

Differences in bike-sharing usage and its associations with station-surrounding characteristics: A multi-group analysis using machine learning techniques

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ARTICLE INFO

Keywords:

Bike-sharing
Built environment
Machine learning
Non-linearity
Social equity
Micro-mobility
Tartu (Estonia)

ABSTRACT

The bike-sharing system offers a wide range of benefits to promote human mobility for all. However, many bike-sharing systems are most used by specific demographic groups (e.g., younger people and males), suggesting that the resulting benefits are not equally distributed among the public. We aim to empirically examine the differences in bike-sharing usage among varying demographic groups and its association with station-surrounding characteristics (i.e., land use, transportation infrastructure, and population distribution) in Tartu (Estonia) using a machine learning approach (i.e., gradient boosting decision trees). The results revealed that the floor area ratio played an extremely important role in promoting bike-sharing usage, but such a strong positive impact was not observed within senior groups. Instead, bike-sharing usage by seniors was strongly positively associated with the commercial land and bike lanes. It also detected that male teenagers and young adults were less likely to be influenced by the public land than their female counterparts when using shared bikes. Shared bikes located in areas with dense male senior residents gained high usage by them; however, such phenomenon was not observed from their female counterparts. These findings can provide significant insights for interventions targeting demographic-specific bike-sharing usage to promote inclusivity and equity in urban transportation.

1. Introduction

Existing shared mobility practices have generated tremendous benefits for addressing major challenges faced by urban transportation systems, such as air pollution, traffic congestion, and limited accessibility (Machado et al., 2018; Sun et al., 2021). Compared to ride-hailing and scooter programs, the bike-sharing system stands out by its affordability and positive effects on users' physical health (Cheng et al., 2022; Teixeira et al., 2021). However, it is widely reported that the bike-sharing system was in favor of particular demographic characteristics (e.g., younger people and males) – the bike-sharing system is differentially used by gender (Goodman and Cheshire, 2014; Murphy and Usher, 2015) and by age (Hossain et al., 2023; Ma et al., 2020). This suggests that the resulting benefits from bike-sharing programs are not equally distributed among the public (Ricci, 2015; Woodcock et al., 2014).

To construct more equally utilized bike-sharing systems, it is important to understand factors affecting bike-sharing usage of varying demographic groups, especially for those under-represented. Existing studies have extensively investigated the relationships between various built and demographic environments and bike-sharing usage (Eren and Uz, 2020; Zhang and Kamargianni, 2023). However, few studies took the gender and age of bike-sharing users into account when exploring the effect of various factors on bike-sharing usage because most bike-sharing system holders do not have such information in their datasets. Meanwhile, existing studies seldom considered the distance decay effect when quantifying explanatory variables, leading to over-estimations of attributes that are far away from the bike-sharing trips. To this end, this study aims to empirically examine the associations of various station-surrounding characteristics with demographic-specific bike-sharing usage in Tartu (Estonia) by an explainable machine learning approach,

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<https://doi.org/10.1016/j.jtrangeo.2025.104201>

Received 10 September 2024; Received in revised form 2 March 2025; Accepted 12 March 2025

Available online 19 March 2025

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considering spatial heterogeneity of station-surrounding characteristics. Specifically, two research questions were answered by this study: 1) Is there a difference in bike-sharing usage by various demographic groups, and what is the difference? And 2) How do various station-surrounding characteristics (i.e., land use, transportation infrastructure, and population distribution) influence bike-sharing usage of different demographic groups?

2. Related work

2.1. Factors affecting bike-sharing usage and their measurements

A large number of studies have empirically examined the effects of various built and demographic environments on bike-sharing usage (Eren and Uz, 2020; Zhang and Kamargianni, 2023). The influencing factors can be classified into three categories, i.e., 1) land use, 2) transportation infrastructure, and 3) population distribution. First of all, bike-sharing usage could vary across urban areas due to the spatial distribution of land uses. This is because that cyclists' travel behavior is closely related to the diverse use of lands where bike-sharing trips occur (Ross-Perez et al., 2022; Wang et al., 2022a; Xing et al., 2020). For instance, individuals riding to commercial areas are most likely to go there for shopping, while those riding to urban green spaces are largely for recreational purposes. To this end, earlier studies quantified the land use factor by calculating proportions of diverse land uses as well as land use mix (He et al., 2022; Lee et al., 2022). Some studies also took the floor area ratio into account since it indicates the land development intensity (Meng and Zacharias, 2021; Tu et al., 2019).

Transportation infrastructure is another vital factor influencing bike-sharing usage (Wu et al., 2021; Xu et al., 2019). Road networks (especially the bike lane system) enable individuals to cycle from one location to another. Bike stations located in areas with higher road connectivity are more likely to be frequently used (Yang et al., 2020). Therefore, most existing studies qualified this factor by the road density (Gao et al., 2022; Gao et al., 2021) or the road intersection density (Hossain et al., 2023; Yang et al., 2020). Other public transits such as bus/metro stops are also important determinants for shaping bike-sharing usage because the bike-sharing system serves as the first-and-last mile solution in many cities. Existing studies generally quantified this variable by the bus/metro density (Ma et al., 2020; Xiao and Wei, 2023).

Bike-sharing usage could be also affected by the station-surrounding population distribution (Schimohr et al., 2023). For instance, Feng and Li (2016) found that gender was the most important factor affecting people's willingness to use the bike share system, compared to other variables; Hossain et al. (2023) discovered that areas with younger age profiles were likely to generate a larger number of bike-sharing trips. Therefore, these variables were typically quantified by the density/proportion of varying demographic groups (Hossain et al., 2023; Ma et al., 2020).

Regarding the measurement of variables, it is widely recognized that the use of shared bikes could be largely influenced by the surrounding characteristics of where bike sharing trips take place (Fishman, 2016). Therefore, all of the above variables should be measured within a specific bike-sharing catchment area. However, few studies have taken into account the distance decay effect when measuring variables; instead, they have treated all characteristics within the catchment area as the same, no matter how far they are from the location of bike-sharing trips. This could lead to problematic estimations, as the characteristic that is closer to the bike station is likely to have a greater impact on bike-sharing trip generation and therefore should be weighted more heavily. Given this, it is required to optimize the existing approach to measuring explanatory variables of bike-sharing usage in the future studies.

2.2. Demographic differences in bike-sharing usage

The demographics of bike-sharing users are closely related to their travel behavior (Eren and Uz, 2020; Wang et al., 2018). This is to say, people with varying demographics could be differently affected by the same factor when using shared bikes. Gender and age are one of the main demographics causing such differences (Teixeira and Cunha, 2023). To begin with, the gender-based difference in bike-sharing usage could be attributed to three aspects. First, road safety is one of the main concerns – it is widely reported that females were more sensitive to road safety when cycling on the road (AitBihiOuali and Klingen, 2022; Pearson et al., 2023). For instance, females are less likely to visit relatively hidden areas (Beckers et al., 2024; Khademi et al., 2024); they are also less likely to violate traffic rules when traveling, compared with their male counterparts (Baker et al., 2022). Second, given the intrinsic gender differences in physical conditions, it also varies in cycling frequencies and distances between genders. In general, male users could generate longer and a larger number of bike-sharing trips than female users, as reported by (Goodman and Cheshire, 2014; Murphy and Usher, 2015). Third, such a difference could be caused by unequal access to bike-sharing services by gender (Fortes et al., 2024; Jin and Sui, 2024). For instance, Jin and Sui (2024) has reported a nationwide inequality of accessibility to bike-sharing stations in female-dominated areas in the United States.

In addition to gender factors, the differences in bike-sharing behavior could be also caused by age effects (Wang et al., 2018) and cohort effects (de Haas et al., 2022). Age effects indicate that different age groups may have different needs when using the bike-sharing system. For instance, seniors typically have higher requirements on road aesthetic, as they cycle mostly for recreational and exercise purposes (Böcker et al., 2020; Fishman et al., 2015). By contrast, young people are more likely to cycle for commuting purposes (Grudgings et al., 2021). Given that, the shortest path to their destinations might be their major choices, although they might be exposed to higher-level noises and air pollutants along the way. Cohort effects could be another important indicator determining demographic differences in travel behavior (Heinen et al., 2018). For example, younger generations typically drive less and use multiple other modes of transportation (e.g., public transportation and shared bikes) than senior generations due to the influence of lifestyles and adoption of information and communication technologies (de Haas et al., 2022; Wang et al., 2018).

In recent years, a few bike share system owners have recorded the gender and age of users and included this information into their datasets. This allows for comparative analyses of bike-sharing usage by different gender and age groups (Böcker et al., 2020; Kim and Cho, 2023). However, existing studies merely focus on comparisons between gender groups or age groups; few studies combined both age and gender to gain a more comprehensive understanding of bike-sharing usage by varying demographic groups. Therefore, the difference in bike-sharing usage by different gender and age groups remains under-explored, and it also remains unclear regarding discrepancies in the effects of various station-surrounding characteristics on bike-sharing usage by varying demographic groups.

2.3. Research gaps

Given the above, we make contributions to the existing literature in two key ways. First, previous studies seldom examined the disparities in effects of various station-surrounding characteristics on demographic-specific bike-sharing usage due to data unavailability. We filled this knowledge gap by focusing on a large-scale bike-sharing dataset containing the information of bike-sharing users' gender and age. Second, few scholars considered the distance decay effect when quantifying explanatory variables of bike-sharing usage. It could over-estimate the effect of the station-surrounding characteristics that are relatively far from the location of bike-sharing trips. To address this problem, we

applied a Gaussian function to generate a series of coefficients to weigh various station-surrounding characteristics based on their distance to bike stations. By doing so, the estimates of the effect of station-surrounding characteristics on bike-sharing usage could be more realistic.

3. Materials and methods

3.1. Study area

Tartu is the second largest city in Estonia, occupying an urban area of with about 38.82 km² residing nearly one hundred thousand population until 2023.¹ The local transportation system consists of buses as the only public transportation (no metros or trams) in the Tartu urban area, running along fifteen routes.² In the city of Tartu, the modal split according to the main mobility mode is as follows: car 44 %, foot 43 %, public transportation 10 %, bicycle 8 %, and taxi and ride sharing 1 % (Transportation Administration, 2021). The local government established the bike-sharing system in June 2019, comprised of 750 bikes in 69 bike stations. Till 2022, the number of bikes remains unchanged, but the number of bike stations has increased to 103, largely improving residents' accessibility to shared bikes. Out of 750 shared bikes, there are 500 electric and 250 regular bikes. Out of 103 bike stations, 87 stations are located in the city of Tartu. The remaining 16 stations are sparsely distributed in the surrounding fourteen villages (Fig. 1). Given that the station-surrounding characteristics in urban areas are significantly different from ones in villages, this study only took stations within the Tartu urban area into account; it is where the shared bikes are intensively used (occupying 94.43 % of total trips). Additionally, one station in the urban area was excluded since no trip records were detected. As a result, a total of 86 bike stations were included in the following analysis.

3.2. Data sources and pre-processing

3.2.1. Bike-sharing data

Bike-sharing data was obtained from the Tartu city government, consisting of two parts. The first part is the geographic location (i.e., latitude and longitude) of bike stations, and the second part contains two-month bike-sharing trip records ($n = 180,595$) from May 1 to June 30 in 2022, at the time when the transportation system in Europe has almost recovered from the COVID-19 pandemic (Teixeira and Cunha, 2023). This period of the year was selected because the bike-sharing system in Tartu had the most frequent usage in these two months throughout the year. Each trip record contains two types of features: 1) route-related features: route code, unlock date and time, lock date and time, name of start and end stations; and 2) user-related features: user identification (ID), membership types, and the first three digits of users' personal ID code (containing information of users' age and gender). Based on the gender and age of bike-sharing users, these trips were further categorized into eight groups (Table 1).

3.2.2. Built environment data

Four built environment datasets were included in this study: 1) land use, 2) buildings, 3) bus stops, and 4) bike lanes. The first three datasets were acquired from the Tartu city government, while the last dataset was obtained from OpenStreetMap. Land use and building data were stored in polygon formats; bus stop and bike lane data were stored in point and linestring formats respectively. Noticeably, it is a challenge to measure the distance of built environments to bike stations when these data are not stored in point formats, such as linestring or polygon formats. A common way for doing so by existing studies is based on the centroid of the linestring or the polygon data to identify the location of

built environments. However, it could be problematic when there is a large variation in the polygon size or the linestring length. For instance, a large land parcel or a long bike lane could have some parts very close to bike stations, serving as a critical factor influencing bike-sharing users' travel behaviors; however, it may be excluded from evaluations because its centroid is beyond the maximum distance threshold.

To handle this problem, this study partitioned all land parcels into identical fine-scale grids (30 m*30 m), and the grid centroid was used to locate a specific land use type for calculating its distance to the bike station (Fig. 2a). The same way was applied to bike lanes – every bike lane was converted into a series of points with an identical distance interval of 30 m (Fig. 2b). Additionally, the centroid of building boundaries was directly applied to locate the buildings given that they were stored already in fine-scale polygon formats (Fig. 2b). After these pre-processing steps, all built environment features around bike stations were stored in the point format so that their distance decay effects on bike-sharing usage could be handled in the following analysis (specified in Section 3.3).

3.2.3. Demographic data

Demographic data was acquired from Statistics Estonia, consisting of two attributes. The first attribute is the ethnicity (i.e., Estonian, Russian, and foreigners), and another attribute contains residents' gender and age. Both attributes are stored at the grid of 100 m by 100 m. The centroid of these grids was generated for calculating their distance to the nearby bike stations. The census moment for both datasets is by 31 December 2021; thus, the data has a relatively consistent temporal range with the bike-sharing data given the assumption that people's residences did not change significantly before May 2022.

3.3. Variables

One goal of this study is to examine how station-surrounding environments affect bike-sharing usage of different demographic groups. Given it, the station-level average daily trips by every demographic group were calculated as the dependent variable (Table A.1 in Appendix A), and a range of explanatory variables were selected through a comprehensive literature review (Eren and Uz, 2020; Zhang and Kamargianni, 2023). These explanatory variables are further classified into three categories, including 1) **land use**: the proportions of residential land, commercial land, institutional land, industrial land, and public land, as well as land use mix and the floor area ratio; 2) **transportation infrastructure**: proximity to roads, bike lanes, bus stops, and downtown; and 3) **population distribution**: the number of Estonian, Russian, and foreigner residents, as well as the proportion of residents having the same gender and age range with the bike-sharing users of the specific demographic group. Further, four variables (i.e., proximity to roads, land use mix, the number of Estonian residents, and proximity to downtown) were removed because these variables had their variance inflation factor values above 10, indicating a high possibility of collinearity among these variables with others. As a result, a total of eleven explanatory variables were taken into account for further analysis (Table A.2 in Appendix A).

To reflect the distance decay effect, a series of coefficients are generated by the Gaussian function to weigh station-surrounding characteristics based on their distance to bike stations. One challenge for considering distance decay effects is to identify an appropriate distance threshold. This study selected 150 m as the service radius of bike stations, even though most earlier studies set the distance threshold between 200 and 300 m (Bao et al., 2017; He et al., 2022). Some may doubt if the distance of 150 m is adequate for the station-based bike share system because the user opts to park the bike at a nearest available station that might be far beyond 150 m. However, in this way, people may adopt other modes of transportation (e.g., by bus) instead of shared bikes for traveling because the bus stop density in Tartu (about nine bus stops per square kilometer within the study area) is quite high. Plus,

¹ <https://www.stat.ee/en>

² <https://tartu.ee/en/inner-city-bus-transportation>

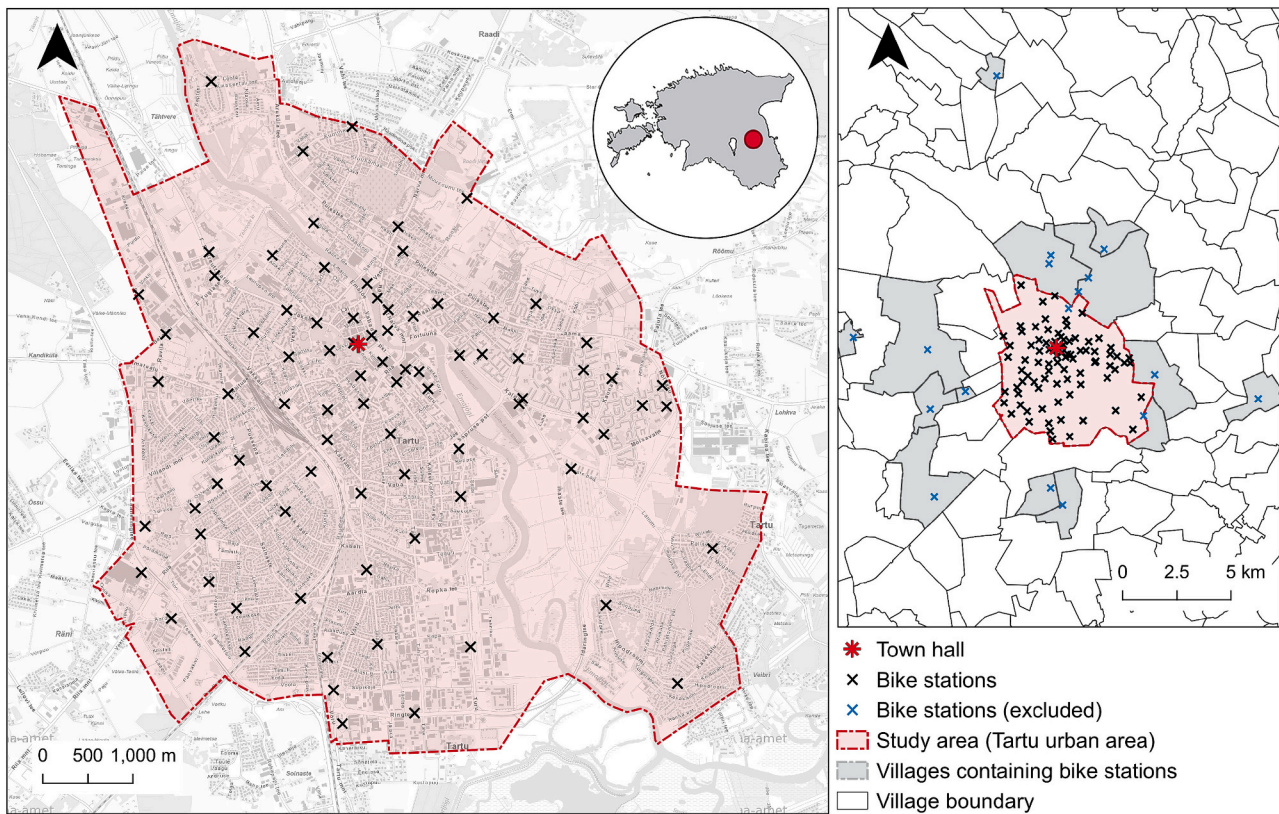


Fig. 1. The study area and the bike share system in Tartu, Estonia.

Table 1
Description of bike-sharing usage by eight demographic groups.

Gender	Age	Representative	Total trips (percentage)	Number of unique users (percentage)	Average trips per person
Male	13–19	Male teenagers	43,489 (24.1 %)	1125 (16.9 %)	39
	20–34	Male young adults	40,570 (22.5 %)	1332 (20.0 %)	30
	35–64	Male middle-aged adults	20,013 (11.1 %)	689 (10.4 %)	29
	≥ 65	Male seniors	2194 (1.2 %)	79 (1.2 %)	28
Female	13–19	Female teenagers	24,315 (13.5 %)	1044 (15.7 %)	23
	20–34	Female young adults	29,947 (16.6 %)	1524 (22.9 %)	20
	35–64	Female middle-aged adults	17,879 (9.9 %)	778 (11.7 %)	23
	≥ 65	Female seniors	2188 (1.2 %)	80 (1.2 %)	27
		Sum	180,595	6651	27

Tartu is a small city with its urban areas occupying no more than 40 km². As a result, the travel distance within the urban area is rather short – if it requires people to walk a long distance to/from a bike station, they are more likely to walk to their destinations directly. Therefore, both above-mentioned aspects indicate that the distance threshold of 200-300 m, applied by earlier studies with large cities as case studies (Bao et al., 2017; He et al., 2022), might be over-estimated for this study. Given that, the threshold distance of 150 m was selected, as supported by Lam et al. (2022) – they examined that 150 m is the most appropriate distance that people are willing to walk to a public transit station when comparing with 500 m and 1000 m. The equations (considering the distance decay effect) for calculating eleven explanatory variables are presented in Appendix B.

3.4. Research methodology

Scholars have been dedicated to measuring associations of various factors with bike-sharing usage by multiple regression models. First of all, traditional non-spatial regression models have been applied to measure their linear relationships in earlier studies (Lee et al., 2022;

Meng and Zacharias, 2021). Afterwards, some studies considering spatial heterogeneity emerged, holding that bike-sharing usage can be affected by various characteristics in a different way in different regions across the city (Hossain et al., 2023; Ma et al., 2020). Nevertheless, such spatial phenomena may not be observed from small-scale bike-sharing systems with a limited number of bike stations (Yang et al., 2020).

According to these studies, it enables to be aware of how various characteristics affect bike-sharing usage in a linear way. However, these traditional approaches fail to compare the relative importance of station-surrounding characteristics for affecting bike-sharing usage. For instance, several studies empirically verified the positive association of both commercial and residential facilities with the number of bike-sharing trips (Lee et al., 2022); however, which characteristic is more important than another for boosting bike-sharing usage? Understanding such differences can provide bike-sharing system owners with justifications for finding optimal locations for installing bike stations. More importantly, the relationships between various factors and active travel behaviors are likely to be more sophisticated than linearity (Wang et al., 2022b; Xiao and Wei, 2023). To this end, an increasing number of studies have attempted machine learning techniques to fill this

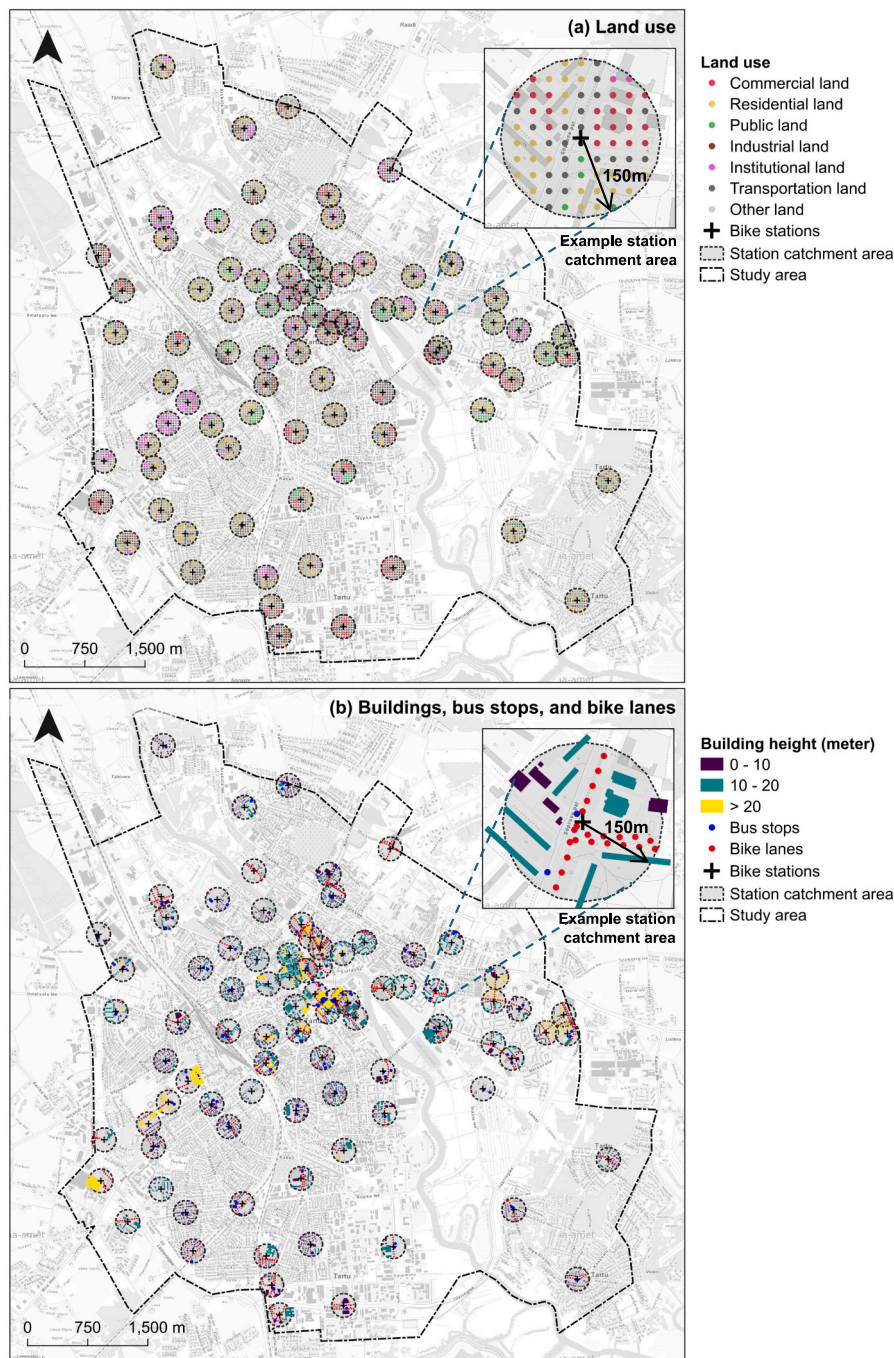


Fig. 2. Spatial distribution of built environments (i.e., land use, buildings, bus stops, and bike lanes) within the catchment area of bike stations.

knowledge gap in the most recent years (Du et al., 2019; Schimohr et al., 2023).

Given the above, the gradient boosting decision trees (GBDT) algorithm was selected to examine the non-linear associations of various station-surrounding characteristics with bike-sharing usage. This is an ensemble machine learning algorithm that creates a strong learner by combining multiple weak learners (i.e., decision trees). To be more specific, it works by multiple decision trees, and every subsequent decision tree is trained to predict the error made by the previous decision tree until the final prediction is accurate enough, but no evident overfitting is observed. Specially, eight GBDT regression models were built to examine the non-linear associations of station-surrounding environments on bike-sharing usage by eight demographic groups respectively. Seventy percent of data served as the training set, while the remaining

30 % of data served as the test set. The optimal parameters for training each model were identified based on the GridSearchCV method (Pedregosa et al., 2011), and the five-fold cross-validation method was applied. The parameter grid was defined as follows: {"n_estimators": [100, 150, 200, 250, 300], "learning_rate": [0.05, 0.055, 0.06, 0.065, 0.07, 0.075, 0.08], "max_depth": [3, 4, 5, 6], "max_features": [0.4, 0.5], "min_samples_leaf": [3, 4], "subsample": [0.5, 0.6]}. After 5600 iterations, eight models with the optimal performance were acquired. The values of R-squared range from 0.704 to 0.821, indicating a good fit of models to the data (Appendix C).

To illustrate the outcome of regression analyses, this study calculated the relative importance (RI) of eleven explanatory variables in each model. By comparing RIs among GBDT regression models, it could identify the station-surrounding characteristics that play an important

role in affecting bike-sharing usage by each demographic group. Besides, the partial dependence plot (PDP) was drawn to display and compare the non-linear associations of various station-surrounding characteristics with demographic-specific bike-sharing usage.

Plus, this study also conducted non-parametric tests (i.e., the Mann-Whitney *U* test) to identify if there is a difference in bike-sharing usage (i.e., the station-level average daily trips) among demographic groups. The non-parametric test was chosen because the station-level average daily trips of eight demographic groups were not normally distributed. Besides, the hot spot analysis was conducted to examine where higher and lower daily average bike-sharing trips were clustered respectively (Choi et al., 2023).

4. Results

4.1. Differences in bike-sharing usage among varying demographic groups

The results revealed that bike-sharing usage by male users was significantly different from that by female users within teenager and young adult groups (Fig. 3a and b). Male teenagers and young adults used the bike-sharing system more frequently than their female counterparts, and such a gender-based difference was more evident within the teenager group as there was a larger gap of mean ranks between male and female users (Fig. 3a and b). However, no significant gender-based difference in bike-sharing usage was observed from middle-aged adult and senior groups (Fig. 3c and d). Male middle-aged adults and seniors had slightly higher bike-sharing usage than their female counterparts as lower mean ranks were found in female groups (Fig. 3c and d). As for age-based differences, it found a common existence of age-based bike-sharing usage disparities as almost all age group pairs (except the pair of teenagers and young adults) had their *p*-values below 0.05 (Fig. 4). Age-based bike-sharing usage varied at a greater level

among male groups than female groups with larger mean rank differences in male groups (Fig. 4).

No evident spatial disparity was observed between genders for teenager and young adult groups by comparing Fig. 5a and b with Fig. 5e and f respectively. Teenagers of both genders had their bike-sharing trips clustered in the urban center and eastern suburbs but had low bike-sharing usage in western inner suburbs (within the 3 km-buffer area) (Fig. 5a and e). Young adults of both genders also had their high bike-sharing usage clustered in the urban center, while their lower bike-sharing usage was clustered in outer suburbs (outside of the 3 km-buffer area) (Fig. 5b and f). By contrast, the spatial disparity in bike-sharing usage between genders was much more evident among middle-aged adults and seniors. For middle-aged adults, the main gender-based difference was that males had relatively lower bike-sharing usage in the southern and southeastern outer suburbs (Fig. 5c), while females had additional high bike-sharing usage clusters in the eastern suburb besides central clusters (Fig. 5g); male seniors had some bike-sharing trips clustered in the urban center, but the range of hot spots was much less widespread than other age groups (Fig. 5d). Surprisingly, no hot spots were observed within the 1 km-buffer area for female seniors; their bike-sharing trips were widely clustered in the direction of eastern and southeastern suburbs (Fig. 5h). The above indicates that seniors used the bike-sharing system in the urban center at an evidently lower frequency than other age groups.

4.2. Factors affecting bike-sharing usage of varying demographic groups

4.2.1. The impact of land use on bike-sharing usage

Among six land use variables, the floor area ratio had the most important effect on bike-sharing usage because its RIs ranked very high in a majority of models (Table 2). According to Fig. 6f, its overall positive association with bike-sharing usage was observed. Both results

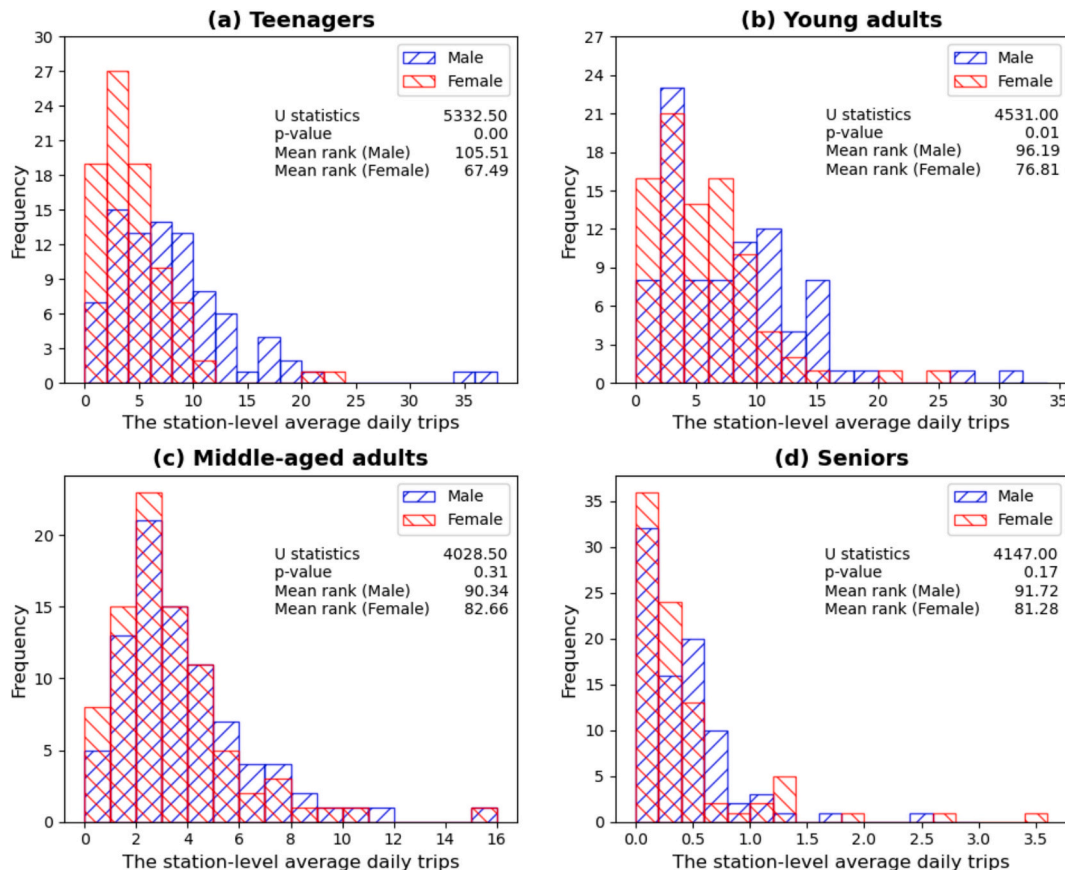


Fig. 3. Gender-based differences in the station-level average daily trips.

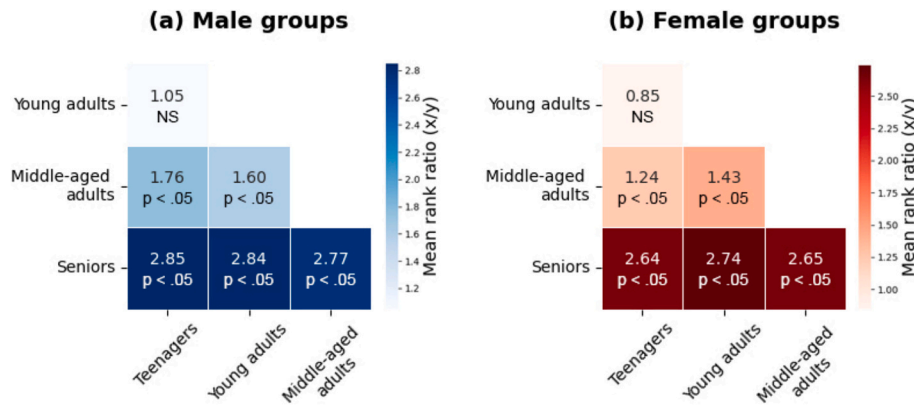


Fig. 4. Differences in the station-level average daily trips among age group pairs.

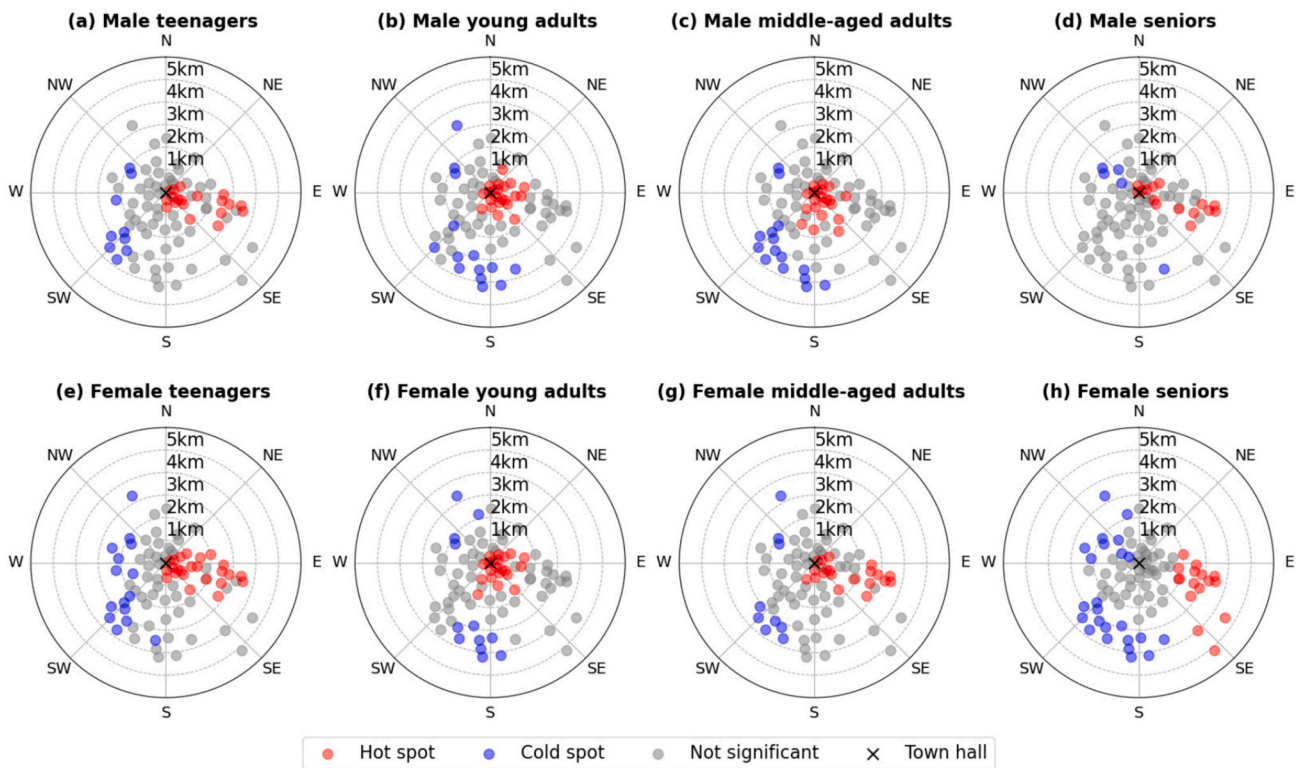


Fig. 5. Clusters of the station-level daily average trips by eight groups.

indicate that the bike-sharing system was used intensively in the area with the high area floor ratio (e.g., areas occupied by high-rise apartment buildings, office buildings, or shopping malls). However, such a strong positive impact was not observed for senior groups as the RI of the floor area ratio ranked fifth and sixth in Models 4 and 8 respectively (Table 2). In addition, the RIs for female teenager and young adult groups were only slightly higher than male ones, while it is opposite for middle-aged and senior groups (Table 2), suggesting no evident gender-based differences in bike-sharing usage.

It is followed by the proportion of commercial land (Table 2), and Fig. 6b illustrates its positive impact on bike-sharing usage. Especially, a very high RI (i.e., 0.208) was observed in the Model 4; it also detected high RI values (ranked third or higher) in Models 1, 5, and 8 (Table 2). This suggests that teenagers and seniors frequently use the bike share system in commercial areas. Even though it found that the commercial land was important for bike-sharing usage of both groups, their travel purposes might be different. For instance, teenagers probably use shared

bikes in commercial areas for recreational purposes, while seniors are more likely to cycle in commercial areas for grocery shopping purposes. By contrast, the positive impact of commercial land was relatively weak for young adult groups as their RIs ranked relatively lower than other groups (Table 2).

The public land also played a relatively important role in bike-sharing usage. Fig. 6e shows an apparent positive relationship between public land and bike-sharing usage. Such a positive impact was especially important for middle-aged adults as the RI values ranked first and third in Models 3 and 7 respectively (Table 2). Notably, the public land played the most important role in bike-sharing usage of male middle-aged adults. By contrast, male teenagers and young adults are less likely to be influenced by the public land than their female counterparts since relatively lower RI values were observed in male groups (Table 2).

The impact of the residential land on bike-sharing usage is only relatively important for a few groups. The RI value of residential land

Table 2
Relative importance (RI) of explanatory variables influencing bike-sharing usage by eight demographic groups.

Variable	Male teenagers		Male young adults		Male middle-aged adults		Male seniors		Female teenagers		Female young adults		Female middle-aged adults		Female seniors	
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
	RI	Rank	RI	Rank	RI	Rank	RI	Rank	RI	Rank	RI	Rank	RI	Rank	RI	Rank
Land use (n = 6)																
Residential land	0.095	4	0.111	4	0.067	6	0.068	8	0.053	9	0.106	5	0.097	5	0.065	8
Commercial land	0.168	2	0.083	6	0.096	4	0.208	1	0.149	3	0.107	4	0.165	2	0.161	2
Institutional land	0.055	9	0.058	9	0.059	7	0.047	10	0.032	10	0.050	10	0.037	10	0.029	10
Industrial land	0.025	11	0.008	11	0.010	11	0.033	11	0.018	11	0.030	11	0.020	11	0.021	11
Public land	0.084	6	0.071	8	0.217	1	0.090	4	0.104	4	0.077	6	0.123	3	0.101	5
Floor area ratio	0.212	1	0.187	1	0.193	2	0.084	5	0.217	1	0.200	1	0.170	1	0.074	6
Transportation infrastructure (n = 2)																
Bike lanes	0.106	3	0.084	5	0.083	5	0.128	3	0.079	5	0.052	9	0.066	8	0.135	3
Bus stops	0.084	5	0.071	7	0.040	10	0.070	7	0.057	7	0.066	8	0.061	9	0.036	9
Population distribution (n = 3)																
Russian residents	0.051	10	0.057	10	0.050	8	0.059	9	0.067	6	0.074	7	0.101	4	0.202	1
Foreigner residents	0.059	8	0.140	2	0.136	3	0.078	6	0.171	2	0.131	2	0.092	6	0.104	4
Population composition	0.061	7	0.131	3	0.048	9	0.134	2	0.053	8	0.107	3	0.068	7	0.073	7
Sum	1.000		1.000		1.000		1.000		1.000		1.000		1.000		1.000	

ranked fourth in Model 1 (Table 2), suggesting that the residential land played a relatively important role in bike-sharing usage of male teenagers. However, their relationship fluctuated, with the highest bike-sharing usage when the proportion of weighted residential land stood at around 0.25 (Fig. 6a). Besides, it observed an overall negative relationship between bike-sharing usage and the proportion of residential land for young adults (Fig. 6a). Meanwhile, the RI values in Models 2 and 6 were relatively high (all above 0.1). This indicates that young adults were less likely to use shared bikes in areas where the residential land dominated. The negative impact was also observed for female middle-aged adults (Fig. 6a). This might be due to the fact that several bike stations were located in sparsely populated residential areas in suburbs where residents were largely dependent on private vehicles/buses for commuting to urban central areas given their farther travel distance demands. Finally, the RI values for other groups ranked quite low (Table 2), indicating that residential land is not a determinant affecting their usage of shared bikes.

Besides, this study did not observe an evident impact of the institutional and industrial land on bike-sharing usage as their RIs ranked very low in all models (Table 2). Especially, the industrial land ranked last in all models (Table 2). Fig. 6c and d also display almost horizontal lines for most groups, indicating that bike-sharing usage remained stable no matter how high/low the proportion of the institutional or industrial land was. However, it still detected a positive impact of the institutional land on bike-sharing usage of male teenagers and young adults (Fig. 6c). This suggests that shared bikes located around schools or university buildings served as the important transportation tool for accommodating male students' commuting needs.

4.2.2. The impact of transportation infrastructure on bike-sharing usage

The transportation infrastructure factor consists of two variables, i. e., bike lanes and bus stops. Fig. 7a illustrates the overall positive association of bike lanes with bike-sharing usage for all groups. When combined this with RIs in Table 2, it can be seen that bike lanes played a fairly important role in increasing bike-sharing usage of seniors, as the RIs of bike lanes ranked third in both Model 4 and Model 8. One possible explanation for this might be that senior users were more sensitive to road safety than younger users – bike lanes could largely reduce the threat from motorized vehicles on the road, and therefore increase the likelihood of bike-sharing usage by senior groups. In addition, proximity to bus stops is not regarded as an important determinant of bike-sharing usage since their RIs ranked quite low in most models (Table 2),

although Fig. 7b shows an overall positive correlation of proximity to bus stops with bike-sharing usage.

4.2.3. The impact of population distribution on bike-sharing usage

The results in Table 2 indicate that the variable of foreigner residents played an important role in bike-sharing usage of young adults and middle-aged adults, as it had very high RIs from corresponding models (i.e., Models 2, 3, 6, and 7), ranking second or third. According to Fig. 8b, it observed an evident positive relationship between the number of foreigner residents and the daily average trips of these age groups. Tartu is a university town, and its main foreigner source is international students and graduates of the University of Tartu (mainly residing in the urban central area where major university buildings and companies are located). Therefore, the shared bike is the most likely to be the choice of these foreigners for commuting to schools or companies in urban central areas. By contrast, the number of Russian residents was not considered to be an important determinant of bike-sharing usage in general, as its RIs ranked quite low in most models (Table 2). Only one high RI (at 0.202, ranking first) was observed in model 8 (Table 2), having overall positive associations with bike-sharing usage (Fig. 8a). This suggests that Russian female seniors are largely likely to be the potential bike-sharing users.

In addition, population composition played an important role in affecting bike-sharing usage by male seniors, as it ranked second in Model 4 (Table 2). According to Fig. 8c, a positive association was observed between population composition and bike-sharing usage of male seniors. Both results indicate that shared bikes located in areas with dense male senior residents gained high usage by them. Such an interpretation was also applied for male young adults according to the high RI of population composition (ranking third among eleven variables) in the Models 2 and 6 (Table 2) and its PDP (indicated by the orange solid line) in Fig. 8c.

5. Discussion

5.1. Gender-based differences in bike-sharing usage

The results revealed gender-based differences in bike-sharing usage, and the difference varied between age groups. Male teenagers and young adults used the bike-sharing system more frequently than their female counterparts, although no evident spatial disparity was observed between genders within these two groups. By contrast, no statistically

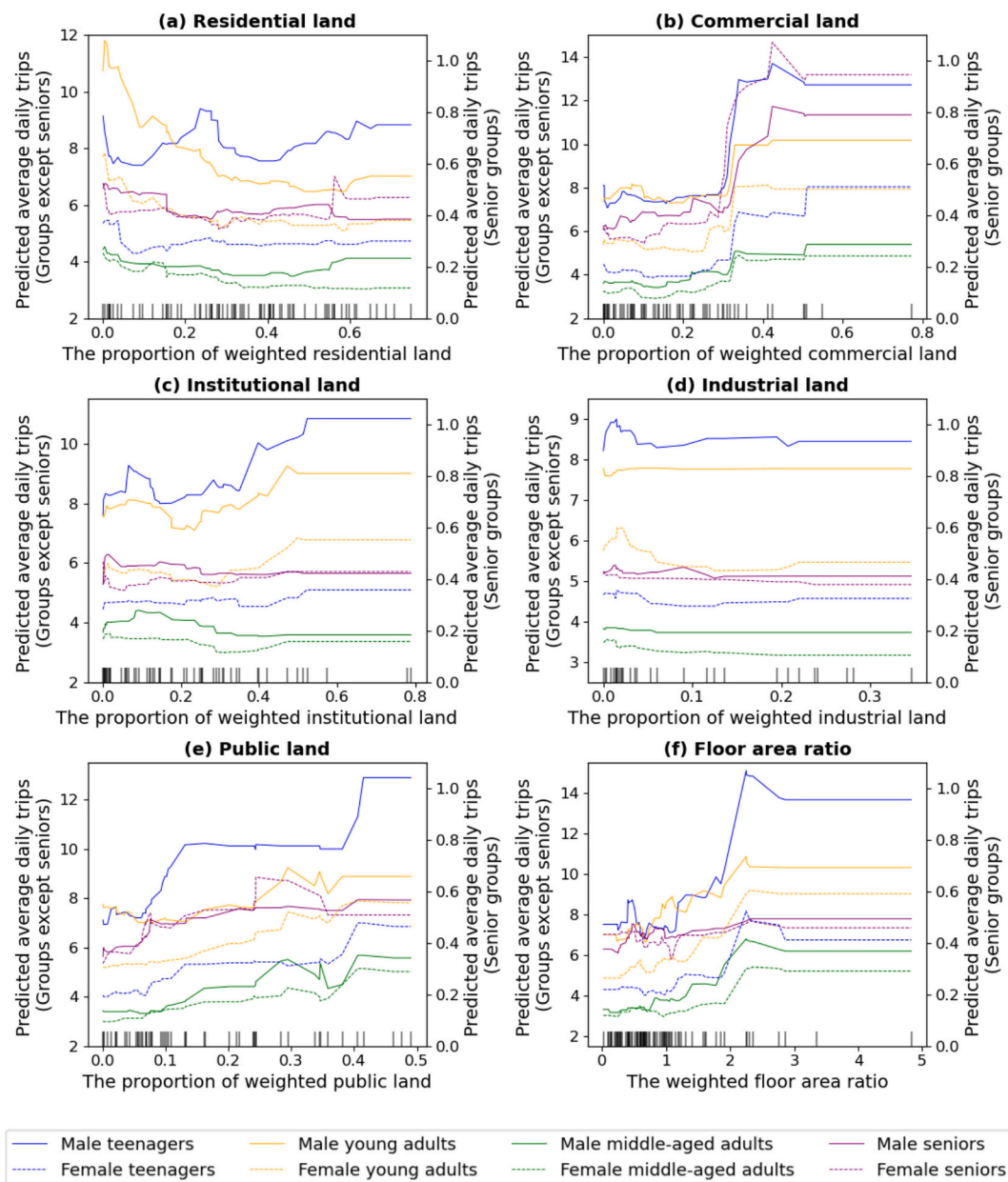


Fig. 6. Non-linear associations of station-surrounding land use with bike-sharing usage: (a) residential land, (b) commercial land, (c) institutional land, (d) industrial land, (e) public land, and (f) floor area ratio.

significant gender-based difference in bike-sharing usage was observed among middle-aged adults and seniors. However, their spatial bike-sharing usage patterns differed by gender - female middle-aged adults and seniors used shared bikes in suburbs significantly more frequently than their male counterparts. These findings complemented understandings from previous studies (Goodman and Cheshire, 2014; Murphy and Usher, 2015), which concluded that male users consistently dominated bike-sharing usage without considering the influence of age.

Furthermore, this study has examined the impact of various determinants on gender-based differences in bike-sharing usage. First of all, a large number of studies has found positive impact of the floor area ratio and the commercial land on bike-sharing usage (Meng and Zacharias, 2021); however, no noticeable impact was detected from these two variables on differentiated bike-sharing usage by gender. This indicates that bike-sharing users of both genders were almost equally influenced by the floor area ratio and the commercial land. Besides, the residential land has an apparently more important impact on bike-

sharing by males than females for teenager groups. It found that the association of the residential land with bike-sharing of male teenager was not always positive, which is inconsistent with existing empirical evidence (Lee et al., 2022; Xiao and Wei, 2023). The negative impact largely results from the discrepancy in population density – if there is a relatively even population distribution, a higher proportion of the residential land around bike stations in general indicates a larger number of residents there, potentially increasing the bike-sharing usage. However, this phenomenon is not applied to Tartu because several bike stations were located around sparsely populated suburbs, occupying a larger proportion of residential land. Given that these stations can only serve a few nearby residents but have limited attractiveness to generate trips by visitors, it could cause the negative impact on the usage of shared bikes there. By contrast with the impact of the residential land, male younger generations were less likely to be influenced by the public land than their female counterparts when using shared bikes. This can be explained by that females may visit the public land more frequently than

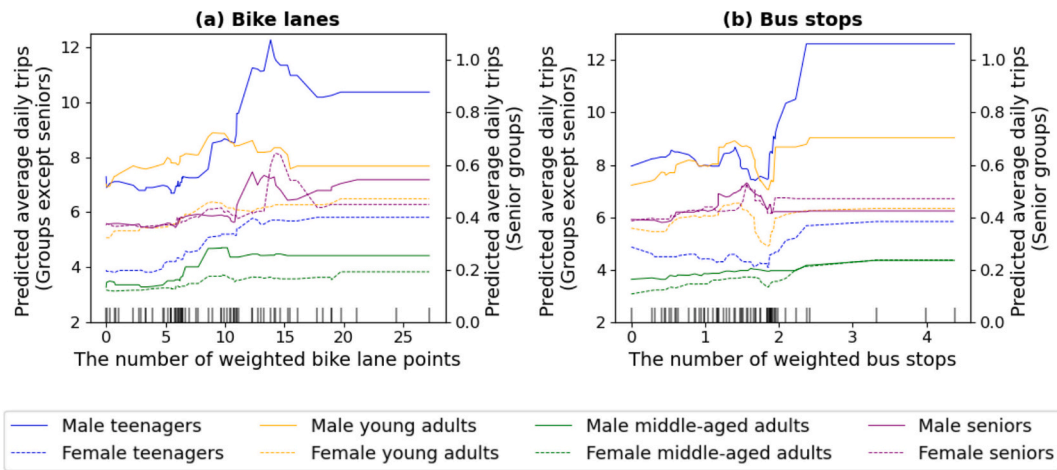


Fig. 7. Non-linear associations of station-surrounding transportation infrastructure with bike-sharing usage: (a) bike lanes and (b) bus stops.

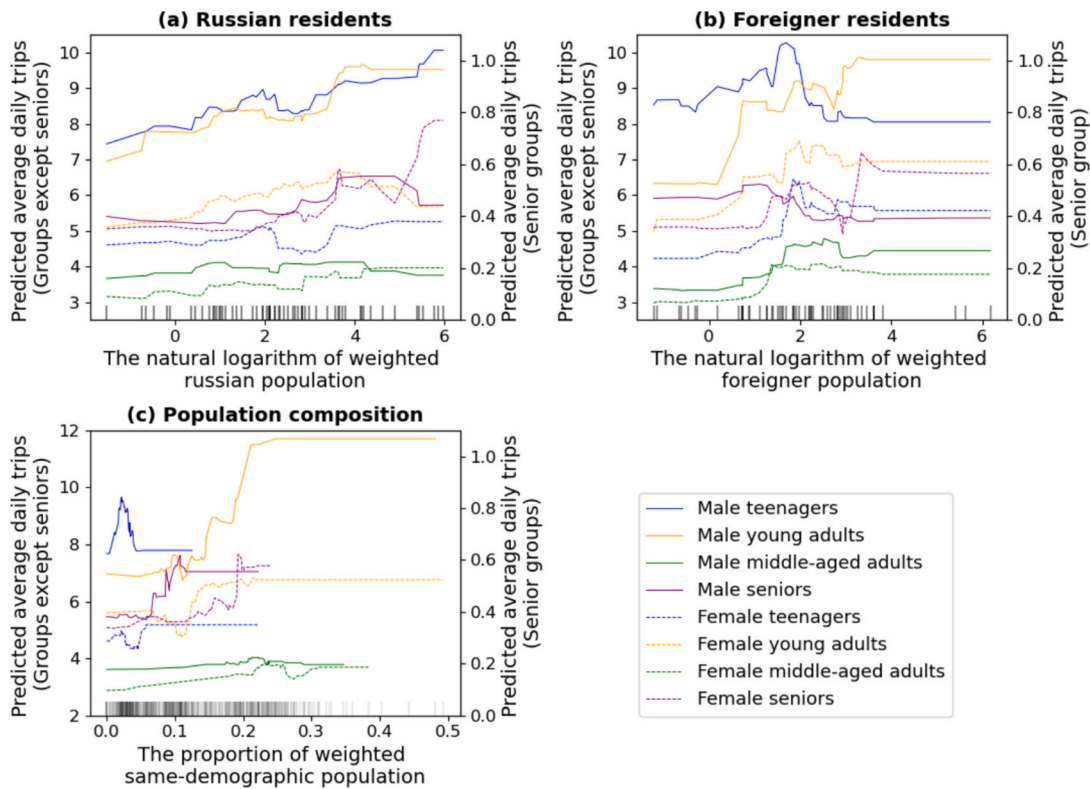


Fig. 8. Non-linear associations of station-surrounding demographics with bike-sharing usage: (a) Russian residents, (b) foreign residents, and (c) population composition.

males, and therefore the shared bikes there are more likely to be used by them during their visits.

We did not detect the strong impact of bus stops on bike-sharing usage, although a large number of existing studies have emphasized the role of the bike share system in connecting with other transports such as metros and buses (Wu et al., 2021; Xu et al., 2019); it is because that these bike-sharing systems are located in metropolises where people are required to travel longer distances and thus necessarily transfer different means of transportation to their destination. By contrast, Tartu is a small city with an urban area of no more than 40 km². Especially, it has densely distributed bus stops and bike stations, allowing residents to reach their destinations by a single trip. Therefore, a combination of different public transit systems would largely not happen in Tartu,

Estonia.

5.2. Age-based differences in bike-sharing usage

There was a common existence of bike-sharing usage between varying age groups, despite no statistically significant difference in bike-sharing usage between teenagers and young adults. Meanwhile, it observed that young adults had their bike-sharing usage clustered only in the urban center where senior bike-sharing users were highly representative. In particular, female seniors seldom used shared bikes in the urban center. Such a bike-sharing usage segregation is partly because younger groups visit the urban center much more frequently than seniors to meet diverse social needs. On the other hand, seniors in general

reside in suburbs and tend to have relatively limited mobility patterns, leading them to use shared bikes primarily near their homes (i.e., mainly in suburbs).

This study further analyzed how various station-surrounding characteristics cause the aged-based differences in bike-sharing usage. To begin with, it found that the floor area ratio played an extremely important role in promoting bike-sharing usage; however, such a strong positive impact was not observed within senior groups. This is largely because seniors typically reside in their own houses with the constant low floor area ratio in these areas, and thereby it is difficult to predict bike-sharing usage of seniors by this variable. By contrast, accommodation types of other age groups are more diverse. Some may consider residing in houses (with the lower floor area ratio) for better living quality, generating relatively less bike-sharing trips in these areas. However, some may choose to reside in multi-story apartment buildings (with the higher floor area ratio) given their affordability. These buildings can accommodate a quite larger number of residents than houses, thus potentially bringing more bike-sharing trips. Therefore, the floor area ratio could serve as a decisive feature for predicting bike-sharing usage of these age groups.

Moreover, it found that the commercial land played the most important role in increasing bike-sharing usage by seniors, while middle-aged adults exhibited a strong positive association with the public land. Therefore, it is highly suggested that the government should expand bike-sharing services to the commercial and public land to meet the needs of under-represented middle-aged adults and seniors. Relevant stakeholders could also consider building new bike stations in areas with dense Russian residents because shared bikes located around Russian residents gained high usage of female middle-aged adults and seniors. In Estonia, local residents have two main ethnicities (i.e., Estonian and Russian), and Russian residents are generally with the relatively disadvantageous socio-economic status when compared with Estonian residents. Given that, many deprived groups could also reside in the area with dense Russian residents. Therefore, installing bike stations in these areas could be helpful for meeting the travel needs of these vulnerable groups. Last but not least, bike lanes were of particular concern to senior users due to road safety issues. However, it can be seen that the existing bike lanes around bike stations were under-developed in Tartu (Fig. 2b) – more than one fifth of bike stations ($n = 19$) were not connected by bike lanes. Therefore, local governments could be dedicated to constructing a more accessible bike lane system to encourage bike-sharing usage by senior groups.

6. Conclusions

To conclude, by means of a machine learning approach and with the distance decay effect considered, this study identified the most important station-surrounding characteristics affecting bike-sharing usage for varying demographic groups and extracted their non-linear associations. These findings can provide significant insights into interventions for

increasing bike-sharing usage of under-represented groups, so that inclusivity and equity in urban transportation could be promoted. More importantly, the findings of this study can provide small-scale bike-sharing system stakeholders with significant insights for increasing their local bike-sharing usage. Many large cities established bike-sharing systems around one decade ago or longer, and therefore most related studies have been conducted based on case studies of large-scale bike-sharing systems. However, the development of bike-sharing systems in small cities is still in their initial phase, and their development patterns are significantly different from that of bike-sharing systems in large cities given the dramatic differences in population structures, land use, and transport systems. Therefore, policy implications from large-scale bike-sharing case studies cannot be directly used in the development of these small-scale bike share systems, but this problem is exactly what our study helped figure out.

However, this study still has some limitations. For instance, this study did not contain the trip records occurring in the winter, and the weather factor was also not taken into account - males might be more resilient to extreme climate and weather than females, and the younger groups could also do better than the elderly. In addition, given the data unavailability, this study did not include several socio-economic variables, e.g., occupation, income, and educational attainment. Therefore, future work could contribute to these aspects to further provide insights into urban micro-mobility equity.

CRediT authorship contribution statement

Xiao Cai: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xinyue Gu:** Writing – review & editing, Validation, Methodology, Data curation, Conceptualization. **Siiri Silm:** Writing – review & editing, Supervision, Resources, Funding acquisition. **Amnir Hadachi:** Writing – review & editing, Supervision, Resources, Funding acquisition. **Tanhua Jin:** Writing – review & editing, Supervision. **Frank Witlox:** Writing – review & editing, Supervision.

Declaration of competing interest

No potential conflict of interest was reported by the authors.

Acknowledgements

We greatly appreciate the efforts made from two anonymous reviewers, whose comments have played a significant role in improving the quality of our manuscript. We also would like to thank Dr. Elias Willberg, Prof. Tuuli Toivonen, and other Digital Geography Lab members for their valuable suggestions on the manuscript, and the University of Helsinki for supporting this article published with open access.

Appendix A

Table A.1

Descriptive statistics of the dependent variable.

Gender	Age	Representative	Avg.	Std.	Min.	Med.	Max.
Male	13–19	Male teenagers	8.290	6.242	0.033	6.516	37.082
	20–34	Male young adults	7.734	5.577	0.016	7.074	31.246
	35–64	Male middle-aged adults	3.815	2.615	0.016	3.238	15.705
Female	≥ 65	Male seniors	0.418	0.398	0.000	0.352	2.525
	13–19	Female teenagers	4.635	3.775	0.016	3.910	22.279
	20–34	Female young adults	5.709	4.256	0.000	5.107	24.803

(continued on next page)

Table A.1 (continued)

Gender	Age	Representative	Avg.	Std.	Min.	Med.	Max.
	35–64	Female middle-aged adults	3.408	2.399	0.000	2.910	15.574
	≥ 65	Female seniors	0.417	0.556	0.000	0.254	3.426

Table A.2

Description of explanatory variables.

Variable	Description	Avg.	Std.	Min.	Med.	Max.
Land use (n = 6)						
Residential land	The proportion of weighted residential land	0.294	0.216	0.000	0.297	0.749
Commercial land	The proportion of weighted commercial land	0.132	0.161	0.000	0.071	0.771
Institutional land	The proportion of weighted general institutional land (e.g., schools, hospitals, governments, and others)	0.135	0.186	0.000	0.033	0.789
Industrial land	The proportion of weighted industrial land	0.033	0.076	0.000	0.000	0.346
Public land	The proportion of weighted public land (e.g., urban green space, playgrounds, and others)	0.102	0.136	0.000	0.054	0.490
Floor area ratio	The weighted floor area ratio	0.908	0.800	0.018	0.663	4.828
Transportation infrastructure (n = 2)						
Bike lanes	The number of weighted bike lane points	7.348	6.508	0.000	6.229	27.179
Bus stops	The number of weighted bus stops	1.084	0.946	0.000	1.131	4.381
Population distribution (n = 3)						
Russian residents	The number of weighted residents whose native language is Russian	33	77	0	4	392
Foreigner residents	The number of weighted residents whose native language is neither Russian nor Estonian	19	63	0	4	482
Population composition						
Male teenager residents	The proportion of weighted male residents aged 15–19 (for Model 1)	0.026	0.023	0.000	0.024	0.125
Male young residents	The proportion of weighted male residents aged 20–34 (for Model 2)	0.115	0.086	0.000	0.110	0.481
Male middle-aged residents	The proportion of weighted male residents aged 35–64 (for Model 3)	0.178	0.096	0.000	0.206	0.347
Male senior residents	The proportion of weighted male residents aged ≥ 65 (for Model 4)	0.056	0.046	0.000	0.059	0.222
Female teenager residents	The proportion of weighted female residents aged 15–19 (for Model 5)	0.029	0.029	0.000	0.027	0.222
Female young residents	The proportion of weighted female residents aged 20–34 (for Model 6)	0.116	0.089	0.000	0.108	0.493
Female middle-aged residents	The proportion of weighted female residents aged 35–64 (for Model 7)	0.198	0.104	0.000	0.236	0.383
Female senior residents	The proportion of weighted female residents aged ≥ 65 (for Model 8)	0.107	0.074	0.000	0.107	0.241

Appendix B

This study used the Gaussian function (i.e., Eq. (1)) to generate a series of coefficients to quantify the differentiated effect of station-surrounding characteristics on bike-sharing usage. Coefficients range between 0 and 1 – the shorter the distance from the characteristic to the bike station, the larger the coefficient attached to that characteristic. These coefficients were incorporated into the calculation of explanatory variables. Specifically, the proportion of weighted residential, commercial, institutional, industrial, and public land was calculated by Eq. (2). The weighted floor area ratio was calculated by Eq. (3). Proximity to bike lanes and bus stops were calculated by Eq. (4) and Eq. (5), respectively. The number of weighted Russian and foreigner residents was calculated by Eq. (6). The population composition variable was calculated by Eq. (7)

$$G(d_{ik}) = \begin{cases} \frac{e^{-\frac{1}{2} \left(\frac{d_{ik}}{d_{max}}\right)^2} - e^{-\frac{1}{2}}}{1 - e^{-\frac{1}{2}}}, & d_{ik} < d_{max} \\ 0, & d_{ik} \geq d_{max} \end{cases} \tag{1}$$

Where i is the index of bike stations, k is the index of characteristics around bike stations (i.e., land use, buildings, bike lanes, bus stops, and population grids), d_{ik} is the distance between the station i and the characteristic k , d_{max} is the distance threshold beyond which the characteristics have few effect on bike-sharing usage.

$$land_prop_{il} = \frac{\sum_{p=1}^p G(d_{il})}{\sum_{k=1}^m G(d_{ik})} \tag{2}$$

Where i is the index of bike stations, k is the index of land grids, l is the index of the land grids of a specific land use type, m is the total number of all land grids, p is the total number of land grids of a specific land use type.

$$floor_area_ratio_i = \frac{\sum_{z=1}^b G(d_{iz}) FA_z}{\sum_{k=1}^m 900^* G(d_{ik})} \tag{3}$$

Where i is the index of bike stations, z is the index of buildings, k is the index of land grids, d_{iz} is the distance between the station i and the building z , d_{ik} is the distance between the building i and the land grid k , FA_z is total floor areas of the building z , m is the total number of all land grids, b is the total number of buildings.

$$proximity_bike_lane_i = \sum_{c=1}^a G(d_{ic}) \tag{4}$$

Where i is the index of bike stations, c is the index of bike lane points, d_{ic} is the distance between the station i and the bike lane point c , a is the total number of bike lane points.

$$proximity_bus_stop_i = \sum_{s=1}^S G(d_{is}) \tag{5}$$

Where i is the index of bike stations, s is the index of bus stops, d_{is} is the distance between the station i and the bus stop s , S is the total number of bus stops.

$$pop_ethnicity_i = \sum_{o=1}^O Pop_o G(d_{io}) \tag{6}$$

Where i is the index of bike stations, o is the index of population grids, Pop_o is the number of residents living in the population grid o , d_{io} is the distance between the station i and the population grid o , O is the total number of population grids.

$$pop_composition_i = \frac{\sum_{f=1}^F Pop_f G(d_{if})}{\sum_{h=1}^H \sum_{u=1}^U Pop_u G(d_{iu})} \tag{7}$$

Where i is the index of bike stations, f and u are the indices of population grids, h is the index of demographic groups, Pop_f and Pop_u is the number of residents living in the population grids f and u respectively, d_{if} is the distance between the station i and the population grid f , d_{iu} is the distance between the station i and the population grid u , F and U are the total number of population grids in a single demographic group, H is the number of demographic groups.

Appendix C

Table C
Model performance.

Model No.	Representative	Training sets			Test sets		
		R ²	RMSE	MAE	R ²	RMSE	MAE
Model 1	Male teenagers	0.976	0.901	0.602	0.712	3.725	2.767
Model 2	Male young adults	0.983	0.648	0.412	0.750	3.287	2.151
Model 3	Male middle-aged adults	0.962	0.490	0.361	0.718	1.479	1.197
Model 4	Male seniors	0.946	0.094	0.049	0.730	0.191	0.137
Model 5	Female teenagers	0.955	0.868	0.650	0.750	1.377	1.085
Model 6	Female young adults	0.974	0.649	0.461	0.719	2.434	1.851
Model 7	Female middle-aged adults	0.929	0.660	0.394	0.821	0.914	0.749
Model 8	Female seniors	0.950	0.135	0.078	0.704	0.219	0.169

Note: RMSE refers to the root mean squared error; MAE refers to the mean absolute error.

Data availability

The authors do not have permission to share data.

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