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Geo-fence planning for dockless bike-sharing systems: a GIS-based multi-criteria decision analysis framework

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Abstract

The inappropriate parking of free-floating shared bikes is a critical issue that needs to be addressed to realize the potential environmental, socioeconomic, and health benefits of this emerging green mode of transport. To address this challenge, this paper developes a Geographic Information Systems (GIS) based Multi-Criteria Decision Analysis (MCDA) framework for geo-fence planning of dockless bike-sharing systems based on openly accessible data. The Analytic Hierarchy Process (AHP) and the VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje) method are applied in the proposed framework to derive optimal geo-fence locations. The proposed framework is validated in a case study using a dataset of dockless bike-sharing trips from February 2020 in the City of Zurich and comparing the selected geo-fence locations with the existing bike-sharing stations. The assessment results show that the calculated geo-fence locations have a smaller average distance of 1395 m than that of 1692 m, and a larger demand coverage of 81% than that of 77% for bike-sharing stations. Overall, the proposed framework and the insights from the case study can help transport planners better implement shared micro-mobility hence facilitating the uptake of this sustainable mode of urban transport.

Keywords: Dockless bike-sharing, Geo-fence planning, Multi-criteria decision analysis, AHP, VIKOR, GIS

1 Introduction

Over the past two decades, bike-sharing, as an environmentally friendly urban transport mode, has become increasingly popular in many cities all over the world. Bike-sharing systems allow users to check out a bike at one location and return it at another within the same city (DeMaio, 2009; Frade & Ribeiro, 2015), which can mitigate greenhouse gas emissions from fossil fuel vehicles, improve travel convenience of citizens by solving the first/last-mile problem, and have positive effects on people's health (Guo & He, 2020; Li, Gao, et al., 2021; Otero et al., 2018). Modern bike-sharing systems can be split into two categories, namely docked and dockless. Compared with the bikes fixed at rental stations in docked bike-sharing systems, dockless bike-sharing allows users to rent a bike via a mobile application or website and return the bike anywhere within the service area (Shen et al. 2018; Lazarus et al., 2020; Li, Zhao, et al., 2021). Due to its flexibility and convenience, dockless bike-sharing is attracting more attention and being embraced by city managers as one of the effective ways to promote sustainable transportation in urban contexts (Gao et al., 2021; Ma et al., 2020).

Although dockless bike-sharing can bring various environmental, socioeconomic, and health benefits, the unrestricted nature of the dockless bike-sharing system also causes some critical urban problems (e.g., Hirsch et al., 2019). One of the most serious issues is the user's random and inappropriate parking behavior. On the one hand, random and irregular bike parking activities make cities messy, such as blocking sidewalks and public

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spaces. On the other hand, parking bikes at inappropriate places (e.g., the entrance of the viaduct, expressway isolation zone) sometimes may cause traffic accidents. Therefore, effectively dealing with the inappropriate parking of dockless bike-sharing requires more research to eventually achieve sustainable transportation and smart cities objectives.

Geo-fencing has been proposed and analyzed as a possible solution to the parking issue mentioned above (Hirsch et al., 2019; Shui & Szeto, 2020; Zhang et al., 2019). Geo-fencing is a technology used for monitoring mobile objects (e.g. persons, vehicles) with location-based technology like Global Navigation Satellite System (GNSS), which can check whether the tracked objects are inside or outside the geo-fenced areas (Reclus & Drouard, 2009). A geo-fence for dockless bike-sharing is a predetermined virtual fence, which can be used as a parking zone for dockless bikes. Users who park bikes outside the allowed geo-fences cannot return them and will continue to be charged (Zhang et al., 2019). A schematic diagram of geo-fence for dockless bike-sharing is presented in Fig. 1. Compared with the coarse-scale parking areas of the existing dockless bike-sharing systems at a city scale, geo-fence can help operators to specify where bikes can be parked properly at a road level, thereby preventing dockless bikes from being locked randomly and disorderly.

In recent years, various optimization models have been developed to determine the locations of bike-sharing stations sharing (e.g., Conrow et al., 2018; Frade & Ribeiro, 2015; García-Palomares et al., 2012; Mix et al., 2022; Nikiforiadis et al., 2021). For instance, Frade and Ribeiro (2015) developed a maximal covering location approach to determine the locations of bike-sharing stations that maximizes the demand coverage and takes the available budget as a constraint. Conrow et al. (2018) applied an optimization approach to defining the site selection of bicycle share stations across an urban region, which considers the tradeoff between demand coverage and users' access. Zhang et al. (2019) developed a location-allocation model to determine parking zones based on the big data of bike trips in Shanghai, which primarily considers the distribution of parking demand. Nikiforiadis et al. (2021) presented a methodological approach to determine the optimal locations of bike-sharing stations, which maximizes the demand from the user's side and minimizes the need for bike redistribution from the operator's side. Mix et al. (2022) proposed an integrated approach to determine the optimal location of stations in the bike-sharing system based on the built environment and accessibility-based variables. Overall, the existing studies are mainly concentrated on optimizing the locations of bike-sharing stations by developing spatial optimization models to maximize demand coverage. However, bike-sharing trip data are normally provided by operators, which are not always available for developing such optimization models.

Fig. 1 An exemplary geo-fence for dockless bike-sharing[1] Source: https://commons.wikimedia.org/wiki/File:Dockless_bike_parking_area_on_Lonsdale_Street_August_2018.jpg

Moreover, the site selection of geo-fences involves multiple evaluation criteria. Various geographical and social constraints (e.g., proximity to cycling paths, proximity to public transit, population density) should be considered during the planning process. Hence, a multi-criteria decision-making methodology could be applied to solve this problem. Multi-criteria Decision Analysis (MCDA), as a typical method to solve complex decision-making problems (Hwang & Yoon, 1981), has been widely used to deal with site selection problems (e.g., Dang et al., 2021; Erbaş et al., 2018; Jelokhani-Niaraki & Malczewski, 2015; Latinopoulos & Kechagia, 2015; Veronesi et al., 2017; Yesilnacar et al., 2012). MCDA has also been used to determine the optimal bike-sharing stations in recent years. For instance, Kabak et al. (2018) developed a GIS-based MCDM approach for the evaluation of bike-sharing stations in Karsiyaka, Izmir based on 12 criteria. By comparing to the existing stations, the suggested locations were demonstrated to be superior. Guler and Yomralioglu (2021) investigated the determination of locations of bike-sharing system stations and bicycle lanes simultaneously by proposing a workflow that integrates GIS and MCDM methods. Eren and Katanalp (2022) developed a hybrid model based on fuzzy-based GIS, AHP, and VIKOR for the site selection of bike-sharing stations. Compared with the existing studies on optimizing the locations of bike-sharing stations with GIS-based MCDA, this study takes into account the capacity of geo-fences in the site selection process.

In this paper, a GIS-based MCDA framework was developed for geo-fence planning of dockless bike-sharing systems based on openly accessible data. Firstly, the evaluation criteria for optimizing the site selection of geo-fences were determined according to the literature review and expert opinions, which consist of eight criteria. The criteria include one criterion in the user dimension (i.e. population density), three criteria in the transportation dimension (i.e. proximity to large public transit, proximity to small public transit, proximity to cycling paths), and four criteria in the urban life dimension (i.e. proximity to sports facilities and parks, proximity to higher education organizations, density of commercial facilities, density of entertainment facilities). Secondly, the importance of each criterion is weighted by the AHP method. Then, candidate locations of geo-fences were ranked using the VIKOR method. Last, the determined geo-fences were evaluated based on the bike-sharing demand coverage. Using real dockless bike-sharing data from the city of Zurich, the validity of the developed framework was tested. It should be noted that the proposed method is not only applicable to Zurich but all cities where the related data are available for our framework. Since the framework is not constrained by the real bike-sharing trip/demand data, it could serve as a planning tool for municipal urban planners that aim at managing bike-sharing activity in their city as well as for bike-sharing companies that want to establish bike-sharing systems in new cities. The objectives of this research are listed as follows:

- To propose a methodological framework to support geo-fence planning for dockless bike-sharing services, which can be applied in any urban context without dependence on bike-sharing trip data.
- To apply the framework in the case study of Zurich and present the determined geo-fences.
- To evaluate the performance of the selected geo-fences based on real bike-sharing trip data and the existing bike-sharing stations.

2 Study area and data used

The case study was conducted in the city of Zurich, Switzerland. Zurich is the largest Swiss city with a population of over 435,000 Inhabitants (Stadt Zurich 2021). Zurich has high levels of cycling with 15% of its population cycling daily and 20% cycling 2–5 times per week. The vehicle availability data from one dockless bike-sharing system was collected from February 1 to 23, 2020 to validate the proposed GIS-based MCDA framework in this study. The dataset was obtained by scanning the available bikes in each area every 30 s on average. The trip identification method in the study by Zhao et al. (2021) was utilized to identify trips from the collected vehicle availability data. After data processing, 5321 biking trips were obtained, which contain information on longitude, latitude, and timestamp of origin and destination for each trip. As shown in Fig. 2, the spatial distribution of origins and destinations is visualized in the study area.

To quantify and model the criteria that affect bike-sharing suitability, a dataset including train stations, tram and bus stops, cycling paths, sports facilities and parks, education facilities, entertainment facilities, commercial facilities, and population density was collected from various data sources (e.g. OpenStreetMap, governmental organizations). In addition, to determine the candidate

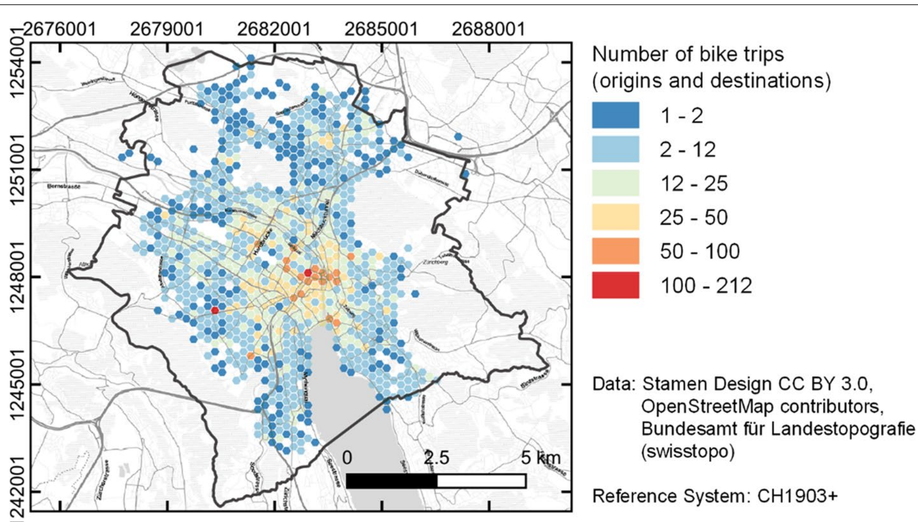

Fig. 2 Origin and destination of the extracted trips in the study area

locations of geofences, a publicly accessible dataset on bike racks was collected from the city of Zurich, which comprises 1932 bike and motorcycle parking spaces. A dataset of existing bike-sharing stations was acquired and used to evaluate the suggested geofences in the experiment.

3 Methodology

This section introduces the developed GIS-MCDA framework for the selection of geo-fence locations for dockless bike-sharing. The framework is divided into four main steps, as shown in Fig. 3. Firstly, the criteria that influence bike-sharing demand and parking suitability are determined based on authors, experts, and literature review. Secondly, geographic data collection is conducted based on the selected criteria. Thirdly, the GIS-MCDA framework is developed and implemented, which involves four subsequent analyses: (1) criteria layer generation using GIS, (2) derivation of criteria weights using AHP, (3) suitability map generation using a weighted linear combination, and (4) the ranking of the candidate locations using VIKOR. Lastly, the obtained geo-fences are evaluated by examining the degree to which the actual bike-sharing usage is covered by the geo-fences. A brief description of the key steps is given below.

3.1 Identifying evaluation criteria

Various studies have investigated what factors contribute to the decision of people to use bike-sharing and bikes as means of transportation. Early studies focused mainly on the use of bicycles for commuting (e.g., Buehler & Pucher, 2012; Eren & Uz, 2020; Krizek & Johnson, 2006). With the rise of bike-sharing, research shifted towards exploring various factors that affect the usage of bike-sharing systems (Faghih-Imani & Eluru, 2015; Fuller et al., 2011; Guo et al., 2017; Li et al., 2020; Wang et al., 2018). Based on the literature review and expert opinions, eight criteria are determined and used for the site selection of geo-fences, which have been demonstrated to have a significant influence on bike-sharing usage and demand. The eight criteria almost cover all the main urban facilities related to bike-sharing usage and activities, including public transit, cycling paths, sports facilities and parks, education organizations, commercial facilities, and entertainment facilities. The selected criteria are described as follows:

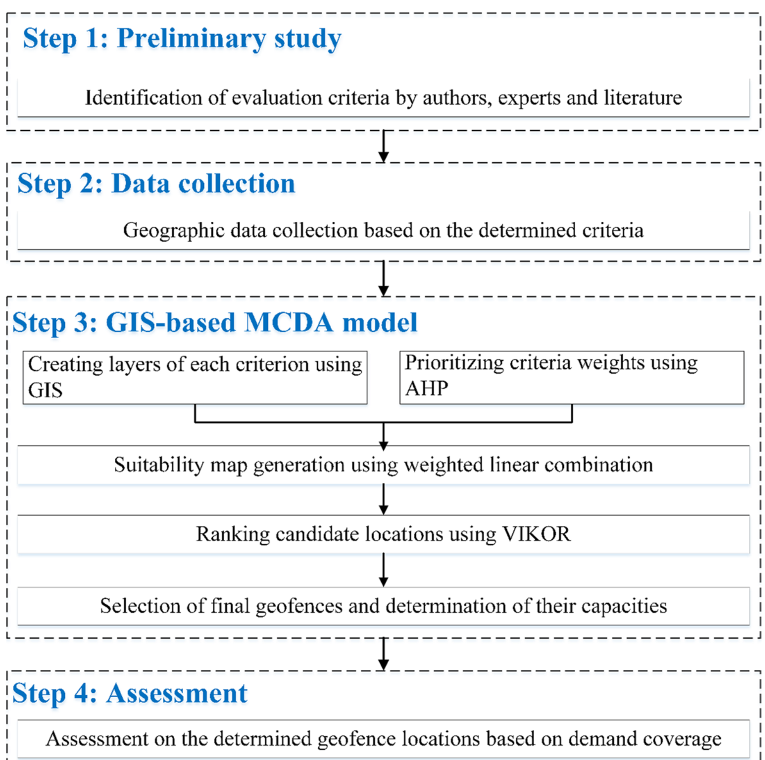

Fig. 3 Flowchart of the methodology

1) Population density (POP). Population density refers to the number of people per unit of area, usually quoted per square kilometer. Intuitively, a region with a high density of residents should have cycling demand, which has been indicated to have a positive influence on bike-sharing usage (e.g., Faghih-Imani et al., 2017; Li et al., 2020).
2) Proximity to public transit large (PTL). It is well known that public transit transports a large number of passenger flows, which has been demonstrated by many studies (e.g., Conrow et al., 2018; Faghih-Imani & Eluru, 2015). Due to the remarkable difference in passenger flows between large and small public transits, public transits are considered in two criteria separately according to their sizes. The close distance to large public transit like train stations normally corresponds to higher biking demand.
3) Proximity to public transit small (PTS). Although the passenger flow of small public transit (i.e. tram and bus stops) is not so high as that of large public transit, the proximity to small public transit can still facilitate the usage of bikes due to the first- and last-mile problem in transportation (Martin & Shaheen, 2014).
4) Proximity to major bike/cycling paths (MBP). Previous studies indicate that a strong and complete bike infrastructure can increase the usage of bikes (Eren & Uz, 2020; Schoner & Levinson, 2014). Especially, cycling paths can create a more reliable space for cyclists and play an important role in promoting cycling since they are separated from motor vehicle traffic. Therefore, the locations with long distances to bike paths should be omitted while planning geo-fences.
5) Proximity to sports facilities and parks (SP). Several studies indicate that nearby areas with recreational facilities like sports facilities and parks have high bike-sharing usage (Mateo-Babiano et al., 2016; Tran et al., 2015). Thus, the proximity to sports facilities and parks can also lead to bike-sharing usage for recreational activities.
6) Proximity to higher education organizations (EDU). Considering that young people are the main user group of bike-sharing systems, it is common to plan bike-sharing stations in higher education organizations (i.e. universities and colleges) to meet the high bike-sharing usage and demand (Faghih-Imani et al., 2017). Accordingly, the proximity to higher education organizations could also have high cycling demand.
7) Density of commercial facilities (COM). Different land-use types might attract users with different travel purposes. The areas with a high density of commercial facilities such as shopping malls, tend to promote bike-sharing ridership and lead to high bike-sharing usage of cycling activities in commercial areas (Wang et al., 2017; Zhang et al., 2017).
8) Density of entertainment facilities (ET). Entertainment facilities like theaters, stadiums, and cinemas can also facilitate bike-sharing usage (Chen & Ye, 2021; Lin et al., 2020). Hence, the areas with a high density of entertainment facilities could have high cycling demand.

3.2 Creating layers of each criterion using GIS

After determining the criteria, the criteria layers to be used should be created for the site selection of geo-fences with the GIS-MCDA approach. Criteria layers are created by implementing various spatial analyses within the GIS environment based on the collected geographic data. GIS is capable of displaying the criteria information on multiple criteria layers in the format of digital maps. For each criterion, a separate layer is created. Each pixel value in a layer quantifies the suitability of the criterion in the corresponding spatial area. All the criteria layers will be used to generate a suitability map.

For each criterion layer, a target raster covering the study area with a spatial resolution of 50 m is created in this work. It is assumed that the suitability would not significantly change over this small distance. This resolution was chosen as a compromise between detail and processing time. Considering that geo-fence location should be along a road or cycling path for the convenient use of bikes, a 10 m buffer along the bike network within the study area is calculated to select the suitable and qualified cells. Only the cells that have an overlap with the buffer will be used to further analysis. To achieve this, a network graph of cycling paths is created from OSM data using the OSMnx Python module (Boeing, 2017). For the proximity layers, the shortest path from each cell in the target raster to the instance of each criterion is calculated. For the density layers, a neighborhood analysis is performed for each cell in each raster layer, in which all instances (e.g. restaurants, theaters, shops, or office buildings) within a 2 km buffer around the cell center are registered. The buffer size is derived from previous studies that found that 90% of the bike trips in dockless and station-based bike-sharing are shorter than 2 km (e.g., Liu et al., 2018; Ma et al., 2020). It can be assumed that criteria facilities outside of the 2 km buffer are not of high relevance for the suitability of a location as most of the bike trips will not reach them.

3.3 Prioritising criteria weights using AHP

Based on the selected criteria, the AHP method is implemented to assess the influence level of the individual criteria and to quantify them as priority weights. The AHP was proposed by Saaty (1988) as a method for structuring decision problems in social, economic, and management sciences. The method consists of four steps: (1) the structuring of the decision problem, (2) the pair-wise comparison, (3) the calculation of weights and consistency of the pair-wise comparison, and (4) the aggregation of local weights for each alternative. The main strength of AHP is that it can structure the partly strongly diverging views of different stakeholders, which has been the most common MCDA method with growing usage (Kabir et al., 2014).

Based on the problem of planning geo-fences for dockless bike-sharing systems, the pair-wise comparison of the selected criteria is conducted. Potential experts for this study are contacted by studying the bike-sharing market, relevant municipal and research activity related to bike-sharing. To ensure that the experts have good knowledge of the study area, only people who are active in Zurich are approached. The experts are asked to fill out a survey and give a ranking for each pair of criteria. This ranking scale varied from the intensity scale used in AHP, ranging from 1 to 9. It is decided to use a simpler and shorter scale for the survey to make it easier for the respondents to answer the survey. Before compiling the rankings into a pair-wise comparison matrix, they are transformed into the scale used in the AHP, as displayed in Table 1.

The pair-wise comparison rankings assigned by the experts are aggregated by computing the geometric mean. The means are entered in an $n \times n$ pair-wise comparison matrix A. w_i and w_j are the intensity weights of each pair-wise comparison. In the next step, the pair-wise intensity weights are aggregated by obtaining the normalized eigenvector of the comparison matrix. This vector is called the priority vector and contains weights for each criterion that sum up to 1. These weights are used for the following parts of the GIS-MCDA.

$$\boldsymbol{A} = \left(\frac{w_i}{w_j}\right)_{n\times n} = \begin{pmatrix} w_1/w_1 & w_1/w_2 & \cdots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \cdots & w_2/w_n \\ \vdots & \vdots & \ddots & \vdots \\ w_n/w_1 & w_n/w_2 & \cdots & w_n/w_n \end{pmatrix} \quad (1)$$

By integrating the GIS process and AHP process, the criteria layers can be combined using a Weighted Linear Combination (WLC) which is one of the most common algorithms for GIS-MCDA. The core operation of the algorithm is intuitive to understand, which is described by Eq. (2) (Pereira & Duckstein, 1993):

$$V(A_i) = \sum_{k=1}^{n} w_k v(a_{ik}) \quad (2)$$

where $V(Ai)$ is the combined suitability value, w_k is the weight, and $v(a_{ik})$ is the value function for the criterion. The raster layers comprising the standardized values are multiplied with the corresponding weights that will be determined using AHP. Thus, a suitability map is generated, which can be used to find alternative locations for geo-fences.

3.4 Ranking candidate locations using VIKOR

The placement of candidate locations can be challenging for the selection of the final geo-fences, particularly when the limited urban space is being used for many different purposes. Previous studies on the planning of bike-sharing stations and geo-fences have either placed potential locations with an even spacing along with a road network, utilized bike-trip data, or manually selected potential locations (Conrow et al., 2018; Kabak et al., 2018; Zhang et al., 2019). The framework developed in this study is designed to function even in cities where no bike-trip data is available. The study by García-Palomares et al. (2012) used the existing infrastructure such as public transit stations for placing candidate locations. In this study, a dataset of bike parking spots was acquired and

Table 1 Conversion of ranking weights used in the survey to intensity weights used in AHP

Survey ranking	AHP intensity weights	Definition
1	1/9	Criterion *i* contributes extremely less than criterion *j*.
2	1/7	Criterion *i* contributes very strongly less than criterion *j*.
3	1/5	Criterion *i* contributes strongly less than criterion *j*.
4	1/3	Criterion *i* contributes moderately less than criterion *j*.
5	1	Both criteria contribute equally.
6	3	Criterion *i* contributes moderately more than criterion *j*.
7	5	Criterion *i* contributes strongly more than criterion *j*.
8	7	Criterion *i* contributes very strongly more than criterion *j*.
9	9	Criterion *i* contributes extremely more than criterion *j*.

used as a source for candidate locations of geo-fences. The ranking of candidate locations is realized in a discrete location selection model that applies a suitability ranking of the alternatives using VIKOR.

VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje) is developed for the multi-criteria analysis of complex systems by Opricovic and Tzeng (2004), which aims to reach a compromise solution that is closest to the ideal solution by ranking the candidate locations. It expresses the suitability of an alternative in terms of its closeness to the ideal solution in the compromise decision index Q_j. As Q_j represents the closeness to the ideal solution, smaller values are more suitable. The VIKOR ranking can be divided into a four-step process:

(1) The first step is to find the best $\left(f_i^*\right)$ and worst $\left(f_i^-\right)$ score among the candidate locations for each criterion. For criteria that should be minimized, the best score is equal to the lowest criteria value and the worst score is the highest one. The opposite applies to criteria that should be maximized.
(2) The measures S_j and R_j are computed for each candidate location. These measures are the weighted normalized Manhattan distance L_1 and the weighted normalized Chebyshev distance L_∞ respectively. They are used as boundary measures for the ranking of alternatives in VIKOR. S_j can be interpreted as the distance in criteria space of the j-th alternative to the ideal solution and is computed according to Eq. (3).

$$S_j = \sum_{i=1}^{n} \frac{w_i\left(f_i^* - f_{ij}\right)}{f_i^* - f_i^-} \tag{3}$$

where x_{ij} is the criteria score of the i-th criterion and the j-th alternative, and w_i is the i-th criterion's weight that was determined in the AHP. Selecting the alternative with the smallest S_j as a solution would mean maximizing group utility. R_j is computed by Eq. (4) which returns the largest summand of eq. 9. This can be interpreted as the closeness of the worst-performing criterion for the j-th alternative to the ideal solutions criteria score for this criterion.

$$R_j = \max_j \left[\frac{w_i\left(f_i^* - f_{ij}\right)}{f_i^* - f_i^-}\right] \tag{4}$$

(3) The measure Q_j that aims to balance S_j and R_j is calculated for each candidate location, which is expressed as Eq. (5):

$$Q_j = \nu \frac{\left(S_j - S^*\right)}{\left(S^- - S^*\right)} + (1-\nu)\frac{\left(R_j - R^*\right)}{\left(R^- - R^*\right)} \tag{5}$$

where the weight ν is set according to a strategy of maximum group utility. A value of 0.5 represents a consensus-driven strategy and is commonly used in VIKOR. S^*, S^-, R^*, R^- are the minimum and maximum values of S_j and R_j among all alternatives:

$$S^* = \min_j S_j, S^- = \max_j S_j, R^* = \max_j R_j, R^- = \max_j R_j \tag{6}$$

(4) The last step is to order the candidate locations according to their Q_j ranking. As Q_j is a measure of closeness to the ideal solution, a small value is favored.

3.5 Selecting final geo-fences and determining their capacities

The selection of locations for the geo-fences is conducted by taking the spatial distribution of the candidate locations relative to each other and their suitability into consideration. It is realized in a novel discrete location selection model that applies a suitability ranking of the alternatives and a variable minimum distance constraint between the candidate locations. First, the candidate locations are ranked using VIKOR, then they are iteratively added to the final set of geo-fences. Specifically, it is initialized by adding the highest-ranking candidate location to the geo-fence selection. Next, the second-highest-ranking candidate location is evaluated by checking its distance to the previously added location. If the distance exceeds a minimum distance, the current candidate location is added to the final set. This is repeated for all other candidate locations by checking the distance to all geo-fences previously added to the final geo-fence set. The minimum spacing is determined based on studies by Fuller et al. (2011) and Tran et al. (2015) who found a spacing of 200 to 500 m between bike-sharing facilities suitable for optimizing usability and increasing usage of bike-sharing systems. Therefore, for the most and least suitable candidate locations, distance constraints of 200 m and 500 m are set respectively in this study. The spacing values between these thresholds are determined by defining a linear function between spacing and suitability. The least suitable candidates are regarded as unsuitable and excluded from the selection process as they are entirely located on the outskirts of the study area.

Regarding the determination of capacities of the final geo-fences, the previous research by Zhang et al. (2019)

and Cheng et al. (2019) showed that the capacity planning of bike-sharing stations can be transferred to geo-fence capacity determination. However, these approaches are based on bike-sharing trip data. To develop a more generalizable and applicable approach, this study adopts the suitability ranking as a proxy for demand to derive the geo-fence capacity instead of using the bike trip data directly. Hence, the proposed approach can also be applied to a city where bike-sharing trip data is not available. According to Zhang et al. (2019), in practice, it is common to select a fixed number of bikes for each geo-fence for instance 10 or 20. The range between 10 and 20 is used in this study as well. The capacity is computed based on the available bike racks and the suitability ranking. The high-ranking candidate locations correspond to a large geo-fence capacity. However, in order to avoid conflict with regular bike users, it is decided to include the available number of bike racks at the geo-fence locations in the capacity determination. The maximum number of shared bikes parked at a geo-fence is limited to 50% of the bike racks available at a location. This is because bike-sharing should not compete with normal bike users who also seek bike parking.

3.6 Evaluating geo-fence locations

To assess the proposed geo-fence locations, the actual bike-sharing demand computed from the trip data is utilized. Bike-sharing demand studies are commonly conducted by aggregating the origins and destinations of trips on a zonal level. In this study, the demand covered by the geo-fences is evaluated on the geo-fence level by computing the number of bike trip origins and destinations (OD) within a 500 m buffer around each geo-fence. This buffer size was determined according to the service area of bike-sharing stations with a 500 m radius (Frade & Ribeiro, 2015; Wang et al., 2018. Additionally, the proportion of ODs that are within 500 m network distance is calculated for each geo-fence. To assess the general accessibility of the geo-fence locations, the average network distance from any point within the street network of the study area is computed. This aims to test the extent to which the demand for bike-sharing is covered by the determined geo-fences. Furthermore, the determined geo-fence locations are compared with the existing bike-sharing stations in the study area to examine how well the geo-fence locations perform.

4 Results

4.1 Determination of weights of criteria

The implementation of AHP is based on the responses from five experts to determine the criteria weights. Regarding the five experts, two came from the bike-sharing industry, one was active in related research, one worked at the municipal traffic planning administration, and one was from a non-governmental organization working to promote cycling. The pair-wise comparison matrix was aggregated from the expert ranking, as shown in Table 2. The criteria EDU and PTL are found to contribute more to bike-sharing usage than the other criteria, which receive priority weights of 0.23 and 0.21 respectively. They are followed by the criteria ET, COM, POP, and SP, the corresponding weights range from 0.10 to 0.14. The criteria that receive the lowest weights are PTS and MBP, the latter obtains a marginal weight of 0.04. The consistency analysis shows that the comparison matrix is consistent with a consistency ratio of 0.017. This expresses that the rankings are 1.7% as inconsistent as if they were made randomly. According to Saaty (1980), a consistency ratio smaller than 0.1 can be accepted. Hence, the results of the AHP conducted in this study can be used for the GIS-MCDA analysis.

4.2 Creation of criteria layers and suitability map

According to section 3.2, the map layers were produced for each criterion. The criteria layers were further standardized for visualization by applying Keeney's value

Table 2 Pair-wise comparison matrix with intensity weights aggregated from the expert ranking. The priority weights are shown in the right-most column

	MBP	PTL	PTS	EDU	SP	COM	POP	ET	Priority weights
Major Bike paths (MBP)	1.00	0.23	0.68	0.22	0.34	0.30	0.32	0.25	**0.04**
Public Transit large (PTL)	4.36	1.00	3.16	0.80	2.37	1.90	1.53	2.29	**0.20**
Public Transit small (PTS)	1.48	0.32	1.00	0.40	0.53	0.52	0.64	0.35	**0.06**
Higher education (EDU)	4.58	1.25	2.54	1.00	3.32	2.54	1.93	1.72	**0.23**
Sports facilities and parks (SP)	2.95	0.42	1.904	0.30	1.00	0.80	1.64	0.58	**0.10**
Commercial areas (COM)	3.32	0.53	1.93	0.39	1.25	1.00	0.95	1.00	**0.11**
Population density (POP)	3.16	0.65	1.55	0.52	0.61	1.05	1.00	0.73	**0.11**
Entertainment (ET)	4.08	0.44	2.85	0.58	1.72	1.00	1.38	1.00	**0.14**

function (Keeney, 1996). Standardizing the criteria layer within the range between 0 and 1 also makes it possible to compare their suitability values. The standardized criteria layers display a clear spatial distribution of high and low suitability for bike-sharing, as shown in Fig. 4. All criteria layers indicate higher suitability for bike-sharing towards the city center which is located north of the lake. This is most prominent for the criteria COM and ET, which have very high suitability exclusively in the city center and a drammatic decreasing suitability toward the suburbs. Other criteria such as MBP and PTS have mostly high suitability in large parts of the study area. The remaining three criteria layers for PTL, SP, and EDU exhibit high suitability for most parts of the study area except for some patches of low suitability mostly at the edge of the city.

The overall suitability was calculated via the weighted linear combination based on the criteria layers and their

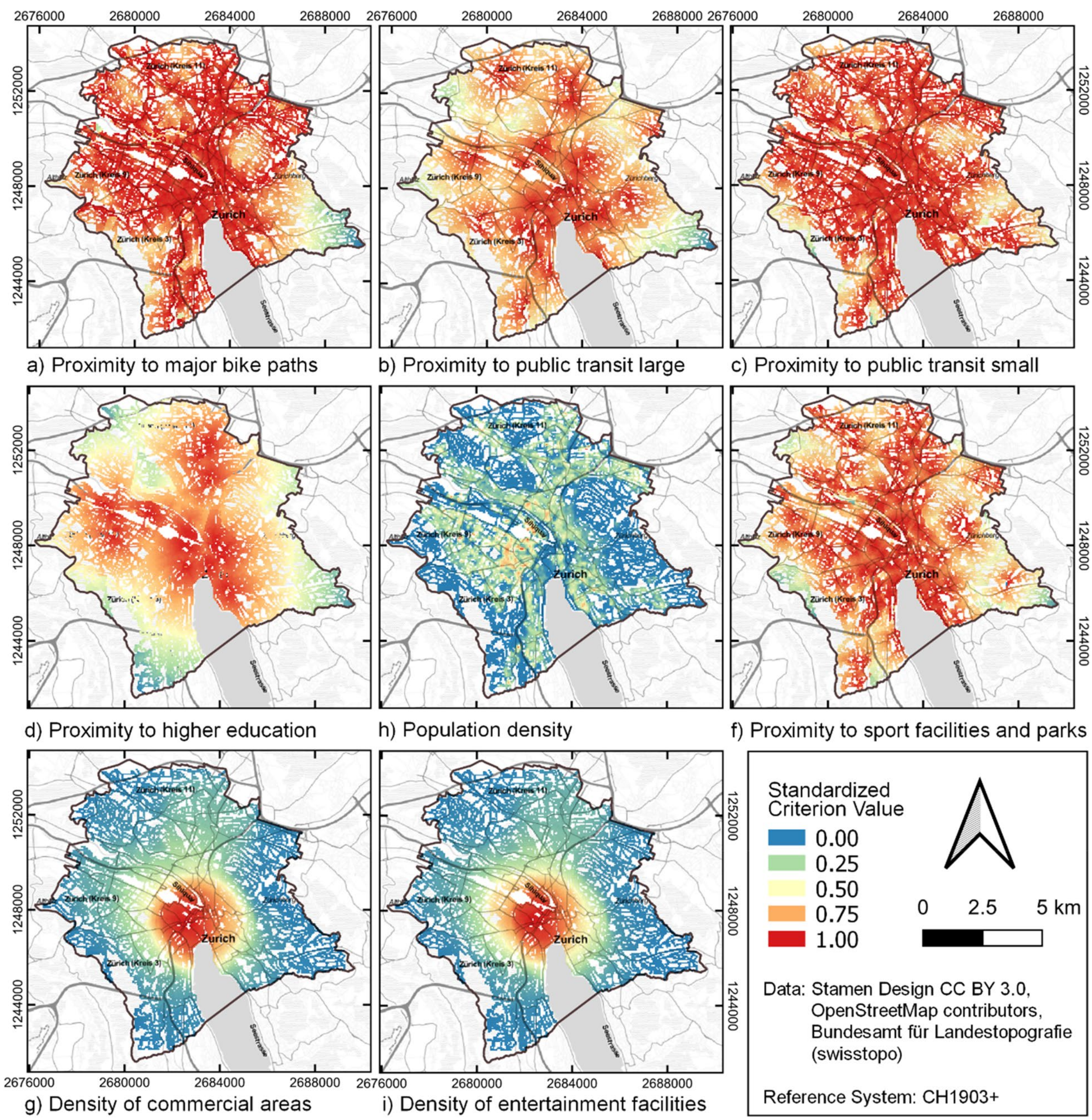

Fig. 4 Maps of each criterion. The standardized criteria values with 1 representing high and 0 representing low criteria scores

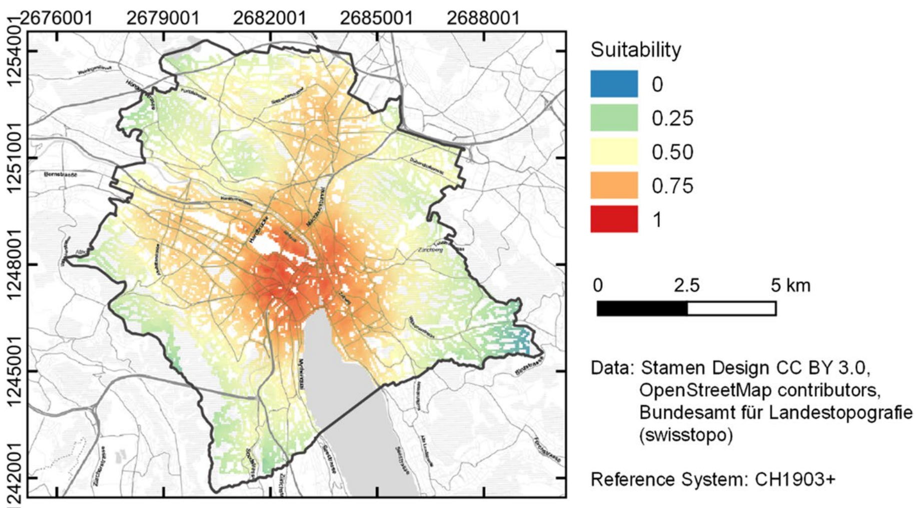

Fig. 5 Suitability map for geo-fences

weights, as shown in Fig. 5. The suitability map reflects the suitability distribution in different parts of the study area for potential geo-fences. It can be observed that the high suitability areas are concentrated in the city center and northwest of Zurich. Most areas on the outskirts of the study area receive rather low suitability values.

4.3 Determination of final geo-fence locations

VIKOR was used to rank the candidate locations according to their closeness to the ideal solution. Figure 6(a) shows the statistical distribution of the Qj measure that was used for the ranking. As Qj represents the closeness to the ideal solution, smaller values are more suitable. The distribution is left-skewed with a mean of 0.3 and a median of 0.26. The minimum and maximum values are 0.03 and 0.89 respectively. The 90% percentile was used as a threshold to filter unsuitable stations. This resulted in 120 candidate locations being excluded from the selection process. The majority of these candidates were in the outskirts of the study area, in the South, North-West, and South-East. Furthermore, 114 candidate locations were located outside of the criteria layers, which were also excluded from the selection process.

To test how well the suitability ranking related to actual bike-sharing demand, the number of ODs in a 500 m buffer around each candidate location was computed. The OD count per candidate location was plotted as a function of the Q suitability measure to test how well the suitability ranking related to bike-sharing levels, as shown in Fig. 6(b). The plot supports the assumption that a relationship between the Q value of a geo-fence and the high bike-sharing level in its vicinity exists. Q values larger than the 90% percentile of 0.512 have low OD counts with a mean of 49, whereas the overall mean

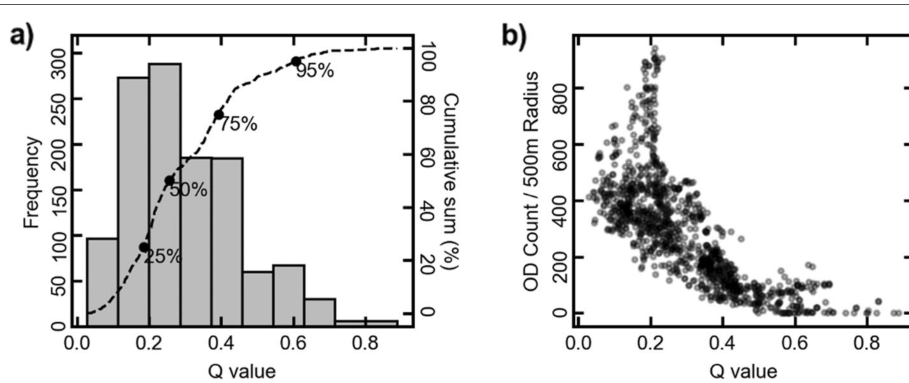

Fig. 6 Ranking results with VIKOR. a Statistical distribution of the Q value assigned to the candidate locations, and b the number of origins and destinations of bike trips (OD) in a 500 m buffer around a candidate location as a function of the candidate location's Q value. A low Q value represents high suitability

is 281. The relationship between OD count and Q yielded a Spearman coefficient of −0.81 which indicates a high negative correlation. The correlation was significant with a *p*-value smaller than 0.001.

According to the statistical distribution of Qj values, the candidate locations with Q values larger than 0.512 were filtered out. As shown in Figs. 7, 155 candidate locations were selected for geo-fences. The geo-fence locations with high Q values are mainly distributed in the city center.

5 Discussion

5.1 Assessment of geo-fence locations and capacities

In this section, the selected geo-fence locations were further evaluated based on the real bike-sharing OD data and the existing bike-sharing stations. We explored the statistical distribution of Q_j suitability values of the selected geo-fences and the shortest distance to a geo-fence from the ODs, as shown in Fig. 8. As shown in Fig. 8(a), the geo-fences have a minimum Q_j suitability value of 0.03 and a maximum of 0.51. The mean and median are 0.26 and 0.24 respectively. Fig. 8(b) displays the statistical distribution of the shortest distance to a geo-fence from the origins and destinations. The distance analysis shows that nearly 80% of the origins and destinations are within a 500 m buffer of at least one geo-fence. Only 5% of the ODs are out of the 1000 m buffers of geo-fences. The result indicates that the selected geo-fences have good coverage on the bike-sharing demand without impacting the convenient use of bikes for users.

The selected geo-fence locations were further compared to the existing bike-sharing stations in the study area in terms of accessibility and demand coverage. We measured the accessibility based on two metrics, namely the nearest distance from origin/destination to geo-fence/station (Distance from OD), and the distance

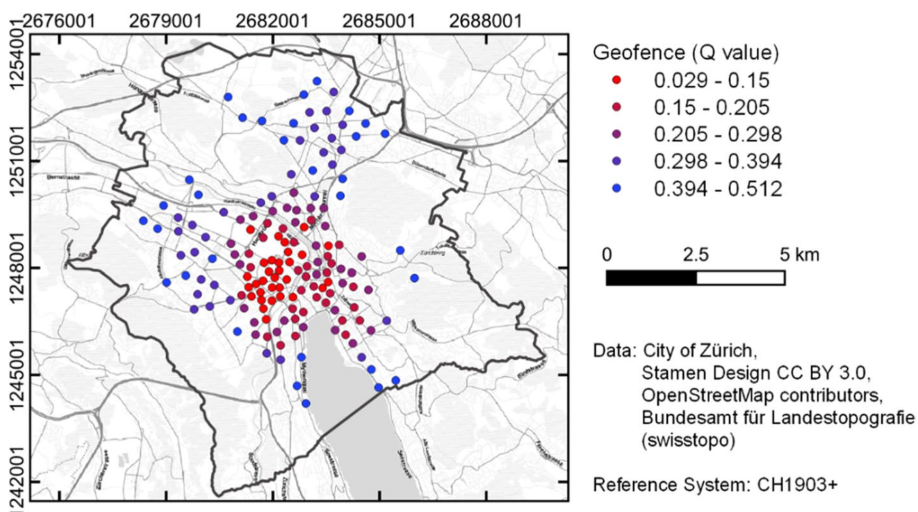

Fig. 7 The selected geo-fence locations

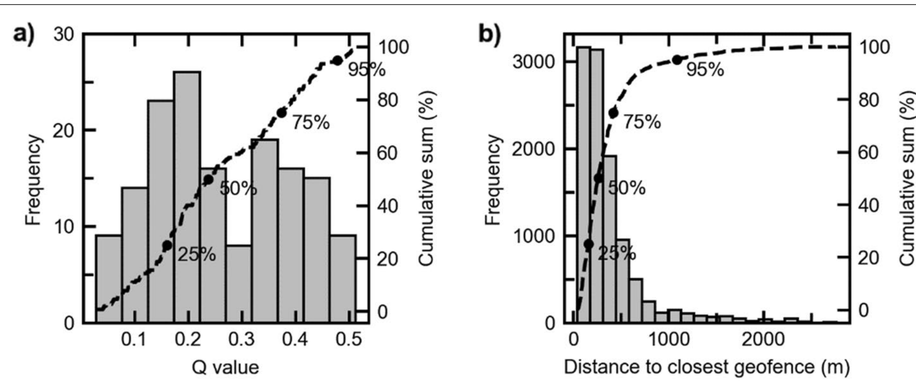

Fig. 8 Assessment results. **a** Statistical distribution of the Qj suitability measure for the selected geo-fence locations. **b** Statistical distribution of the network distance to the closest geo-fence from origins and destinations of bike trips in the study area

from vertices of road segments in the road network to the nearest geo-fence/station (Distance from road network). The demand coverage was measured by calculating the number of origins and destinations within the 500 m buffer (network distance)of geo-fence/station. Table 3 displays the statistics of the three metrics. In terms of Distance from OD, the selected geo-fences have slightly smaller average distances to the ODs with 341 m compared to 374 m for the bike-sharing stations. With regards to Distance from the road network, the average distance of 1395 m for geo-fences is also smaller than that of 1692 m for bike-sharing stations. By calculating the demand coverage based on geo-fences and bike-sharing stations respectively, the selected geo-fences have on average fewer ODs but cover a slightly larger proportion of the total count within a 500 m buffer of any geo-fence or station. It should also be noted that the number of the geo-fences is less than that of the bike-sharing stations, which implies a lower construction cost from an economic perspective. In summary, the assessment results demonstrate the superiority and validity of the proposed framework.

5.2 Sensitivity analysis

In the GIS-MCDA framework, the selection of the spatial resolution to discretize the study area has an influence on the final results. In this section, the effect of the parameter cell size is examined by conducting a sensitivity analysis while keeping other parameters fixed. In the sensitivity analysis, we attempted a finer resolution of 10 m, the assessment of the selected geo-fences is displayed in Table 4. Compared with the determined 155 geo-fence locations at 50 m resolution, 137 geo-fence locations are determined at 10 m resolution. As aforementioned, the selection process starts with the most suitable candidate location and continues down to the less suitable locations. Due to the change of suitability map resolution, it can cause the cases that the location located in a 50 m cell can fall into different 10 m cells. Hence, the suitability value Q which was formerly the same in a single 50 m cell becomes different in 10 m cells. Thus the selection will follow a different order and might result in a different set of locations. By comparing the assessment results at 50 m resolution (in Table 3) and 10 m resolution (in Table 4), it can be observed that the descriptive statistics at the two resolutions are close in terms of distance-based metrics. With regards to demand coverage, the results at 10 m resolution show higher demand coverage.

5.3 Limitations

This study has two limitations that deserve to be further studied in future work. First, we mainly consider the geographic and built environment factors that influence bike-sharing demand and social factors as the criteria in geo-fence planning, some other factors, such as the cost of geo-fences and land cost, could also be taken into consideration. By considering these economic criteria, the calculated geo-fence locations would be more realistic. Second, the framework involves the threshold settings for another two parameters. One is regarding the calculation of the density-related criteria, which are computed in a 2 km radius around a cell based on previous studies (e.g., Liu et al., 2018; Ma et al., 2020). The attempt of different buffer sizes could help determine the appropriate

Table 3 Descriptive statistics to assess the selected geo-fences at 50 m resolution by comparing them with the existing bike-sharing stations

	Count	Distance from OD (m)		Distance from road network (m)		Demand coverage		
		Mean	Std. Dev	Mean	Std. Dev.	Median	Std. Dev.	Total (%)
Geofences	155	341	311	1395	1051	262	347	81
Stations	170	374	340	1692	1076	269	361	77

Table 4 Descriptive statistics to assess the selected geo-fences at 10 m resolution by comparing them with the existing bike-sharing stations

	Count	Distance from OD (m)		Distance from road network (m)		Demand coverage		
		Mean	Std. Dev	Mean	Std. Dev.	Median	Std. Dev.	Total (%)
Geofences	137	387	382	1489	1054	281	187	90
Stations	170	374	340	1692	1076	269	361	77

search radius for the density computation and examine its effects on the site selection results. The other threshold setting is related to determining the buffer size while evaluating geo-fence locations. In this study, the service areas of bike-sharing stations are determined as 500 m network distance buffers (Frade & Ribeiro, 2015; Wang et al., 2018). The assumption is that users would prefer not to use bike-sharing services when the walking distance exceeds 500 m. Understanding the effects of walking distance on the evaluation results is also desirable. Third, the spacing of geo-fences is determined using an assumed linear relationship between spacing and suitability in this study. This assumed relationship with suitability is unknown, a variation in spacing between more and less suitable locations can be explored and aimed for based on non-linear relationships.

6 Conclusion

Although dockless bike-sharing systems have become increasingly popular worldwide to facilitate sustainable transportation, the inappropriate parking of shared bikes also brings serious urban problems (e.g., the illegal and irregular parking concerns on free-floating bikes). Geo-fence planning provides an effective way to manage the parking of shared bikes while maintaining their convenience. This study aims to provide a multi-criteria decision analysis framework for geo-fence planning of dockless bike-sharing systems based on openly accessible data. Unlike the existing optimization-based models, the framework is independent of the real bike-sharing demand data. The whole framework was tested by applying it to a dataset in Zurich. The results demonstrate that the framework is effective in determining the sites for geo-fences by quantifying the bike-sharing demand coverage of the final geo-fence locations and comparing them with the existing bike-sharing stations. The proposed framework can be applied to plan gen-fences for shared micro-mobility systems (e.g., shared bikes and e-scooters) where parking is an important issue. The main contributions are summarized as follows:

First, the proposed framework can help quantify the weights of various influencing criteria and determine the optimal locations of geo-fences for better decision-making. In this work, a scheme for effectively managing free-floating bikes in cities is provided, which is beneficial for establishing geo-fence facilities to mitigate the above-mentioned illegal parking issues while introducing them to cities. Second, compared with the previous studies that rely heavily on bike-sharing trip data, the proposed GIS-MCDA framework is implemented to quantify the related criteria based on the openly accessible data. In particular, it is more appropriate for cities where bike-sharing data is not available. Hence, the proposed framework is more applicable than the methods based on bike-sharing trip data. When introducing dockless bike-sharing systems to cities, geo-fence facilities can be established simultaneously. This study can help transport planners better implement shared micro-mobility systems to facilitate the development of sustainable transportation.

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Authors' contributions
Max Mangold: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. Pengxiang Zhao: Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing. He Haitao: Conceptualization, Methodology, Investigation, Writing - review & editing. Ali Mansourian: Conceptualization, Investigation, Writing - review & editing. The author(s) read and approved the final manuscript.

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Declarations

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References

Boeing, G. (2017). OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Computers, Environment and Urban Systems*, *65*, 126–139.
Buehler, R., & Pucher, J. (2012). Cycling to work in 90 large American cities: New evidence on the role of bike paths and lanes. *Transportation*, *39*(2), 409–432.
Chen, E., & Ye, Z. (2021). Identifying the nonlinear relationship between free-floating bike sharing usage and built environment. *Journal of Cleaner Production*, *280*, 124281.
Cheng, G., Guo, Y., Chen, Y., & Qin, Y. (2019). Designating city-wide collaborative geofence sites for renting and returning dock-less shared bikes. *IEEE Access*, *7*, 35596–35605.
Conrow, L., Murray, A. T., & Fischer, H. A. (2018). An optimization approach for equitable bicycle share station siting. *Journal of Transport Geography*, *69*, 163–170.

Dang, R., Li, X., Li, C., & Xu, C. (2021). A MCDM framework for site selection of island photovoltaic charging station based on new criteria identification and a hybrid fuzzy approach. *Sustainable Cities and Society*, *74*, 103230.
DeMaio, P. (2009). Bike-sharing: History, impacts, models of provision, and future. *Journal of Public Transportation*, *12*(4), 3.
Erbaş, M., Kabak, M., Özceylan, E., & Çetinkaya, C. (2018). Optimal siting of electric vehicle charging stations: A GIS-based fuzzy multi-criteria decision analysis. *Energy*, *163*, 1017–1031.
Eren, E., & Katanalp, B. Y. (2022). Fuzzy-based GIS approach with new MCDM method for bike-sharing station site selection according to land-use types. *Sustainable Cities and Society*, *76*, 103434.
Eren, E., & Uz, V. E. (2020). A review on bike-sharing: The factors affecting bike-sharing demand. *Sustainable Cities and Society*, *54*, 101882.
Faghih-Imani, A., & Eluru, N. (2015). Analysing bicycle-sharing system user destination choice preferences: Chicago's divvy system. *Journal of Transport Geography*, *44*, 53–64.
Faghih-Imani, A., Hampshire, R., Marla, L., & Eluru, N. (2017). An empirical analysis of bike sharing usage and rebalancing: Evidence from Barcelona and Seville. *Transportation Research Part A: Policy and Practice*, *97*, 177–191.
Frade, I., & Ribeiro, A. (2015). Bike-sharing stations: A maximal covering location approach. *Transportation Research Part A: Policy and Practice*, *82*, 216–227.
Fuller, D., Gauvin, L., Kestens, Y., Daniel, M., Fournier, M., Morency, P., & Drouin, L. (2011). Use of a new public bicycle share program in Montreal, Canada. *American Journal of Preventive Medicine*, *41*(1), 80–83.
Gao, K., Yang, Y., Li, A., Li, J., & Yu, B. (2021). Quantifying economic benefits from free-floating bike-sharing systems: A trip-level inference approach and city-scale analysis. *Transportation Research Part A: Policy and Practice*, *144*, 89–103.
García-Palomares, J. C., Gutiérrez, J., & Latorre, M. (2012). Optimizing the location of stations in bike-sharing programs: A GIS approach. *Applied Geography*, *35*(1–2), 235–246.
Guler, D., & Yomralioglu, T. (2021). Bicycle station and lane location selection using open source GIS technology. In *Open source geospatial science for urban studies*, (pp. 9–36). Cham: Springer.
Guo, Y., & He, S. Y. (2020). Built environment effects on the integration of dockless bike-sharing and the metro. *Transportation Research Part D: Transport and Environment*, *83*, 102335.
Guo, Y., Zhou, J., Wu, Y., & Li, Z. (2017). Identifying the factors affecting bike-sharing usage and degree of satisfaction in Ningbo, China. *PloS one*, *12*(9), e0185100.
Hirsch, J. A., Stratton-Rayner, J., Winters, M., Stehlin, J., Hosford, K., & Mooney, S. J. (2019). Roadmap for free-floating bikeshare research and practice in North America. *Transport Reviews*, *39*(6), 706–732.
Hwang, C. L., & Yoon, K. (1981). Methods for multiple attribute decision making. In *Multiple attribute decision making*, (pp. 58–191). Berlin, Heidelberg: Springer.
Jelokhani-Niaraki, M., & Malczewski, J. (2015). The decision task complexity and information acquisition strategies in GIS-MCDA. *International Journal of Geographical Information Science*, *29*(2), 327–344.
Kabak, M., Erbaş, M., Çetinkaya, C., & Özceylan, E. (2018). A GIS-based MCDM approach for the evaluation of bike-share stations. *Journal of Cleaner Production*, *201*, 49–60.
Kabir, G., Sadiq, R., & Tesfamariam, S. (2014). A review of multi-criteria decision-making methods for infrastructure management. *Structure and Infrastructure Engineering*, *10*(9), 1176–1210.
Keeney, R. L. (1996). *Value-focused thinking*. Harvard University Press.
Krizek, K. J., & Johnson, P. J. (2006). Proximity to trails and retail: Effects on urban cycling and walking. *Journal of the American Planning Association*, *72*(1), 33–42.
Latinopoulos, D., & Kechagia, K. (2015). A GIS-based multi-criteria evaluation for wind farm site selection. A regional scale application in Greece. *Renewable Energy*, *78*, 550–560.
Lazarus, J., Pourquier, J. C., Feng, F., Hammel, H., & Shaheen, S. (2020). Micromobility evolution and expansion: Understanding how docked and dockless bikesharing models complement and compete–a case study of San Francisco. *Journal of Transport Geography*, *84*, 102620.
Li, A., Gao, K., Zhao, P., Qu, X., & Axhausen, K. W. (2021). High-resolution assessment of environmental benefits of dockless bike-sharing systems based on transaction data. *Journal of Cleaner Production*, *296*, 126423.
Li, A., Zhao, P., Haitao, H., Mansourian, A., & Axhausen, K. W. (2021). How did micro-mobility change in response to COVID-19 pandemic? A case study based on spatial-temporal-semantic analytics. *Computers, Environment and Urban Systems*, *90*, 101703.
Li, A., Zhao, P., Huang, Y., Gao, K., & Axhausen, K. W. (2020). An empirical analysis of dockless bike-sharing utilization and its explanatory factors: Case study from Shanghai China. *Journal of Transport Geography*, *88*, 102828.
Lin, P., Weng, J., Hu, S., Alivanistos, D., Li, X., & Yin, B. (2020). Revealing spatio-temporal patterns and influencing factors of dockless bike sharing demand. *IEEE Access*, *8*, 66139–66149.
Liu, Z., Shen, Y., & Zhu, Y. (2018). Inferring dockless shared bike distribution in new cities. In *In Proceedings of the eleventh ACM international conference on web search and data mining*, (pp. 378–386). New York: ACM.
Ma, X., Ji, Y., Yuan, Y., Van Oort, N., Jin, Y., & Hoogendoorn, S. (2020). A comparison in travel patterns and determinants of user demand between docked and dockless bike-sharing systems using multi-sourced data. *Transportation Research Part A: Policy and Practice*, *139*, 148–173.
Martin, E. W., & Shaheen, S. A. (2014). Evaluating public transit modal shift dynamics in response to bikesharing: A tale of two US cities. *Journal of Transport Geography*, *41*, 315–324.
Mateo-Babiano, I., Bean, R., Corcoran, J., & Pojani, D. (2016). How does our natural and built environment affect the use of bicycle sharing? *Transportation Research Part A: Policy and Practice*, *94*, 295–307.
Mix, R., Hurtubia, R., & Raveau, S. (2022). Optimal location of bike-sharing stations: A built environment and accessibility approach. *Transportation Research Part A: Policy and Practice*, *160*, 126–142.
Nikiforiadis, A., Aifadopoulou, G., Grau, J. M. S., & Boufidis, N. (2021). Determining the optimal locations for bike-sharing stations: Methodological approach and application in the city of Thessaloniki, Greece. *Transportation Research Procedia*, *52*, 557–564.
Opricovic, S. and Tzeng, G.H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European journal of operational research*, *156*(2), 445-455.
Otero, I., Nieuwenhuijsen, M. J., & Rojas-Rueda, D. (2018). Health impacts of bike sharing systems in Europe. *Environment International*, *115*, 387–394.
Pereira, J. M., & Duckstein, L. (1993). A multiple criteria decision-making approach to GIS-based land suitability evaluation. *International Journal of Geographical Information Science*, *7*(5), 407–424.
Reclus, F., & Drouard, K. (2009). Geofencing for fleet & freight management. In *In 2009 9th International Conference on Intelligent Transport Systems Telecommunications, (ITST)*, (pp. 353–356). Lille, France: IEEE. https://doi.org/10.1109/ITST.2009.5399328.
Saaty TL. (1980). The analytic hierarchy process. McGraw-Hill International Book Co., New York
Saaty, T. L. (1988). What is the analytic hierarchy process? In *Mathematical models for decision support*, (pp. 109–121). Berlin, Heidelberg: Springer.
Schoner, J. E., & Levinson, D. M. (2014). The missing link: Bicycle infrastructure networks and ridership in 74 US cities. *Transportation*, *41*(6), 1187–1204.
Shen, Y., Zhang, X. and Zhao, J. (2018). Understanding the usage of dockless bike sharing in Singapore. *International Journal of Sustainable Transportation*, *12*(9), 686-700.
Shui, C. S., & Szeto, W. Y. (2020). A review of bicycle-sharing service planning problems. *Transportation Research Part C: Emerging Technologies*, *117*, 102648.
Stadt Zürich. (2021). Zürich in Zahlen. https://www.stadt-zuerich.ch/portal/de/index/portraet_der_stadt_zuerich/zuerich_in_zahlen.html. Accessed 27 Jan 2021.
Tran, T. D., Ovtracht, N., & d'Arcier, B. F. (2015). Modeling bike sharing system using built environment factors. *Procedia Cirp*, *30*, 293–298.
Veronesi, F., Schito, J., Grassi, S., & Raubal, M. (2017). Automatic selection of weights for GIS-based multicriteria decision analysis: Site selection of transmission towers as a case study. *Applied Geography*, *83*, 78–85.
Wang, K., Akar, G., & Chen, Y. J. (2018). Bike sharing differences among millennials, gen Xers, and baby boomers: Lessons learnt from new York City's bike share. *Transportation Research Part A: Policy and Practice*, *116*, 1–14.
Wang, X., Lindsey, G., Schoner, J. E., & Harrison, A. (2017). Modeling bike share station activity: Effects of nearby businesses and jobs on trips to and from stations. *Journal of Urban Planning and Development*, *142*(1), 04015001.
Yesilnacar, M. I., Süzen, M. L., Kaya, B. Ş., & Doyuran, V. (2012). Municipal solid waste landfill site selection for the city of Şanliurfa-Turkey: An example

using MCDA integrated with GIS. *International Journal of Digital Earth*, *5*(2), 147–164.
Zhang, Y., Lin, D., & Mi, Z. (2019). Electric fence planning for dockless bike-sharing services. *Journal of Cleaner Production*, *206*, 383–393.
Zhang, Y., Thomas, T., Brussel, M., & Van Maarseveen, M. (2017). Exploring the impact of built environment factors on the use of public bikes at bike stations: Case study in Zhongshan, China. *Journal of Transport Geography*, *58*, 59–70.
Zhao, P., Haitao, H., Li, A., & Mansourian, A. (2021). Impact of data processing on deriving micro-mobility patterns from vehicle availability data. *Transportation Research Part D: Transport and Environment*, *97*, 102913.

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