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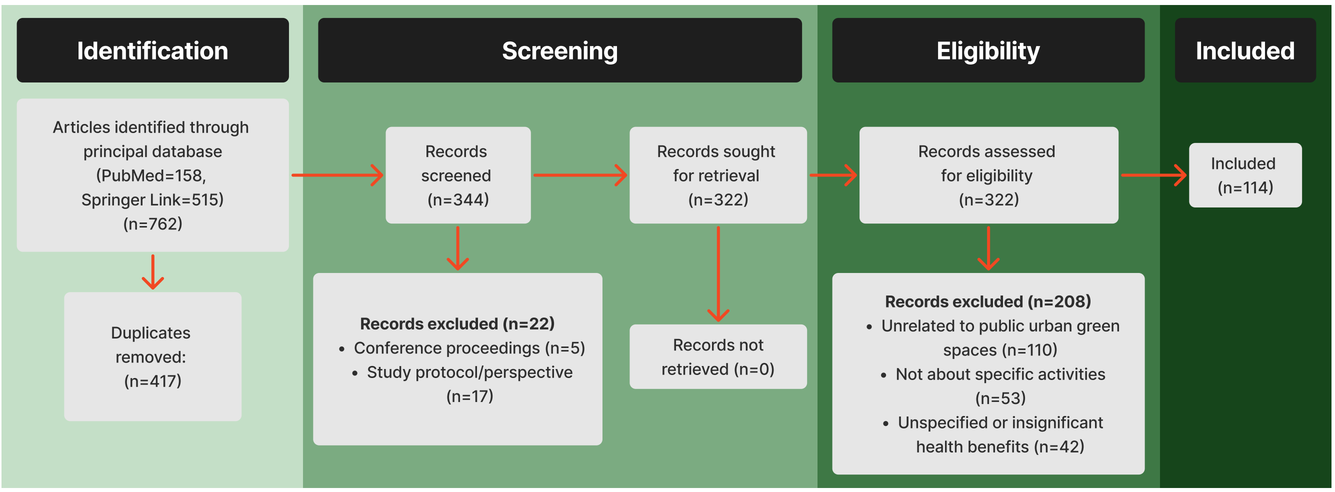
Understanding the potential of urban parks to promote well-being

In the format provided by the authors and unedited

1 Scoping Review to Map Activity Categories to Health Benefits

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[1], 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.



Suppl. Fig. 1. Our PRISMA Statement: Process of identification, screening, and determining eligibility for articles in our literature survey.

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)

Following the PRISMA statement depicted in Suppl. Fig. 1, 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

Suppl. Tab. 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[3]
	General health	longevity[4,5]
	Mental health	stress reduction[6–10], depression prevention[10–17], anxiety reduction[14], various[18], mood improvement[19]
	Physical health	weight reduction[4,20–26], increase of physical activity[7,9,13,15,27–49], blood pressure reduction[16], diabetes prevention[4,50], various[18], increase of leisure activities[51], hypertension[4], cardiovascular health improvements[24,50,52–54], bone development[24]
	Social health	various[18,55], social cohesion[13,16,56,57]
	Well-being	increase restorative capacity[58], enhanced social interactions[59], quality of life[3,15,37,44,54]
Nature-appreciation	Cognitive health	attention fatigue reduction[60]
	General health	lower morbidity[61]
	Mental health	positive emotions[62,63], depression prevention[12,13,15,16,64–67], anxiety reduction[65,66,68,69], suicide prevention[70,71], mood improvement[19,60,67,72], relaxation[63], mindfulness[63], calmness[69], stress reduction[7,60,65,66,72–78]
	Physical health	mood improvement[72], improved ghq-12 scores[79], blood pressure reduction[16,72,80], antenatal health[81], respiratory health[82], increase of physical activity[7,13,15,46,79,83,84], blood oxygen saturation[72]
	Social health	increased social capital[85], social loneliness reduction[86], various[55], social cohesion[13,16]
	Well-being	stress reduction[65,72,77], quality of life[15,64,65,77,87–89], blood pressure reduction[72], increase restorative capacity[90]
Environmental	Cognitive health	restorative effect against cognitive failures[91]
	General health	lower morbidity[61]
	Mental health	stress reduction[76,92], anxiety reduction[93,94], improved sleep[93,94], depression prevention[64,94]
	Physical health	cardiovascular health improvements[95], inflammation reduction[91], respiratory health[95], access to healthy produce[96], immune system improvement[97], increase of physical activity[29,98], improved sleep[93]
	Social health	access to healthy produce[96], social cohesion[92,96]
	Well-being	nutritional diversity[99], quality of life[64,93,100,101], improved sleep[93], increase restorative capacity[102]
Social	Cognitive health	dementia prevention[3], restorative effect against cognitive failures[91]
	General health	longevity[5]
	Mental health	mood improvement[103], depression prevention[10,11], various[104], improved mental health inventory (mhi-5) scores[105], stress reduction[10,92]
	Physical health	access to healthy produce[96], various[104], inflammation reduction[91], increase of physical activity[44,49]
	Social health	social cohesion[56,57,92,96,103,106], various[55], access to healthy produce[96], increased social capital[107], social loneliness reduction[108], improve sense of social belonging[109–111]
	Well-being	increase restorative capacity[102], quality of life[3,44,112], enhanced social interactions[59]
Cultural	Cognitive health	dementia prevention[3]
	General health	various[113]
	Physical health	increase of physical activity[114]
	Well-being	quality of life[3,112,114]
Mindfulness	Mental health	stress reduction[74], anxiety reduction[14], depression prevention[14,17]
	Physical health	increase of physical activity[49]
	Well-being	quality of life[115]

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 (Suppl. Tab. 1).

Results

A can be seen in Suppl. Tab. 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[20–22], cardiovascular improvements[50,52], metabolic activity[28,29]. 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[7,73] and anxiety[65,68] and preventing depression[12,13,15,16,65–67]. They also contribute to physical health (14 articles) and overall well-being (12 articles).

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[109–111] and improving mood[103]. Environmental activities, such as gardening, offer diverse benefits, including cognitive restoration[91] and improved general health[61].

Finally, *cultural* and *mindfulness 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). Likewise, mindfulness activities and nature-based therapeutic interventions, such as forest therapy[116] provide health benefits, but have not been studied in the context of urban parks, highlighting a potential gap in the scientific literature that warrants future exploration.

In summary, we found that all the different activities we identified have a *distinct but overlapping set of health benefits*. For example, both physical and nature-appreciation activities help prevent depression, but only physical activities help bone development, and only nature-appreciation brings calmness.

2 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, UK. 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

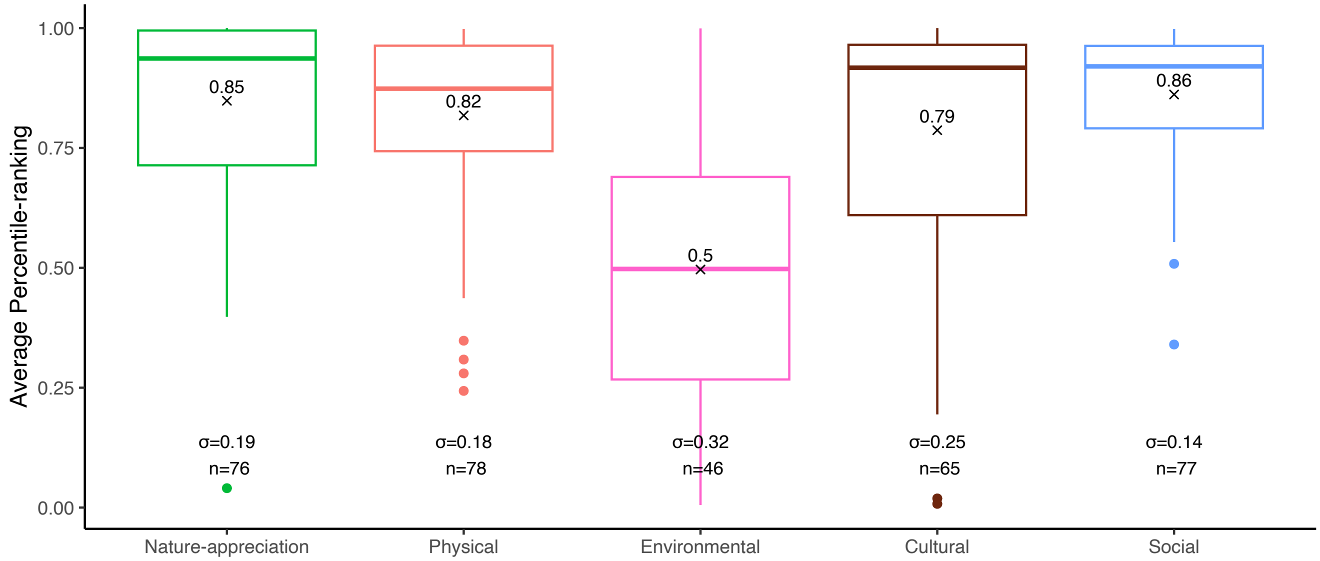
The metric we used to quantify how well the citizen response aligned with our health scores is the average percentile-ranking[117,118], which captures how highly the selected park was placed in the overall ranking of parks for the corresponding activity. A value close to 1 means parks with the highest 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 Suppl. Tab. 2, 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.

Suppl. Tab. 2. 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.

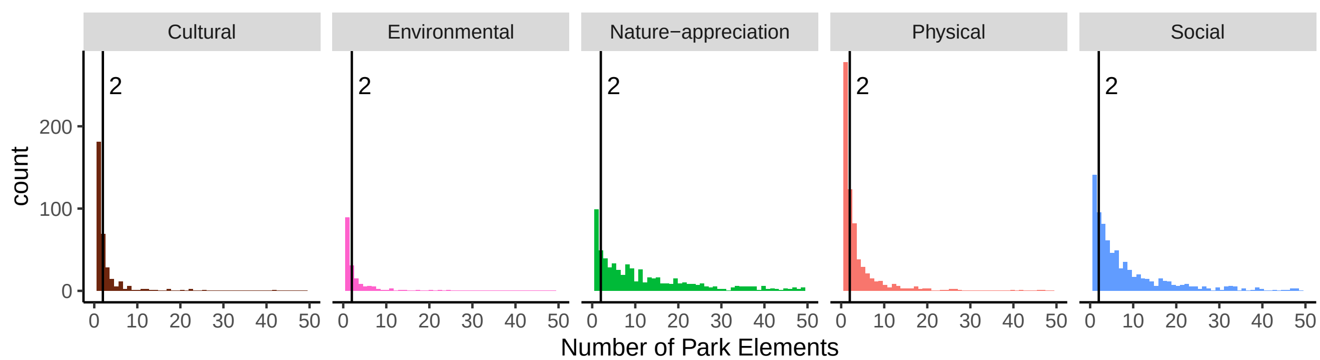


Suppl. Fig. 2. The online survey results as box-whisker plots. Standard box plot with Q1, median, Q3; whiskers at 1.5× interquartile range.The values indicated with the x represent the mean values.

3 Supplementary Methodological Details

3.1 Determining the Threshold Values for Computing the Linear Models

Suppl. Fig. 3 and Suppl. Fig. 4 depict histograms of park elements and park spaces. The plots supplement the determination of thresholds for excluding parks with insufficient activity data.

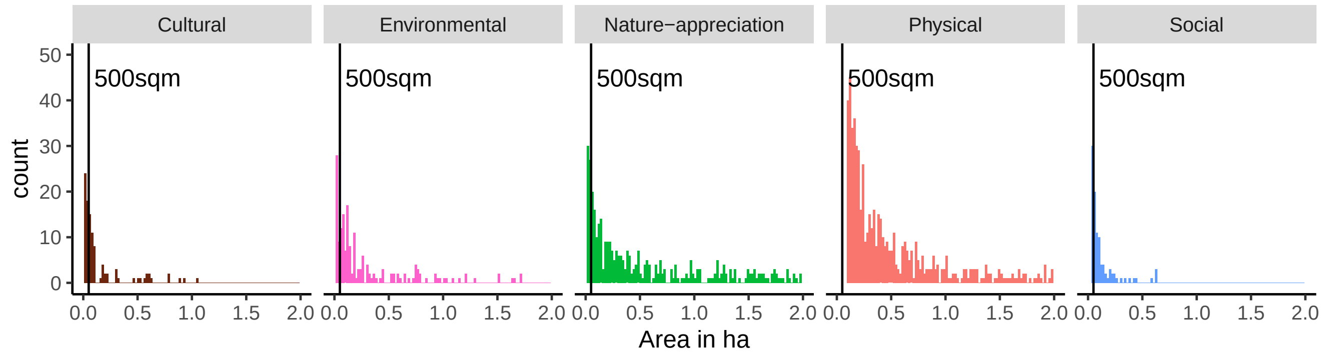


Suppl. Fig. 3. Histogram of park elements. We set 2 as the minimum number per activity category.

3.2 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



Suppl. Fig. 4. Histogram of park spaces. We set 0.05ha (500 m^2) as the minimum size per activity category.

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*.

3.3 Benchmarking LLM Classifiers

To evaluate the suitability of large language model (LLM) classifiers as annotators for OpenStreetMap (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[119] and GPT-4[120] using the OpenAI API[121]. 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`[120], *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 Suppl. Fig. 5.

Suppl. Fig. 5 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[122] 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

Suppl. Tab. 3. 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

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:

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

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

$$FN' = FN^i_{main} \cdot reliability^i + FN^i_{2nd} \cdot (1 - reliability^i) \quad \text{(false negatives)} \quad (3)$$

$$reliability^i = \frac{mean(reliability^i_{main})}{mean(reliability^i_{main}) + mean(reliability^i_{2nd})} \quad \text{(Ratio of reliability between main and secondary category)} \quad (4)$$

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 configuration in Suppl. Tab. 3. 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 annotation quality (cf. last column of Suppl. Tab. 3). 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.

3.4 Modeling Average Park Offerings

To model average park offerings, we used independent regression models for *park elements* and *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 Suppl. Fig. 3 and Suppl. Fig. 4.

3.5 Orthogonality of Park Elements and Spaces

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[123]. 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 Extended Data Table 4. 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.

3.6 Semantic Matching of Flickr Labels and OSM Tags

In our validation, 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[124, 125]. To obtain semantically equivalent representations of Flickr labels and OSM tags, we employed Sentence-BERT (S-BERT[126]) 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[127] Language Detection Model[128]. 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[129].

To further improve the quality of embeddings, we augmented the OSM tags with short definitions sourced from the OSM mapping guidelines[123]. 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", which did not capture the specific role of water features in parks in promoting health. We manually adjusted this to `water=river`, which better reflects bodies of water commonly found 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*. 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.

Suppl. Fig. 6 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.

3.7 User Studies with Urban Designers and Park Maintenance Experts

We conducted three semi-structured interviews, each lasting about 30 minutes, with urban designers and park maintenance experts. Participants were recruited through our network and by direct email to municipalities. The experts' backgrounds were as follows:

- Lecturer and urban designer (E1). 20 years of practical and academic experience in Hong Kong and London.
- Urban designer and master planner (E2). 30 years of experience in the United States, United Kingdom, Europe, and the Middle East.
- Parks development manager at a local council (E3). 12 years of experience as consersvationalist, arboricultural manager in diverse contexts.

The online interviews consisted of 4 steps.

1. **Introduction**. Three questions to understand their experience in urban park design and management.
2. **Study brief.** A summary of our study and main findings.
3. **Visualization.** Interacting with the visualization and exploring a chosen city.
4. **Debriefing.** Open-ended questions and feedback on the project.

We qualitatively analyzed the interview transcripts[130,131] (recorded with consent) to understand the implications of our work for professional practice, verify inter-cultural validity, and to further validate the taxonomy of activities.

⇒ 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.

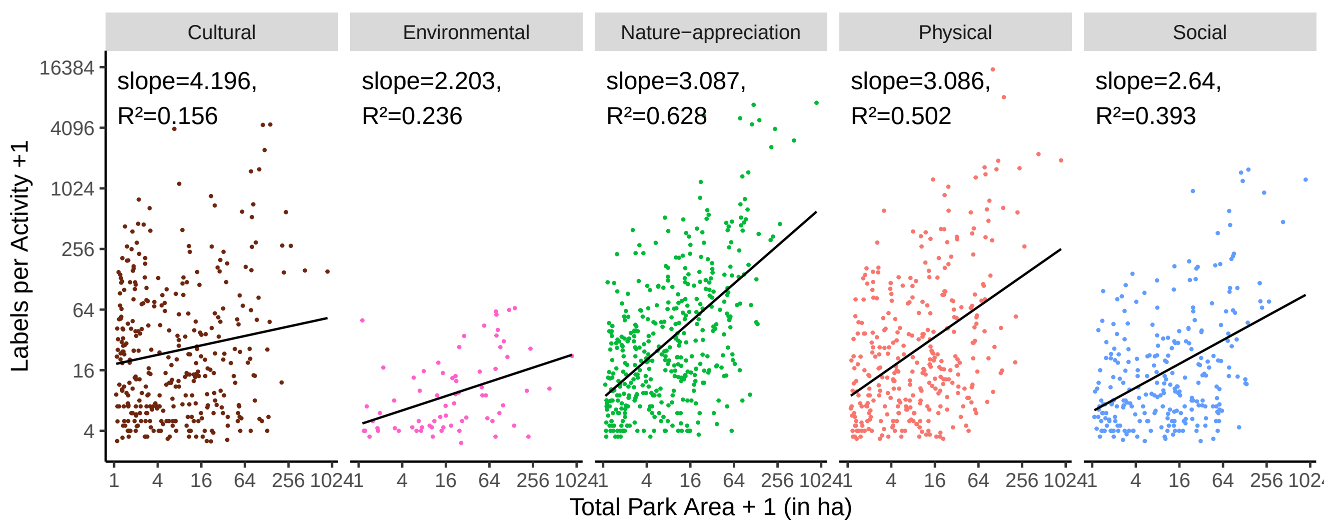
⇒ natural=wood

⇒ 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.

Suppl. Fig. 5. 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.



Suppl. Fig. 6. 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).

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