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Demand And/oR Equity (DARE) method for planning bike-sharing

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A B S T R A C T

Most bike-sharing systems in cities aim to maximize demand, an approach that tends to inadvertently favor wealthier neighborhoods. Therefore, we developed a heuristic and data-mining-based method to weigh both Demand And/oR Equity (DARE) in the station distribution and allocation process of planning bike-sharing. Equity is measured using a deprivation index and the potential demand is estimated using structural equation models via the built and social environment. The DARE method was applied first to the BSS service area in Munich, Germany, and then, to the area surrounding Munich, demonstrating the method's transferability. Incorporating equity resulted in disadvantaged areas being better served by bike-sharing stations while favoring ridership (demand) tended to cluster stations in the wealthier city center. This method allows decision-makers to build scenarios for allocating infrastructure based on their desired fairness criterion, and can also be applied to other shared modes or public transport.

1. Introduction

Bike-sharing systems (BSS) can provide an opportunity to access cycling regardless of a person's purchasing power (Lucas, 2019). However, "most bike share schemes were never designed with equity or social justice in mind...[but] designed around environmental and economic goals intended to stimulate urban renewal" (de Chardon, 2019; Hoffmann, 2016). BSS studies have shown inequality in the implementation, usage, and benefits across demographics. The common profile of a BSS user tends to be a young white male, who is highly educated, higher income, already engaged with cycling, and has access to bank accounts and credit cards (Fishman et al., 2015; Ogilvie and Goodman, 2012; McNeil et al., 2017; Stöckle, 2020; Mooney et al., 2019). Historically, the distribution of stations and the service areas have been focused on central and densely populated regions, (Fishman et al., 2015; Duran-Rodas et al., 2019; Chen et al., 2019) where residents tend to reflect BSS user profile (Chen et al., 2019; Ursaki et al., 2015; Mooney et al., 2019). Deprived and low-income areas are reported to have less access to BSS infrastructure (Ursaki et al., 2015; Mooney et al., 2019; Ogilvie and Goodman, 2012; Smith et al., 2015), even though many BSS promote themselves as being equitable (Duran-Rodas et al., 2020b).

Are BSS planned fairly? Justice involves rules that are based on a shared understanding of morality among individuals in a global, cultural, or circumstantial context (Goldman and Cropanzano, 2015; Leventhal, 1980). "*Fairness*" is a subjective judgment that varies depending on whether justice rules are applied or not (Goldman and Cropanzano, 2015). What is fair for one person may not be fair for other people (Goldman and Cropanzano, 2015; Duran-Rodas et al., 2020c). Distribution of a particular resource is considered as fair

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when the distribution meets criteria that certain individuals believe is fair (Leventhal, 1980). The most common criteria for the spatial distribution of resources are: a) spatialequality or horizontal equity (equal distribution of resources), b) spatial equity or vertical equity (distribution according to people's needs in terms of social status, opportunities, and abilities), c) spatial efficiency (distribution according to the people's ability to contribute or access resources) (Leventhal, 1980; Talen, 1998; Duran-Rodas et al., 2020c). These distribution criteria are "*fair*" depending on the point of view of each individual (Duran-Rodas et al., 2020c).

We identified three gaps in the existing research on the fair allocation of stations and service area boundaries. First, only a few studies have considered equity as an input for planning BSS, such as Caggiani et al. (2020). Previous systematic planning methods for BSS have not prioritized infrastructure distribution according to the neediest populations in terms of social status and opportunities. The second research gap is that in systematic methods, the opportunity to balance efficiency and equity has not been deeply explored. Finally, the third research gap is the failure to account for confounding variables when estimating BSS ridership (spatial efficiency) and its associated spatial factors. Exploring causality can increase the generalization and transferability of the model (Thakkar, 2020). Usually, linear regressions are performed by learning from historical trips using spatial factors from the built and social environment. However, with linear regressions, we cannot detect confounding variables. For instance, an increase in population density has a high probability of generating an increase in the number of trips. However, the relationship between population density and ridership is not causal: trips are not caused because of the number of people but rather their need for mobility to perform activities (Wegener and Fürst, 1999).

There is a need to consider spatial equity when planning the distribution of BSS infrastructure, which means prioritizing underprivileged areas or areas where people have the greatest needs in terms of social status, opportunity, or ability. However, this can be balanced with spatial efficiency by also prioritizing the distribution of infrastructure where higher ridership is expected. Therefore, we aim to develop a heuristic and fairness-based method in which the fairness criteria (equity and/or efficiency) for the distribution of stations and service areas can be depending on the desired focus: spatial equity as represented by deprivation, spatial efficiency represented by the potential ridership, or a balance of both. Based on these criteria, and accounting for limited resources, the method ranks zones of analysis based on four heuristic algorithms to prioritize the allocation of infrastructure. The resulting allocation is then assessed based on the resulting coverage area and density.

We applied this method to the hybrid bike-sharing system (HBSS) in Munich, Germany. Testing a hybrid system was advantageous because HBSS are rarely studied in the literature. Additionally, since HBSS have characteristics of both docked and dockless systems, our method can be implemented with those types of BSS as well.

The second contribution of this study is the estimation of potential ridership as an indicator of spatial efficiency using Structural Equation Models (SEMs). To train SEMs, the paper will also build a theoretical structure of links between BSS ridership and its previously associated spatial factors from the built and social environment. This structure will be shaped by merging two theoretical models: a) "land-use and transport interactions" that includes the factors from the built environment (Wegener and Fürst, 2004; Wulfhorst, 2003), and b) "urban mobility cultures" that includes factors from the social environment (Kuhnimhof and Wulfhorst, 2013; Deffner et al., 2006; Klinger et al., 2013).

This paper continues with a literature review of BSS concepts and previously used methods to plan BSS and estimate potential ridership demand. Hence, it presents the DARE (Demand And/oR Equity) method followed by the results of its application. Finally, it discusses the strengths, limitations, and possible future applications for this method.

2. Literature review

2.1. Bike-sharing: overview

BSS are programs in which people can pick up a bike and drop it off in the public space within a service area (Büttner and Petersen, 2011; Toole Design Group, 2012). BSS have the potential to improve access to cycling and its benefits as a healthy and convenient transport mode, enhance last-mile connections to transit, increase transport resilience, help build support for future cycling initiatives, and change attitudes towards cyclists (Cohen and Shaheen, 2018; Shaheen et al., 2014; Teixeira and Lopes, 2020; Manca et al., 2019; de Chardon, 2019; Bauman et al., 2017). BSS can also reduce CO2 emissions in a city, depending on the balancing system of bicycles and their ability to replace trips that would otherwise be made by private motorized vehicles (Ricci, 2015). However, BSS have also faced some challenges. For example, improper sizing and distribution of stations can lead to areas that are over- or under-supplied with bicycles (McNeil et al., 2017; Li et al., 2019; Sun, 2018; Ma et al., 2018). The sustainability of BSS can also be compromised by the massive amounts of waste that are generated when bicycles are no longer used (de Chardon, 2019), or by the emissions of the rebalancing and maintenance operations (Ricci, 2015). Projected health benefits can also be overstated when bike-sharing trips replace walking or private cycling trips that provide comparable health benefits (Ricci, 2015; de Chardon, 2019; Bauman et al., 2017).

BSS include conventional bicycles, cargo, tandem, or e-bikes in three types of systems: a) docked or station-based, b) dockless or free-floating, and c) hybrid, a mix of docked and dockless (HBSS) (Shaheen et al., 2020). Docked systems have the advantage of designated parking and easy-to-locate bikes. On the other hand, dockless systems have lower capital costs, a more flexible service area, and provide greater convenience to users since the trip can end anywhere in the service area. However, dockless systems can also be more difficult for users to locate a bike nearby and require more effort for operators to rebalance the fleet (Shaheen et al., 2020). If not carefully monitored, bikes can accumulate in one area and improperly parked bikes may conflict with pedestrians, especially those with limited mobility. Analysis of social media sites such as Twitter reveal that people often complain about piles of dockless bikes encountered in certain areas (Duran-Rodas et al., 2020b). However, Brown et al. (2020) performed a systematic observation of parking behavior of different transport means including bike-sharing, and concluded that only 0.3% of the bikes presented conflicts with pedestrians. Hybrid systems share advantages of dockless and docked systems (Yanocha et al., 2018) but have not been studied in great depth. Therefore, we aimed to develop a method that would help to plan these systems.

2.2. Bike-sharing: planning process

According to guidelines in North America and Europe, four "macro" steps are commonly used for planning BSS (Yanocha et al., 2018; Gauthier et al., 2014; Anaya Boig and para la Diversificación y Ahorro de la Energía, 2007; Büttner and Petersen, 2011; Toole Design Group, 2012): I) set goals, II) estimate the potential demand and potential bike-sharing users, III) define the potential location of stations and service area, and IV) fix the locations (Fig. 1).

The planning process of BSS (Fig. 1) often starts with the definition of the system's goals (e.g. mobility, sustainability, equity). Next, historical data from systems in comparable cities are used to build potential demand models. The potential station locations and service area boundaries are defined using design inputs such as budget, rebalancing method and strategies, and key performance metrics (e.g. stations density, number of bicycles). BSS guidelines recommend preparing a "first draft" of the design and then adjusting it based on-site visits and stakeholder involvement (Gauthier et al., 2014). If potential sites are not accepted or cannot support BSS stations, new sites should be identified until suitable locations are found. Should a system change its goals, expand, or relocate to a new area, the process begins anew. The goals of BSS could be potentially modified when systems do not fulfill the requirement of, for example, expected ridership, service, or equity. Therefore, assessing inequity in a system, as in previous studies (Ogilvie and Goodman, 2012; McNeil et al., 2017; Fishman et al., 2015), can justify changing a system's goals and looking for new locations of stations or service areas in a more equitable way.

2.3. Bike-sharing: estimation of potential demand

Past research has studied how the spatial factors are associated with the historical trips of BSS to estimate the potential demand. Some common spatial factors that have been studied are shown in Table 1. The social environment factors most associated with ridership are population and employment density, while the most common built environment factors are transit stations and cycling infrastructure, leisure, and student-oriented activities.

Ordinary least squares models have been one of the most frequently implemented techniques to build potential demand models and identify the most influential factors on BSS ridership (Duran-Rodas et al., 2019; Faghih-Imani et al., 2014; El-Assi et al., 2017; Wang et al., 2015; Faghih-Imani et al., 2017; Mattson and Godavarthy, 2017; Zhao et al., 2014). Other approaches have performed robust linear regression (Chardon et al., 2017; Tran et al., 2015) and negative binomial regression (Noland et al., 2016), among others. The dependent variable in these studies is typically the logarithm of the number of bicycles' rentals or returns in an area or station (Wang et al., 2015; El-Assi et al., 2017; Faghih-Imani and Eluru, 2016). Although Ranaiefar and Rixey (2016) built SEMs for predicting potential ridership for BSS, a limitation of all these studies is that causal relationships between factors were not examined.

2.3.1. Milieus as a spatial indicator of the social environment

In the application of the study's method, milieus were considered the spatial factors representing the social environment for estimating the potential demand. Milieus are groups of like-minded people concerning the social status and core values (INTEGRAL, 2018). Milieu clusters categorize socio-spatial characteristics including people's attitudes, values, lifestyles, etc. (SINUS, 2017). They represent an approximation of perceptions and lifestyle orientations in this study. This categorization, therefore, expands on traditional social demographics by considering core values. Milieus have been tested for market segmentation in "leading manufacturers of branded goods and well-known service providers from politics, media, and associations as well as advertising and media agencies" (SINUS, 2017).

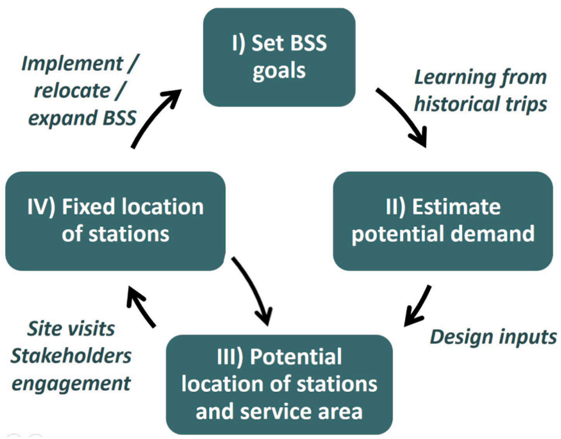


Fig. 1. Typical planning cycle for BSS.

Table 1
Influential factors on bike-sharing ridership: literature review.

Factors			Source									
			A	B	C	D	E	F	G	H	I	J
Social environment	**Population**	City population	✓	✓	✓				✓			
		Population density	✓	✓		✓				✓	✓	
		Employment density			✓			✓			✓	
	Socio-Demography	Age					✓	✓				
		Gender						✓		✓		
	Household income						✓	✓				
		Household size					✓			✓		
		Education level					✓					
Mobility Behaivor	Mode to commute (work/school)		✓		✓		✓					
	Time/ distance to commute						✓					
	Bicycle ownership							✓				
	Cycling propose							✓				
	Driver license ownership							✓				
	Already combine cycling and PT							✓				
Built environment	**Topography**	Slope (max 4%)	✓			✓						
		Altitude							✓	✓		
	Urban Structure	Distance to city center	✓	✓				✓			✓	
		Accessibility		✓	✓			✓				
		Mixed use land use	✓	✓								✓
		Industrial land use		✓								
		Single land use		✓								
		Residential land use										✓
		Commercial activity				✓						
	Transport Infrastructure	PT stops	✓	✓	✓	✓						
		Metro									✓	✓
		Railway station							✓			
		Major roads									✓	
		Streets									✓	
		Embankment road							✓			
		Transport POIs								✓		
		Cycling infrastructure	✓	✓	✓	✓					✓	
	POIs	Student residence							✓			
		Cinema							✓			
		Worship POIs								✓		
		Hotel								✓		
		Restaurant							✓	✓	✓	
		Universities	✓			✓					✓	
		Parks		✓								
		Sports Centers	✓									
		Recreation POIs								✓		
		Tourist attractions				✓						

A: Anaya Boig and para la Diversificación y Ahorro de la Energía (2007),Gauthier et al. (2014), C: Büttner and Petersen (2011),Toole Design Group (2012), E: Efthymiou et al. (2013),Bachand-Marleau et al. (2012), G: Tran et al. (2015),Faghih-Imani et al. (2017), I: Faghih-Imani et al. (2014), Noland et al. (2016)

This additional inclusion of core values of the inhabitants (e.g.. tradition, adventure, modernization) is the main advantage for using milieus for the sociodemographic analysis. Milieus also help overcome the limitation of the so-called "sociodemographic twins" (Sociovision, 2018) where areas with the same sociodemographic parameters are expected to behave similarly. The prominent orientation or values helped to further categorize and further divide the social environment and better understand the social environment of an area. In a previous study, values were even found to have a higher correlation with BSS use than traditional sociodemographics (Duran-Rodas et al., 2020a).

Milieus have been used in transport research e.g. for agent-based modeling (Schwarz and Ernst, 2009; Jensen et al., 2016), multi-agent simulation (Soboll et al., 2011), marketing research (Diaz-Bone, 2004), as well as for understanding social changes (Manderscheid and Tröndle, 2008) and mobility preferences (Von Jens, 2018; Sinus Markt und Sozialforschung GmbH, 2019).

2.4. *Bike-sharing: methods for searching the potential location of stations*

Gavalas et al. (2016) summarized four types of algorithm approaches for determining optimal station locations:

1. *Integer programming-based approaches* take into account BSS' historical trips to optimize the level of service and costs (travel, operation, infrastructure) to identify the optimal location of stations (Lin and Yang, 2011; Sun et al., 2019; Caggiani et al., 2018; Reiss and Bogenberger, 2015).

2. *Heuristic approaches* use (meta) heuristic techniques that search for the near-optimal solution. Cintrano et al. (2020) use five meta-heuristic techniques to solve the p-median problem (minimize the distance to stations to all points). Also, Lin et al. (2013) developed a heuristic method for station location based on costs for both users and operators.
3. *GIS-based approaches* are developed using geographic information systems tools. For instance, Banerjee et al. (2020) calculated a bike station suitability score using GIS tools. Another example is García-Palomares et al. (2012), who used a GIS-based methodology to develop a heuristic approach, locating stations by minimizing impedance (p-median), and maximizing coverage based on the density of spatial features associated with BSS ridership.
4. *Data mining-based approaches* use data to discover knowledge to plan BSS. Gehrke and Welch (2019) clustered existing stations based on built environment factors. Every candidate station was classified into five different groups on a suitability spectrum. In a similar approach, Vogel et al. (2011) proposed to plan BSS by clustering stations based on the bicycles' pick-ups and drop-offs and then correlated them to their most common geographical information.

Most of these techniques share a common approach of learning from historical trips to estimate potential demand, locate stations, and define the service area. However, techniques that learn from unfair systems are likely to perpetuate the same systematic inequities. Our proposed approach provides an opportunity to target equity and thereby break an unfair planning cycle.

2.5. *Bike-sharing: Overcoming inequalities*

Including spatial equity when planning BSS can lead to a reduction in social disparities and social exclusion (Fainstein, 2009), resulting in less social conflict and more social peace (Tomlinson, 2016). Providing access to those who have the greatest needs can allow them to participate in new transport trends. Even though lower-income neighborhoods with BSS supply have shown low usage Caspi and Noland (2019), a high level of fairness perceived by the population can reduce resistance towards implementation, increase project consent, or generate greater political acceptance (Ariely and Uslaner, 2017; Wüstenhagen et al., 2007). Moreover, prioritizing the neediest does not mean that a project is not serving those that contribute the most. Both private or public systems can be developed to be economically efficient, where spatial factors allow for higher demand (Willing et al., 2017). Those most in need have the potential to be customers when provided with information and incentives (Hoe, 2015).

Commonly, when BSS include a goal of equity, access is improved in these two ways: a) reducing barriers to entry into the system, and b) improving physical access to the infrastructure in underprivileged areas. Yanocha et al. (2018) recommended reducing barriers to entry into the system for ensuring equity in BSS, such as higher accessibility for people with different abilities, affordable pricing, or renting mechanisms that do not require smartphones or credit cards. For example, in Philadelphia, fees can be paid with cash at local convenience stores, or in Boston, residents classified as "low-income" only pay an annual fee of 5 U.S. dollars Yanocha et al. (2018). Moreover, system fleets have included adaptive bicycles such as electric bikes and standard trikes for people with less physical abilities (MacArthur et al., 2020). Regarding the access to infrastructure, in Philadelphia, extra stations were placed after considering the income levels and public participation in the planning (Hoe, 2015).In New York, one system has concentrated shared bicycles in low-income communities that have low access to transit (Kodransky and Lewenstein, 2014).

Only a few studies have incorporated equity-based concepts in the planning cycle (Fig. 1) of BSS. Conrow et al. (2018) optimized the distribution of stations by minimizing the average distance to stations in the service area and maximizing the potential demand. While this approach is referred to as equitable, it does not prioritize the neediest population. Therefore, according to our definitions, this study targeted spatial equality. In a similar approach, Caggiani et al. (2020) optimized the location of stations by minimizing walking distances to access the system and distributing a similar number of bicycles in all the districts of the city. To the best of the authors' knowledge, Caggiani et al. (2017) is the only study that systematically considers the concept of spatial equity by including the neediest population when planning BSS. They develop an allocation method that prioritizes areas with greater underprivileged populations using a bike equity index. The system cost was also made more equitable by funding the implementation of dockless BSS in deprived areas using toll payments collected in other areas.

After reviewing the literature, we aim to develop a heuristic fairness-based method for planning BSS that would incorporate spatial fairness criteria according to its targeted goals. Thus, our method employs a mixed approach of heuristics, data-mining, and equity criteria to develop the "first draft" of station locations and service area boundaries. As described above, previous studies and applications have considered equity in the sitting of stations by prioritizing lower-income neighborhoods or increasing coverage areas. In this study, we expanded the spatial equity concept of underprivileged by including areas with poor access to basic opportunities (e.g. health, food, education). Since resources are limited and stations or service areas cannot be placed everywhere, we developed a method called Demand And/oR Equity (DARE) to build scenarios for station locations and coverage areas. This method provides an opportunity to balance the priorities of serving underprivileged areas and serving areas with high potential ridership with an alternative to balance the priority in underprivileged areas and also areas where it is expected to be high ridership.

3. Demand And/oR Equity (DARE) method for planning bike-sharing systems

Demand And/oR Equity (DARE) is a heuristic-based method for planning the allocation of BSS stations and their service area based on spatial fairness. Spatial fairness summarizes three criteria for transport supply allocation: spatial equity, efficiency, and equality (Leventhal, 1980; Talen, 1998; Duran-Rodas et al., 2020c). Spatial equity has a broad justice focus and it refers to a spatial distribution of resources that prioritizes areas where people have the greatest need in terms of social status, opportunities or abilities. For example, if spatial equity alone were to be considered in the distribution of BSS's infrastructure, the allocation would be predominantly in underprivileged areas. Hence, people in these areas could not cycle to privileged areas as the city center. Spatial efficiency has a narrow concept of justice, focusing on the allocation of resources to maximize ridership. If spatial efficiency is considered, underprivileged areas might be excluded from access to the system. It should be emphasized that this study incorporates distribution according to (estimated) effective demand or ridership into spatial efficiency. It is inferred that effective demand occurs when people can "contribute", or have an ability to access or pay a mobility system. Another way of defining spatial efficiency is a distribution of public resources favoring those who pay more taxes, in other words, those who "contribute" the most. Spatial equality is related to the equal distribution of resources regardless of need or potential ridership. It is achieved when spatial resources are evenly distributed across an area, i.e.. resources are not specifically prioritized in any area and all areas receive the same amount of resources. Spatial equality was not considered in this approach because resources are limited and the difficulty of evaluating and compensating equally each individual's access to resources.

The primary goal of DARE is to create scenarios in which stations are located and service areas are bounded based on the preferred fairness criteria for design: spatial equity, spatial efficiency, or a balance of both. In general, DARE divides a study area into analysis zones (ZAs). In each of these zones, indicators of spatial equity and spatial efficiency are calculated. Then, the zones are ranked by their weighted combination of spatial equity and spatial efficiency. Finally, these scenarios are evaluated based on the resulting coverage and density of infrastructure. Specifically, DARE includes the following seven main steps (Fig. 2).

3.1. *Choosing a study area and defining zones of analysis.*

The first step in the DARE method is to select a study area which is further divided into a training area with an existing BSS and an implementation area with similar characteristics where bike share will be added or modified. Historical data from the training area is then used to build a ridership model with which to estimate behavior in the implementation area. The learning area and the implementation area are each subdivided into zones of analysis (ZAs), which define the spatial resolution of the results.

The shape of the ZAs is typically determined by administrative boundaries, such as neighborhoods (Cintrano et al., 2020; Mooney et al., 2019), districts (Caggiani et al., 2020), traffic zones (Caggiani et al., 2017) census blocks (Frade and Ribeiro, 2015), buffer radius from candidate stations (Chen et al., 2015; García-Palomares et al., 2012), demand-based delimitation (Reiss and Bogenberger, 2015), grid-based hexagons (Albiński et al., 2018), squares (Lin et al., 2020) or road network-based (Noland et al., 2016). Of these, road network-based delimitation is recommended because it best aligns with natural cycling barriers such as buildings, highways, railways, and water bodies.

The distance for delimiting the areas (*Dmin*) determines the size of the ZAs and it should be based on desired station density or the maximum distance that a user is willing to walk to access the system. Distances ranging from 200 to 400 meters are commonly used in previous research (Tran et al., 2015; Chardon et al., 2017; Duran-Rodas et al., 2019; Wang et al., 2015; Noland et al., 2016; Faghih-Imani et al., 2014; El-Assi et al., 2017; Chen et al., 2015; García-Palomares et al., 2012; Caggiani et al., 2020). According to Kabra et al. (2019), most BSS ridership originates within 300 meters of stations, and it is the recommended value in guidelines (Yanocha et al., 2018) and in Banerjee et al. (2020).

3.2. *Spatial data collection, feature generation & dimensionality reduction*

Three main types of spatial data must be collected: (1) historical BSS trips, including the time and location of rentals' origins and destinations, station locations, and service area boundaries, (2) built environment data (e.g. transport infrastructure, POIs), and (3) social environment (e.g. transport's mode choice, milieu, sociodemographics).

The spatial data for each ZA may be represented in different types of units. In this approach, spatial data types can be represented in

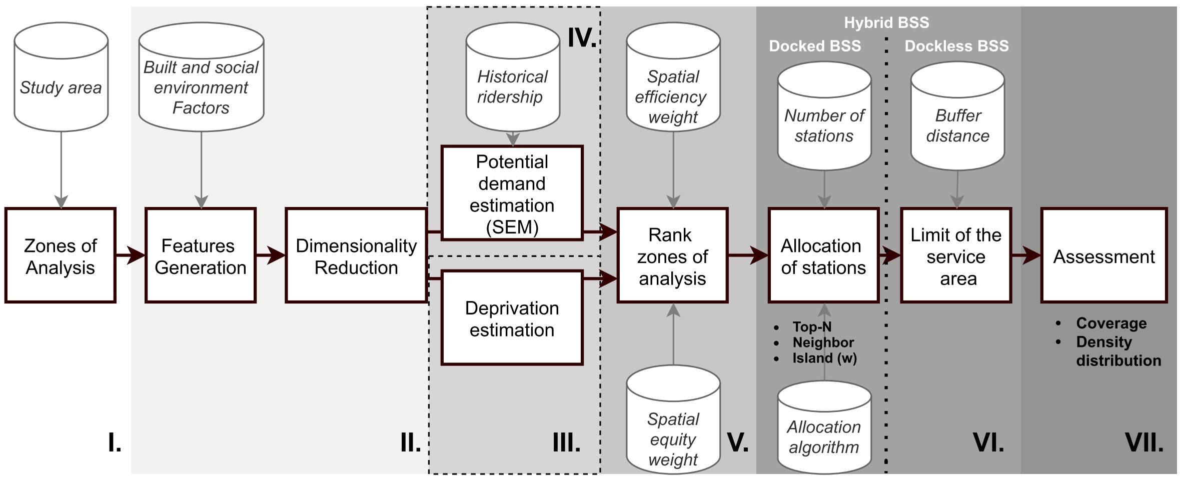


Fig. 2. DARE method procedure.

terms of 1) feature density for each spatial unit, 2) feature percentage by category within each ZA, or 3) walking accessibility from the centroid of the ZA, which is measured with the exponential cost function (Geurs and van Wee, 2004):

$$A_{ij} = min(e^{-\beta c_{ij}}),\ j = 1, 2, 3, \ldots n_{op} \tag{1}$$

where A_{ij} is the walking accessibility, defined as the lowest cost to access n_{op} opportunities of category j in ZA_i, c_{ij} is the travel cost from the centroid of ZA_i to the opportunities, and β is a cost sensitivity parameter. Eq. 1 assumes that the effect of an opportunity on the zone's accessibility to the centroid diminishes as the distance from the zone centroid increases (Geurs and van Wee, 2004).

Multicollinearity might be present between variables of the same category. For instance, the density of cafes in a ZA may be highly correlated with the density of restaurants. Therefore, we used a hierarchical agglomerative clustering method (HC) for dimensionality reduction to group highly associated variables belonging to the same category. HC represents the dissimilarities between the different types of variables using a distance matrix (Everitt et al., 2011). Initially, each variable is distinct. Then, each variable is clustered to its closest neighbor, with the distance being estimated using linkage methods (Everitt et al., 2011). This procedure continues iteratively until there is only one cluster. We used HC because the results are plotted as dendrograms, which helped visualize which variables clusters should be included in the model.

3.3. Estimating the neediest population in terms of opportunities and social status

After creating ZAs and collecting the spatial data, the next step is estimating the neediest population in terms of opportunities and social status. This need is based on access to opportunities and social status demographics and is calculated using a deprivation index for each zone of analysis. The Deprivation Index (DI) is an indicator of how deprived and unprivileged a ZA is (Duran-Rodas et al., 2020c) and is adapted from the concept of deprivation defined by Townsend (1987)): "a state of observable and demonstrable disadvantage". Based on this concept, we calculated this index using the percentage of the underprivileged population (e.g. migration background, low-level education, low income, and manual occupations), such as in Messer et al. (2006); Eibner and Sturm (2006); Pampalon et al. (2012), as well as the level of access to basic opportunities (e.g. groceries, healthcare, public transportation). An example of how access to basic opportunities influences deprivation is provided by Pearce et al. (2007) who correlated deprived areas to those with less access to healthy food. Therefore, our formulation of the deprivation index includes the average walking accessibility to basic opportunities (Geurs and van Wee, 2004; Büttner et al., 2018) (Eq. 2).

$$DI_i = \frac{UP_i}{1 \Big/ n_B \sum_{k=1}^{n_B} A_{ik}} \tag{2}$$

where DI_i is the deprivation index of ZA_i, UP_i is the percentage of the underprivileged population, A_{ik} is the walking accessibility to the k basic opportunity, and n_B is the number total types of basic opportunities considered in the study. Thus, a high deprivation index represents an area of a greater underprivileged population and/or limited access to basic opportunities.

3.4. Estimating the potential demand

As described in the literature review, different regression methods can be used to estimate potential demand in each zone of analysis. The recommended variable for potential demand is the density of arrivals in a zone of analysis. Arrivals are often more closely correlated with spatial factors than departures are. Table 1 showed examples of the various factors in the built and social environment that are associated with the potential demand for BSS.

We chose Structural Equation Models (SEMs) as the regression method to estimate the density of bike arrivals for each zone. SEMs help to predict behavior using multiple types of variables and searches for causal relationships, which improves the generalization and transferability of the model (Thakkar, 2020). SEMs are multi-equation frameworks applied to a multivariate problem to understand the interactions between dependent and independent variables in a system using one causal network (Lefcheck, 2016; Grace and Keeley, 2006). The result accounts for "the roles of the multiple factors in a single analysis" and separates the direct effects from the indirect effects (Grace and Keeley, 2006). Every hypothesis of a causal relationship is represented by a linear model in which every path is the coefficient of the regression. Therefore, SEMs help to mitigate the impact of potential multicollinearity between the built and social environment.

When using SEMs, it is important to consider that they are linear models having a constant distribution of the error term for all observations. To normalize the distribution and increase the data fit of the model, non-linear transformation techniques can be used, such as square root, logarithmic (Bishara and Hittner, 2012), or box-cox (Box and Cox, 1964). The first variable to be included in the model is the one having the highest correlation with BSS ridership, followed by the one with the second-highest correlation, and so on. Variables that neither improve the goodness of fit ($CFI > 0.9$) nor help reduce the poorness of fit ($RMSEA < 0.1$) (Hooper et al., 2008) of the model are omitted. Randomness in the fitting process of both techniques is mitigated by modeling with a training data-set and validating with a testing set (Natekin and Knoll, 2013). Moreover, we performed cross-validation with k-folds as a re-sampling procedure of the training and test sets in order to control biased results.

3.5. Ranking the zones of analysis

The most important design input for DARE is the weights (from 0 to 1) that are applied to efficiency and/or equity. These weights are the heart of the fairness-based method. They are set based on the preferred fairness allocation criteria of the decision makers, planners, stakeholders, or politicians developing the system and steer the allocation of infrastructure for the BSS being implemented, expanded, or restructured.

Efficiency is related to the estimated demand and equity is based on the deprivation index. A weight of 0 for efficiency means an allocation that prioritizes deprived areas, whereas a weight of 0 for equity prioritizes areas with higher estimated BSS usage. Both weights range from 0 to 1, subject to $Eq_w + Ef_w = 1$. $Eq_w = 1$ signifies consideration of equity alone, whereas $Ef_w = 1$ means only efficiency is considered.

After estimating the potential demand and *DI* for each *ZA* and assigning the respective weights for spatial efficiency and equity, we calculated the rank index (*RI*). *RI* is an indicator for each ZA that orders and prioritizes the allocation of stations in each ZA. *RI* is defined in Eq. 3:

$$RI_i = scale(DI_i) * Eq_w + scale(PD_i) * Ef_w \tag{3}$$

where *RI* is the rank index in ZA_i, Eq_w and Ef_w are the equity and efficiency weights respectively, DI_i is the scaled value of the deprivation index in each ZA_i, and PD_i of the estimated potential ridership. DI_i and PD_i are scaled based on their distributions. If the distribution of DI_i and PD_i are not similar, mathematical transformations should be performed to obtain comparable distributions. Another alternative for different distributions of DI_i and PD_i is to consider the rank position of DI_i and PD_i respectively instead of scaling (Eq. 4).

$$RI_i = rank(DI_i) * Eq_w + rank(PD_i) * Ef_w \tag{4}$$

3.6. Setting different scenarios for the potential location of stations and boundaries of the service area

At this point, all zones of analysis in the implementation area should be ranked. After setting policies, regulations, system operation strategies, financial models (Yanocha et al., 2018), design inputs should be established (such as budget, rebalancing method and strategies, and key performance metrics) (Gauthier et al., 2014; Büttner and Petersen, 2011; Toole Design Group, 2012). The number of stations (n_S) is dependent on the available budget. We propose four different algorithms yielding different results in coverage and station density. The algorithms' inputs are the potential number of zones in the implementation area, the number of stations (n_S), and *RI* for each ZA. All algorithms start by ordering the ZAs in descending fashion based on the RI_i. The output of each algorithm is the zones named *ZSt* in which stations are allocated.

1. **Top-N**. *ZSt*'s are the top-n_S zones based on their RI_i, a similar approach as in (Chen et al., 2015). This algorithm tends to result in high coverage but a low density of stations.
2. **Neighbor**. This algorithm starts by creating a matrix of the ZAs, in which the cells take a value of 1 if two ZAs are contiguous and 0 otherwise. We order the *ZAs* based on RI_i, and start by allocating a station in the highest raked zone ZSt_1 (the ZA with the highest *RI*). The procedure continues by allocating a station in zone ZSt_2, which is the zone contiguous to ZSt_1 with the highest *RI*. This step is repeated until the desired number of stations n_S are allocated. If a neighbor of a *ZSt* has already been chosen, the next ranked neighbor is selected. However, if all the possible neighbors have already been selected, the next ranked ZA_i, which is not a neighbor of ZSt_k, is chosen (Appendix A: Algorithm 1). This algorithm tends to have a high density of stations but low coverage.
3. **Island**. This algorithm is a mix of the Top-N and Neighbor algorithms. It starts like the Top-N algorithm by setting n_{isl} number of zones (''islands'') with fixed stations $ZSt's$. Then, the remaining stations are split equally among the fixed stations $ZSt's$ and allocated using the Neighbor algorithm for each "island".
4. **Island weighted**. This algorithm is the same as the basic island algorithm, except that the remaining stations are not equally split between islands, but instead follow a weighted distribution. The allocation algorithm with the weighted distribution is shown in Eq. 5

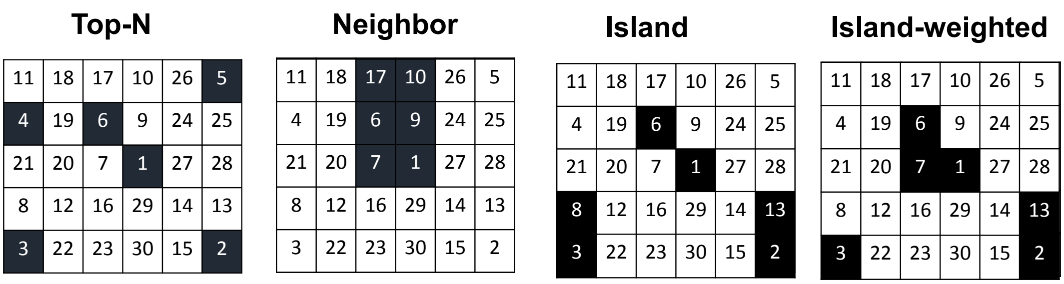


Fig. 3. Hypothetical example of application of the four algorithms. ($n_S = 6, n_{isl} = 3$).

$$n_{neighbor}(x_i) = n_{isl} * \frac{n_{isl} - x_i}{n_{isl}^2 - \sum_{i=1}^{n_{isl}} x_i}, \; for \; x_i = 1, 2, 3, \ldots n_{isl} \tag{5}$$

The Island and Island weighted algorithms represent a middle ground between the first two algorithms. They tend to have higher coverage than the Neighbor algorithm and higher density values than the Top-N algorithm. As a hypothetical example of the application of the four algorithms, Fig. 3 shows the allocation of six stations in 30 *ZAs*.

In dockless systems, the stations are virtual and a service area boundary must be defined as an additional step. The service area is defined as a buffer area of a distance B_{min} around the shortest path tree connecting the selected stations. The distance B_{min} defines the buffer distance an average person is willing to walk in order to access the supply of BSS. This distance B_{min} is often similar to D_{min}.

3.7. Assessment of scenarios

The most commonly used approach for assessing or optimizing the allocation of infrastructure for docked systems is to minimize the impedance (p-median) and maximize the coverage area (García-Palomares et al., 2012). However, these approaches do not consider the balancing costs of the system. The allocation goal in this study is to minimize the balancing costs while maximizing the coverage area. This requires a dense station network. Therefore, we considered the bi-problem which minimizes the percentage of ZAs without access to the system ("non-coverage" area) and maximizes the distribution of the Gaussian kernel density estimate (KDE) of stations (density distribution). This approach considers the impedance.

We aim to maximize the distribution of the KDE, which maximizes the number of areas that have a high density of stations and therefore minimizes the balancing costs. KDE for $ZSt_1, \ldots, ZSt_{n_S}$ zones of analysis which have a station is defined by Eq. 6.

$$\widehat{f}_h(x) = (n_S h)^{-1} \sum_{i=1}^{n_S} K((x - ZSt_i) \big/ h) \tag{6}$$

where K is the normal kernel function, and h is the buffer distance of the area to account for stations' density. The outcome is a raster with values $\widehat{f}_h(x)$, in which the average is calculated for each ZA. The distribution of the average KDE is assessed using a Gini coefficient, for which the Lorenz curve is a cumulative line of the percentage of ZAs which have a station and the cumulative percentage of the KDE. Gini coefficients range from 0 (signifying an equal distribution in all ZA), to 1 (meaning only one zone gets all the resources).

In summary, the three inputs in DARE that can be modified to build different scenarios are the equity weighting, the number of stations, and the number of islands. Coverage and density of stations are indicators suggested for comparing the different scenarios. Top-n presented higher coverage, neighbor presented higher density and the island algorithms fall in between both. The equity weighting can be adjusted depending on the desired spatial fairness criteria, the number of stations depending on the budget, and the number of islands depending on the desired balance between coverage and density. A coverage goal can improve equality (equal distribution of resources) in the allocation because it serves more people and thus more parts of the community (Walker, 2012). In addition, users have more destination choices and may perceive high service quality. However, high coverage but low density can lead to inefficient service. In this situation, stations may be located far apart, which may be especially inconvenient for users of docked systems if a station does not have empty racks and a bike cannot be returned. Moreover, balancing bikes between stations involves higher costs for the operator due to the greater distances involved.

4. Application

4.1. Choosing an area of study and setting zones of analysis.

We applied the fairness-based DARE method to a hybrid BSS in Munich, Germany. In 2018, the system reached around 90,000 users with its 1,200 bicycles and 118 stations (Rube, 2019). Users can pick-up and drop-off bicycles at stations or at a free-floating location in the public realm. To incentive station use, users get a 10 min discount on the trip if a bicycle is returned to a station. The rental of a bike costs 0.08 euros per min (or 0.05 euros per min for students). Users can also pay 12 euros to use a bike for the whole day. There is also a 48 euro subscription package in which users can rent a bike for 30 min every day for six months (12 euros for students) (MVG-Rad, 2019).

Munich's hybrid BSS provides data on the bicycles' locations every five minutes when they are not being rented (Transit.robbi5, 2019). It is assumed that a trip ends when a bike "appears" in a new area since there is no location available during the trip. We call this a bike movement, which approximates a drop-off or end of a bicycle rental. Bike movements longer than 150 min or with a displacement of fewer than 100 meters are not considered in the study. Rebalancing of bikes might be counted as movements within the dataset. In total 93,615 bike movements were collected from March 15, 2017 to October 10, 2017. However, within this time period, only 138 days with complete information were considered in this study. The month with the greatest number of bike movements was in July and movements tended to decrease in winter.

To delimit the ZAs based on the road network, we first created a point grid (virtual stations) separated a distance *Dmin* in the study area based on the values previously described. We then removed virtual stations in areas where it was not possible to locate stations, such as water bodies or railways. Then, a service area for each virtual point was generated by assigning the road network that can be reached within a distance *Dmin* from each virtual station. Finally, to split overlapping service areas, they were intersected with Voronoi diagrams (Voronoï, 1908) created from vertices and intersection points of the road network.

Next, we generated the service area for each virtual point by calculating the road network that can be reached within a distance *Dmin* from each virtual station. Finally, we split overlapping ZAs using Voronoi diagrams created from vertices and intersection points of the road network.

For the study area, the service area from the current hybrid BSS system was used as the training area. Two implementation areas were considered: 1) the same service area but a reallocation of stations and 2) the outskirts of Munich County as an implementation approach with new infrastructure. The minimum distance between stations (D_{min}) was 300 meters, which is the most common distance used in previous studies and is also recommended in guidelines (Yanocha et al., 2018). The ZAs were thus created based on a grid of virtual stations separated $D_{min} = 300$ meters apart within Munich's service area and excluding areas within railways and water bodies.

4.2. Spatial data collection

As a dependent variable, we considered the density of bicycle drop-offs observed in each ZA instead of the count due to the heterogeneity of the ZAs' shape. To pick-up a bicycle, the user must walk to the place where it is located, which may be in a different ZA from where the activity was performed. Since we wanted to develop demand models based on the built environment, considering bicycle drop-offs rather than pick-ups offered a greater accuracy in studying the ZA of the trip purpose.

Built environment information was downloaded from OpenStreetMap (OSM) (OpenStreetMap, 2017). OSM is an online platform, in which volunteers geolocalize built environment features and make them publicly available. Information collected from OSM includes transit stations, POIs, land-use, roadways, cycleways, railways, and waterways.

Milieus data, representing the social environment in this approach, was collected from the Sinus-Geo-Milieus data-set from 2014. In this data-set, every address in Munich was probabilistically assigned one out of ten Sinus-Milieus categories (Fig. 4) based on ground values (tradition, modernization, individualization, re-orientation) and social status (low, middle, high) (SINUS, 2017). Sinus-Milieus® on a spatial scale are called Sinus-Geo-Milieus and are defined as the probability of every address in Germany to belong to a certain milieu group (Küppers, 2018). Sinus-Geo-Milieus use data from Sinus-Milieus® interviews, official national survey data, and data collected from the marketing company Microm (https://www.microm.de/). Then, a multinomial regression model was run on all the addresses in Germany to calculate the probability of each house in Germany belonging to one of the ten milieus (Küppers, 2018). Population density was also extracted from the Sinus-Geo-Milieus dataset.

Mode split data was collected from the national mobility survey "Mobilität in Deutschland 2017" (Nobis and Kuhnimhof, 2018) with a spatial accuracy of 500x500m. Mode split was extracted from questions related to the mode ridership frequency (daily, 1–3 times a week, 1–3 times a month, less than monthly, never) of the following modes: bicycle, car, transit (local and regional), and car-sharing.

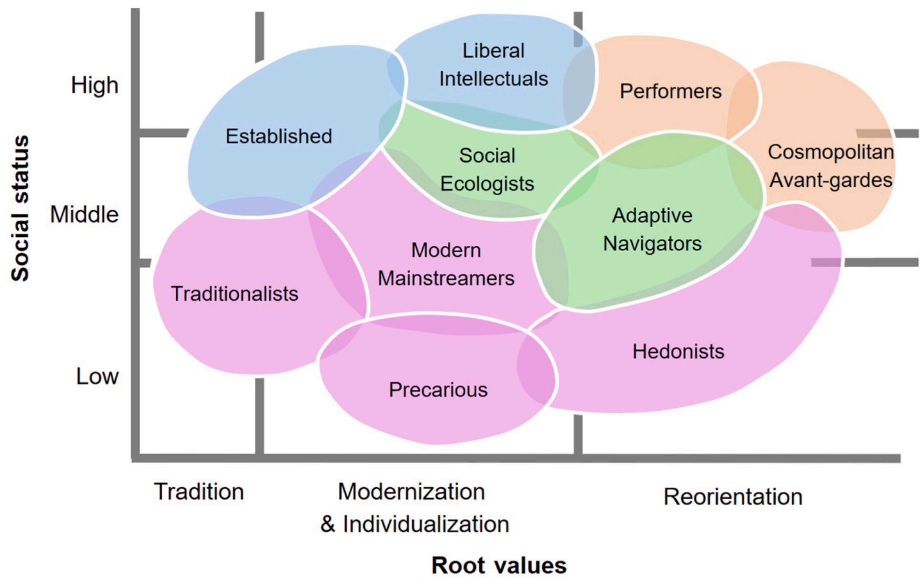


Fig. 4. Sinus-milieus definition of categories. (SINUS, 2017).

4.3. Feature generation & dimensionality reduction

In order to calculate walking accessibility to POIs and transport infrastructure, we used the values of $\beta = log(1.0126) + 0.013$ for distances to the centroid of the ZA in Eq. 1. These values were estimated in feet and were taken from Zhao et al. (2003) who studied the walking accessibility to public transport. The spatial units used for land-use, milieus, and mode choice were the percentage of each category in each ZA. Furthermore, we included an index of walkability as an additional spatial factor, defined as the density of street crossings (crosswalks) (Moudon et al., 1997). Walkability is an indicator that an area may also be more attractive for cycling since walkable areas make it easier for BSS users to walk to rent a bike.

Once the units of measure of the built and social environment were estimated, we clustered milieus and POIs using hierarchical clustering. Milieus were clustered into four categories: a) Cosmopolitans-Performers, b) Traditionalists-Precarious-Hedonists-Modern Mainstreamers, c) Socioecologists-Adaptive navigators, and d) Established Liberal-Intellectuals. POIs were clustered using hierarchical clustering into 15 categories: essential needs POIs, essential services POIs, luxury shops, non-luxury shops, public building, doctors, education, food service, children-friendly, do-it-yourself shops, tourist attractions, open-air activities, convenience stores, department stores, and cinemas & theaters.

4.4. Estimating people's need with regard to opportunities and social status

The deprivation index for each ZA was calculated based on the number of households with low social-status milieus: Traditionalists-Precarious-Hedonists with reduced access to basic opportunities: pharmacies, supermarkets, organic food stores, bakeries, butchers, transit stations, cycle-ways. Fig. 5 shows the spatial distribution of the deprivation index and the density of bike drop-offs.

4.5. Estimating the potential demand

Prior to the station assignment, potential demand was estimated using SEM for each ZA as an indicator of spatial efficiency. In order to build SEMs, the first step was to set up a structure with the linkages between the independent variables (built and social environment) among them and also with the dependent variables (BSS ridership). Linkages between the built environment and ridership were taken from the theoretical model "land-use and transport interactions " (Wegener and Fürst, 2004; Wulfhorst, 2003), while the linkages between the social environment were taken from "urban mobility cultures" (Kuhnimhof and Wulfhorst, 2013; Deffner et al., 2006; Klinger et al., 2013).

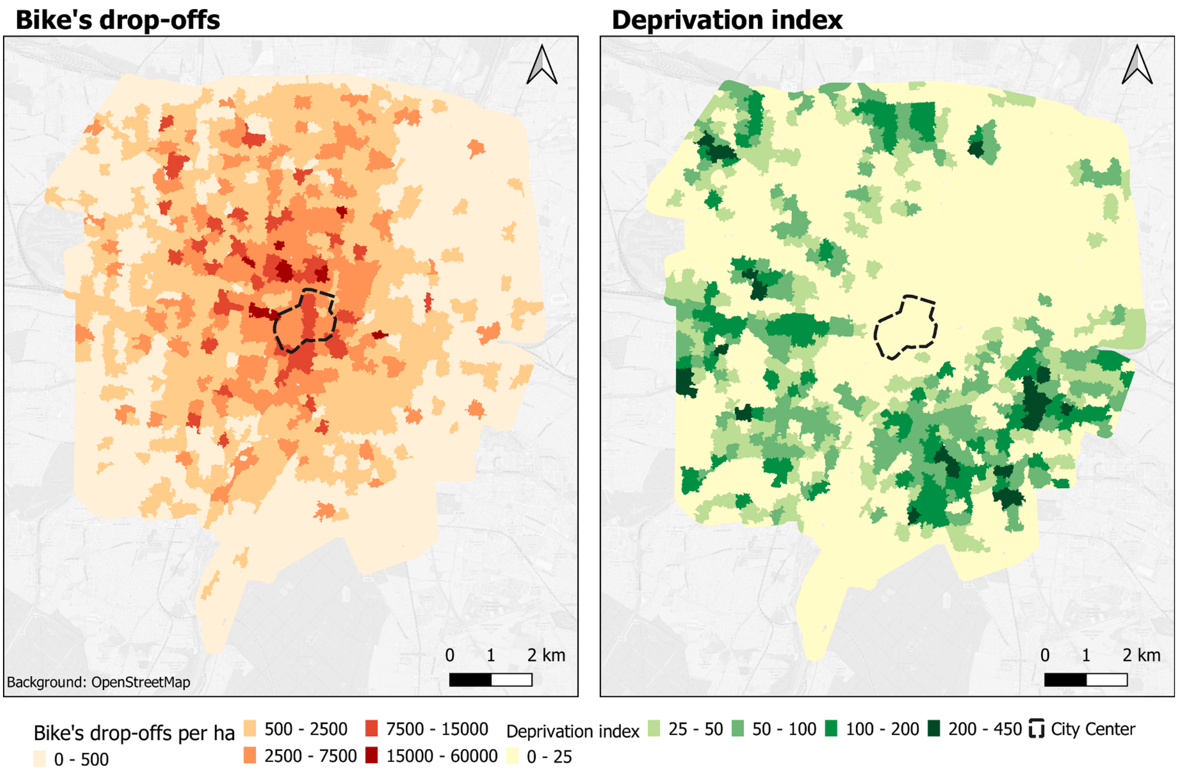


Fig. 5. Map of the density of bike drop-offs vs the deprivation index.

The land-use and transport interactions model is based on the “land-use and transport feedback cycle” (Wegener and Fürst, 2004). Different land-uses (e.g. residential, industrial) determine the location of activities (e.g. shopping, living, working, leisure), and their distribution in space requires a transport system (transport demand) to overcome the distance between these activities. Accessibility serves as a measure of the distribution of transportation systems (transport supply), and its spatial distribution guides decisions to change land-use (Wegener and Fürst, 2004; Wulfhorst, 2003). The three chosen spatial factors from this theoretical model are:

- *Urban structure.* Built environment 3D’s (Cervero and Kockelman, 1997): density (population density), diversity (land-use), and design (walkability)
- *Attractiveness.* Walking easiness (cost) to reach activities (e.g. points of interest). This actor can be also called accessibility to activities. The attractiveness of a zone is higher when different activities are easier to reach.
- *Accessibility to transport supply.* Walking easiness (cost) to reach transport infrastructure (e.g. cycleways, public transport).

The urban mobility culture model involves socio-material interactions between material characteristics (e.g. transport supply), and subjective components (e.g. attitudes, preferences, lifestyles, milieus) (Deffner et al., 2006; Klinger et al., 2013). Kuhnimhof and Wulfhorst (2013) summarized this theoretical model in four key dimensions: spatial structure and transport supply, policy-making and governance, perceptions and lifestyle orientations, and mobility behavior. The three chosen spatial factors links from the urban mobility culture definition are the spatial structure and transport supply, perceptions and lifestyle orientations, and mobility behavior. Perceptions and lifestyle orientations include milieus and mobility preferences. The policy-making and governance dimension was not included in our approach because it is more likely to be quantified at the city level rather than at the local level.

The land-use and transport interactions model and the urban mobility culture model are linked together by the common factor of transport demand (or mobility behavior). This factor refers to the effective (observed) demand for a mode of transportation (e.g. bike-sharing). The unit of measurement for this study is the density of aggregated origins and destinations for BSS trips in the study area.

Fig. 6 shows the spatial factors and their interactions. Green links are taken from the land use and transport interactions model, while the orange links are from the urban mobility cultures model. Table 2 lists the supporting concepts for the theoretical linkages between the spatial factors. We selected the spatial factors and their interaction links from these two theoretical models. (see Table 3).

For better model fit and to meet the requirement of homoscedasticity in linear regressions i.e. uniform variance of the error, the data set was mathematically transformed. Various transformations were established (e.g. log, squared root), however, the power of 2/7 presented the lowest heteroscedasticity. Appendix B shows the variables selected to build the model and Spearman’s correlation coefficient. Also, we adapted the theoretical structure, in which we combined “Urban structure” and “accessibility to transport supply” into one latent variable. There was not a significant direct relationship between transport supply and bike drop-offs. SEM was estimated with the package “lavaan” (Rosseel, 2012) developed for the R programming language (www.r-project.org). The results (Table 4) revealed a good fit model with RMSEA = 0.065 (90% CI:0.056–0.075, p = 0.03), and CFI = 0.955. After 100 runs of splitting the data into training data (70%) and testing data (30%) and performing cross-validation, the median of the R^2 from the training set was 0.587, and the median from the test set was 0.582.

4.6. Setting different scenarios for the potential location of stations and boundaries of the service area

We chose 100 stations to be allocated among 1234 zones of analysis. and the buffer distance (B_{min}) for the service area was assumed to be 300 meters. Then, we applied each of the four algorithms previously presented, and determined which zones of analysis would be allocated a station in each algorithm. We studied the two extreme cases, allocating infrastructure entirely based on spatial equity ($Eq_w = 1$), and entirely based on spatial efficiency ($Eff_w = 1$) (Fig. 7a). In the estimation of RI (Eq. 3), deprivation index and estimated

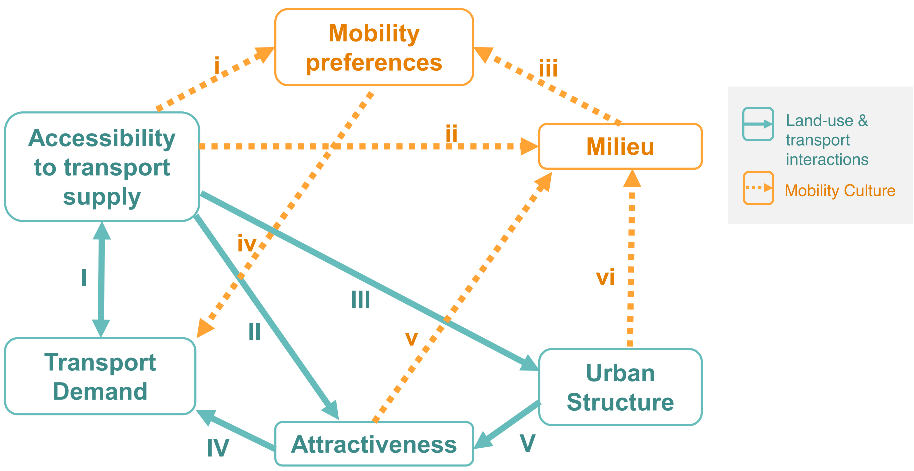


Fig. 6. Theoretical links of the spatial factors associated to BSS ridership.

Table 2
Theoretical links between spatial factors associated to BSS ridership.

LINK	TO	FROM	DESCRIPTION
v, ii, vi	Milieus	Attractiveness, Transport Supply, Urban Structure	Lifestyle, as part of the milieus, are decisive at the moment of choosing a residence location (Aeroe, 2001; Handy et al., 2005), based on different preferences towards access to opportunities and transport supply (Klinger et al., 2013).
i	Mobility preferences	Transport supply	Different mobility preferences depend on the transport infrastructure available. "Locations with good accessibility by car will produce more car trips, locations with good accessibility by public transport will produce more public transport trips" (Wegener and Fürst, 2004). Preference for a transport mode is not possible if this mode is not accessible. For example, train orientation is not possible in areas without a train connection. Klinger et al. (2013) stated that a possible reason why US cities are car-dependent is because of the lack of public transport systems.
iii	Mobility preferences	Milieu	"Mobility is not limited to purely rational decisions, but is influenced by a cluster of feelings, norms, value orientations, desires, and fears" (Deffner et al., 2006), i.e. milieus.
III	Urban structure	Transport supply	"The distribution of accessibility in space co-determines location decisions and so results in changes of the land use system." (Wegener and Fürst, 2004). For example, industrial areas are more attracted to be located close to motorways or railways, or office areas are attracted to areas close to airports, railway stations, or motorways (Wegener and Fürst, 1999).
IV	Transport demand	Attractiveness	Locations with high accessibility to multiple activities will generate more travel demand (Wegener and Fürst, 2004).
iv	Transport demand	Mobility preferences	Mobility orientations and attitudes have shown to be particularly relevant to behavior (Hunecke, 2002). When there is a choice or preference towards a mode of transport, its ridership will increase.
I	Transport demand	Transport supply	Access to transport supply enables intermodal transportation (e.g. bike and ride, park and ride), which can raise trips to a certain location to change from one transport mode to another.
I	Transport supply	Transport Demand	This linkage happens when demand is considered as allocation criteria for transport infrastructure (spatial efficiency) (Duran-Rodas et al., 2020c), and therefore, supply is higher accessible in areas where there is higher demand.
V	Attractiveness	Urban Structure	"The distribution of land uses, such as residential, industrial or commercial, over the urban area determines the locations of human activities such as living, working, shopping, education or leisure." (Wegener and Fürst, 2004).

Table 3
Descriptive statistics from the selected spatial factors.

Statistic	Unit	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Bikes' drop-offs density***	[#/ ha]	1,620.52	3,162.81	0.00	160.48	1,715.03	57,383.25
Department stores*	[acc.]	2.04	1.16	0.09	1.13	2.84	6.12
Food services*	[acc.]	0.28	0.25	0.00	0.11	0.36	1.88
Tourist attraction*	[acc.]	0.27	0.21	0.00	0.12	0.37	1.52
Cinema and theater*	[acc.]	1.38	0.93	0.02	0.64	1.99	4.55
Transit stations*	[acc.]	0.21	0.14	0.00	0.11	0.28	0.93
Cycle ways*	[acc.]	0.11	0.10	0.00	0.03	0.15	0.64
Population density****	[#/ ha]	4,439.24	4,413.58	0.00	870.1	6,792.20	21,385.00
Road intersections (Walkability)*	[#/ ha]	4,230.01	3,996.90	0.00	1,965.07	5,283.01	51,690.53
Cosmopolitan-Performers****	[%]	0.23	0.25	0.00	0.02	0.40	1.00
Car ridership: 1–3 a month***	[%]	0.09	0.09	0.00	0.00	0.10	1.00
Car-sharing ridership: < monthly***	[%]	0.17	0.11	0.00	0.10	0.20	0.00

Data Source: * OpenStreetMap (2017), ** www.bmvi.de/, *** Transit.robbi5 (2019), **** www.microm.de

ridership presented similar non-normal distributions. Therefore, min–max normalization was performed, assigning 0 to the minimum value and 1 to the maximum value, and the range of RI_i thus being from 0 to 1.

Finally, we applied DARE in the surrounding county of Munich, which is the peripheral region of the city (Fig. 7b). We excluded this region when building the demand model in order to use it as a validation set, demonstrating the method's transferability. There are 107 stations in this peripheral region. We applied the island-weighted algorithm to assign the same number of stations. In addition, we used different equity weights (Eq_w) and the number of islands (n_{isl}) to test the different scenarios when these variables change. In the estimation of RI (Eq. 3), deprivation index and estimated ridership presented similar non-normal distributions. Therefore, min–max normalization was performed, assigning 0 to the minimum value and 1 to the maximum value, and the range of RI_i thus being from 0 to

Table 4
SEM results.

LATENT VARIABLES:		**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**
Attractiveness=~					
	Department stores	1			
	Food service	1.220	0.077	15.746	0
	Tourist attraction	1.066	0.077	13.889	0
	Cinema & theater	0.946	0.069	13.622	0
Urban structure =~					
	Transit station	1			
	Cycle ways	0.511	0.087	5.876	0
	Population density	−2.373	0.155	−15.353	0
	Walkability	−1.051	0.067	−15.672	0
Mobility preference =~					
	Car ridership: 1–3 a month	1			
	Car-sharing ridership: < monthly	1.246	0.115	10.831	0
Milieu =~					
	Cosmopolitan-Performers	1			
REGRESSIONS:					
		Estimate	**Std.Err**	**z-value**	**P(>|z|)**
Attractiveness~					
	Urban structure	0.871	0.072	12.108	0
Mobility preference~					
	Milieu	0.025	0.025	1.034	0.301
	Urban structure	−1.291	0.148	−8.715	0
Milieu~					
	Urban structure	−2.549	0.407	−6.266	0
	Attractiveness	0.045	0.356	0.128	0.899
Bikes' drop-offs density~					
	Attractiveness	−1.511	0.113	−13.415	0
	Mobility preference	0.151	0.050	2.989	0.003
INTERCEPTS:					
		Estimate	**Std.Err**	**z-value**	**P(>|z|)**
.Department stores		0.725	0.004	161.615	0
.Food service		0.579	0.005	126.148	0
.Tourist attraction		0.663	0.005	138.235	0
.Cinema & theater		0.699	0.005	140.480	0
.Transit station		0.660	0.004	155.020	0
.Cycle ways		0.578	0.006	95.587	0
.Population density		0.569	0.009	66.910	0
.Walkability		0.506	0.004	138.777	0
.Car ridership: 1–3 a month		0.692	0.008	88.702	0
.Car-sharing ridership: < monthly		0.470	0.010	47.486	0
.Cosmopolitan-Performers		0.546	0.011	50.871	0
.Bikes' drop-offs density		0.327	0.005	64.495	0

Note: RMSEA = 0.089, CFI = 0.917

1.

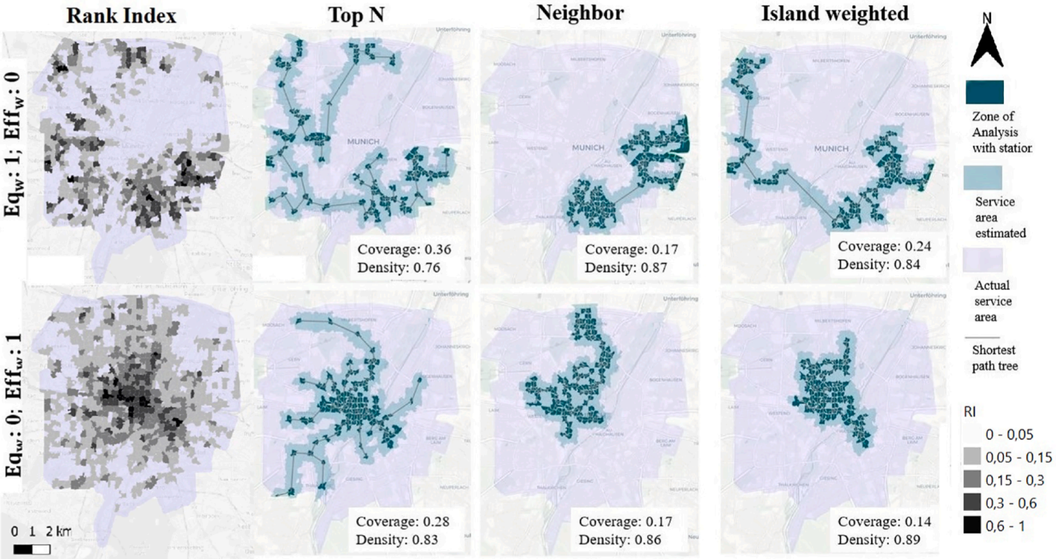
5. Discussion

The presented method can be used as a "first draft" 1) to relocate stations based on shifting priorities or goals (e.g. Fig. 7a), 2) to expand BSS after learning from an existing system (e.g. Fig. 7b), or 3) to implement new systems, after applying the method to a city with similar characteristics. This method can help planners prioritize the distribution of infrastructure according to their BSS goals by adjusting the spatial equity and efficiency weights, and to communicate these design priorities transparently.

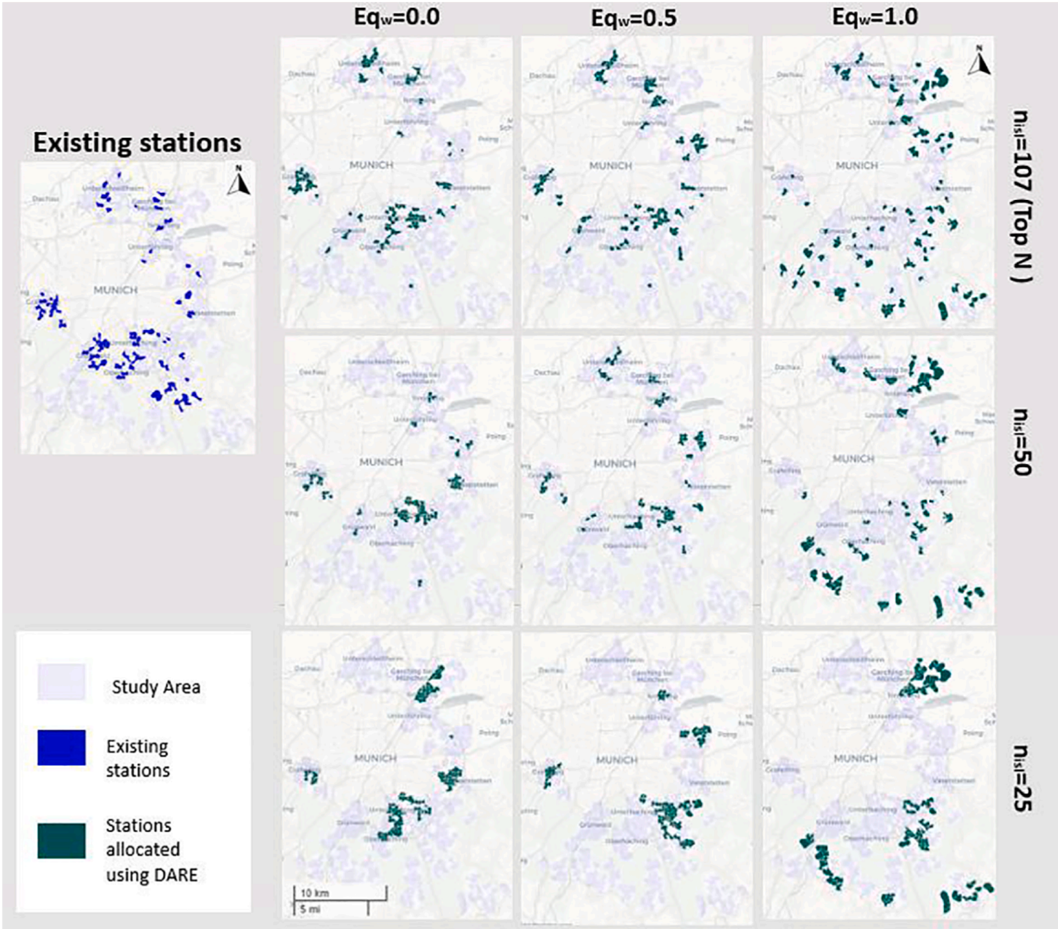
5.1. DARE as a method

DARE method can be summarized by the following steps which can be further applied in other systems:

1. selecting a study area, and dividing it into zones of analysis,
2. collecting data from the built and social environment, generating features and aggregating them into categories,
3. estimating deprivation in each analysis zone or an index showing where underprivileged people live,
4. estimating potential ridership in each analysis zone or other variables related to "productivity" (e.g. systems' earnings),
5. ranking zones of analysis in terms of equity (step IV) and efficiency (step V),



(a) Allocation of stations and service area in Munich ($n_S = 100$, $n_{isl} = 10$)



(b) Island weighted algorithm results for the allocation of stations in the county of Munich

Fig. 7. Application of DARE in Munich, Germany.

6. creating scenarios based on the number of (virtual) stations according to the available budget and the four algorithms previously presented (e.g. Top-n) for infrastructure allocation. For dockless systems, a service area is set using the collective buffer distance from the virtual stations.
7. comparing scenarios in terms of density and coverage.

Depending on the desired fairness criteria of decision-makers, the allocation of stations can be oriented toward equity, efficiency, or a combination of the two. An equilibrium between efficiency and equity can potentially be found, in which deprived areas are not abandoned but the system can still be efficient (e.g. Fig. 7b). Previous methods have considered minimizing impedance (García-Palomares et al., 2012; Conrow et al., 2018) such that all areas of a city or region would have access to the system. However, when the cost for this approach is considered too high, identifying priority areas could be useful for planners to distribute infrastructure according to their budget, while taking into account the weights of the preferred fairness criteria. Furthermore, DARE has the strength to automate the development of multiple scenarios, which can assist decision-making. Moreover, having different scenarios available can help decision-makers justify and be transparent about the planned BSS service area and station distribution.

Furthermore, DARE provides transparency in terms of the efficiency and equity weights selected, and the varying actors involved in BSS planning can aim to reach a consensus on a preferred scenario. Methods for public participation can include online map-based commenting, smartphone app crowdsourcing platform, public hearings, public opinion survey, consensus conference, citizens' panels, focus groups, and others (Rowe and Frewer, 2000; Griffin and Jiao, 2019). Further recommendations are to integrate the physical design, technology, and payment methods for the system with those of other public transportation and shared means of transport. Finally, the process of determining station locations should include site visits and the involvement of the general public and other stakeholders.

A limitation of DARE is the lack of stakeholder inputs in the decision-making method. This method could be improved by adding an extra parameter to the rank index based on crowd-sourcing or community input and also an extra weight considering the environmental impact. Another improvement might include the modeling of ridership and spatial factors in terms of trips between zones, rather than exclusively origins or destinations.

5.2. Application of DARE in Munich, Germany

For our application of DARE to the HBSS service area in Munich, we compared both extreme cases of maximum spatial equity vs maximum spatial efficiency with a low budget of 100 stations (Fig. 7a). When spatial equity was desired, deprived areas were served. However, there were a very limited number of stations in the city center, making it difficult for people living in deprived areas to cycle to and from the city center. In contrast, spatial efficiency focused on the city center and deprived areas were poorly served. It is worth mentioning that some areas were well served under both criteria, mainly those deprived areas that had significant potential demand for bike-sharing.

Regarding the algorithms for building different scenarios. The Top-n algorithm prioritized the highest ranked areas, and based on the spatial parameters, it provided a higher coverage and lower density of stations than the other algorithms. More people could access such a system but it might be expensive for balancing the bicycles during the operation. The neighbor algorithm provided a dense allocation of stations but only located them in a few neighborhoods. The island algorithm combined the advantages of the two previous methods. It resulted in adequate density with reasonable coverage. However, the method that we recommend is the island weighted algorithm, in which zones with the highest-ranking are provided with a denser network of stations, thus prioritizing the whole neighborhood. Though having multiple allocation algorithms might increase the method's complexity, developers can then build different scenarios with varying balances of coverage and density.

DARE was also applied in the peripheral region of Munich by using the SEM built in the central part. With a lower equity weight, the stations were located closer to the city of Munich. The Top-n algorithm with a higher efficiency weighting presented similarities (40%) with the existing allocation of stations, as opposed to 8% when equity weighting was considered. This analysis suggests efficiency was the fairness criterion chosen to allocate the stations. In addition, when the number of stations is small, the neighbor algorithm tended to be similar to the island algorithm because of the lower population density in the peripheral region.

In this study, we applied DARE specifically to a hybrid BSS. However, the method could also be used for docked or dockless BSS because hybrid BSS share characteristics of both systems. A key difference when studying station-based systems is that the service area is not required in the design. Completely dockless systems, in contrast, use virtual to help design the service area that defines the system.

5.3. SEMs for estimating potential ridership and understanding causal relationships between the social and built environment

This study uses SEMs to estimate the potential ridership of bike-sharing by associating historical trips with spatial factors from the built and social environment using their linkages from a hypothesized theoretical structure (Fig. 6). Every spatial factor included in the theoretical structure represents one latent variable, which is a set of observed variables associated with BSS ridership (Table 1). If spatial efficiency is desired over spatial equity, areas with higher estimated ridership would be prioritized with an allocation of stations.

SEMs presented a good fit of the data and theoretical interactions. Areas with a high historical ridership were estimated with the model to have potential demand and vice versa when considering spatial efficiency. These areas were densely populated, highly walkable, had a low preference for cars, many leisure and touristic activities, a predominance of cosmopolitan and performers residents, and good accessibility to transit stations. If we consider only spatial efficiency, the population with a low social-status population would be poorly served by the system. The variables identified were in line with guidelines (Büttner and Petersen, 2011; Gauthier et al., 2014) and studies (García-Palomares et al., 2012) that recommended locating stations in densely populated areas close to transit stations, cultural and tourists attractions, and major public spaces and parks (high walkable areas).

SEMs are a common tool for causal inference. Our use of SEMs to distinguish features that have causal effects from those that are purely correlative gives us a better understanding to predict behavior in a new domain. Other advantages of using SEMs are the incorporation of multicollinearity, which in linear regression would not have been possible. Moreover, we were able to test the hypothesized theoretical structure (Fig. 6). A good model fit was shown after merging urban structure and accessibility to transport supply as one latent variable, which validated the concept of urban design including transport infrastructure (Cervero and Kockelman, 1997). Even though SEMs served to avoid multicollinearity between the factors, spatial factors might still have a spatial autocorrelation between zones. This issue should be considered in further research or applications.

Using SEMs, we also validated the theory that different milieus choose their residence based on the urban structure and the theory that urban structure determines mobility preferences. Therefore, we can infer that attractiveness, milieus, and mobility preferences are dependent on the urban structure. The two directly-linked factors determining bike drop-offs were attractiveness and mobility preferences. However, attractiveness had ten times the correlation with the drop-offs compared to mobility preferences. These results of the cosmopolitan population associated with BSS ridership were complementary with the survey by Stöckle (2020), where the main value of BSS users in Munich was adventure (progressive values) but not tradition and security (traditionalist values). The drawback of using milieus is the complexity of their estimation and the lack of availability in other countries. Hence, in the absence of milieus for further research, sociodemographic characteristics, perceptions, or attitudes can be included as social environments.

SEMs have learned from the past by using spatial factors. When implementing BSS in a new area, the estimated ridership based on spatial factors is assumed to be the induced demand for BSS because there is no existing system in the area. To improve current practice, which mostly provides infrastructure to areas with higher estimated demand, we propose to include underprivileged areas in the ranking with a weighting in terms of spatial equity. Duran-Rodas et al. (2020a) showed that areas with underprivileged residents and traditional values had low BSS use. Possible reasons for this may include cultural barriers and attitudes toward bicycling (Stöckle, 2020; Pochet and Cusset, 1999; Van der Kloof, 2015).

6. Conclusions

Demand And/or Equity (DARE) is a method that can be used for building scenarios to allocate stations and limit the service area of BSS where fairness is considered as an input in the planning process. The distribution of stations and the service area boundaries are determined by the weights planners assign to spatial equity versus efficiency. This method was explored through a case study based on ridership as well as people's needs with regard to social status and opportunities. DARE provides transparent decision-making support for supply distribution and presents an alternative where the benefits of BSS are extended beyond privileged populations.

We validated a theoretical structure with SEM for estimating potential ridership. The social environment previously associated with BSS ridership (Faghih-Imani et al., 2017) was an approximation of the urban structure but not directly connected to the ridership. The variables associated directly with high BSS ridership were low car ridership and especially the attractiveness of a zone (defined mostly by leisure activities). Both of these variables depended on the urban structure.

Further research includes the adaptation of the method for decision-making with feedback from stakeholders. Also, possible weights for the ranking index can be suggested by stakeholders from different cities to obtain an average score. Additionally, further applications of DARE can include sensitivity analyses for using different design inputs, such as the minimum distance between stations, sizes, and shapes of the zones of analysis, beta values to estimate walking accessibility or a varying shape and size of zones depending on the location. To improve the usability of the method, DARE should be further developed as a practice-relevant user tool. This method can also be applied further to study the implementation of new bike-sharing systems and even to assist in planning for other transport modes such as car-sharing, scooter-sharing, or public transport. Moreover, the method can extend beyond transport to be other logistical and operational services that aim for spatial fairness.

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Appendix A. Neighbor algorithm

Algorithm 1. Neighbor algorithm

A Neighbor algorithm

Data: n_S, $ZA_1 ... ZA_n$, $Neighbor_{matrix}$

Result: $ZSt_k;\ k = 1, 2, 3 ... n_S$

$ZSt_1 = ZA_1$;

i = 2 ;

while $i <= n_S$ **do**

    ZSt_i = Neighbor of ZSt_{i-1} with the highest RI from $Neighbor_{matrix}$;

    if *ZSt_i has been already selected* **then**

        chose the next ranked neighbor;

        if *all neighbors of ZSt_{i-1} have been selected* **then**

            chose the next ranked ZA which has not been chosen yet;

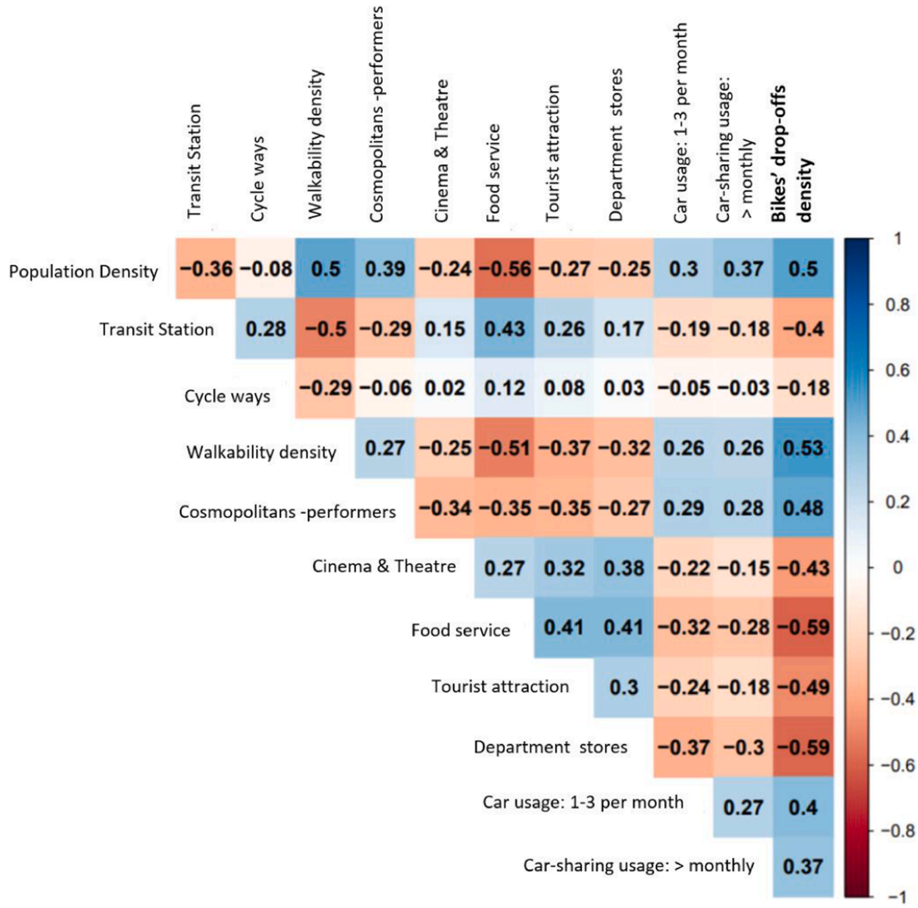
        end

    end

    i = i+1

end

Appendix B. Spearman correlation between selected variables



Spearman correlation between selected variables.

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