

Contents lists available at ScienceDirect

# Journal of Transport Geography



journal homepage: www.elsevier.com/locate/jtrangeo

# *E*-scooter and bike-share route choice and detours: Modelling the influence of built environment and sociodemographic factors

Jerònia Cubells<sup>a,\*</sup>, Carme Miralles-Guasch<sup>a,b</sup>, Oriol Marquet<sup>a,b</sup>

<sup>a</sup> Grup d'Estudis en Mobilitat, Transport i Territori (GEMOTT), Departament de Geografia, Universitat Autònoma de Barcelona, Carrer de la Fortuna s/n, 08193 Bellaterra (Cerdanyola del Vallès), Barcelona, Spain

<sup>b</sup> Institut de Ciència i Tecnologia Ambientals (ICTA), Universitat Autònoma de Barcelona – Edifici ICTA-ICP, Campus de Bellaterra, 08193 Cerdanyola del Vallès, Barcelona, Spain

# ARTICLE INFO

Keywords: Route choice Bicycle Electric scooter Travel behaviour GPS Built environment

#### ABSTRACT

Micromobility is often presented as a sustainable, affordable, and active urban transport option, in comparison to motorised modes. Understanding users routing preferences could help policymakers adapt and design facilities that attract a myriad of micromobility users. Whereas previous research largely focused solely on the built infrastructure, the ways in which sociodemographic factors affect micromobility route choice and infrastructure preferences are unclear. This study examines how elements of the built environment and sociodemographic attributes influence the route selection of 115 e-scooter and bike-share users in Barcelona, Spain. We also compare participants' GPS-tracked trips to the shortest path that they could have followed and develop a multilevel model to estimate how urban and sociodemographic factors affect the decision to deviate from the shortest path. The findings show that micromobility users rarely choose the shortest path since urban elements related to safety, accessibility and aesthetics seem to shape their wayfinding decisions. Results help us comprehend cyclists' and e-scooter riders' distinct route preferences and further illustrate how the gender identity of micromobility users influences route choice and detour. The models indicate that, on average, women take shorter detours than men. We observe gender differences in the way cyclists and e-scooter riders favour certain elements in their trips, such as parked cars and cycling infrastructure. Our findings offer valuable insights into how sociodemographic factors interact with infrastructure and built environment conditions to influence micromobility users' route choice and open up the potential to use these results to manage micromobility flows within cities.

#### 1. Introduction

Cities have witnessed unprecedented growth in micromobility levels over the last decade, which draws environmental and social challenges, but also opportunities to the traditional transport system (Felipe-Falgas et al., 2022; Pucher and Buehler, 2017). Electric scooters (e-scooters hereafter) and bicycles attract new users due to their innovativeness, sustainability, affordability and speed (Bhandal and Noonan, 2022; Bretones and Marquet, 2022). This wave of popularity has brought an increasing interest in understanding how the built environment favours micromobility use (Codina et al., 2022; Cole-Hunter et al., 2015), along with how specific urban elements affect riding behaviour. Among the latter group of studies, the issue of route choice has drawn significant attention. It has been seen that cyclists and e-scooter riders travel longer distances to avoid traffic and its impacts, such as injuries, noise and pollution (Desjardins et al., 2021b; Scott et al., 2021). This excess travel requires more energy consumption per trip and thus can thwart the attractiveness of micromobility modes by decreasing their convenience and extending travel times. Additionally, numerous detours that outstretch travel distances may hinder these modes contribution to reducing transport externalities, which can be translated into health and economic extra costs (Gössling et al., 2019). However, deviating from the shortest path may just be a consequence of the increased adaptability of these modes to the user's needs and preferences. Because of their novelty, not much is known yet on how elements of the built environment differently impact multiple social groups in their micromobility detour decisions. While research recognizes that route choice is ultimately influenced by personal preferences and fears (Hardinghaus and

\* Corresponding author. *E-mail addresses:* jeronia.cubells@uab.cat (J. Cubells), carme.miralles@uab.cat (C. Miralles-Guasch), oriol.marquet@uab.cat (O. Marquet).

https://doi.org/10.1016/j.jtrangeo.2023.103664

Received 28 December 2022; Received in revised form 8 July 2023; Accepted 11 July 2023 Available online 14 July 2023

0966-6923/© 2023 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Weschke, 2022; Ravensbergen et al., 2020a), sociodemographic factors such as gender tend to be overlooked, with only a handful of exceptions (Bernardi et al., 2018; Fitch and Handy, 2020; Prato et al., 2018).

Filling this gap is important both to better assess the impacts of micromobility and to improve the design of urban spaces aimed to invite a myriad of cyclists and e-scooter users. With that objective, this paper examines how route choice is influenced by elements of the built environment and sociodemographic attributes using the GPS-tracked trips of 115 e-scooter and bike-share users in Barcelona, Spain. We further compare those trips to the shortest paths that participants could have followed and build a multilevel model to estimate how urban attributes and sociodemographic factors affect the decision to detour from the shortest path. Moreover, we contribute to the literature by investigating e-scooter and bike-sharing route preferences within the same spatial context.

#### 2. Literature review

In recent years, several attempts have been made to analyse bicycle route choice, whereas research on e-scooter wayfinding is still limited. Most of these studies acknowledge that cyclists tend to prefer short and simple routes. Li et al. (2017), for instance, found that cyclists' route choice is greatly influenced by distance, while Lu et al. (2018) observed that cyclists tend to avoid intricate routes. Nonetheless, Zimmermann et al. (2017) demonstrated that the built environment largely affects cyclists' route preferences and their likeliness to deviate from the shortest path. Extensive research has shown cyclists' willingness to detour to look for dedicated cycling infrastructure (Ghanayim and Bekhor, 2018; Rupi et al., 2019; Wang et al., 2022). It has been noticed that cyclists often favour well-paved and well-lit bicycle lanes, separated from traffic and parked cars (Chen et al., 2018; Desjardins et al., 2021b; Majumdar and Mitra, 2019). In the same vein, cyclists tend to skirt urban elements that slow down their pace such as crosswalks, traffic lights and stops (McArthur and Hong, 2019; Prato et al., 2018).

With that, some cyclists are willing to pedal further to integrate parks and green areas into their trips (Bernardi et al., 2018; Hardinghaus and Nieland, 2021; Lin and Fan, 2020; Marquart et al., 2020). These findings are important because while recreational cycling has been linked with parks and green streetscapes, utilitarian cyclists are often highly exposed to traffic-related pollutants (Lee and Sener, 2019; Sun et al., 2017). In terms of route choice, no consensus yet exists on whether cyclists integrate shopping into their routes (Orellana and Guerrero, 2019; Sarjala, 2019) or cycle away from shops and restaurants (Park and Akar, 2019; Skov-Petersen et al., 2018). In the same line, historical points of interests and, presumably, the presence of tourist seem to repel bicycle rides of local cyclists (Desjardins et al., 2022).

In addition to environmental factors, sociodemographic factors have also been found to influence cyclists' route choice (Fitch and Handy, 2020). Schneider et al. (2021) observed that women are less likely to detour from the shortest path than men. When asked about this, women alleged that, pressed for time, balancing productive and reproductive work constrained the possibility of extending their bicycle trips (Ravensbergen et al., 2020b; Sersli et al., 2020). Although women on average present shorter detours than men, they seem willing to pedal further to use protected bicycle lanes (Hardinghaus and Weschke, 2022). To understand why women might outstretch their trips to use cycling infrastructure in a context of limited time availability, it is worth noting that cycling, in comparison to walking, has often been reckoned to magnify the visibility of women and people of colour, drawing unsolicited attention and eliciting harassment (Lubitow et al., 2019). Sersli et al. (2022) found that cycling through traffic requires women to negotiate their presence in the public space and be exposed to aggressions, which some might be unwilling to do. Accordingly, this would trigger the decision to travel greater distances to avoid specific areas even in a context of time constraints. Consequently, safety concerns related to sexism and racism in public spaces are found to shape and limit cyclists' route

choice (Heim LaFrombois, 2019; Ravensbergen, 2022; Ravensbergen et al., 2020a). Similarly, Aldred et al. (2017) suggested that risk tolerance to traffic might also be different across age groups, which translates into older people having stronger preferences for separated infrastructure. Women and older adults also seem to take longer detours than men to ride through parks and quiet neighbourhoods (Hardinghaus and Weschke, 2022; Nawrath et al., 2019). Notwithstanding, these route preferences seem to take effect only during daylight, as fear and prospects of harassment and assault appear to override these paths during nigh-time (Pellicer-Chenoll et al., 2021; Sersli et al., 2022).

Previous literature has found that parents cycling with children are also willing to deviate to run into green areas (Hardinghaus and Weschke, 2022). Indeed, cycling with kids or through pregnancy is perceived to entail an increased sense of responsibility that translates into seeking routes with protected bicycle lanes while eluding parked cars, traffic and narrow streets (Desjardins et al., 2021a; Heim LaFrombois, 2019; Russell et al., 2021; Sersli et al., 2020). These route preferences have relevant social implications within the context of highly gendered travel behaviours. Combining care work and cycling entails developing specific strategies, not only for parents but also for cyclists that incorporate caring tasks such as shopping into their rides. As such, some have suggested combining frequent bike routes with access to everyday and grocery shopping as means of facilitating complex travel schedules (Janke and Handy, 2019; Russell et al., 2021). Nevertheless, Ravensbergen et al. (2020b) investigated how accommodating grocery shopping on cyclists' routes might reproduce, and even reinforce, a gendered division of household labour and care work.

In comparison to bicycle route choice, the study of e-scooter route preferences is still incipient. It is noteworthy that differences in route preference between these vehicles might be due to the distinct sociodemographic characteristics of their riders. The fleet of e-scooter users is on average younger, less affluent, and includes a higher share of men riders than the fleet of cyclists (Bieliński and Ważna, 2020). This finding has also been noted in Barcelona, where cyclists also report higher education levels (Roig-Costa et al., 2021). The scarce literature on escooters route choice shows that, overall, e-scooter users appear to favour well-lit cycling infrastructure, but also sidewalks and one-way roads (Caspi et al., 2020; Yang et al., 2022; Zhang et al., 2021; Zuniga-Garcia et al., 2021). Furthermore, e-scooter riders seem likely to detour to go through green as well as commercial areas (Bai and Jiao, 2020; Yang et al., 2022).

To date, only a handful of studies have simultaneously compared escooter and bicycle rides in the same spatial context. McKenzie (2019) acknowledged slight differences in their spatial occurrence: while bikes dominated in the downtown, e-scooters presented a broader adoption in the periphery of Washington, D.C.. In contrast, shared bikes had a more widespread distribution in comparison to shared e-scooters in Singapore (Zhu et al., 2020). Haworth et al. (2021) found major variance in cycling infrastructure use, due to differentiated regulations on where each vehicle should be ridden. Yet, cycling facilities use is similar between both vehicles in cities in which e-scooters and bicycles share a regulatory framework on where they can be used (Cubells et al., 2023). Regarding vehicle ownership, most of the research gathered spatial data offered by e-scooter-sharing companies (Bai and Jiao, 2020; Caspi et al., 2020; McKenzie, 2019; Yang et al., 2022; Zhang et al., 2021). Therefore, route choices of private e-scooter owners have, to our knowledge, only been investigated using observational data (Haworth et al., 2021; Tuncer et al., 2020). Indeed, this approach let the authors reflect on the easiness of riders to dismount their vehicles and swap from the roadway to the sidewalk, which might facilitate shortcutting (Tuncer et al., 2020). However, it is worth noting that there could be differences in decisionmaking processes between shared and private e-scooters. In the latter case, vehicle availability and economic cost, could be relevant for users to decide their route.

Recent attempts to assess preference for route attributes have greatly

benefited from GPS data. GPS tracking has the strength to infer travel behaviour indicators, such as route choice, and frame them within the surrounding built environment (Park and Akar, 2019). Most studies investigating route choice from GPS-tracking data, however, have failed to disaggregate data by gender (Cho and Shin, 2022; Li et al., 2017; Lin and Fan, 2020; Lu et al., 2018; Pritchard et al., 2019; Sadeghinasr et al., 2021; Wang et al., 2022; Zhang et al., 2021; Zuniga-Garcia et al., 2021) or tracked only a small sample size of cyclists who did not identify as men (Ghanayim and Bekhor, 2018; Lee and Sener, 2019; McArthur and Hong, 2019; Orellana and Guerrero, 2019; Sun et al., 2017; Zimmermann et al., 2017), with very few exceptions (Bernardi et al., 2018; Fitch and Handy, 2020; Prato et al., 2018). Other approaches to assess route choice determinants have used stated preferences surveys and interviews. This body of literature has been particularly successful in reviewing how multiple identities -including gender- influence cyclists' route preferences (Desjardins et al., 2021a; Hardinghaus and Weschke, 2022; Marquart et al., 2020; Nawrath et al., 2019). In contrast to GPS data, surveys ability to measure the use of cycling infrastructure and other elements of the built environment on the way is limited (Fitch and Handy, 2020).

#### 3. Methodology

# 3.1. Study area

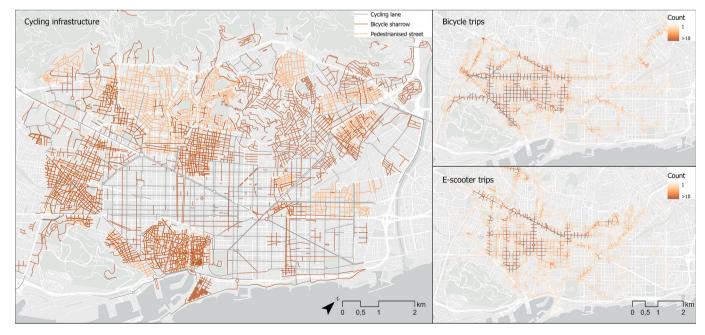
Barcelona, with a population of 1.6 million residents (2020), is located on the northwest coast of the Mediterranean Sea. The city has a compact and mixed urban planning, a uniform distribution of services and an extensive cycling infrastructure (Fig. 1) (Lind et al., 2021; Marquet and Miralles-Guasch, 2018). Micromobility, which includes shared bikes as well as private bikes and e-scooters, constitute up to 4% of Barcelona's modal share (IERMB, 2021). Part of these bicycle trips is performed with shared bikes from the city's public operator *Bicing*. This service can be acquired through an annual subscription and their users perform 2 out of 10 of the micromobility trips registered in the city. This dock-based bike-sharing system covers all city districts, and its >100,000 subscribers undertake about 50,000 trips daily (Soriguera and Jiménez-Meroño, 2020). On the contrary, the city does not provide an escooter-sharing platform as it does not allow private e-scooter sharing companies to operate within the municipality's boundaries. Therefore, all e-scooters ridden in Barcelona are individually owned and their trips represent 26% of the overall micromobility share.

#### 3.2. Data source

In this context, we recruited 902 micromobility users through an intercept survey (more details to be found in Roig-Costa et al. (2021)). Between September 2020 and July 2021, we surveyed 326 e-scooter owners and 325 bike-sharing cyclists through the CAPI (Computer Assisted Personal Interviewing) methodology. From the initial sample, 65 e-scooter riders and 70 bike-sharing cyclists dwelling in Barcelona were further asked to wear a GPS device (QStartz BT-Q1000XT; QStarz International Co., Ltd., Taiwan, R.O.C.) at all times during a week. The GPS logged the location of the recruited cyclists and riders at each 15 s epoch. This study was approved by the Ethics Committee on Animal and Human Experimentation at Universitat Autònoma de Barcelona (CEEAH-3656). Apart from GPS data, a second data set from the municipal open data repository containing characteristics of the built environment and exposure to pollutants was exploited (Ajuntament Ajuntament de Barcelona, 2022a). Both NO2 and acoustic pollution can be understood as proxies of traffic and road hierarchy. Further information on air and acoustic pollution measurement, modelling and mapping can be found elsewhere (Ajuntament Ajuntament de Barcelona, 2022b).

#### 3.3. Data processing

GPS data were processed through the Human Activity Behavior Identification Tool and data Unification System (HABITUS) software. This software identifies trips within trajectories and predicts their transport mode by calculating the distance and speed between consecutive GPS points. HABITUS flagged trips with a 90th percentile speed between 1 and 10 km/h as walking. Following, trips with a 90th percentile speed between 10 and 25 km/h were targeted as micromobility and trips with a 90th percentile speed above the former speed threshold were classified as in vehicle (Kang et al., 2018). This software has been validated to correctly assign micromobility 73% of the time it was actually used (Carlson et al., 2015). Walking and in vehicle trips were filtered out from the analysis.



The remaining GPS points were map-matched to the street network

Fig. 1. Barcelona cycling infrastructure and trip count at each street segment.

to contextualise the routes that micromobility users followed. GPS points were snapped to the street map using a dynamic buffer with an upper search tolerance of 150 m (Li et al., 2020). A total of 1520 routes were then created with the Network Analysis toolset from ArcGIS Pro, based on Dijkstra's algorithm (Lu et al., 2018; Scott et al., 2021). To avoid outliers, we excluded (i) circular trips (174 routes), (ii) trips that lasted <2 min or > 2 h (151 routes), (iii) trips outside the city limits (193 routes), (iv) trips that contained unmatched points to the street network (17 routes), and (v) trips with observations >60 km/h (249 routes) (Clarry et al., 2019; Flügel et al., 2019; Zhang et al., 2021).

To answer whether micromobility users take detours, we compared chosen routes to the shortest path cyclists and e-scooter riders could have followed without committing a traffic infraction. Shortest paths were calculated between each trip origin and destination using the R package 'openrouteservice' (Oleś, 2022). The algorithm inferred the shortest route through the OpenStreetMap (OSM) cycling network, since riding on the sidewalk is generally not allowed in the city (Desjardins et al., 2022; McArthur and Hong, 2019). The output of this process was the shortest route between the first and the last observation of each chosen route. Regardless, it is worth noting that some chosen routes covered a shorter distance than 'openrouteservice' inferred routes due to participants riding through streets that are not catalogued in the OSM cycling network. Also, micromobility vehicles have been reported to momentarily invade the sidewalk or ride contraflow, which might explain the presence of shortcuts in our database (Lind et al., 2021; Tuncer et al., 2020). The detour percentage, or Route Deviation Index, was then computed as the ratio of chosen route distance to its shortest route distance (Park and Akar, 2019; Ta et al., 2016):

Detour percentage = 
$$\left(\frac{Chosen route distance}{Shortest route distance} - 1\right) x 100$$

The 95 percentile of the detour percentage was excluded (40 routes) as they mainly accounted for outliers (Klein et al., 2021). This process resulted in a final dataset of 696 routes (of which 51.6% were performed by participants who self-identified as women) undertaken on 90 different days by 63 unique bike-sharing cyclists using conventional bicycles (of whom 39.7% self-reported as women) and 52 e-scooter riders (of whom 46.2% self-reported as women). Each user participated for an average of 2.7 days (sd = 1.5) and 6.3 trips (sd = 5.7) over the week they were given the GPS device. Negative detour percentage values were kept in the analysis as they represent shortcuts, such as riding through streets that are not catalogued in the OSM cycling network, sidewalks and/or contraflow (Fig.2).

The next step was to measure the difference between chosen and shortest path. For each pair of routes, we calculated the percentage of ride circulating through cycling facilities, average pollution exposure and density of urban elements in a 50-m radius (Sarjala, 2019). Cycling facilities included cycling lanes (segregated infrastructure away from traffic), bicycle sharrows (demarcated streets where the driveway is shared with cars) and pedestrianised streets (low-speed areas where the pavement is shared with both cars and pedestrians). We also evaluated the average exposure to NO<sub>2</sub> ( $\mu g/m^3$ ), daytime noise (dB) and Normalized Difference Vegetation Index (NDVI) of each trip, as well as the density of the following urban elements: crosswalks, traffic lights and stops, streetlights, car parking places, historical points of interest, restaurants, intersections, upslopes, shops, and trees. We then calculated the difference in cycling infrastructure use, exposure and built environment between each pair of chosen and shortest routes. Due to the diverse nature and magnitude of the variables, they were normalized using z-scores prior to model building.



Fig. 2. Examples of chosen and shortest paths between three origin and destination pairs.

# 3.4. Statistical analysis

Descriptive statistics and bivariate analysis were used to characterise trip attributes and the urban environment in the route vicinity. Furthermore, a set of multilevel linear mixed-effects models was built, modelling the detour percentage. All the models included user-specific random effects to control for unobserved heterogeneity (Kang and Fricker, 2018). Since each participant performed multiple routes, users represent the highest level of the analysis. In contrast, dependent variables related to the built environment, pollutant exposure, transport mode and sociodemographic characteristics constitute the lowest level. The first model tested detour percentage as a sum of urban elements and environmental exposure, while the second model added sociodemographic variables. The third model ran the same variables as the second model although stratified by transport mode. The sociodemographic variable with the highest estimate that tested for statistical significance in the analysis of variance (type II Wald chi-square tests) was gender. Hence, the fourth (only bicycle trips) and fifth models (only e-scooter trips) were additionally stratified by gender. To facilitate the interpretation of the results, marginal effects were calculated and plotted for those variables that tested for statistical significance in the model analysis of variance.

Regardless the survey handled out to participants offered multiple options to reflect their demographic diversity, particularly in terms of gender identity (woman, man, non-binary), all the participants selfidentified as either women or men, and therefore the results structured gender following the two reported categories.

#### 4. Results

#### 4.1. Trip characteristics

Bike-share cyclists and e-scooter users rode for an average of 2.32 km (sd = 2.15) (Table 1). That was 1.16 km (sd = 1.65) longer than the average shortest path. A comparison between transport modes illustrates that bike-share cyclists travelled a slightly greater distance, 2.48 km (sd = 1.97), than e-scooter riders, with 2.19 km (sd = 2.31). These bicycle trips surpassed the shortest route by 1.06 km (sd = 1.44), while e-scooter rides deviated an average of 1.25 km (sd = 1.83). Most trips included some sort of deviation since 87.93% of them increased the shortest trip distance by at least 5%. Nevertheless, the detour percentage varied significantly between modes: half of the cyclists detoured at least 45.69% from the shortest path whereas half of the e-scooter riders, at least 71.80%. On the contrary, 7.61% of the trips included a megative detour. In this sense, some riders were able to shortcut and almost halve the distance of the inferred shortest route (Fig. 2).

The routes participants followed presented different urban elements than the estimated shortest paths (Table 2). Micromobility users seem to be consciously choosing to travel through streets with a significantly higher density of crosswalks, intersections, and bicycle sharrows, while avoiding stops, traffic lights and parked cars. Incidentally, cyclists and riders are also dismissing pedestrianised areas and streets with lots of shops and streetlights. In the same vein, chosen routes hold higher NO<sub>2</sub> and noise exposure levels than the shortest path.

# Table 2

Characteristics of chosen and shortest routes.

	Chosen route Shortest Differen route		Difference	Paired <i>t</i> -test (p-value)
	mean (sd)	mean (sd)	(%)	
Built environment				
Bicycle sharrow <sup>a</sup>	29.56 (29.66)	0.36 (1.25)	98.78	<0.001
Crosswalks <sup>b</sup>	151.10 (36.25)	128.02 (25.70)	15.27	< 0.001
Historical points of interest <sup>b</sup>	18.66 (23.96)	17.769 (25.58)	4.77	0.151
Intersections <sup>b</sup>	493.39 (258.84)	516.61 (278.85)	4.60	< 0.001
Upslope 15% <sup>a</sup>	1.28 (5.69)	1.32 (5.28)	3.08	0.627
Trees <sup>b</sup>	3618.74 (1139.60)	3645.14 (1247.61)	-0.73	0.267
Restaurants <sup>b</sup>	358.16 (182.75)	363.05 (194.65)	-1.37	0.137
Streetlights <sup>b</sup>	889.47 (275.81)	909.60 (299.80)	-2.26	<0.001
Shops <sup>b</sup>	1195.51 (549.55)	1230.31 (587.79)	-2.91	< 0.001
Stops and traffic lights <sup>b</sup>	4213.60 (1567.95)	4377.91 (1719.91)	-3.90	<0.001
Car parking places <sup>b</sup>	1990.58 (1513.74)	2087.96 (1653.84)	-4.89	0.004
Cycling lane <sup>a</sup>	30.35 (35.98)	33.46 (39.55)	-10.25	0.002
Pedestrianised street <sup>a</sup>	31.49 (38.16)	36.83 (42.21)	-16.96	< 0.001
Environmental expos	ure			
NO <sub>2</sub> (μg/m <sup>3</sup> )	32.86 (4.57)	32.08 (4.68)	2.37	< 0.001
Noise (dB) NDVI	42.00 (4.97) 0.02 (0.05)	41.19 (5.08) 0.02 (0.05)	1.93 0,00	<0.001 0.452

<sup>a</sup> Percentage of route conducted within; <sup>b</sup> Density expressed in units/km<sup>2</sup>.

#### 4.2. Built environment and exposure

The results of the first model show how the built environment, pollutant exposure and transport mode were associated with the detour percentage. The significance and meaningfulness of each of these urban elements to influence detour percentage are captured in the coefficients of Model 1 (Table 3). According to the model, crosswalks are the urban element that explains detour the most. Hence, micromobility users seem to perform greater deviations to run into areas with a high density of crosswalks. On the contrary, pedestrianised streets, bicycle sharrows, stops and traffic lights have the opposite effect as participants tend to dodge them. In terms of exposure, chosen paths were significantly more exposed traffic-related (nitrogen dioxide) and acoustic pollution. The statistical analysis further illustrated that detour percentage varied significantly by transport mode, with e-scooters being associated with higher detour percentages.

# 4.3. Sociodemographic factors and micromobility mode

In comparison with the first model, the second model included sociodemographic variables. This model improved the estimation of the first one (p-value = 0.05) and revealed that sociodemographic attributes

Table	1

Route distances and detour percentage.

	Chosen route (km)			Shortest	Shortest route (km)			Detour (km)			Detour (%)		
	Mean	sd	Median	Mean	sd	Median	Mean	sd	Median	Mean	sd	Median	
Bicycle	2.48	1.97	2.01	1.42*	1.11	1.19	1.06	1.44	0.63	117.82*	167.24	45.69	
E-scooter	2.19	2.31	1.45	0.94*	0.81	0.63	1.25	1.83	0.57	161.14*	196.43	71.80	
Total	2.32	2.15	1.67	1.17	1	0.83	1.16	1.65	0.61	139.98	183.91	54.65	

Significant *p*-values (<0.05) in the ANOVA test between transport modes.

# Table 3

Detour percentage according to the built environment, exposure, transport mode and sociodemographic variables.

		Model 1:		Model 2:		Model 3:			
		Built environment and environmental exposure		Built environment, environmental exposure and sociodemographic variables		Built environment, environmental exposure and sociodemographic variables		Interaction term: Transport mode	
Fixed effects		Coeff <sup>a</sup>	CI 95% <sup>a</sup>	Coeff	CI 95%	Coeff	CI 95%	Coeff	CI 95%
Intercept		126.8	[106.1–147.5]	127.4	[96.8–157.9]	122.5	[85.6–159.4]	-	-
Built environment									
Crosswalks		40.0**	[25.1–55]	41.6**	[26.6-56.5]	36.2**	[15.8–56.7]	9.9	[-20.9-40.7]
Streetlights		2.1	[-13.2-17.5]	2.0	[-13.3-17.3]	-16.7	[-37.6-4.1]	40.5*	[9.1–71.9]
Car parking places		9.24	[-4.8-23.3]	8.2	[-5.9-22.3]	27.9	[5.2–50.5]	-30.6*	[-59.6-1.5]
Historical points of intere	st	4.24	[-10.5 - 19]	0.9	[-14-15.8]	-6.4	[-26.6 - 13.8]	14.5	[-15.9-44.9]
Restaurants		-6.0	[-21.6-9.7]	-7.4	[-23.1-8.3]	-9.0	[-31.2-13.3]	10.7	[-21-42.4]
Stops and traffic lights		-31.3**	[-47.6-15.1]	-30.5**	[-46.6-14.3]	-29.2**	[-53.3-5.2]	-5.7	[-38.9-27.5]
Shops		7.89	[-7.9-23.6]	7.1	[-8.6-22.9]	18.0	[-5.3-41.2]	-17.1	[-49.3-15.2]
Trees		-24.6**	[-39-10.3]	-24.2**	[-38.7-9.9]	-13.8**	[-34.5-6.8]	-19.6	[-48.6-9.3]
Cycling lane		7.97	[-6.4-22.3]	6.5	[-7.8-20.9]	-4.6	[-22.5-13.3]	50.3*	[18.6-82]
Pedestrianised street		-38.2**	[-53.7-22.7]	-37.4**	[-7.3-20.9] [-52.9-22]	-38.9**	[-22.3-13.3] [-60.3-17.5]	-3.0	[-34.5-28.4]
Bicycle sharrow		-32.3**	[-46.1-18.4]	-33.1**	[-46.8-19.4]	-36.2**	[-56.1-16.4]	-5.1	[-23.5-33.8]
Intersections		10.6	[-4.3-25.6]	9.8	[3.5–62.7]	10.5	[-12-32.9]	-1.2	[-32-29.5]
Upslope 15%		0.54	[-14.1-15.2]	0.3	[-5.1-24.7]	-1.3	[-27.2-24.7]	5.3	[-26.5-37]
Environmental exposure									
NO <sub>2</sub>		29.68**	[11.8-47.5]	30.8**	[12.9-48.7]	29.9**	[4.8-55]	3.2	[-32.6-39]
Noise		32.5**	[13.9–51.1]	31.8**	[13.1–50.4]	31.0**	[5.3–56.7]	-0.9	[-38.5-36.8]
NDVI		5.7	[-7.7-19.2]	7.3	[-6-20.7]	6.9	[-13.8-27.6]	-1.4	[-29-26.1]
Turner out words									
Transport mode	D:1-								
Transport mode	Bicycle	=ref	5 0 4 60 03	=ref		=ref	5 05 4 04 03	=ref	
	E-scooter	30.2*	[-0.4-60.8]	33.1*	[-14.4-14.9]	23.2*	[-35.4-81.8]	-	-
Sociodemographic variab	les								
Gender	Woman	-	-	=ref		=ref		=ref	
	Man	-	-	31.5*	[2.3-60.7]	20.2*	[-22.5-63]	25.7	[-36-87.3]
Parent of a minor child	No	_	_	=ref	-	=ref	-	=ref	
	Yes	_	_	-26.8	[-59.8-6.2]	-23.9	[-71.9-24]	18.5	[-51.4-88.4]
Age	16-24	_	_	-17.3	[-58.3-23.7]	-18.3	[-73.8-37.2]	21.9	[-63-106.8]
	25-34	_	_	=ref		=ref	[ /010 0/12]	=ref	[ 00 100.0]
	35-44	_	_	-19.0	[-57.9-19.9]	12.1	[-41.3-65.5]	-50.4	[-131.1-30.2]
	>45	_	-	-12.9	[-54.5-28.6]	4.2	[-55.4-63.9]	-18.6	[-105.3-68]
Random effects		016 (06 2	->	506 0 600	-	<b>FRO</b> 0 (00)	0		
User-specific variance (sd) Residual variance (sd)		916 (30.27)		506.8 (22.5)		572.9 (23.			
Residual variance (sd)		24,325 (1	55.97)	24,436.9 (	(156.32)	23,628.2 (	(153.7)		
Model parameters									
AIC		7155.2		7154.3		7156.1			
BIC		7241.4		7262.1		7354.4			
p-value <sup>b</sup>						0.007			

<sup>a</sup> Abbreviations: coefficient and confidence interval.

\* Significant *p*-values (<0.05) in the analysis of variance (type II Wald chi-square tests).

\*\* Significant *p*-values (<0.001) in the analysis of variance (type II Wald chi-square tests).

also influenced the detour percentage, together with the previously modelled urban elements, environmental exposure and transport mode (Table 3). From the second model, it is apparent that men performed significantly longer detours than women. The other sociodemographic variables, which were age group and being a parent, did not influence detour percentage significantly.

Since detour percentage varies significantly and greatly by transport mode (an average of 43,32% detour difference between bikes and escooters), the third model intersected the transport mode with all the previously run variables. As result, Model 3 statistically outperformed the fitness of the first model (p-value = 0.007). This last model tested whether the built environment, exposure and sociodemographic characteristics explained cyclists' and e-scooter riders' deviation from the shortest path differently. Indeed, the third model presents that, for escooter trips, the chosen path had a greater share of cycling lanes and accounted for more streetlights and fewer car parking places, while the opposite was observed for bicycle rides.

Models 1 to 3, although adjusted by transport mode, included both bicycle and e-scooter trips. In the next set of models, the two vehicles were split into different data sets and analysed separately. The variables of the following pair of models were additionally intersected with gender. In the only-bicycles model (Model 4) it is apparent that cyclists detoured longer distances seeking to use paths with numerous crosswalks (Table 4). For e-scooters (Model 5), greater deviations from the shortest path were associated with selecting routes that run through dedicated cycling lanes and with a higher density of crosswalks. Both cyclists and e-scooter riders seemed to avoid routes with abundancy of stops, traffic lights, pedestrianised streets and bicycle sharrows, as illustrated in Fig.3. Results also suggest that both cyclists and e-scooter riders would have been less exposed to traffic-related pollutants if they

# Table 4

Detour percentage according to the built environment, exposure, transport mode and sociodemographic variables, stratified by transport mode.

Age $16-24$ $26.9$ $[-43.8-97.5]$ $-120.8$ $[-221.7-19.9]$ $116.1$ $[17.5-214.6]$ $-232.1^{\pm}$ $[-386-78.2]$ $25-34$ $=ref$ $=ref$ $=ref$ $=ref$ $=ref$ $=ref$ $=ref$ $35-44$ $21.3$ $[-39.3-82]$ $-46.4$ $[-135.9-43.2]$ $84.5$ $[-35.4-204.5]$ $-167.1^{*}$ $[-318.7-15.4]$ $>45$ $-12.0$ $[-99.3-75.3]$ $8.5$ $[-100.7-117.6]$ $64.2$ $[-47.3-175.7]$ $-149.4^{*}$ $[-309.4-10.5]$ Random effects			Model 4: Bicycles Model 5: E-scooter						ooters			
$\begin{array}{c c c c c c c c c c c c c c c c c c c $					Interactio	n term: Gender			Interaction	term: Gender		
Built environment           Built environment           Crosswalls         24.8**         [-01-49.7]         21.4         [-15.8-58.6]         43.1**         [66-79.5]         -1.0         [-52.9-38.4]           Streetlights         -1.0         [-42.27.26]         -6.6         [-32.6-27.9]         -4.2         [-41.4-32.9]         36.9         [-17.5-91.3]           Crospandia         7.7         [-22.9-38.4]         37.4         [-37.6-28.3]         -51.0*         [-94.2-7.5]           Stops and traffic lights         -4.3         [-94.2-7.5]           Stops and traffic lights         -4.3         [-92.9-37.7]           Trees         -20.8         [-46.4-4.9]         1.0         [-56.2-15.9]         2.2         [-27.3-77.7]           Trees         -3.1         [-58.9-12.8]         [-36.6-3.7]         7.0         [-53.7-39.4]         [-7.0         [-53.7-39.4]	Fixed effects		Coeff	CI 95% <sup>a</sup>	Coeff	CI 95%	Coeff	CI 95%	Coeff	CI 95%		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Intercept		106.0	[70.3–141.7]	-	-	86.7	[22.8–150.6]	-	-		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Built environment											
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Crosswalks		24.8**	[-0.1-49.7]	21.4	[-15.8-58.6]	43.1**	[6.6–79.5]	-1.0	[-53-51.1]		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Streetlights		-10.5	[-36.8 - 15.8]	-10.0	[-48 - 27.9]	-4.2	[-41.4-32.9]	36.9	[-17.5 - 91.3]		
Restaurans       -8.3 $[-42.7-26]$ -5.0 $[-47.7-37.7]$ -5.9 $[-37.5-25.8]$ 21.9 $[-32.4-76.1]$ Stops and traffic lights       -47.9° $[-80.8-15.1]$ 26.0 $[-17.6-69.5]$ $-37.1^\circ$ $[-73.3-0.8]$ 11.4 $[-39.8-62.6]$ Stops and traffic lights       -43.3 $[-29.37.7]$ 19.0 $[-23.3-61.4]$ -20.1 $[-56.2-15.9]$ 25.2 $[-27.3-77.7]$ Trees       -20.8 $[-46.4-4.9]$ 4.9 $[-34.4-44.1]$ $-34.4^{+*}$ $[-68-0.7]$ 5.4 $[-41.7-52.6]$ Cycling lane       -17.4 $[-30.6-4.7]$ 34.0° $[1.9-66.2]$ 56.1° $[10.46-37.3]$ $7.0^\circ$ $[22.0-132.0]$ Bicycle sharrow       -24.9° $[-48.1-1.8]$ $-22.1$ $[-58.9-12.8]$ $-28.9^\circ$ $[-63-5.2]$ $-7.0$ $[-53.7-39.8]$ Intersections       18.3 $[-10.7-47.3]$ $-8.5$ $[-48.6-31.5]$ $4.9$ $[-27.9-37.8]$ $9.9$ $[-39.58.7]$ Upslope 15%       62 $[-23.2-35.6]$ $-14.3$ $[-63.6-34.9]$ $-7.9$ $[-74.3-58.6]$ $22.1$ $[-48.3-92.6]$	Car parking places		7.7	[-22.9-38.4]	37.4	[-2.6-77.4]	29.9	[1.5–58.3]	-51.0*	[-92.2-9.9]		
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Historical points of interes	st	-6.6	[-36-22.9]	4.0	[-33.6-41.5]	32.3	[-3.7-68.3]	-43.3	[-94.2-7.5]		
Shops4.3 $[-29-37.7]$ 19.0 $[-23.3-61.4]$ $-20.1$ $[-56.2-15.9]$ 25.2 $[-27.3-77.7]$ Trees $-20.8$ $[-46.4.4.9]$ 4.9 $[-34.4.44.1]$ $-34.4^{+*}$ $[-68-0.7]$ 5.4 $[-41.7-52.6]$ Cycling lane $-17.4$ $[-39.6.4.7]$ $34.0^{\circ}$ $[1.9-66.2]$ $56.1^{\circ}$ $[15.5-96.8]$ $-38.8$ $[-97.3-97.7]$ Predestrianised street $-31.4^{+*}$ $[-646-1.8]$ $-16.5$ $[-57.7-24.6]$ $-70.9^{+*}$ $[1-04.6-37.3]$ $77.0^{+*}$ $[22.0-132.0]$ Bicycle sharrow $-24.9^{-*}$ $[-48.1-1.8]$ $-23.1$ $[-58.9-12.8]$ $-28.9^{+*}$ $[-63-5.2]$ $-7.0$ $[-53.7-39.8]$ Intersections18.3 $[-10.7-47.3]$ $-8.5$ $[-48.6-31.5]$ $4.9$ $[-27.9-37.8]$ $9.9$ $[-39-58.7]$ Upslope 15% $6.2$ $[-23.2-35.6]$ $-14.3$ $[-63.6-34.9]$ $-7.9$ $[-74.3-58.6]$ $22.1$ $[-48.3-92.6]$ Environmental exposure $8.3$ $[-10.7-47.3]$ $-8.5$ $[-48.6-31.5]$ $4.9$ $[-22.9-50.9]$ $41.1$ $[-20.8-102.9]$ Noise $12.1^{+}$ $[-19.2-43.5]$ $46.4^{+}$ $[0.9-92]$ $45.4^{+}$ $[0.7-90.3]$ $-6.4$ $[-71.2-58.3]$ NDVI $5.7$ $[-19.9-31.2]$ $16.3$ $[-21.1-53.8]$ $21.4$ $[-53.48.1]$ $-28.8$ $[-73.5-15.9]$ Sociodemographic variables $-eff$ $-ref$ $-ref$ $-ref$ $-ref$ $-ref$ GenderWoman $=ref$ $=ref$ $=re$	Restaurants		-8.3	[-42.7-26]	-5.0	[-47.7-37.7]	-5.9	[-37.5-25.8]	21.9	[-32.4-76.1]		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Stops and traffic lights		-47.9*	[-80.8 - 15.1]	26.0	[-17.6-69.5]	-37.1*	[-73.3-0.8]	11.4	[-39.8-62.6]		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Shops		4.3	[-29-37.7]	19.0	[-23.3-61.4]	-20.1	[-56.2-15.9]	25.2	[-27.3-77.7]		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	•		-20.8	[-46.4-4.9]	4.9	[-34.4-44.1]	-34.4**	[-68-0.7]	5.4	[-41.7-52.6]		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Cycling lane		-17.4	[-39.6-4.7]	34.0*	[1.9-66.2]	56.1*	[15.5–96.8]	-38.8	[-97.3-19.7]		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Pedestrianised street		-31.4**	[-64.6 - 1.8]	-16.5	[-57.7 - 24.6]	-70.9**	[-104.6-37.3]	77.0**	[22.0-132.0]		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Bicycle sharrow		-24.9**	[-48.1 - 1.8]	-23.1	[-58.9 - 12.8]	-28.9**	[-63-5.2]	-7.0	[-53.7-39.8]		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Intersections		18.3	[-10.7-47.3]	-8.5	[-48.6-31.5]	4.9		9.9			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Upslope 15%		6.2	[-23.2-35.6]	-14.3	[-63.6-34.9]	-7.9	[-74.3-58.6]	22.1	[-48.3-92.6]		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Environmental exposure											
Noise $12.1^{\circ}$ $[-19.2-43.5]$ $46.4^{\circ}$ $[0.9-92]$ $45.4^{\circ}$ $[0.7-90.3]$ $-6.4$ $[-71.2-58.3]$ NDVI $5.7$ $[-19.9-31.2]$ $16.3$ $[-21.1-53.8]$ $21.4$ $[-5.3-48.1]$ $-28.8$ $[-73.5-15.9]$ Sociodemographic variablesGenderWoman $=ref$ $=ref$ $=ref$ $=ref$ $=ref$ Man $59.4$ $[4.3-114.5]$ $  156.3$ $[64.2-248.4]$ $-$ Parent of a minor childNo $=ref$ $=ref$ $=ref$ $=ref$ $=ref$ Yes $-6.5$ $[-62.3-49.3]$ $22.4$ $[-66.2-111.1]$ $-51.3$ $[-146.1-43.5]$ $28.0$ $[-101.5-157.6]$ Age $16-24$ $26.9$ $[-43.8-97.5]$ $-120.8$ $[-221.7-19.9]$ $116.1$ $[17.5-214.6]$ $-232.1^{\circ}$ $[-386-78.2]$ $25-34$ $=ref$ $=ref$ $=ref$ $=ref$ $=ref$ $=ref$ $=ref$ $35-44$ $21.3$ $[-39.3-82]$ $-46.4$ $[-135.9-43.2]$ $84.5$ $[-35.4-204.5]$ $-167.1^{\circ}$ $[-309.4-10.5]$ $8.5$ $[-100.7-117.6]$ $64.2$ $[-47.3-175.7]$ $-149.4^{\circ}$ $[-309.4-10.5]$ Random effects	-		64.9*	[36-93.9]	-76.4*	[-120.8 - 32.2]	11.0	[-28.9-50.9]	41.1	[-20.8 - 102.9]		
NDVI       5.7 $[-19.9-31.2]$ $16.3$ $[-21.1-53.8]$ $21.4$ $[-5.3-48.1]$ $-28.8$ $[-73.5-15.9]$ Sociodemographic variables       Gender       Woman $=ref$			12.1*		46.4*		45.4*		-6.4			
GenderWoman=ref=ref=ref=ref=refMan $59.4$ $[4.3-114.5]$ 156.3 $[64.2-248.4]$ Parent of a minor childNo=ref=ref=ref=ref=refYes-6.5 $[-62.3-49.3]$ $22.4$ $[-66.2-111.1]$ -51.3 $[-146.1-43.5]$ $28.0$ $[-101.5-157.6]$ Age $16-24$ $26.9$ $[-43.8-97.5]$ -120.8 $[-221.7-19.9]$ $116.1$ $[17.5-214.6]$ -232.1* $[-386-78.2]$ $25-34$ =ref=ref=ref=ref=ref=ref=ref $35-44$ $21.3$ $[-39.3-82]$ -46.4 $[-135.9-43.2]$ $84.5$ $[-35.4-204.5]$ -167.1* $[-318.7-15.4]$ >45-12.0 $[-99.3-75.3]$ $8.5$ $[-100.7-117.6]$ $64.2$ $[-47.3-175.7]$ -149.4* $[-309.4-10.5]$ Random effects	NDVI		5.7	[-19.9-31.2]	16.3	[-21.1-53.8]	21.4	[-5.3-48.1]	-28.8			
GenderWoman=ref=ref=ref=ref=refMan $59.4$ $[4.3-114.5]$ 156.3 $[64.2-248.4]$ Parent of a minor childNo=ref=ref=ref=ref=refYes-6.5 $[-62.3-49.3]$ $22.4$ $[-66.2-111.1]$ -51.3 $[-146.1-43.5]$ $28.0$ $[-101.5-157.6]$ Age $16-24$ $26.9$ $[-43.8-97.5]$ $-120.8$ $[-221.7-19.9]$ $116.1$ $[17.5-214.6]$ $-232.1^{\circ}$ $[-386-78.2]$ $25-34$ =ref=ref=ref=ref=ref=ref=ref $35-44$ $21.3$ $[-39.3-82]$ $-46.4$ $[-135.9-43.2]$ $84.5$ $[-35.4-204.5]$ $-167.1^{\circ}$ $[-318.7-15.4]$ >45 $-12.0$ $[-99.3-75.3]$ $8.5$ $[-100.7-117.6]$ $64.2$ $[-47.3-175.7]$ $-149.4^{\circ}$ $[-309.4-10.5]$ Random effects	Sociodemographic variab	les										
Parent of a minor childNo=ref=ref=ref=refYes $-6.5$ $[-62.3-49.3]$ $22.4$ $[-66.2-111.1]$ $-51.3$ $[-146.1-43.5]$ $28.0$ $[-101.5-157.6]$ Age $16-24$ $26.9$ $[-43.8-97.5]$ $-120.8$ $[-221.7-19.9]$ $116.1$ $[17.5-214.6]$ $-232.1^*$ $[-386-78.2]$ $25-34$ =ref=ref=ref=ref=ref=ref $35-44$ $21.3$ $[-39.3-82]$ $-46.4$ $[-135.9-43.2]$ $84.5$ $[-35.4-204.5]$ $-167.1^*$ $[-318.7-15.4]$ $>45$ $-12.0$ $[-99.3-75.3]$ $8.5$ $[-100.7-117.6]$ $64.2$ $[-47.3-175.7]$ $-149.4^*$ $[-309.4-10.5]$ Random effects	• •		=ref		=ref		=ref		=ref			
Parent of a minor childNo=ref=ref=ref=refYes $-6.5$ $[-62.3-49.3]$ $22.4$ $[-66.2-111.1]$ $-51.3$ $[-146.1-43.5]$ $28.0$ $[-101.5-157.6]$ Age $16-24$ $26.9$ $[-43.8-97.5]$ $-120.8$ $[-221.7-19.9]$ $116.1$ $[17.5-214.6]$ $-232.1^*$ $[-386-78.2]$ $25-34$ =ref=ref=ref=ref=ref $35-44$ $21.3$ $[-39.3-82]$ $-46.4$ $[-135.9-43.2]$ $84.5$ $[-35.4-204.5]$ $-167.1^*$ $[-318.7-15.4]$ $>45$ $-12.0$ $[-99.3-75.3]$ $8.5$ $[-100.7-117.6]$ $64.2$ $[-47.3-175.7]$ $-149.4^*$ $[-309.4-10.5]$ Random effects		Man	59.4	[4.3–114.5]	_	_	156.3	[64.2-248.4]	_	_		
AgeYes $-6.5$ $[-62.3-49.3]$ $22.4$ $[-66.2-111.1]$ $-51.3$ $[-146.1-43.5]$ $28.0$ $[-101.5-157.6]$ Age $16-24$ $26.9$ $[-43.8-97.5]$ $-120.8$ $[-221.7-19.9]$ $116.1$ $[17.5-214.6]$ $-232.1^{*}$ $[-386-78.2]$ $25-34$ $=ref$ $=ref$ $=ref$ $=ref$ $=ref$ $=ref$ $35-44$ $21.3$ $[-39.3-82]$ $-46.4$ $[-135.9-43.2]$ $84.5$ $[-35.4-204.5]$ $-167.1^{*}$ $[-309.4-10.5]$ $>45$ $-12.0$ $[-99.3-75.3]$ $8.5$ $[-100.7-117.6]$ $64.2$ $[-47.3-175.7]$ $-149.4^{*}$ $[-309.4-10.5]$ Random effects	Parent of a minor child	No	=ref		=ref		=ref		=ref			
Age $16-24$ $25-34$ $26.9$ $=ref$ $[-43.8-97.5]$ $=ref$ $-120.8$ $=ref$ $[-221.7-19.9]$ $=ref$ $116.1$ $=ref$ $[17.5-214.6]$ $=ref$ $-232.1^{\pm}$ $=ref$ $[-386-78.2]$ $=ref$ $35-44$ $>45$ $21.3$ $=12.0$ $[-39.3-82]$ $=99.3-75.3]$ $-46.4$ $=135.9-43.2]$ $84.5$ $=100.7-117.6]$ $[-35.4-204.5]$ $=167.1^{\pm}$ $-167.1^{\pm}$ $=149.4^{\pm}$ $[-309.4-10.5]$ Random effectsRandom effects		Yes		[-62.3-49.3]	22.4	[-66.2-111.1]	-51.3	[-146.1-43.5]	28.0	[-101.5-157.6]		
25-34       =ref       =ref       =ref       =ref         35-44       21.3       [-39.3-82]       -46.4       [-135.9-43.2]       84.5       [-35.4-204.5]       -167.1*       [-318.7-15.4]         >45       -12.0       [-99.3-75.3]       8.5       [-100.7-117.6]       64.2       [-47.3-175.7]       -149.4*       [-309.4-10.5]         Random effects	Age	16-24	26.9		-120.8		116.1		-232.1*			
35-44       21.3       [-39.3-82]       -46.4       [-135.9-43.2]       84.5       [-35.4-204.5]       -167.1*       [-318.7-15.4]         >45       -12.0       [-99.3-75.3]       8.5       [-100.7-117.6]       64.2       [-47.3-175.7]       -149.4*       [-309.4-10.5]         Random effects	0											
>45 -12.0 [-99.3-75.3] 8.5 [-100.7-117.6] 64.2 [-47.3-175.7] -149.4* [-309.4-10.5] Random effects				[-39.3-82]		[-135.9-43.2]		[-35.4-204.5]		[-318.7-15.4]		
										[-309.4-10.5]		
	Random effects											
User-specific variance (sd) 96.6 (9.8) 1260 (35.5)		1	96.6 (9.8)				1260 (35.5	)				
Residual variance (sd) 17.179.9 (131.1) 27.213 (164.96)	1 ,		• •	131 1)			-					

<sup>a</sup> Abbreviations: coefficient and confidence interval.

<sup>\*</sup> Significant *p*-values (<0.05) in the analysis of variance (type II Wald chi-square tests).

\*\* Significant p-values (<0.001) in the analysis of variance (type II Wald chi-square tests).

had followed OSM route recommendations.

Results indicate that gender greatly explains detour, as it accounted for the highest coefficient in Model 2 among sociodemographic variables (Table 3). In addition, Model 3 further revealed that women took shorter detours than men regardless of the micromobility vehicle used. In Models 4 and 5, the variable gender was additionally intersected with route attributes to evaluate whether men and women favoured them differently (Table 4). This analysis highlighted that bike-share cyclists seem to equally value the elements of the surrounding built environment, except for cycling lanes (Fig. 4). Results show that men cyclists appear to pedal further to incorporate cycling lanes into their routes. In contrast, there are gender differences in the way e-scooter riders integrate specific route attributes in their rides. Compared to women, men riding e-scooters deviate further from the shortest route to avoid car parking places while seeking to go across pedestrianised streets. Furthermore, detour percentages were significantly associated with the age of the e-scooter riders. The cohort that encapsulated 25 to 34-yearold participants was the age group with the greatest gender gap in terms of detour percentage, in which men travelled further from the shortest path than women (Table 4).

#### 5. Discussion

# 5.1. Detour

Our results indicate that only a minority of micromobility trips actually used the shortest path available. In fact, almost 9 of every 10 trips deviated from the shortest route to some extent, which is consistent with previous research (Park and Akar, 2019). However, micromobility users in Barcelona seem to have picked circuitous routes that, on average, surpass the detour percentage of other study cases (Chen et al., 2018; Fitch and Handy, 2020; Ghanayim and Bekhor, 2018; Lu et al., 2018). These differences might be indicative of a more fragmented network of dedicated infrastructure. Nonetheless, our sample being composed of both e-scooter and bike-sharing trips might also be skewing our results towards longer and more frequent detours, as e-scooter trips have been estimated to account for longer deviations than shared bicycle. The reasons explaining e-scooters' greater detour are threefold. First, riding an e-scooter is not as physically demanding as it is to ride a bicycle (López-Dóriga et al., 2022). Therefore, outstretching an escooter trip does not result in a physical payoff. Second, e-scooter use has often been regarded to support riding for leisure, tourism or for fun sake (McKenzie, 2019; Roig-Costa et al., 2021; Weschke et al., 2022), which would side with not selecting the most direct route. Thirdly, variations in vehicle ownership may contribute to the observed differences in detouring behaviour between e-scooters and shared bicycles. In

J. Cubells et al.

Journal of Transport Geography 111 (2023) 103664

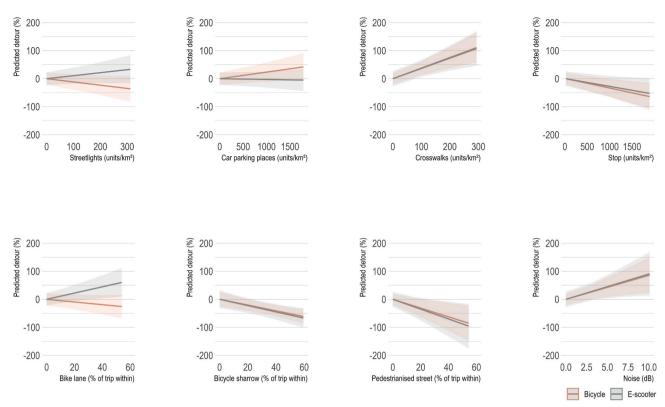


Fig. 3. Route attributes and detour trade-off calculated using Models 3-5 marginal effects.

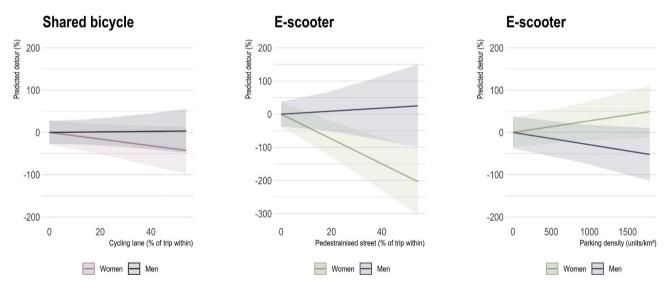


Fig. 4. Route attributes of e-scooter trips and detour trade-off by gender calculated using Model 5 marginal effects.

Barcelona, e-scooters are exclusively privately owned, while shared bicycles operate under a fee structure that imposes charges on users exceeding a 30-min ride duration (Bustamante et al., 2022). This pricing mechanism could potentially be incentivizing bike-share users to prioritize shorter, more direct routes, in contrast to e-scooters. In addition to detour, our analysis also revealed the presence of shortcuts. Shortcuts can represent wrong-way riding but also participants using infrastructure that is not catalogued as cyclable by OSM (Dhakal et al., 2018). Both e-scooters and shared bikes are light vehicles that make it possible to engage in a series of small infractions such as temporarily invading the sidewalk or riding contraflow, which might explain the presence of shortcuts in our database (Lind et al., 2021; Tuncer et al., 2020).

#### 5.2. Built environment and environmental exposure

Our analysis confirms previous studies finding that built environment conditions effectively impact wayfinding and route choices (Zimmermann et al., 2017). In this regard, previous work has noticed the importance of dedicated cycling infrastructure to explain detour (Lu et al., 2018; Wang et al., 2022). As shown in our results, e-scooter riders are willing to deviate significantly from the shortest path to travel through bicycle lanes. This behaviour might be related to the feeling of insecurity when sharing space with cars, or the feeling of being a nuisance for pedestrians when riding through the sidewalk (Gibson et al., 2022). Our findings corroborate those of Zhang et al. (2021) and Zuniga-Garcia et al. (2021) on e-scooter riders' preference for cycling lanes. However, neither bike-share cyclists nor e-scooter riders seem to detour to favour routes with a high proportion of bicycle sharrows or pedestrianised streets. For the case of bicycle sharrows, our results contradict earlier research (Park and Akar, 2019; Rupi and Schweizer, 2018; Yang et al., 2022) although this might be due to OSM route engines tending not to recommend routes with bike sharrows (Table 2). Avoiding pedestrianised areas, on the other hand, is in accordance with prior findings (Lee and Sener, 2019; Skov-Petersen et al., 2018). These authors argue that micromobility users avoid sharing the space with pedestrians because it slows down their pace.

Similarly, cyclists and e-scooter riders tend to plan their routing to skirt stops and traffic lights, as evidenced in our results and the literature (Prato et al., 2018). One could expect this behaviour to be a consequence of trying to maximize travel speed and flow (Cubells et al., 2023). Notwithstanding, this narrative is countered by the fact that micromobility users are also found to be selecting routes that have a higher density of crosswalks. Previous research has also documented micromobility users' preference for spaces with clear formal traffic rules that increase space readability, and lower riding uncertainty (Cho and Shin, 2022; Li et al., 2017). Streets with delimited spaces for different uses and a high density of designated crosses are perceived as safer by most micromobility users. This might explain micromobility users in our sample selecting routes with numerous crosswalks, which appears to represent a safer way of interacting with pedestrians (Skov-Petersen et al., 2018). Indeed, it is often claimed that perception of risk along with risk-mitigating attitudes might be as relevant as distance in micromobility route choice (Kang and Fricker, 2018; Majumdar and Mitra, 2019). This is in line with our results showing that e-scooter riders favour well-lit routes and avoid streets with numerous car parking places (Yang et al., 2022).

Regarding environmental exposure, our results seem to suggest that participants are not detouring to integrate urban greenness into their rides. While there is extensive literature on cyclists' and e-scooter riders' willingness to ride further to include greenery (Bernardi et al., 2018; Lin and Fan, 2020; Marquart et al., 2020; Yang et al., 2022), our results offer significant nuance on a compact-city spatial context with low levels of green areas but a homogeneous high tree coverage (Baró et al., 2019). Thus, our findings point out that users are not choosing to detour in order to encounter higher tree density. Yet, other life-forms of vegetation, such as shrubs and grasses, or even bare soil were not accounted for in the tree database and were only captured when analysing land coverage through NDVI.

In terms of land use, results are not conclusive on whether micromobility users integrate or avoid shopping while riding (Desjardins et al., 2022; Orellana and Guerrero, 2019; Schneider et al., 2021; Soltani et al., 2022). Neither restaurants nor historical points of interests have a clear positive or negative effect on route choice, as noticed by Sarjala (2019). Remarkably, Desjardins et al. (2022) and Fitch and Handy (2020) reported that the presence of restaurants and historical points of interests repelled micromobility users. Overall, this constitutes one of the first attempts to understand how e-scooter riders integrate both shopping and green elements into their rides (Bai and Jiao, 2020; Yang et al., 2022).

Results also reveal that wayfinding strategies of micromobility users might inevitably expose them to higher levels of traffic-related (NO<sub>2</sub>) and acoustic pollution than those of shortest routes. This clearly contrasts with findings from previous studies that have used stated preference surveys and have observed a self-reported disposition to select routes with less traffic and thus less pollution exposure (Desjardins et al., 2021a; Gössling et al., 2019). Our objective GPS tracking data finds that micromobility users are still highly exposed to pollution and noise, as noticed elsewhere (Lee and Sener, 2019; Willberg et al., 2023; Wu et al., 2021).

# 5.3. Sociodemographic factors

Drawing on the results of state preference surveys, several authors have hypothesised how research using spatial data could largely benefit from including sociodemographic variables known to influence route choice (Hardinghaus and Nieland, 2021; Lu et al., 2018; Park and Akar, 2019; Scott et al., 2021). Of all the sociodemographic factors included in our study, neither the age of participants nor their parental status seemed to significantly influence route choice. These findings build on Aldred et al. (2017) conclusions that route choice might not stem directly from participants' age, but rather from other factors such as previous cycling experience or familiarity with the cycling infrastructure network. Additionally, although neither shared bikes nor private escooters support travelling with an extra passenger, we could not exclude the possibility that parents might have been riding with children by their side. In any case, elements of the built environment did not seem to shape parents' route choice when, most likely, riding solo.

In contrast, our results reveal the importance of acknowledging participants' gender to understand route choice. It is apparent that women perform shorter detours than men in Barcelona, particularly cyclists. This is in line with earlier research that observed that women, on average, tend to outstretch their cycling trips to a lesser extent than men (Schneider et al., 2021). Preferring the straightest route to chain trips might also be in accordance with time constraints. Women cyclists have reported feeling pressed for time, juggling care and productive work, and this came across to curtail opportunities for bicycling (Ravensbergen et al., 2020b; Sersli et al., 2020). Apart from the likeliness to detour and its extension, the findings also reflect gender differences in route preferences. Although stated preference surveys surfaced women's willingness to pedal further to incorporate bike lanes into their rides, our GPS data shows that women might not be extending their trips to favour dedicated cycling infrastructure (Hardinghaus and Weschke, 2022). Among e-scooter riders, men's greater deviation comes with the opportunity to elude parked cars while favouring pedestrianised streets. This finding is contrary to previous studies examining bicycle route choice. In those, women pedalled further to run into calm streetscapes, while our results point to the opposite direction among e-scooter riders (Hardinghaus and Weschke, 2022). To the best of our knowledge, this is the first time that gender route-preference differences among e-scooter users are considered.

# 6. Conclusions

This study set out to comprehend how elements of the built environment influenced the trip route choice and detours of 115 bike-share and e-scooter users while acknowledging sociodemographic factors. Micromobility riders in Barcelona did not always choose the shortest path since the presence of cycling infrastructure and urban elements together with personal preferences shaped their route choice. Hence, participants seemed to choose to extend their trips in order to select routes that had a higher density of crosswalks and bicycle sharrows, while avoiding stops, traffic lights and parked cars. Incidentally, riders also avoided pedestrianised areas and streets with lots of shops and streetlights. The results also revealed that cyclists and e-scooter riders shared preferences for certain elements of the built environment (such as crosswalks and stops), whereas they placed different value on others (such as cycling lanes, streetlights, and car parking places). In addition, gender appeared to influence participants' willingness to detour as well as route choice preferences. These gender differences were more salient among private e-scooter users than among bike-share members.

This research is not without limitations. The generalisability of the results is subject to the urban environment and mobility schemes of Barcelona. We note that further investigation is required to assess the applicability of the findings elsewhere and to include other transport modes, such as private bicycles and shared e-scooters, as well as to account for the economic cost and gendered spatial occurrence of trips.

Moreover, since participants were asked to wear the GPS device all day long, the study is limited by the accuracy of trip detection and transport mode inference methods. Future research will greatly benefit from efforts put into improving the GPS processing of micromobility data (Berjisian and Bigazzi, 2022; Lißner and Huber, 2021). While the sample size is not large, this work accounts for an even gender representation of men and women and hence offers valuable insights into gender differences in travel behaviour. Being limited to participants' answers on gender identity, however, this study could not regard route choice of non-binary riders and thus, further efforts ought to be made at exploring the travel behaviour of gender non-conforming people, but also other social groups, such as people with racialised or LGBTQI+ experiences (Lubitow et al., 2020, 2019; Nello-Deakin and Harms, 2019).

The present study is among the first to explore micromobility route selection and detour while accounting for multiple micromobility modes and understanding their distinct detour triggers. Consequently, we contribute to closing the gap between cyclists' and e-scooter riders' different preferences for urban attributes within the same spatial context (McKenzie, 2019). This is an important step given the increasing need for scientific evidence that can help reliably forecast micromobility flows and demand within cities. Similarly, our study is also among the first ones to incorporate the sociodemographic characteristics of the users as predictors of detour and route choice. Our results clearly demonstrate the gendered nature of such decisions and reiterate previous calls on the importance of continuing to take an intersectional approach in our understanding of micromobility use.

#### CRediT authorship contribution statement

Jerònia Cubells: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft. Carme Miralles-Guasch: Resources, Supervision, Project administration. Oriol Marquet: Conceptualization, Methodology, Validation, Resources, Writing – review & editing, Supervision, Project administration.

#### **Declaration of Competing Interest**

None.

# Data availability

The authors do not have permission to share data.

# Acknowledgements

The authors would like to thank the participants who shared their time for this project. We wish to express our gratitude to Oriol Roig-Costa for conducting the data-gathering process. Our research colleagues Zeynep Akinci, Laia Mojica, and Guillem Vich have also shared valuable comments during the design and development of this research. Furthermore, the authors are grateful to the anonymous reviewers and the editor for providing insightful feedback that helped to improve the manuscript. This work was supported by the Spanish Ministry of Science and Innovation (ECOMOV project, TED2021-129280B-I00 and MICROMOV project, PID2019-104344RB-I00); by the Social Observatory of the "la Caixa" Foundation as part of the project: STEPP SR22-00147. J. Cubells is supported by a PhD grant by the Agency for Management of University and Research Grants (AGAUR, FI\_B 00063, 2022) and O. Marquet is funded by a Ramón y Cajal fellowship (RYC-2020-029441-I), awarded by the Spanish Ministry of Science and Innovation. This work was supported by the Spanish Ministry of Science and Innovation (ECOMOV project, TED2021-129280B-I00 and MICROMOV project, PID2019-104344RB-I00); by the Social Observatory of the "la Caixa" Foundation as part of the project: STEPP SR22-00147. J. Cubells is supported by a PhD grant by the Agency for Management of University

and Research Grants (AGAUR, FI\_B 00063, 2022) and O. Marquet is funded by a Ramón y Cajal fellowship (RYC-2020- 029441-I), awarded by the Spanish Ministry of Science and Innovation.

#### References

- Aldred, R., Elliott, B., Woodcock, J., Goodman, A., 2017. Cycling provision separated from motor traffic: a systematic review exploring whether stated preferences vary by gender and age. Transp. Rev. 37, 29–55. https://doi.org/10.1080/ 01441647.2016.1200156.
- Bai, S., Jiao, J., 2020. Dockless E-scooter usage patterns and urban built environments: a comparison study of Austin, TX, and Minneapolis. MN. Travel Behav. Soc. 20, 264–272. https://doi.org/10.1016/j.tbs.2020.04.005.
- Baró, F., Calderón-Argelich, A., Langemeyer, J., Connolly, J.J.T., 2019. Under one canopy? Assessing the distributional environmental justice implications of street tree benefits in Barcelona. Environ. Sci. Pol. 102, 54–64. https://doi.org/10.1016/j. envsci.2019.08.016.
- Berjisian, E., Bigazzi, A., 2022. Evaluation of methods to distinguish trips from activities in walking and cycling GPS data. Transp. Res. Part C Emerg. Technol. 137, 103588 https://doi.org/10.1016/j.trc.2022.103588.
- Bernardi, S., Geurs, K., Puello, L.L.P., 2018. Modelling route choice of dutch cyclists using smartphone data. J. Transp. Land Use 11, 883–900. https://doi.org/10.5198/ jtlu.2018.1143.
- Bhandal, J., Noonan, R.J., 2022. Motivations, perceptions and experiences of cycling for transport: a photovoice study. J. Transp. Health 25, 101341. https://doi.org/ 10.1016/j.jth.2022.101341.
- Bieliński, T., Ważna, A., 2020. Electric scooter sharing and bike sharing user behaviour and characteristics. Sustain. Switz. 12, 1–13. https://doi.org/10.3390/su12229640.
- Bretones, A., Marquet, O., 2022. Sociopsychological factors associated with the adoption and usage of electric micromobility. A literature review. Transp. Policy 127, 230–249. https://doi.org/10.1016/j.tranpol.2022.09.008.
- Bustamante, X., Federo, R., Fernández-i-Marin, X., 2022. Riding the wave: predicting the use of the bike-sharing system in Barcelona before and during COVID-19. Sustain. Cities Soc. 83, 103929. https://doi.org/10.1016/j.scs.2022.103929.
- Carlson, J.A., Jankowska, M.M., Meseck, K., Godbole, S., Natarajan, L., Raab, F., Demchak, B., Patrick, K., Kerr, J., 2015. Validity of PALMS GPS scoring of active and passive travel compared with SenseCam. Med. Sci. Sports Exerc. 47, 662–667. https://doi.org/10.1249/MSS.000000000000446.
- Caspi, O., Smart, M.J., Noland, R.B., 2020. Spatial associations of dockless shared escooter usage. Transp. Res. Part Transp. Environ. 86, 102396 https://doi.org/ 10.1016/j.trd.2020.102396.
- Chen, P., Shen, Q., Childress, S., 2018. A GPS data-based analysis of built environment influences on bicyclist route preferences. Int. J. Sustain. Transp. 12, 218–231. https://doi.org/10.1080/15568318.2017.1349222.
- Cho, S.-H., Shin, D., 2022. Estimation of route choice behaviors of bike-sharing users as first- and last-mile trips for introduction of mobility-as-a-service (MaaS). KSCE J. Civ. Eng. 26, 3102–3113. https://doi.org/10.1007/s12205-022-0802-1.
- Clarry, A., Faghih Imani, A., Miller, E.J., 2019. Where we ride faster? Examining cycling speed using smartphone GPS data. Sustain. Cities Soc. 49, 101594 https://doi.org/ 10.1016/j.scs.2019.101594.
- Codina, O., Maciejewska, M., Nadal, J., Marquet, O., 2022. Built environment bikeability as a predictor of cycling frequency: lessons from Barcelona. Transp. Res. Interdiscip. Perspect. 16, 100725 https://doi.org/10.1016/j.trip.2022.100725.
- Cole-Hunter, T., Donaire-Gonzalez, D., Curto, A., Ambros, A., Valentin, A., Garcia-Aymerich, J., Martínez, D., Braun, L.M., Mendez, M., Jerrett, M., Rodriguez, D., de Nazelle, A., Nieuwenhuijsen, M., 2015. Objective correlates and determinants of bicycle commuting propensity in an urban environment. Transp. Res. Part Transp. Environ. 40, 132–143. https://doi.org/10.1016/j.trd.2015.07.004.
- Cubells, J., Miralles-Guasch, C., Marquet, O., 2023. Gendered travel behaviour in micromobility? Travel speed and route choice through the lens of intersecting identities. J. Transp. Geogr. 106, 103502 https://doi.org/10.1016/j. jtrangeo.2022.103502.
- Ajuntament de Barcelona, 2022a. Open Data BCN [WWW Document]. Serv. Dades Obertes. URL https://opendata-ajuntament.barcelona.cat/ (accessed 9.20.22).
- Ajuntament de Barcelona, 2022b. Environmental data maps [WWW Document]. Ecol. Urban Plan. Infrastruct. Mobil. URL https://ajuntament.barcelona.cat/ecologiaurba na/en/environmental-data-maps (accessed 12.2.22).
- Desjardins, E., Apatu, E., Razavi, S.D., Higgins, C.D., Scott, D.M., Páez, A., 2021a. "Going through a little bit of growing pains": a qualitative study of the factors that influence the route choice of regular bicyclists in a developing cycling city. Transp. Res. Part F Traffic Psychol. Behav. 81, 431–444. https://doi.org/10.1016/j.trf.2021.06.005.
- Desjardins, E., Higgins, C.D., Scott, D.M., Apatu, E., Páez, A., 2021b. Using environmental audits and photo-journeys to compare objective attributes and bicyclists' perceptions of bicycle routes. J. Transp. Health 22, 101092. https://doi. org/10.1016/j.jth.2021.101092.
- Desjardins, E., Higgins, C.D., Scott, D.M., Apatu, E., Páez, A., 2022. Correlates of bicycling trip flows in Hamilton, Ontario: fastest, quietest, or balanced routes? Transportation 49, 867–895. https://doi.org/10.1007/s11116-021-10197-1.
- Dhakal, N., Cherry, C.R., Ling, Z., Azad, M., 2018. Using CyclePhilly data to assess wrong-way riding of cyclists in Philadelphia. J. Saf. Res. 67, 145–153. https://doi. org/10.1016/j.jsr.2018.10.004.
- Felipe-Falgas, P., Madrid-Lopez, C., Marquet, O., 2022. Assessing environmental performance of micromobility using LCA and self-reported modal change: the case of

#### J. Cubells et al.

shared E-bikes, E-scooters, and E-mopeds in Barcelona. Sustainability 14, 4139. https://doi.org/10.3390/su14074139.

Fitch, D.T., Handy, S.L., 2020. Road environments and bicyclist route choice: the cases of Davis and San Francisco, CA. J. Transp. Geogr. 85, 102705 https://doi.org/10.1016/ j.jtrangeo.2020.102705.

- Flügel, S., Hulleberg, N., Fyhri, A., Weber, C., Ævarsson, G., 2019. Empirical speed models for cycling in the Oslo road network. Transportation 46, 1395–1419. https:// doi.org/10.1007/s11116-017-9841-8.
- Ghanayim, M., Bekhor, S., 2018. Modelling bicycle route choice using data from a GPSassisted household survey. Eur. J. Transp. Infrastruct. Res. 18 https://doi.org/ 10.18757/ejtir.2018.18.2.3228.

Gibson, H., Curl, A., Thompson, L., 2022. Blurred boundaries: E-scooter riders' and pedestrians' experiences of sharing space. Mobilities 17, 69–84. https://doi.org/ 10.1080/17450101.2021.1967097.

- Gössling, S., Humpe, A., Litman, T., Metzler, D., 2019. Effects of perceived traffic risks, noise, and exhaust smells on bicyclist behaviour: an economic evaluation. Sustainability 11, 408. https://doi.org/10.3390/su11020408.
- Hardinghaus, M., Nieland, S., 2021. Assessing cyclists' routing preferences by analyzing extensive user setting data from a bike-routing engine. Eur. Transp. Res. Rev. 13 https://doi.org/10.1186/s12544-021-00499-x.
- Hardinghaus, M., Weschke, J., 2022. Attractive infrastructure for everyone? Different preferences for route characteristics among cyclists. Transp. Res. Part Transp. Environ. 111, 103465 https://doi.org/10.1016/j.trd.2022.103465.
- Haworth, N., Schramm, A., Twisk, D., 2021. Changes in shared and private e-scooter use in Brisbane, Australia and their safety implications. Accid. Anal. Prev. 163, 106451 https://doi.org/10.1016/j.aap.2021.106451.
- Heim LaFrombois, M.E., 2019. (re)producing and challenging gender in and through urban space: women bicyclists' experiences in Chicago. Gend. Place Cult. 26, 659–679. https://doi.org/10.1080/0966369X.2018.1555142.
- IERMB, 2021. Enquesta Mobilitat en dia Feiner (EMEF) [WWW Document]. Enquestes Mobilitat. URL https://iermb.uab.cat/ca/enquestes/enquestes-de-mobilitat/#144 7843451840-2-0 (accessed 4.5.22).
- Janke, J., Handy, S., 2019. How life course events trigger changes in bicycling attitudes and behavior: insights into causality. Travel Behav. Soc. 16, 31–41. https://doi.org/ 10.1016/j.tbs.2019.03.004.
- Kang, L., Fricker, J.D., 2018. Bicycle-route choice model incorporating distance and perceived risk. J. Urban Plan. Dev. 144, 04018041. https://doi.org/10.1061/(asce) up.1943-5444.0000485.
- Kang, M., Moudon, A.V., Hurvitz, P.M., Saelens, B.E., 2018. Capturing fine-scale travel behaviors: a comparative analysis between personal activity location measurement system (PALMS) and travel diary. Int. J. Health Geogr. 17, 40. https://doi.org/ 10.1186/s12942-018-0161-9.
- Klein, S., Brondeel, R., Chaix, B., Klein, O., Thierry, B., Kestens, Y., Gerber, P., Perchoux, C., 2021. What triggers selective daily mobility among older adults? A study comparing trip and environmental characteristics between observed path and shortest path. Health Place 102730. https://doi.org/10.1016/j. healthplace.2021.102730.
- Lee, K., Sener, I., 2019. Understanding potential exposure of bicyclists on roadways to traffic-related air pollution: findings from El Paso, Texas, using Strava metro data. Int. J. Environ. Res. Public Health 16, 371. https://doi.org/10.3390/ iierph16030371.
- Li, S., Muresan, M., Fu, L., 2017. Cycling in Toronto, Ontario, Canada: route choice behavior and implications for infrastructure planning. Transp. Res. Rec. J. Transp. Res. Board 2662, 41–49. https://doi.org/10.3141/2662-05.
- Li, W., Wang, S., Zhang, X., Jia, Q., Tian, Y., 2020. Understanding intra-urban human mobility through an exploratory spatiotemporal analysis of bike-sharing trajectories. Int. J. Geogr. Inf. Sci. 34, 2451–2474. https://doi.org/10.1080/ 13658816.2020.1712401.
- Lin, Z., Fan, W., 2020. Bicycle ridership using crowdsourced data: ordered Probit model approach. J. Transp. Eng. Part Syst. 146, 04020076. https://doi.org/10.1061/ JTEPBS.0000399.
- Lind, A., Honey-Roses, J., Corbera, E., 2021. Rule compliance and desire lines in Barcelona's cycling network. Transp. Lett.- Int. J. Transp. Res. 13, 728–737. https:// doi.org/10.1080/19427867.2020.1803542.
- Lißner, S., Huber, S., 2021. Facing the needs for clean bicycle data a bicycle-specific approach of GPS data processing. Eur. Transp. Res. Rev. 13 https://doi.org/ 10.1186/s12544-020-00462-2.
- López-Dóriga, I., Vich, G., Koch, S., Khomenko, S., Marquet, O., Roig-Costa, O., Daher, C., Rasella, D., Nieuwenhuijsen, M., Mueller, N., 2022. Health impacts of electric micromobility transitions in Barcelona: a scenario analysis. Environ. Impact Assess. Rev. 96, 106836 https://doi.org/10.1016/j.eiar.2022.106836.
- Lu, W., Scott, D.M., Dalumpines, R., 2018. Understanding bike share cyclist route choice using GPS data: comparing dominant routes and shortest paths. J. Transp. Geogr. 71, 172–181. https://doi.org/10.1016/j.jtrangeo.2018.07.012.
- Lubitow, A., Tompkins, K., Feldman, M., 2019. Sustainable cycling for all? Race and gender–based bicycling inequalities in Portland, Oregon. City Community 18, 1181–1202. https://doi.org/10.1111/cico.12470.
- Lubitow, A., Abelson, M.J., Carpenter, E., 2020. Transforming mobility justice: gendered harassment and violence on transit. J. Transp. Geogr. 82, 102601 https://doi.org/ 10.1016/j.jtrangeo.2019.102601.
- Majumdar, B.B., Mitra, S., 2019. A study on route choice preferences for commuter and non-commuter bicyclists: a case study of Kharagpur and Asansol, India. Transportation 46, 1839–1865. https://doi.org/10.1007/s11116-018-9898-z.
- Marquart, H., Schlink, U., Ueberham, M., 2020. The planned and the perceived city: a comparison of cyclists' and decision-makers' views on cycling quality. J. Transp. Geogr. 82, 102602 https://doi.org/10.1016/j.jtrangeo.2019.102602.

- Marquet, O., Miralles-Guasch, C., 2018. Resilient territories and mobility adaptation strategies in times of economic recession: evidence from the metropolitan region of Barcelona, Spain 2004–2012. Eur. Urban Reg. Stud. 25, 345–359. https://doi.org/ 10.1177/0969776417703158.
- McArthur, D.P., Hong, J., 2019. Visualising where commuting cyclists travel using crowdsourced data. J. Transp. Geogr. 74, 233–241. https://doi.org/10.1016/J. JTRANGEO.2018.11.018.
- McKenzie, G., 2019. Spatiotemporal comparative analysis of scooter-share and bikeshare usage patterns in Washington, D.C. J. Transp. Geogr. 78, 19–28. https://doi. org/10.1016/j.jtrangeo.2019.05.007.
- Nawrath, M., Kowarik, I., Fischer, L.K., 2019. The influence of green streets on cycling behavior in European cities. Landsc. Urban Plan. 190, 103598 https://doi.org/ 10.1016/j.landurbplan.2019.103598.
- Nello-Deakin, S., Harms, L., 2019. Assessing the relationship between neighbourhood characteristics and cycling: findings from Amsterdam. Transp. Res. Proc. 41, 17–36. https://doi.org/10.1016/j.trpro.2019.09.005.
- Oleś, A., 2022. openrouteservice: Openrouteservice API Client.
- Orellana, D., Guerrero, M.L., 2019. Exploring the influence of road network structure on the spatial behaviour of cyclists using crowdsourced data. Environ. Plan. B Urban Anal. City Sci. 46, 1314–1330. https://doi.org/10.1177/2399808319863810.
- Park, Y., Akar, G., 2019. Why do bicyclists take detours? A multilevel regression model using smartphone GPS data. J. Transp. Geogr. 74, 191–200. https://doi.org/ 10.1016/i.itrangeo.2018.11.013.
- Pellicer-Chenoll, M., Pans, M., Seifert, R., López-Cañada, E., García-Massó, X., Devís-Devís, J., González, L.-M., 2021. Gender differences in bicycle sharing system usage in the city of Valencia. Sustain. Cities Soc. 65, 102556 https://doi.org/10.1016/j. scs.2020.102556.
- Prato, C.G., Halldórsdóttir, K., Nielsen, O.A., 2018. Evaluation of land-use and transport network effects on cyclists' route choices in the Copenhagen region in value-ofdistance space. Int. J. Sustain. Transp. 12, 770–781. https://doi.org/10.1080/ 15568318.2018.1437236.
- Pritchard, R., Bucher, D., Frøyen, Y., 2019. Does new bicycle infrastructure result in new or rerouted bicyclists? A longitudinal GPS study in Oslo. J. Transp. Geogr. 77, 113–125. https://doi.org/10.1016/j.jtrangeo.2019.05.005.
- Pucher, J., Buehler, R., 2017. Cycling towards a more sustainable transport future. Transp. Rev. 37, 689–694. https://doi.org/10.1080/01441647.2017.1340234.
- Ravensbergen, L., 2022. 'I wouldn't take the risk of the attention, you know? Just a lone girl biking': examining the gendered and classed embodied experiences of cycling. Soc. Cult. Geogr. 23, 678–696. https://doi.org/10.1080/14649365.2020.1806344.
- Ravensbergen, L., Buliung, R., Laliberté, N., 2020a. Fear of cycling: social, spatial, and temporal dimensions. J. Transp. Geogr. 87, 102813 https://doi.org/10.1016/j. jtrangeo.2020.102813.
- Ravensbergen, L., Buliung, R., Sersli, S., 2020b. Vélomobilities of care in a low-cycling city. Transp. Res. Part Policy Pract. 134, 336–347. https://doi.org/10.1016/j. tra.2020.02.014.
- Roig-Costa, O., Gómez-Varo, I., Cubells, J., Marquet, O., 2021. La movilidad post pandemia: perfiles y usos de la micromovilidad en Barcelona. Rev. Transp. Territ. https://doi.org/10.34096/rtt.i25.10958.
- Rupi, F., Schweizer, J., 2018. Evaluating cyclist patterns using GPS data from smartphones; Evaluating cyclist patterns using GPS data from smartphones. https:// doi.org/10.1049/iet-its.2017.0285.
- Rupi, F., Poliziani, C., Schweizer, J., 2019. Data-driven bicycle network analysis based on traditional counting methods and GPS traces from smartphone. ISPRS Int. J. Geo-Inf. 8 https://doi.org/10.3390/ijgi8080322.
- Russell, M., Davies, C., Wild, K., Shaw, C., 2021. Pedalling towards equity: exploring women's cycling in a New Zealand city. J. Transp. Geogr. 91, 102987 https://doi. org/10.1016/j.jtrangeo.2021.102987.
- Sadeghinasr, B., Akhavan, A., Furth, P.G., Gehrke, S.R., Wang, Q., Reardon, T.G., 2021. Mining dockless bikeshare data for insights into cyclist behavior and preferences: evidence from the Boston region. Transp. Res. Part Transp. Environ. 100, 103044 https://doi.org/10.1016/j.trd.2021.103044.
- Sarjala, S., 2019. Built environment determinants of pedestrians' and bicyclists' route choices on commute trips: applying a new grid-based method for measuring the built environment along the route. J. Transp. Geogr. 78, 56–69. https://doi.org/10.1016/ j.jtrangeo.2019.05.004.
- Schneider, F., Daamen, W., Hoogendoorn, S., 2021. Trip chaining of bicycle and car commuters: an empirical analysis of detours to secondary activities. Transp. Transp. Sci. 1–24 https://doi.org/10.1080/23249935.2021.1901793.
- Scott, D.M., Lu, W., Brown, M.J., 2021. Route choice of bike share users: leveraging GPS data to derive choice sets. J. Transp. Geogr. 90 https://doi.org/10.1016/j. jtrangeo.2020.102903.
- Sersli, S., Gislason, M., Scott, N., Winters, M., 2020. Riding alone and together: is mobility of care at odds with mothers' bicycling? J. Transp. Geogr. 83, 102645 https://doi.org/10.1016/j.jtrangeo.2020.102645.
- Sersli, S., Gislason, M., Scott, N., Winters, M., 2022. Easy as riding a bike? Bicycling competence as (re)learning to negotiate space. Qual. Res. Sport Exerc. Health 14, 268–288. https://doi.org/10.1080/2159676X.2021.1888153.
- Skov-Petersen, H., Barkow, B., Lundhede, T., Jacobsen, J.B., 2018. How do cyclists make their way? - a GPS-based revealed preference study in Copenhagen. Int. J. Geogr. Inf. Sci. 32, 1469–1484. https://doi.org/10.1080/13658816.2018.1436713.
- Soltani, A., Allan, A., Javadpoor, M., Lella, J., 2022. Space syntax in Analysing bicycle commuting routes in inner metropolitan Adelaide. Sustainability 14, 3485. https:// doi.org/10.3390/su14063485.
- Soriguera, F., Jiménez-Meroño, E., 2020. A continuous approximation model for the optimal design of public bike-sharing systems. Sustain. Cities Soc. 52, 101826 https://doi.org/10.1016/j.scs.2019.101826.

- Sun, Y., Moshfeghi, Y., Liu, Z., 2017. Exploiting crowdsourced geographic information and GIS for assessment of air pollution exposure during active travel. J. Transp. Health 6, 93–104. https://doi.org/10.1016/j.jth.2017.06.004.
- Ta, N., Zhao, Y., Chai, Y., 2016. Built environment, peak hours and route choice efficiency: an investigation of commuting efficiency using GPS data. J. Transp. Geogr. 57, 161–170. https://doi.org/10.1016/j.jtrangeo.2016.10.005.
- Tuncer, S., Laurier, E., Brown, B., Licoppe, C., 2020. Notes on the practices and appearances of e-scooter users in public space. J. Transp. Geogr. 85, 102702 https:// doi.org/10.1016/j.jtrangeo.2020.102702.
- Wang, H., Moylan, E., Levinson, D.M., 2022. Prediction of the deviation between alternative routes and actual trajectories for bicyclists. Transp. Find. https://doi.org/ 10.32866/001c.35701.
- Weschke, J., Oostendorp, R., Hardinghaus, M., 2022. Mode shift, motivational reasons, and impact on emissions of shared e-scooter usage. Transp. Res. Part Transp. Environ. 112, 103468 https://doi.org/10.1016/j.trd.2022.103468.
- Willberg, E., Poom, A., Helle, J., Toivonen, T., 2023. Cyclists' exposure to air pollution, noise, and greenery: a population-level spatial analysis approach. Int. J. Health Geogr. 22, 5. https://doi.org/10.1186/s12942-023-00326-7.

- Wu, T.-G., Chang, J.-C., Huang, S.-H., Lin, W.-Y., Chan, C.-C., Wu, C.-F., 2021. Exposures and health impact for bicycle and electric scooter commuters in Taipei. Transp. Res. Part Transp. Environ. 91, 102696 https://doi.org/10.1016/j.trd.2021.102696.
- Yang, H., Bao, Y., Huo, J., Hu, S., Yang, L., Sun, L., 2022. Impact of road features on shared e-scooter trip volume: a study based on multiple membership multilevel model. Travel Behav. Soc. 28, 204–213. https://doi.org/10.1016/j.tbs.2022.04.005.
- Zhang, W., Buehler, R., Broaddus, A., Sweeney, T., 2021. What type of infrastructures do e-scooter riders prefer? A route choice model. Transp. Res. Part Transp. Environ. 94, 102761 https://doi.org/10.1016/j.trd.2021.102761.
- Zhu, R., Zhang, X., Kondor, D., Santi, P., Ratti, C., 2020. Understanding spatio-temporal heterogeneity of bike-sharing and scooter-sharing mobility. Comput. Environ. Urban. Syst. 81, 101483 https://doi.org/10.1016/j.compenvurbsys.2020.101483.
- Zimmermann, M., Mai, T., Frejinger, E., 2017. Bike route choice modeling using GPS data without choice sets of paths. Transp. Res. Part C Emerg. Technol. 75, 183–196. https://doi.org/10.1016/j.trc.2016.12.009.
- Zuniga-Garcia, N., Ruiz Juri, N., Perrine, K.A., Machemehl, R.B., 2021. E-scooters in urban infrastructure: understanding sidewalk, bike lane, and roadway usage from trajectory data. Case Stud. Transp. Policy 9, 983–994. https://doi.org/10.1016/j. cstp.2021.04.004.