for each health-related category. This score represents the potential health benefits of each park.

Counting Health-promoting Elements and Spaces in Parks
In our process of assigning health-promoting activity scores to each park, we first gathered *park elements* and *spaces* within each park. We used the *osmium* library to collect all relevant map resources from OSM that intersected with the shape of each park. For *park elements*, we simply counted all elements found within the park boundaries. But for the *spaces*, we calculated the overlapping area with the park's area. This was important because some spaces, like a river running through the park, might continue beyond the park's edges and should not fully count towards a park's score. After obtaining two lists – one for *park elements* and another for *park spaces* – we then assigned health-promoting activities to these *elements* and *spaces* based on the LLM classification of their associated tags, such as shown in Table 2. We discarded any *elements* or *spaces* whose tags did not match an activity category. In a few instances, *park elements* or *spaces* might have fit into more than one health-promoting activity category. For example, sports fields were often tagged with different labels that contribute to both physical and social categories. In these cases, we proportionally counted the resource, taking into account all the matched categories under which it falls.

Transforming Counts into Health Scores
After tallying up the *park elements* and *spaces* within the park, we measured the overall effect of the park in promoting healthy activities within a city. This score should account for the park's size and the range of facilities it offers for different activities. Our proposed scoring method is based on these considerations.

1. *Density of Health-Promoting Elements and Spaces:* The character of a park is determined by the concentration of health-promoting facilities.
2. *Diminishing Returns with Increased Count:* We posit that as the count of these elements and spaces increases, the associated benefits exhibit diminishing returns.
3. *City-specific Normalization of Park Health Scores:* The value of a single park's facilities for a certain activity is relative to similar facilities in other parks throughout the city.

To reflect these assumptions into our scoring, we proposed a linear regression model to compute the park health scores shown in Equation 1. We used the idea of an *"average park"* in each city to compute a baseline and used the distance of each park to the average park line, i.e., the residual, as score. The average park baseline was determined by computing separate linear regression models for *park elements* and *spaces* in each city, estimating the expected amount of facilities relative to the park area.

$$E_{Act}(log_2(count(Act))) = i + s \cdot log_2(\text{park area}) \mid Act \in \text{Activity Categories}, \quad (1)$$

where i and s represent the intercept and slope of the regression lines, respectively. To obtain regression models for each activity category and both *park elements* and *park spaces*, we utilized the binary logarithm to account for the diminishing returns of an increase in park size. For each city, separate regression models were calculated for each activity category, as well as for *park elements* and *park spaces.* During the computation of the regression models, parks with very low activity counts in a specific category were excluded. This exclusion was necessary to prevent artificially flattening the regression lines due to close-to-zero values, which would distort the normalization. The specific threshold for excluding parks with low activity counts was determined empirically by analyzing the histograms of the values. This approach enabled us to identify an appropriate cutoff point for excluding parks with insufficient activity data, ensuring the reliability of the regression models. For a visual representation of the exclusion process and the determination of the threshold, refer to Figure 12 and Figure 13 in the Appendix.

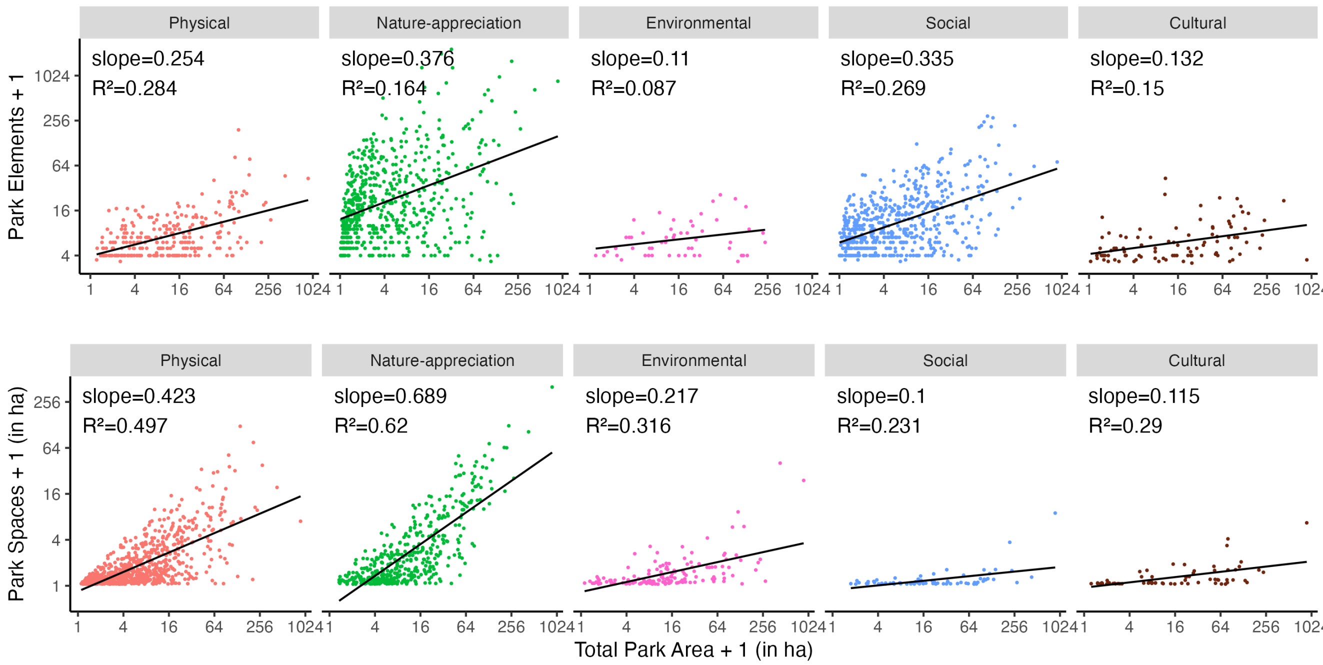

Figure 7. Visualization of the scoring method. The linear regression models for determining the park health scores for the *park elements* (top) and *park spaces* (bottom) in London, UK. The horizontal axis denotes the of the park's area (log_2), while the vertical axis represents of the count of *park elements* and the area occupied by health-promoting *park spaces* (log_2). The modest R^2 values are anticipated, highlighting the variety among parks.

By considering the residuals, we could identify parks that exceeded expectations (positive residuals) and parks that fell short in terms of providing health-promoting resources (negative residuals) for this activity. Making the linear model dependent on the park area, we achieved that the resulting scores of health-promoting *elements* and *spaces* depend on the density. We used the binary logarithm to discount the effects of extremely large counts and parks. Furthermore, we chose to calculate these scores for each city separately rather than using a single global model. This way, we ensured that the benefits accurately represented each city's local situation. To visualize this method, we plotted the linear models and the individual park scores in the $log - log$ space for London, UK, in Figure 7. The regression lines denote expected health scores based on park size. Park scores for *park elements* and *spaces* are residuals from this *average park line* in the model, adjusting for park size when determining health scores.

Combining Scores from Park Elements and Spaces

The regression models gave us individual scores for *park elements* and *park spaces* for each activity. To unify these scores into one combined health score, we examined the co-occurrences of *park elements* and *spaces* and found that they represent orthogonal concepts in practice. *Park elements* include points of interest, individual trees, benches, and similar items. *Park spaces*, however, include areas like forests, sports fields, and buildings. There can be cases where a park area is broken down into its individual parts, like a playground with separately mapped features like swings, slides, or spinning equipment. But these cases are pretty rare in OSM mapping. Likewise, unless a tree is particularly important, areas tagged as `natural=wood` should not include individual trees according to the mapping guidelines[178]. Based on these observations, we hypothesized that it would be acceptable to combine scores from park features and areas linearly, as they contribute differently to the overall offering of facilities for health-promoting activities.

To validate the assumption that *park spaces* and *park elements* are orthogonal, we calculated the pairwise correlation coefficients of their respective scores in all cities and averaged them, as presented in Table 7. The low Pearson Correlation Coefficients supported our observation that the scores of *park spaces* and *park elements* indeed capture largely independent concepts, with all correlations being slightly positive but below 0.2. Consequently, we combined them into one overall score for the park.

To achieve this, we first normalized the scores of *park elements* and *spaces* using the z-score transformation considering all parks in a city. This normalization allowed us to standardize the scores, making them comparable despite being on different scales. Then, we linearly combined these z-scores by averaging them together to create the overall score for the park according

Table 7. The correlations between the scores for *park elements* and *park spaces* are low. This property allowed us to linearly combine them into a unified score.

Activity Category	Mean Pearson Correlation
Physical	0.16
Nature-appreciation	0.05
Environmental	0.18
Social	0.06
Cultural	0.18

to Equation 2.

$$Score(P_{Act}) = \frac{z(residual_{elements}(P_{Act})) + z(residual_{spaces}(P_{Act}))}{2}, \tag{2}$$

where P denotes an individual park, Act is one of the activity categories, the residual scores for element and spaces stem from Equation 1, and $z()$ indicates the z-score transformation.

The combined and normalized scores of *park elements* and *spaces* represent a comprehensive and unified measure of the park's health-promoting amenities and facilities, accounting for both individual elements and cultivated areas. The combination process accounts for the relative importance of each aspect, leading to a more meaningful overall score that represents the park's overall quality in terms of offerings toward health-promoting activities.

4.6 Quantifying Disparities of Park Scores

One outcome of our study was to quantify disparities of health benefits offered by different parks within a city (Section 2.3, *Centralization of Park Quality Within Cities*). To measure the disparities in the presence of amenities and facilities associated with health-promoting activities within a city, we propose the following disparity index. The metric essentially quantifies the inequality of the park health scores, as generally, one could expect that good park management would provide for a similar amount of features and facilities in all parks of a city. Since the park health scores could be negative, we can not directly use a standard inequality metric, such as the Gini Index, but had to min-max normalize the park score before computing the Gini Index (Equation 3).

$$Gini_{Act}(\{X'_{Act} | X_{Act} : p \in c\}), \tag{3}$$

where X_{Act} is the score of activity category $Act \in [physical, cultural, ect.]$ of a park p in city c, and

$$X' = \frac{X - X_{max}}{X_{max} - X_{min}} (min - max\ normalization),$$

and the Gini index was computed in a standard way:

$$Gini = \frac{A}{A+B},$$

where A is the area between the Lorenz curve and the line of perfect equality and B is the area beyond the Lorenz curve[202].

4.7 Semantic Matching of Flickr Labels and OSM Tags

In our validation (Section 2.2), we used a global dataset of geotagged photos from Flickr, from which we selected all 10,711,513 images that were taken within one of the parks from 35 cities in our study. These images came with user-generated labels and were also partially annotated with computer vision labels from a computer vision algorithm[192, 193]. To obtain semantically equivalent representations of Flickr labels and OSM tags, we employed Sentence-BERT (S-BERT[203]) for text embeddings. We formulated this task as an asymmetric semantic search problem, where the Flickr label was the search term, and the goal was to find the closest matching OSM tag. Given the worldwide reach of our study, the multiple languages present in the user-generated Flickr labels created a challenge in mapping them to the corresponding OSM tags, which were all in English. To address this, we identified the top three languages besides English used in the tags of each city, using the Google MediaPipe[204] Language Detection Model[205]. To ensure that the language detection was accurate and to eliminate named entities, we only used labels where the language detection indicated a confidence of 50% or more. We then translated those tags to English using the respective OPUS machine translation models[206].

To further improve the quality of embeddings, we augmented the OSM tags with short definitions sourced from the OSM mapping guidelines[178]. For instance, the OSM tag `sport=table_tennis` was augmented with the definition *"A bat and ball game played over a table."* We were able to expand 66% of the OSM tags with these descriptions. The remaining tags were left without descriptions primarily because of the unregulated nature of tagging in OSM, which led to many undocumented tags or multiple values within one tag, like `sports=soccer;rugby`. Note that these tags were still used for mapping, albeit with less information.

After embedding the OSM tags using S-BERT's `all-mpnet-base-v2` model, we proceeded to match each Flickr label to the closest OSM tag in the embedding space, using the cosine distance as similarity measure. To ensure that the matches were of high quality, we set a strict threshold: the cosine similarity score had to be at least 0.7. We arrived at this value after noticing that when the similarity score was lower than 0.7, the matches became less reliable based on manual inspections. This allowed us to avoid matching labels that did not have meaningful OSM counterparts. For example, abstract labels describing certain phenomena like *"cloud", "rain",* and *"sunset"* were not matched.

A detailed review of the matched pairs revealed that, as anticipated, most pairings were logical based on the text similarity between labels and tags with definitions. However, some minor adjustments were still needed, as some matches were not entirely consistent with the theme of health-promoting activities in parks. For example, the term *"outdoor"* was initially linked to `swimming_pool=outdoor`. But as there cannot be a suitable equivalent for *"outdoor"* on OSM, we removed this pairing and equivalent ones, such as *"park,"* as all photos were taken in parks. Another instance was the pairing of "water" with `substance=water`. This match did not reflect the specific use of water features in parks to promote health, so we manually adjusted this to `water=river`, which better represents bodies of water in parks. Through this review step, we improved the quality of the matched pairs, ensuring they more closely align with the theme of health-promoting park activities. The need for this manual step should not diminish the effectiveness of the semantic search within sentence embeddings. It was merely to eliminate labels that could not meaningfully correspond with an OSM tag and to match a few labels with more domain-relevant tags. This matching process yielded 2,171 label-tag pairs in total. Of these, 1,432 pairs corresponded to an OSM tag with health-promoting benefits, such as *"steeplechase"* being matched to `athletics=steeplechase` involving physical health benefits, while 739 pairs, such as *"Lamp Post"* being matched to `man_made=lamp_post` did not imply health benefits.

We evaluated the accuracy of the resulting label-tag matchings by asking three domain experts to independently assess whether the 20 most frequent matchings from Flickr tags to activity categories were plausible and correct. We aggregated their responses using majority voting. Given the multiple languages present in the dataset, we used only the tags from London in this evaluation step, as they were in English. The experts agreed with 82% of the matchings, which is highly accurate considering they are based solely on individual tags.

Having assured that the matchings are accurate, we proceeded to profile the parks based on the activities associated with the matched OSM tags, following the same scoring approach as what we used for the OSM *park elements* and *spaces* (cf. Equation 2). In our validation, we chose a minimum of 250 images from each park and at least 15 parks in each city. This criterion was established to secure a robust number of images for each park, enhancing the accuracy of our analysis. This approach helped us avoid any potential bias that could have been introduced by individual photographers if a park had only a few images. Figure 15 in the Appendix depicts the linear model of the Flickr labels for London, UK.

Data availability

The replication package contains tables of the park health scores in the cities: `https://github.com/LinusDietz/Health-Promoting-Parks-Replication`. The original OpenStreetMap data used for scoring the parks is publicly available and can be best obtained from one of the third-party download servers, for example from `https://download.geofabrik.de`. The Flickr dataset for the validation can not be shared due to terms of conditions of this dataset.

Code availability

The Python and R code to compute park health scores is available at
`https://github.com/LinusDietz/Health-Promoting-Parks-Replication`.

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Author contributions statement

L.D. conceived and conducted the experiments and drafted the manuscript. S.S., K.Z., and D.Q. conceived the experiments and edited the manuscript. A.F.Z. conducted the literature survey. All authors analyzed the results and reviewed the manuscript.

Ethics declarations

Competing interests

The authors declare no competing interests.

Appendix

A Supplementary Results

A.1 Top Parks by City

The following Table 8 lists the best park of each city by their scores on each activity category.

A.2 Average Park Offerings by City

Figure 8 subdivides Figure 2 by cities offering a more detailed picture of the average park offering in the cities.

A.3 Geographic Influence on Park Scores

Figure 9 complements the findings from Section 2.3 regarding geographic influences on park health scores. The plot provides additional insights subdivided by continents.

Using a correlation analysis between the distance to the city center (discounted using the binary logarithm) and the park health scores, we aimed to provide an additional quantification of the decay in park scores moving away from the city center. Plotting the PCC for each city individually in Figure 9, we observe mostly low to moderate negative correlations.

Table 8. Top parks of the cities by activity category

City	Physical	Nature-appreciation	Environmental	Social	Cultural
Amsterdam	Sloterpark, 2.2	Sloterpark, 2.38	Park Frankendael, 0.88	Westerpark, 2.18	Amstelpark, 2.29
Auckland	Lloyd Elsmore Park, 4.07	Point England Park, 4.52	Paneke / Radonich Park, 2.73	Ambury Regional Park, 3.14	Albert Park, 2.57
Berlin	Tempelhofer Feld, 5.3	Landschaftspark Johannisthal/Adlershof, 4.02	Gärten der Welt, 2.88	Tempelhofer Feld, 2.49	Treptower Park, 4.14
Boston	Franklin Park, 3.64	Charles River Esplanade, 3.62	Temple Street Park, 1.65	Charles River Esplanade, 3.22	Georges Island, 2.25
Buenos Aires	Parque Indoamericano, 4.36	Parque de la Memoria, 3.85	Paseo Arzoumanian, 1.69	Parque de las Ciencias, 2.09	Parque Avellaneda, 3.67
Chicago	Lincoln Park, 2.75	Northerly Island, 2.57	Grant Park, 2.16	Lincoln Park, 4	Grant Park, 1.91
Christchurch	Canterbury Agricutural Park, 4.56	Bottle Lake Forest Park, 4.13	Hagley Park North, 3.84	Avon River Precinct, 3.5	Hagley Park North, 2.65
Copenhagen	Fælledparken, 1.89	Østre Anlæg, 1.55	Husum Bypark, 1.36	Enghaveparken, 1.23	Østre Anlæg, 0.98
Hong Kong	九龍仔公園 Kowloon Tsai Park, 4.29	藝術公園Art Park, 3.92	佐敦谷公園 Jordan Valley Park, 2.23	迪欣湖活動中心 Inspiration Lake Recreation Centre, 4.79	灣仔臨時海濱花園 Wan Chai Temporary Promenade, 2.77
Houston	Hermann Park, 3.65	Hermann Park, 2.55	Wright-Bembry Park, 1.66	Hermann Park, 2.21	Hermann Park, 2.74
London	Old Deer Park, 5.58	Russia Dock Woodland, 4.62	Bushy Park, 3.32	Richmond Park, 3.25	Alexandra Park, 2.37
Madrid	Parque Agustín Rodríguez Sahagún, 4.33	Dehesa de la Villa, 6.59	Parque del Retiro, 3.36	Finca Vista Alegre, 4.18	Parque del Retiro, 2.9
Melbourne	Albert Park, 4.06	Grant Reserve, 4.19	Fitzroy Gardens, 1.21	Albert Park, 2.45	Carlton Gardens, 2.49
Montreal	Parc Jean-Drapeau, 4.73	Parc Angrignon, 5.64	Jardin botanique de Montréal, 2.46	Vieux-Port, 2.68	Parc Jean-Drapeau, 2.93
Moscow	Парк Останкино, 3.9	Бирюлёвский дендропарк, 2.58	Выставка достижений народного хозяйства, 2.91	Тимирязевский парк, 4.82	Выставка достижений народного хозяйства, 3.22
New York	Pelham Bay Park, 3.52	Prospect Park, 3.23	Bronx Park, 3.7	Brooklyn Bridge Park, 3.76	Fort Tilden, 3.8
Paris	Bois de Boulogne, 6.83	Bois de Vincennes, 5.23	Jardin des Plantes, 2.36	Bois de Boulogne, 3.2	Bois de Boulogne, 3.61
Perth	Altone Park, 3.94	Kings Park, 4.91	Hyde Park, 2.98	Christ Church Grammar Playing Fields, 2.98	Victoria Gardens, 1.7
Philadelphia	East Fairmount Park, 3.49	East Fairmount Park, 3.87	East Fairmount Park, 1.73	Race Street Pier, 2.72	Fort Mifflin, 3.19
Rio De Janeiro	Aterro do Flamengo, 5.71	Quinta da Boa Vista, 6.14	Largo da Carioca, 1.02	Campo de Santana, 1.42	Praça Luís de Camões, 2.04
Rome	Villa Borghese, 3.89	Villa Glori, 2.85	Parco Agricolo di Casal del Marmo, 2.5	Riserva Naturale dell'Acquafredda, 2.5	Villa Borghese, 2.98
San Diego	Balboa Park, 3.35	Mission Bay Park, 2.46	Balboa Park, 1.49	Balboa Park, 3.36	Balboa Park, 2.69
San Francisco	Presidio of San Francisco, 2.9	Lake Merced Park, 3.7	Golden Gate Park, 3.11	Presidio of San Francisco, 3.62	Golden Gate Park, 2.99
Seattle	Warren G. Magnuson Park, 4.76	Seward Park, 3.7	Washington Park Arboretum, 4.95	Seattle Center, 2.77	Seattle Center, 4.61
Seoul	올림픽공원, 3.91	매봉산공원, 3.45	서울숲, 2.48	송파나루공원, 3.17	경복궁, 4.19
Singapore	Changi Business Park, 3.72	Windsor Nature Park, 3.6	Singapore Botanic Gardens, 2.52	The Lawn@Marina Bay, 2.45	Singapore Botanic Gardens, 3.16
St Petersburg	парк Героев-Пожарных, 2.82	Парк-дендрарий Ботанического сада Петра Великого, 2.98	Летний сад, 1.68	Приморский парк Победы, 3.73	парк Лесотехнической академии, 4.15
Stockholm	Årstafältet, 1.74	Kungsträdgården, 1.6	Sveaplan, 2.45	Karlaplan, 1.26	Humlegården, 1.01
Sydney	Centennial Park, 6.9	Centennial Park, 4.16	Sydney Park, 1.68	Lawrence Hargrave Reserve, 2.37	Clarkes Point Reserve, 3.21
Taipeh	大安森林公園, 6.47	關渡自然公園, 6.23	士林官邸公園, 2.52	天母運動公園, 3.34	中正紀念公園, 4.14
Tokyo	若洲海浜公園, 6.14	上野恩賜公園, 6.77	北の丸公園, 4.41	上野恩賜公園, 3.54	上野恩賜公園, 7.92
Toronto	Centennial Park, 3.26	Sunnybrook Park, 4.54	Highland Creek Ravine, 2.86	Toronto Island Park, 4.32	Don Valley Brick Works Park, 4.02
Vancouver	Connaught Park, 1.98	Stanley Park, 3.52	Stanley Park, 1.13	Hastings Park, 2.53	Morton Park, 1.4
Vienna	Augarten, 3.63	Draschepark, 3.05	Schlosspark Schönbrunn, 1.45	Schlosspark Schönbrunn, 3.09	Schlosspark Schönbrunn, 2.89
Washington Dc	East Potomac Park, 4.28	National Mall, 3.3	National Mall, 3.08	National Mall, 3.98	National Mall, 4.24

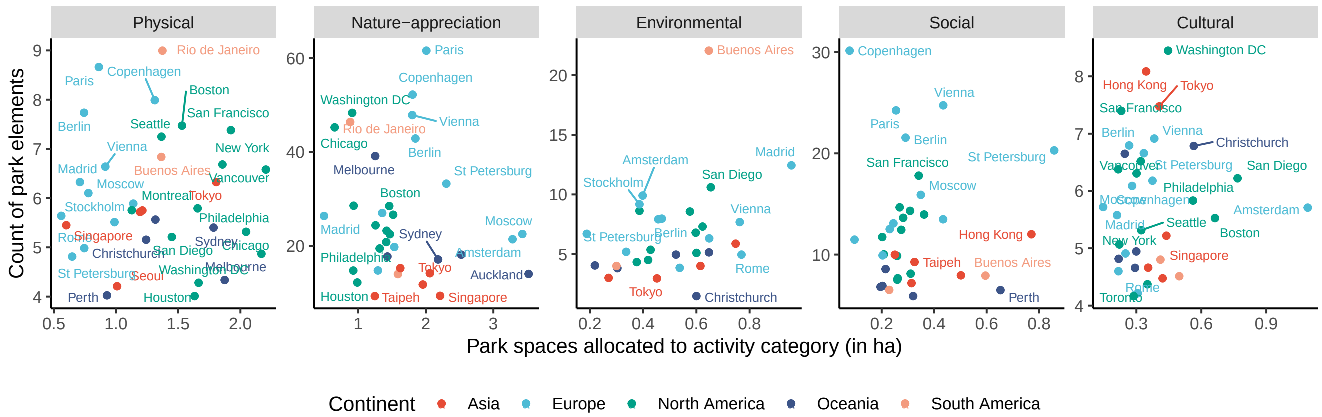

Figure 8. **Area of park spaces (horizontal axis) and count of elements (vertical axis) in a fictional average 8-hectare park dedicated to individual activities.** Nature-appreciation and physical activity spaces are the most common, with elements dedicated to nature appreciation outnumbering those for social and environmental activities. This plot subdivides Figure 2 by cities. Note that for better readability, the scaling of the axes is not fixed.

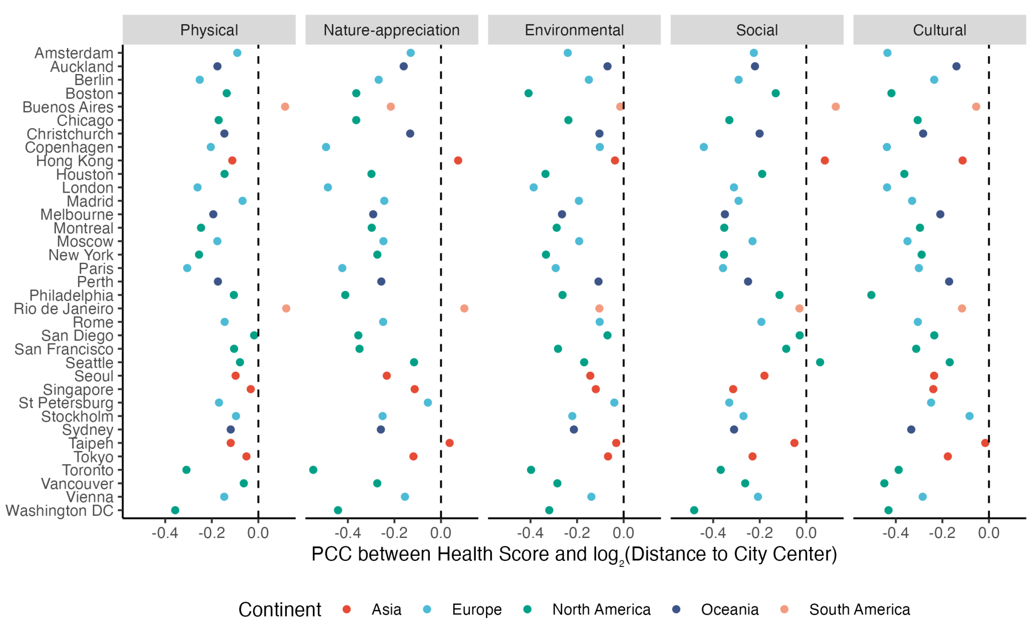

Figure 9. Pearson correlations between park health scores and the distance to the city center (log_2) by city.

A.4 Disparities of Park Scores

Figure 10 provides a visual representation of the data tabulated in Table 6 emphasizing the continent of the cities. This figure supplements the findings in Table 2.3 *The spatial variance contributes to the overall unequal distribution of activity opportunities*.

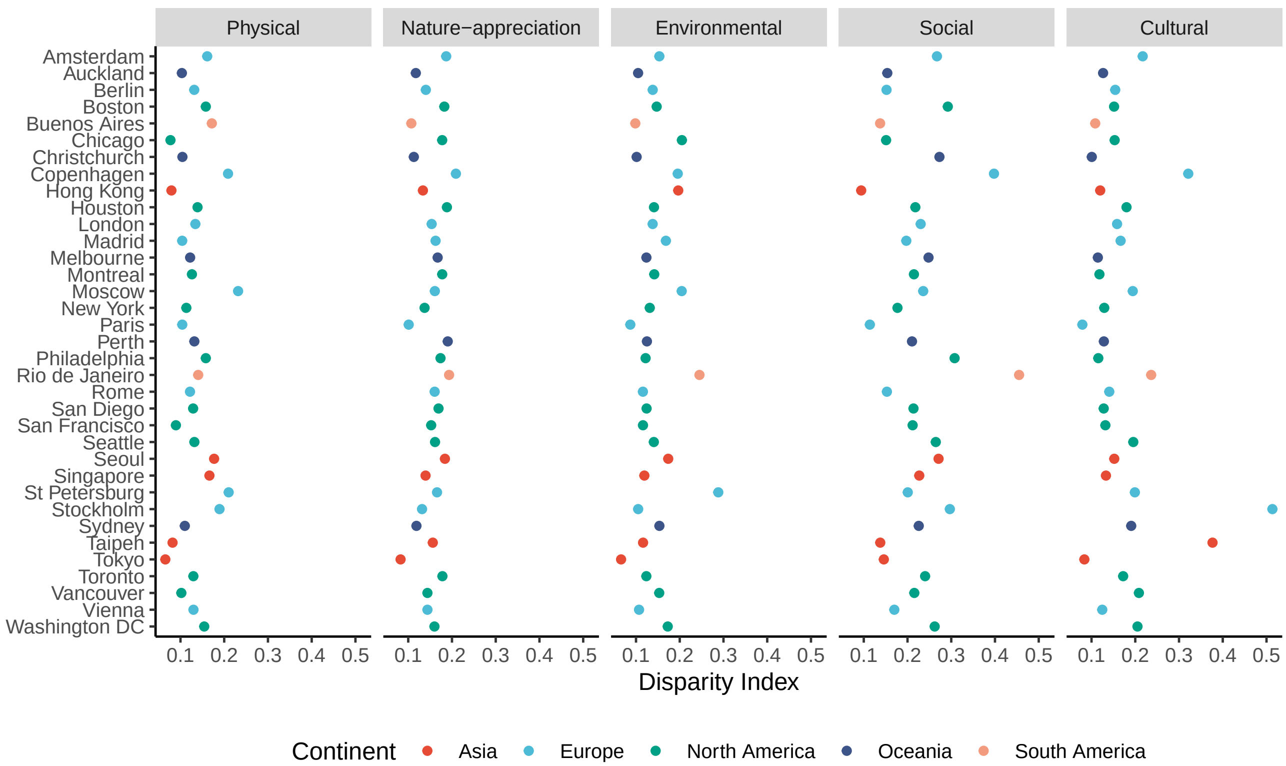

Figure 10. Inequality of park scores in the cities. Overall, nature-appreciation activities show the lowest disparities, whereas the largest differences can be observed in the social activities category.

A.5 Validating the Overall Ranking of Parks through an Online Survey

As an additional means for validating the park scores, we conducted a survey in one city, London. In an online questionnaire, we asked London citizens about suitable parks for performing activities. The main set of questions was phrased as: *"Can you name several parks suitable for **physical activities** (e.g., sports)?*"

Study Information

We recruited the participants using the first author's institutional research recruitment portal as well as mailing lists within scientific institutions in London. The participants were informed about the voluntary nature of their participation and that no personally identifiable information about them was collected. For these reasons, age was collected using 7 age groups (*"Below 18"*, *"18–24"*, *"25–34"*, *"35–44"*, *"45–54"*, *"55–64"*, *"65 and over"*) and as a privacy mechanism only the postal area (e.g., N1) instead of the full postcode was requested. Furthermore, we asked participants how long they have been living in London (*"I don't live in London." – "Less than 1 year." – "1 to 5 years." – "More than 5 years."*). Finally, as a means to identify low-quality responses, we asked people for a park close to their homes, which we could use as an instructional manipulation check in conjunction with the reported postal area. The data collection was registered as a minimal-risk study at the first author's institutional review board (King's College London Research Ethics Office, ID: `MRA-22/23-38802`).

Results

The metric we used to quantify how well the citizen response aligned with our health scores is the average percentile-ranking[207,208], which captures how highly the selected park was placed in the overall ranking of parks for the corresponding activity. A value close to 1 means parks with the highest scores were selected, whereas 0.5 would represent a random selection. The results demonstrate a clear alignment between the freely recalled parks by the participants and the rankings derived from our health scores. As shown in Table 9, the median and mean values of the average percentile-ranking for the parks named by citizens were consistently high. For nature-appreciation, physical activities, cultural activities, and social activities the median scores are above 0.89, highlighting a strong concordance between citizens' perceptions of the park and the quantitative rankings derived from our proposed park profiling method.

Table 9. Result statistics of the online survey. Citizens were asked to name parks that are suitable for the activities. The first three columns show the statistics of the average percentile-ranking of the named parks. **AR** is the answer rate of the respective category, i.e., how many respondents were able to name at least one park), **N** is the number of non-empty responses, and **MR** is the mean number of parks that were named per respondent.

Activity category	median	mean	σ	AR	N	MR
Physical	0.91	0.84	0.17	97.5%	78	4.26
Nature-appreciation	0.95	0.85	0.19	95%	76	2.75
Environmental	0.50	0.50	0.31	57.5%	46	1.80
Social	0.93	0.87	0.13	96.2%	77	4.94
Cultural	0.89	0.75	0.25	81.2%	65	2.27

The result for environmental activities is subpar compared to the other activities, with a mean and median average percentile-ranking of 0.50. Only 57.5% of the respondents could name an environmental park, and on average, 1.8 parks were named in this category by each person, which indicates that parks for environmental activities are harder to think of compared to the other activities. Another explanation for the low scores in this category is that while urban gardening and conservation can be done in many parks, they typically do not occupy much *spaces*, environmental activities are less mainstream in cities, and the number of *park elements* for this category is comparatively low in London's parks impeding high activities scores.

The overall alignment between Londoners' perceptions of parks and our health scores underscores the effectiveness of our approach in accurately capturing and evaluating the health-promoting potential of parks.

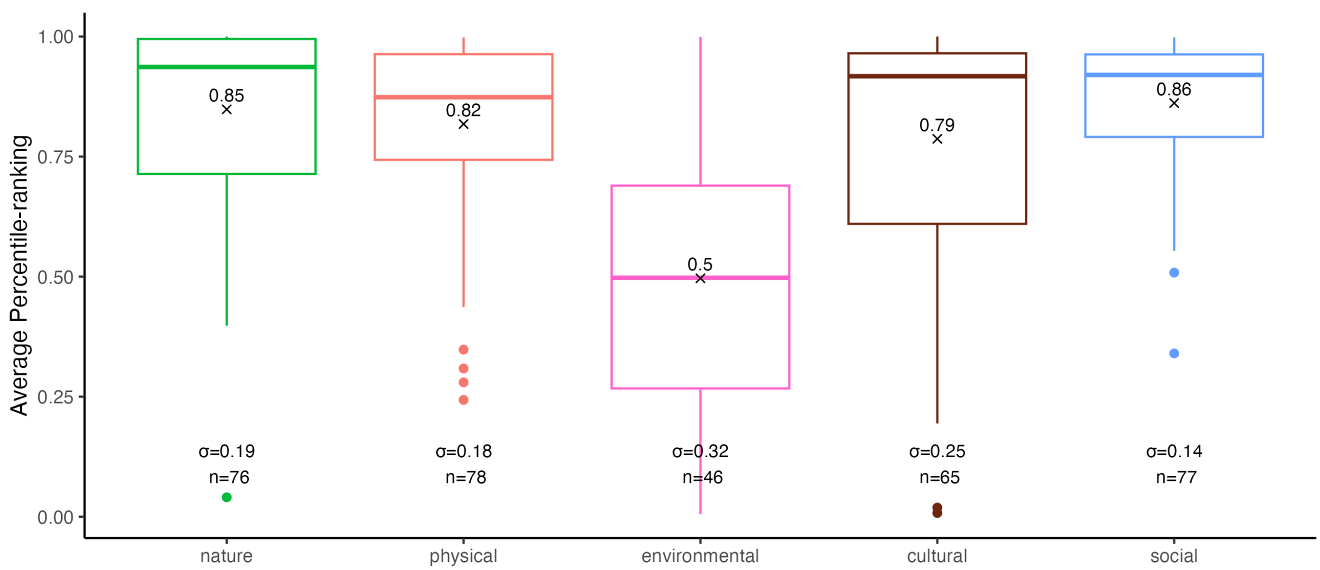

Figure 11. The online survey results as box-whisker plots. Standard box plot with Q1, median, Q3; whiskers at 1.5× interquartile range.The values indicated with the x represent the mean values.

B Supplementary Material

B.1 Determining the Threshold Values for Computing the Linear Models

Figure 12 and Figure 13 depict histograms of park elements and park spaces. The plots supplement the determination of thresholds for excluding parks with insufficient activity data in Section 4.5, *Transforming Counts to Health Scores*.

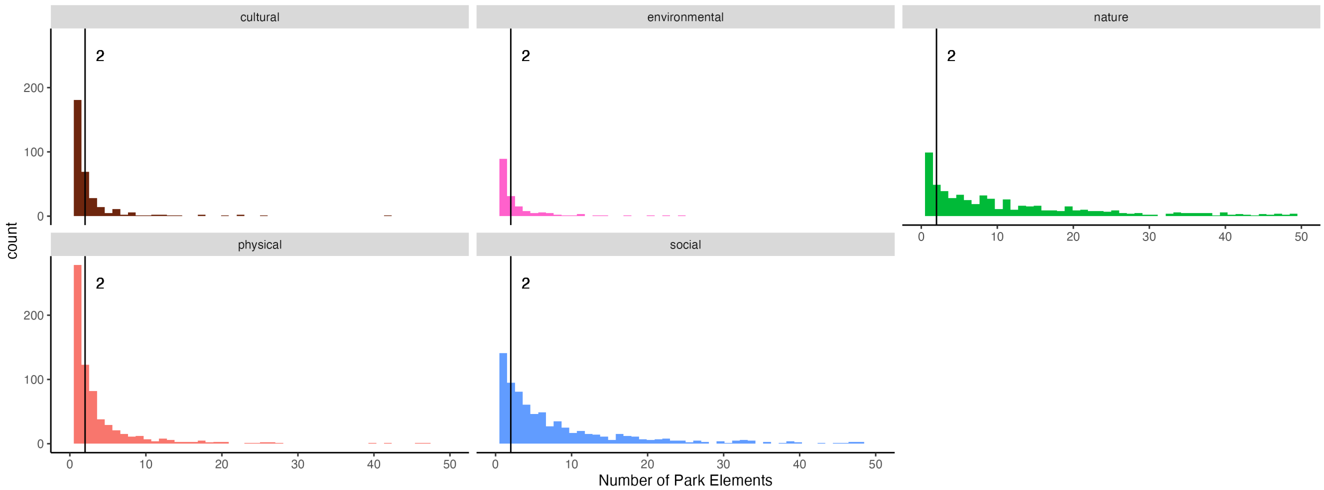

Figure 12. Histogram of park elements. We set 2 as the minimum number per activity category.

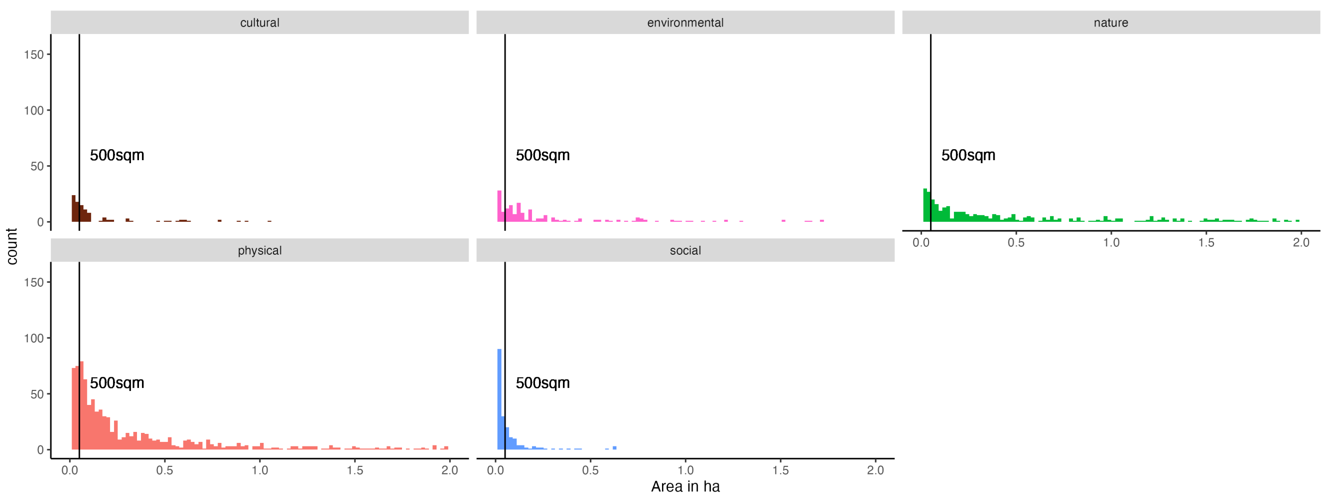

Figure 13. Histogram of park spaces. We set 0.05ha (500 m^2) as the minimum size per activity category.

B.2 Data Cleaning of OSM Tags

This section describes the steps we undertook to exclude OSM tags that are not useful for our analysis.

The first step of the data cleaning process was not specific to annotating health-promoting activities. Instead, the focus was on removing any extra information not necessary for understanding the main purpose of the map object. For example, to identify a bench on a map, one just needs to look for the label `amenity=bench`. However, a bench can also have additional tags like `inscription`, `operator`, `material`, and `backrest`, which offer more specifics about the bench. When it comes to identifying the object's primary purpose for health-promoting activities, this extra information is not only unnecessary but could also lead to confusion. To remove these irrelevant labels, three of the authors created lists of keys and values that were only used to provide extra details when combined with other labels. All co-authors carefully reviewed, discussed, and agreed upon these lists. If there was any doubt about whether to exclude certain labels, they were kept and left for subsequent annotation. The goal was to make sure that only necessary and relevant labels were kept for categorizing *park elements* and *spaces* into health-promoting activity categories.

In the process of cleaning the data, 1926 keys were omitted. These included keys such as `name`, `operator`, and `source`, which cannot provide insight into the object's activity. In addition, 11 values were also left out because they only described metadata and did not help in understanding the primary function or essence of the map object. Examples of such values include `yes/no`, `unknown`, or `Bing`. A full list of these omitted keys and values can be found in the replication repository. This initial data cleaning step significantly reduced the number of tags to 2118, which were the ones we needed to map to health-promoting activities, or none if the object did not support any of them. This streamlined dataset provided a more focused and relevant basis for the subsequent annotation and classification of *park elements* and *spaces*.

B.3 Benchmarking LLM Classifiers

To evaluate the suitability of LLM classifiers as annotators for OSM tags, we created a high-quality, expert-annotated gold standard set consisting of the 100 most frequent tags. To ensure accuracy and reliability, three co-authors independently labeled these 100 items with health-promoting activities or none, and we used the majority voting strategy to aggregate the individual opinions into one final outcome label. In cases where conflicts arose, i.e., where the three annotators provided different labels, a discussion was held to resolve the discrepancies. Through this rigorous annotation process, we established a robust and reliable *"gold standard"* dataset of 100 items. This dataset serves as a benchmark to assess the accuracy of the labels provided by the LLM classifiers.

For generating the annotations, we conducted a systematic exploration of the configuration settings of two LLMs, GPT-3.5-turbo[209] and GPT-4[210] using the OpenAI API[211]. Our goal was to identify the best-performing setting in terms of the weighted F_1 score, which is the harmonic mean of precision and recall in this multi-class classification task. The independent variables were *i)* the large language model, i.e., `gpt-3.5-turbo` or `gpt-4`[210], *ii)* the temperature parameter $t \in \{0.3; 0.6; 0.9\}$, which controls the randomness of the models' completions, and *iii)* the prompt, for which we tested two versions, one with and without providing a brief definition of the OSM tag taken from the OSM wiki. The full prompt is shown in Figure 14.

Figure 14 shows a specific sequence of prompts designed to elicit a main activity and a secondary activity for each OSM tag. The reason behind this approach was our hypothesis that certain OSM tags could support multiple health-promoting activities, as demonstrated by the example of benches that could be argued to be annotated with social, nature-appreciation, or physical activities. Additionally, we obtained a reliability score for each of the model's annotations. These reliability scores offer an indication of the model's confidence in its assigned activities, which could serve as a threshold to actually use the annotations, as low scores might indicate that the annotation is more speculative. By incorporating these main activities, secondary activities, and reliability scores from the LLM models, we hoped to gain a more nuanced insight into how these amenities and facilities in parks can be used. This detailed information allowed us to account for the potential multi-functionality of certain OSM tags and provided data for the evaluation using the proposed benchmark.

Furthermore, we followed the guidelines[212] to optimize the performance of the LLMs annotations. We assigned a system persona, i.e., *'You are an expert in urban planning and public health, with a specialization in urban parks. [...]'*, gave definitions of the six activities with exemplary activities, and provided several correct completions of items as means to few-shot learning. Finally, we provided a clear specification of the desired output format.

To determine the highest agreement between the human-annotated benchmark and the annotations of the LLMs, we used the F_1 score, which is the harmonic mean of the precision and recall. One complication in the evaluation was that the benchmark only comprised one activity label, whereas we asked the LLM annotator for a main and secondary activity for each tag. Thus, we report two F_1 scores: one that uses the label from the main category only and another that is a weighted combination of the main activity category and the secondary activity category. The weighted F_1' score is computed by slightly altering the impact of each element of the confusion matrix as follows:

$$TP' = TP^i_{main} \cdot reliability^i + TP^i_{2nd} \cdot (1 - reliability^i) \qquad \text{(true positives)} \quad (4)$$

$$FP' = FP^i_{main} \cdot reliability^i + FP^i_{2nd} \cdot (1 - reliability^i) \qquad \text{(false positives)} \quad (5)$$

$$FN' = FN^i_{main} \cdot reliability^i + FN^i_{2nd} \cdot (1 - reliability^i) \qquad \text{(false negatives)} \quad (6)$$

$$reliability^i = \frac{mean(reliability^i_{main})}{mean(reliability^i_{main}) + mean(reliability^i_{2nd})} \text{(Ratio of reliability between main and secondary category)} \quad (7)$$

Intuitively, this means that we use the reliability scores stemming from the LLM annotations to estimate the LLM's confidence that a label is correct, thus creating a comparable metric that allows for comparing two annotations for one item to one human-annotated ground truth.

We tested various settings to see which would deliver the best performance, which was GPT-4, set at a temperature of 0.9, and without providing definitions for tags. To give you a clearer picture, we've compiled the results of the top-performing

Table 10. Results of LLM Benchmarking. The highest performance is achieved with GPT-4, using a temperature of 0.9 and not providing definitions for the tags. Annotating a secondary activity did not improve the F_1 scores.

LLM	Definitions	Temperature	F_1-score Main Activity	F_1'-score Weighted Combination
gpt-4	✗	0.9	0.772	0.772
gpt-4	✗	0.6	0.770	0.770
gpt-4	✓	0.3	0.764	0.764
gpt-4	✗	0.3	0.755	0.755
gpt-3.5-turbo	✗	0.6	0.747	0.747
gpt-4	✓	0.6	0.740	0.740
gpt-3.5-turbo	✗	0.9	0.728	0.728
gpt-3.5-turbo	✓	0.3	0.726	0.726
gpt-4	✓	0.9	0.713	0.713
gpt-3.5-turbo	✓	0.6	0.710	0.710
gpt-3.5-turbo	✗	0.3	0.704	0.708
gpt-3.5-turbo	✓	0.9	0.689	0.689

configuration in Table 10. The F_1 scores tabulated in the tables show the best results of systematically adjusting the reliability scores for primary and secondary categories from 0 (using any label, regardless of its reliability) to 1 (annotate "none" in all cases). Generally, GPT-4 outperformed its predecessor, GPT-3.5. Adding definitions actually had a negative effect on label quality, possibly due to misleading keywords in the tagging instructions. When it came to the temperature setting, there was no consistent impact, with minimal differences between otherwise equivalent configurations. Interestingly, adding a secondary activity label didn't improve the quality of the annotation quality (cf. last column of Table 10). In fact, the best results were achieved when the reliability threshold of the secondary annotation was close to 1, rendering all secondary annotations to *"none"*, thus being equivalent to only using the main activity label. This suggests that the primary labels generated by the system are already of high quality, so putting any weight on a secondary label actually harms the overall score. Based on these findings, we decided to use GPT-4, set at a temperature of 0.9 and without definitions, to label all OSM tags and not impose any threshold on the reliability score.

⇒ You are an expert in urban planning and public health, with a specialization in urban parks. You have studied how parks promote health and have an understanding of the various activities that people engage in within them. Proficient in the OpenStreetMap project and skilled in tagging urban elements, particularly those within parks, your responsibility involves assigning activities to specific park elements based on OpenStreetMap tags.
⇒ Consider these 6 categories of activities people do in urban parks:

Physical activities This category is about leisure pursuits that involve physical movement and sports. Example activities are: Walking, hiking, trail running, biking, swimming, rock climbing, canoeing, kayaking, horseback riding, outdoor sports, and group fitness classes.

Mind-body activities This category is about physical practices that combine movement, breathing techniques, and meditation to promote relaxation, stress reduction, and overall well-being. Example activities are: Yoga, meditation, and tai chi.

Nature appreciation activities This category is about leisure pursuits that involve enjoying and exploring the natural world. Example activities are: Bird watching, camping, picnicking, fishing, painting, drawing, photography, and nature journaling.

Environmental activities This category is about gardening and conservation of parks. Example activities are: Gardening, planting trees and flowers, and participating in conservation efforts and volunteering.

Social activities This category is about coming together and communal experiences that involve engaging with others. Example activities are: Attending outdoor festivals and concerts, playing sports, and volunteering.

Cultural activities This category is about activities that celebrate and showcase the cultural diversity and heritage of the community. Example activities may include cultural festivals, art exhibits, music performances, storytelling, and cultural workshops.

Given the categories of ”Physical activities”, ”Mind-body activities”, ”Nature appreciation activities”, ”Environmental activities”, ”Social activities”, ”Cultural activities”, and ”none of the above”; How would you classify the following OpenStreetMap Tags found in a park and which [0,100] reliability scores (even multiple scores) would you give to your assessment? You can assign up to two categories, but you don't have to!
⇒ Provide the answer in the format: Main Activity|Reliability Score (of the main activity)|Secondary Activity (if it exists)|Reliability Score (of the secondary activity)|Explanation (not more than 20 words)
⇒ leisure=playground
⇒ Social|80|Physical|70|Children utilize playgrounds for both physical activity and exercise, as well as for social interactions through cooperative play.
⇒ leisure=pitch
⇒ Physical|90|Social|75|People engage in team sports on sports pitches, encompassing both physical activity and a social aspect due to the collaborative nature of team-based sports.
⇒ leisure=garden
⇒ Nature-appreciation|80|Environmental|60|People utilize gardens to cultivate an appreciation for nature, while gardens also serve as spaces for environmental activities, such as planting flowers and engaging in gardening practices.
⇒ amenity=bench
⇒ Social|80|Nature-appreciation|40|People utilize benches for relaxation and social interaction, fostering a sense of community. Moreover, benches offer the opportunity to immerse oneself in the surrounding nature, encouraging moments of contemplation and introspection.
⇒ natural=wood
⇒ Nature-appreciation|100|None|100|Forested areas, such as woods, primarily serve the purpose of appreciating and connecting with nature.
⇒ amenity=parking_space
⇒ None|90|None|100|A parking space does not inherently cater to a specific activity.

Figure 14. Preparatory prompt provided to the LLM classifiers via the OpenAI API. The tag and the definition were subsequently prompted. Regular text refers to 'user' messages, gray text refers to 'system' messages, and underlined text refers to 'assistant' messages. ⇒ denotes the beginning of a new message. Bold markup was added for improved readability.

B.4 Flickr Labels Scoring Model

Figure 15 depicts the computation of the Flickr activity scores. The method is the same as for the OSM tags; however, on the y-axis, we use the count of the matched Flickr labels instead of the OSM tags. The method for scoring is described in Section 4.5; the mapping of Flickr Labels to OSM tags and activities is explained in Section 4.7.

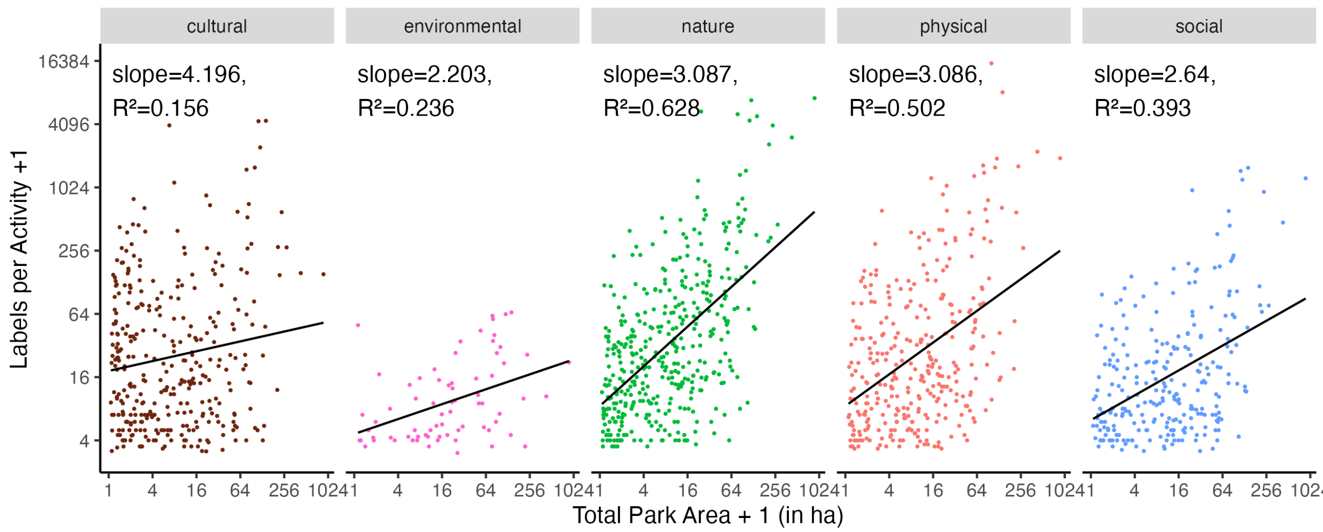

Figure 15. Visualizing the fit of the linear model for determining the park scores using matched Flickr labels for London, UK. The horizontal axis denotes the park's area (log_2), and the vertical axis is the number of categorized labels of images from these parks (log_2).