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Mode choice, substitution patterns and environmental impacts of shared and personal micro-mobility

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ABSTRACT

Shared micro-mobility services are rapidly expanding yet little is known about travel behaviour. Understanding mode choice, in particular, is quintessential for incorporating micro-mobility into transport simulations in order to enable effective transport planning. We contribute by collecting a large dataset with matching GPS tracks, booking data and survey data for more than 500 travellers, and by estimating a first choice model between eight transport modes, including shared e-scooters, shared e-bikes, personal e-scooters and personal e-bikes. We find that trip distance, precipitation and access distance are fundamental to micro-mobility mode choice. Substitution patterns reveal that personal e-scooters and e-bikes emit less CO_2 than the transport modes they replace, while shared e-scooters and e-bikes emit more CO_2 than the transport modes they replace. Our results enable researchers and planners to test the effectiveness of policy interventions through transport simulations. Service providers can use our findings on access distances to optimize vehicle repositioning.

1. Introduction

The usage of shared micro-mobility services has greatly increased in recent years. This development is perhaps best documented in the USA, where 35 M rides were recorded in 2017, 84 M rides in 2018 and 136 M rides in 2019 (NACTO, 2020). Many shared micro-mobility companies have since expanded around the globe and now offer their services in North American, European, Asian and Australian metropolises. In addition to the investor-led diffusion of shared micro-mobility services, the COVID-19 pandemic has expedited the diffusion of personal micro-mobility as alternatives to other means of commute.

Given their rapid diffusion, effective regulation and integrated transport planning of micro-mobility vehicles and services is pertinent. City administrations are further asking how micro-mobility can contribute to increasingly stringent CO_2 reduction targets. Advances in these directions, however, are hindered by our limited understanding of travel behaviour. Most importantly, we do not yet comprehensively understand mode choice between shared micro-mobility services and more established modes (e.g., public transport, private cars). Closing this gap is paramount: mode choice is one of the four essential 'ingredients' to conventional transport planning. Furthermore, mode choice models reveal competition and substitution patterns[1] that enable determination of the net environmental

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[1] We find the following definition of modal substitution by Wang et al. (2021: 4) useful: "Modal substitution means that a certain number of trips made by a new mode of travel displace trips that would have been made by an existing mode; users substitute the new mode for an existing one (e.g. e-scooter substitutes for walking)."

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impact of shared micro-mobility services more precisely than survey-based methods. In the words of Ortúzar and Willumsen (2011: 207), "the issue of mode choice is probably the single most important element in transport planning and policy making".

The scope of the existing empirical literature on shared micro-mobility services strongly varies by mode. While travel behaviour with shared bikes is relatively well understood (e.g., Fishman et al., 2013; Ricci, 2015; Fishman, 2016; Teixeira et al., 2021), the literature on shared e-bikes is more limited (e.g., Campbell et al., 2016; Guidon et al., 2019; He et al., 2019). Shared e-scooters are the latest addition to the micro-mobility mix and researchers have only recently begun to analyse them (e.g., Christoforou et al., 2021; McKenzie, 2019; Noland, 2021; Wang et al., 2021, Younes et al., 2020). Most studies analyse patterns in user characteristics or trip characteristics of a single mode, or compare data on different modes. While they provide valuable indications on factors influencing the choice of a single mode, they cannot explain their relative influence in choice situations between multiple competing modes. To the best of our knowledge, only one study has previously estimated a mode choice model between several shared micro-mobility services (Reck et al., 2021a). That study's use for integrated transport planning is limited, however, as it includes neither public transport and private modes, nor user characteristics.

We contribute by estimating the first mode choice model that includes shared micro-mobility services (e-scooters and e-bikes), public transport, private modes (bike, car, e-bike, e-scooter) and walking, as well as user characteristics. To do so, we conducted a large-scale empirical study with 540 participants in Zurich, Switzerland. For each participant, we collected three months of GPS traces through a smartphone app, booking data for rides conducted with shared micro-mobility services, and socio-demographic information through two surveys. Additionally, we collected GPS points of all available shared micro-mobility vehicles in Zurich at a five-minute interval for the same period through the providers' APIs (48 M GPS points). We then matched all trips (65 K) with selected contextual information (e.g., weather, available vehicles in close vicinity), user characteristics and non-chosen alternatives, and estimated mode choice using a mixed logit model. Finally, we demonstrate the practical utility of the model by deriving precise, distance-based substitution rates for shared micro-mobility services and their privately-owned counterparts, and by calculating their net environmental impacts.

This paper is structured as follows. In Section 2, we review the literature on shared micro-mobility mode choice and substitution patterns. In Section 3, we introduce our data and the empirical context of our study. We develop the methodology, estimate the choice model and present the results in Section 4. In Section 5, we use the estimated model to derive substitution rates and to calculate the net environmental impacts of shared and personal e-bikes and e-scooters. We conclude with a discussion of the results and their implications for research, policy and practice in Section 6.

2. Literature review

This section introduces the key results of previous studies on shared micro-mobility services. The first subsection focuses on mode choice and the second subsection focusses on substitution patterns.

2.1. Mode choice with shared micro-mobility services

We focus on aspects that are hypothesized to influence mode choice with shared micro-mobility services, such as user and household characteristics as well as trip and context characteristics. We aim to synthesize general patterns that are found to hold across all shared micro-mobility services, as well as to highlight differences between individual services to inform subsequent model specification.

Users of shared micro-mobility services are typically young, university-educated males often with full-time employment and few to no children and cars in their households (NACTO, 2020; Reck and Axhausen; 2021; Shaheen and Cohen, 2019; Wang et al., 2021). Users of shared e-bikes, in particular, also include a higher shares of middle age groups (He et al., 2019) while users of shared e-scooters appear to be particularly young (NACTO, 2020; Reck and Axhausen, 2021; Sanders et al., 2020; Wang et al., 2021). Income distributions, in particular for shared e-scooter users, vary by region, but generally correspond to the regional median income (NACTO, 2020; Reck and Axhausen, 2021). Vehicle ownership appears to correlate with shared vehicle usage, i.e. those who own e-scooters/e-bikes are more likely to use shared e-scooters/e-bikes as well (Fishman et al., 2013; Reck and Axhausen, 2021; Shaheen et al., 2011).

Trips with shared micro-mobility services are shorter than with other motorized modes of transport (e.g., private cars, public transport). Shared e-scooters, for example, are used for short distances and most frequently in central business districts or near universities (Bai and Jiao, 2020; Caspi et al., 2020; Hawa et al., 2021; Reck et al., 2021b; Zuniga-Garcia and Machemehl, 2020). Shared e-bikes are used for longer distances than e-scooters or regular bikes, often uphill (Du et al., 2019; Guidon et al., 2019; Guidon et al., 2020; He et al., 2019; Lazarus et al., 2020; MacArthur et al., 2014; Reck et al., 2021b; Shen et al., 2018; Younes et al., 2020). Precipitation and low temperatures negatively influence the usage of all shared micro-mobility services (El-Assi et al., 2017; Gebhart and Noland, 2014; Noland, 2019; Noland, 2021; Zhu et al., 2020). The evidence on use by time of day for shared e-scooters is inconclusive: some studies find evidence of two commuting peaks (Caspi et al., 2020; McKenzie, 2019), others only find single afternoon usage peaks (Bai and Jiao, 2020; Mathew et al., 2019; Reck et al., 2021b; Younes et al., 2020). In comparison to shared docked bikes, commuting use of shared e-scooters seems to be less pronounced (McKenzie, 2019; Reck et al., 2021a; Younes et al., 2020). Finally, vehicle access distance appears to influence usage (Christoforou et al., 2021).

The above studies provide valuable indications on factors influencing the choice of a single shared micro-mobility mode. However, they cannot explain the relative influence of factors in choice situations between multiple competing modes. To the best of our knowledge, only one study has previously estimated mode choice models between several shared micro-mobility services based on revealed preference data. Reck et al. (2021a) collected trip-level data of four different shared micro-mobility modes in Switzerland and estimated a matching mode choice model. Findings include that shared micro-mobility mode choice is dominated by distance, elevation rise, and time of day. While docked (e-)bikes are preferred for longer distances and during commuting times, dockless e-scooters are preferred for shorter distances and during the night. The density of available vehicles at the point of departure further influences mode choice (this effect is strongest for dockless fleets). Two useful extensions to this previous paper would be to include other transport modes (e.g., public transport, private cars) and user characteristics so that the results can be used to incorporate shared micro-mobility services into transport simulations, which is key to effective integrated transport planning.

2.2. Substitution patterns for shared micro-mobility services

The vast majority of previous empirical studies elicit substitution patterns with disaggregate methods such as surveys asking retrospective counterfactual questions (e.g., "If an e-scooter had not been available for your last trip, how would you have made that trip?") (Wang et al., 2021). Response categories usually include a range of alternative transport modes and an option to indicate that the trip would not have been conducted if the original transport mode had not been available.

Four successive reviews have compiled the evidence on substitution effects of bikesharing (Fishman et al., 2013, Ricci, 2015; Fishman, 2016; Teixeira et al., 2021). Most recently, Teixeira et al. (2021: 9) conclude: "most substituted trips by BSS[2] derive from sustainable modes of transport, with only a small part shifting from car." Taking the median of all 19 reviewed studies, bikesharing is found to replace public transport most (41%) followed by walking (29%) and private cars/motorcycles (10%). Several authors have suggested that substitution rates depend on local modal shares (Fishman et al., 2014; Teixeira et al., 2021). In other words, the car substitution rate hypothesized to be higher in places with higher car modal shares. Indeed, this hypothesis is supported by the review data, i.e. the car substitution rates for bikesharing in the USA (Minnesota) and Australia (Brisbane and Melbourne) are substantially higher (19%) than in Europe (9%).

Despite their novelty, several studies already investigated the substitution effects of shared e-scooters. Wang et al. (2021) recently reviewed the emerging evidence and conclude: "shared e-scooter users report walking as the most common transport mode substituted, ranging between 30 and 60% of trips" (Wang et al., 2021: 6). Taking the median of all 19 reviewed studies, shared e-scooters are found to replace walking most (43%), followed by taxis/TNCs (22%) and private cars (13%). A direct comparison between these numbers and the previously reported numbers for bikesharing would be misleading, though. First, 17 out of 19 studies in the Wang review were conducted in the USA (vs. 5 out of 19 in the Teixeira review) thus the share of replaced public transport trips is naturally expected to be lower. Second, the Teixeira review includes mostly peer-reviewed academic studies (11 out of 19), while only 2 out of 19 sources cited in the Wang review were peer-reviewed (most studies were contracted by cities). Three peer-reviewed academic studies published since then suggest that shared e-scooters in Europe mostly replace walking and public transport. Christoforou et al. (2021) conducted a study in Paris finding that shared e-scooters mainly replaced public transport (37%), walking (35%) and only rarely motorized modes (private cars, taxi, motorcycle) (16%). Fearnley et al. (2020) conducted a study in Oslo finding that shared e-scooters mainly replaced walking (60%), public transport (23%) and motorized modes (taxi, private car) (8%). Finally, Laa and Leth (2020) conducted a study in Vienna finding that shared e-scooters mostly replaced walking trips followed by public transport (bus, tram). Interestingly, the latter study found that e-scooter owners tend to substitute private car trips to a much higher degree than shared e-scooter users.

Peer-reviewed empirical evidence on substitution effects of shared dockless e-bikes as previously presented for other shared micro-mobility modes is scarce. Accordingly, the most recent review on the impact of bikesharing on travel behaviour concludes: "new innovations such as dockless systems and e-bikes could induce different modal shifts but have not been properly investigated." (Teixeira et al., 2021: 17) Bourne et al. (2020: 1) further note: "The volume of research has increased since 2017 and primarily examines personal e-bike use, as opposed to e-bike share/rental schemes or organizational e-bike initiatives." The three studies the authors are aware of were conducted by Bieljnski et al. (2021), Fukushige et al. (2021) and by Campbell et al. (2016). Bieliński et al. (2021) examined an electric bike-sharing system in Tricity, Poland, using two matched surveys. They found that shared e-bikes were predominantly used as substitutes for public transport or for walking. Fukushige et al. (2021) investigated modal substitution with shared dockless e-bikes (Jump) in Sacramento, California. They found that shared e-bikes replaced walking (33%) followed by driving (drive alone and carpool, 20%), ride-hailing (16%) and cycling (14%). In this study, public transport was only rarely substituted (5%). Finally, Campbell et al. (2016) conducted an SP experiment in Beijing, China, to estimate the likelihood of cyclists switching to conventional shared bikes or to shared e-bikes and found that the impact of both modes on car replacement was low, yet higher for shared e-bike users (6% vs 3%). Several papers since investigated substitution effects of privately owned e-bikes which might serve as indications though differences in usage between privately owned and shared devices can be expected and have been observed for other modes such as shared e-scooters (Laa and Leth, 2020; Teixeira et al., 2021). Bigazzi and Wong (2020: 1) recently reviewed the evidence of privately owned e-bikes and conclude that "median mode substitution reported in the literature is highest for public transit (33%), followed by conventional bicycle (27%), automobile (24%), and walking (10%)". Several recent papers confirm previous hypotheses that modal shifts largely depend on regional mode splits and available alternatives (Bourne et al., 2020; Kroesen, 2017; Söderberg et al., 2021; Sun et al., 2020). Finally, Söderberg et al. (2021) conducted a noteworthy randomized controlled trial with e-bikes in Sweden. They distributed e-bikes to a treatment group and observed travel behaviour in comparison to a control group leveraging smartphone-based GPS tracks. Their analyses demonstrate that the treatment group increased their cycling activity by 25% at the expense of car use.

[2] Bike Sharing Scheme.

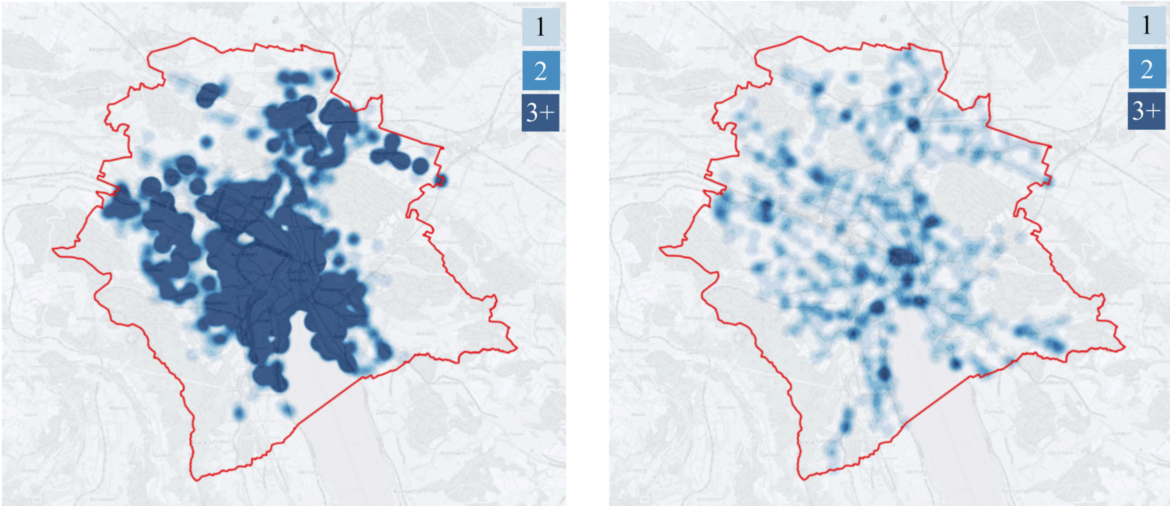

Fig. 1. Spatial coverage of shared micro-mobility services (left) and public transport stations (right) in Zurich on 1 July 2020 (3 pm - 4 pm). Kernel densities with a radius of 150 m (492ft).

Table 1
Zurich city area accessible within 100 m – 400 m from public transport stops/shared micro-mobility vehicle locations.

Mode	100 m	200 m	300 m	400 m
Public transport	14.7%	45.9%	66.1%	76.9%
Shared micro-mobility	23.2%	45.7%	57.8%	66.0%

Methodologically, only few studies depart from the survey approach to elicit substitution patterns empirically. The most relevant one to this article was conducted by Li et al. (2021). They employed a mixed logit model to derive substitution patterns for dockless bike-sharing in Shanghai, China. While the approach was new, a key limitation to the implementation was that only separate (i.e., not matched) booking and survey data was available, and that booking data was restricted to dockless bike-sharing (i.e., no other transport modes). The authors hence estimated their mode choice model on one dataset (survey data) and applied it on the other (booking data) to estimate trip-based substitution patterns, which inevitably leads to biased results as populations in both studies differ.

2.3. Contributions of this study

This study contributes by collecting a first comprehensive dataset that includes revealed preference data on trips conducted with different shared micro-mobility services (e-scooters, e-bikes), public transport, private modes (bike, car, e-bike, e-scooter) and walking, and by estimating a mode choice model between all eight transport modes. We further contribute by deriving distance-based substitution patterns for shared and personal e-bikes and e-scooters from the mode choice model, and by calculating their resulting net environmental CO_2 emissions.

3. Data

3.1. Location and recruitment

Our study is conducted in Zurich, which is Switzerland's largest city with 403 K inhabitants in the city and 1.5 M inhabitants in the metropolitan area. Zurich has a high trip-level public transport mode share of 41% according to the latest Swiss mobility census (MZMV, 2015). The share of trips conducted with private cars has been declining steadily over the past years from 40% in 2000 to 25% in 2015. The remaining trips are conducted with active modes (walking: 26%, (e-) bikes: 8%). Several micro-mobility companies operate in Zurich making it a suitable place to study their usage. They include docked (e-)bikes (Publibike), dockless e-bikes (Bond) and dockless e-scooters (e.g., Lime, Bird, Tier, Voi). Fig. 1 shows the spatial coverage of shared micro-mobility services and public transport in Zurich. Shared micro-mobility services tend to be more available in the city-centre while public transport stations are more evenly distributed across the city boundary. A buffer analysis (Table 1) around the locations of shared micro-mobility vehicles and public transport stops shows that for short distances (i.e., 100 m), a higher amount of the city's total area (87.88 km^2) can be accessed with shared micro-mobility services (23.2%) than with public transport (14.7%). This ratio reverses for longer distances (i.e., 200 m – 400 m), where more area can be accessed with public transport (45.9% – 76.9%) than with shared micro-mobility services (45.7% – 66.0%). This analysis reflects the spatial distribution of the services (Fig. 1).

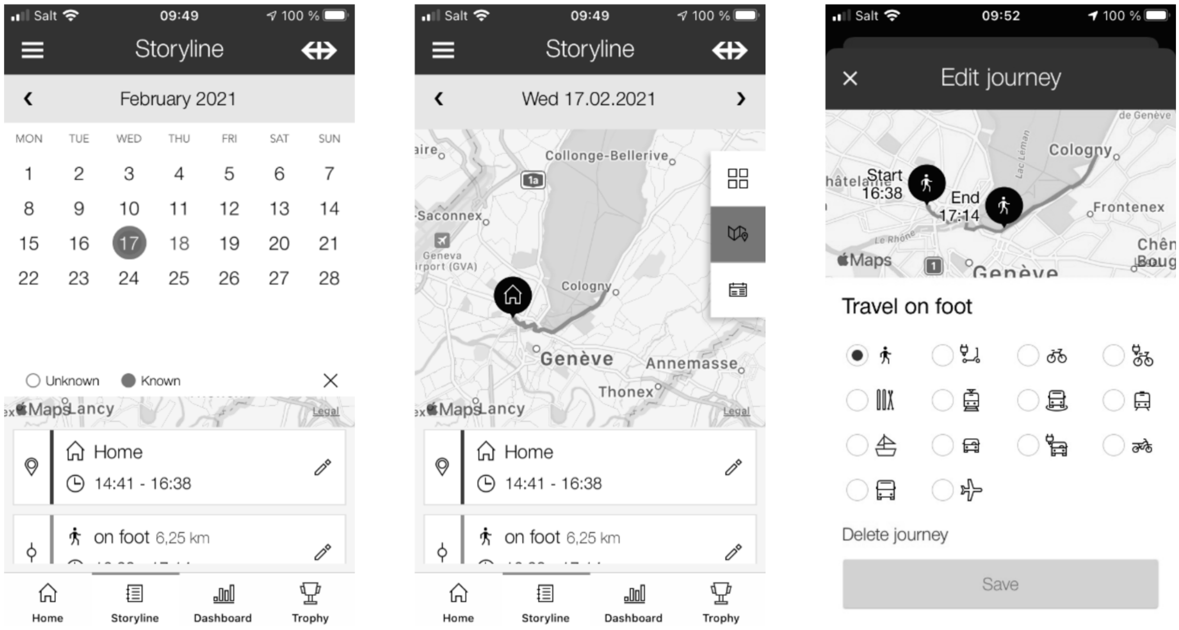

Fig. 2. GPS tracking app on iPhone SE (left: calendar view, middle: map view, right: edit mode view).

Data collection began in June 2020. The cantonal statistical office sent invitations to participate in our mobility study to 10 000 randomly selected inhabits of Zurich municipality of age 18 to 65. The study included two surveys and three months of GPS smartphone tracking. Respondents were offered an incentive of 90 CHF[3] for their participation. All invitation letters included detailed information on the purpose of the study and the methods to collect and process the data in compliance with the EU General Data Protection Regulation. The study design was reviewed and approved by the university's Ethics Committee without reservations.

A total of 1 277 people returned the first survey between June and July 2020. The resulting response rate of 12.7% is well in the expected range for a survey with a considerable response burden of 643 points (Schmid and Axhausen, 2019). Only respondents who completed the first questionnaire were invited to participate in the subsequent GPS tracking and the final survey. A total of 540 (6%) respondents completed the entire study and their data is used for the analyses in this paper. The subsequent subsections introduce the data sources and the data integration flow, and discuss the representativeness of our sample.

3.2. *Data sources and data integration flow*

This subsection gives an overview of each individual data source (survey, GPS tracks, booking records, contextual data) and how they are combined (data integration flow) to conduct the analyses in this paper.

3.2.1. *Survey*

We designed two online surveys that include a total of 171 questions to elicit socio-demographic and mobility-related information. All questions and answer categories were formulated to be equal to the latest available Swiss mobility census to enable direct comparison. Documentation in English[4] and questionnaires in German[5] and French[6] are available online. The surveys were structured into the following three blocks:

- person-specific socio-demographic questions (e.g., year of birth, gender, educational attainment, current occupation),
- household-specific socio-demographic questions (e.g., number of adults and children, monthly income, mobility tool ownership), and
- person-specific mobility questions (e.g., public season ticket ownership, travel priorities, knowledge of and membership in shared (micro-) mobility schemes, frequency of use, access to shared micro-mobility services at home and work).

[3] 1 CHF = 1.08 USD at the time of writing (29 June 2021).
[4] https://www.are.admin.ch/are/en/home/mobility/data/mtmc.html
[5] https://www.bfs.admin.ch/bfs/de/home/statistiken/mobilitaet-verkehr/erhebungen/mzmv.assetdetail.5606052.html
[6] https://www.bfs.admin.ch/bfs/fr/home/statistiques/mobilite-transports/enquetes/mzmv.assetdetail.5606053.html

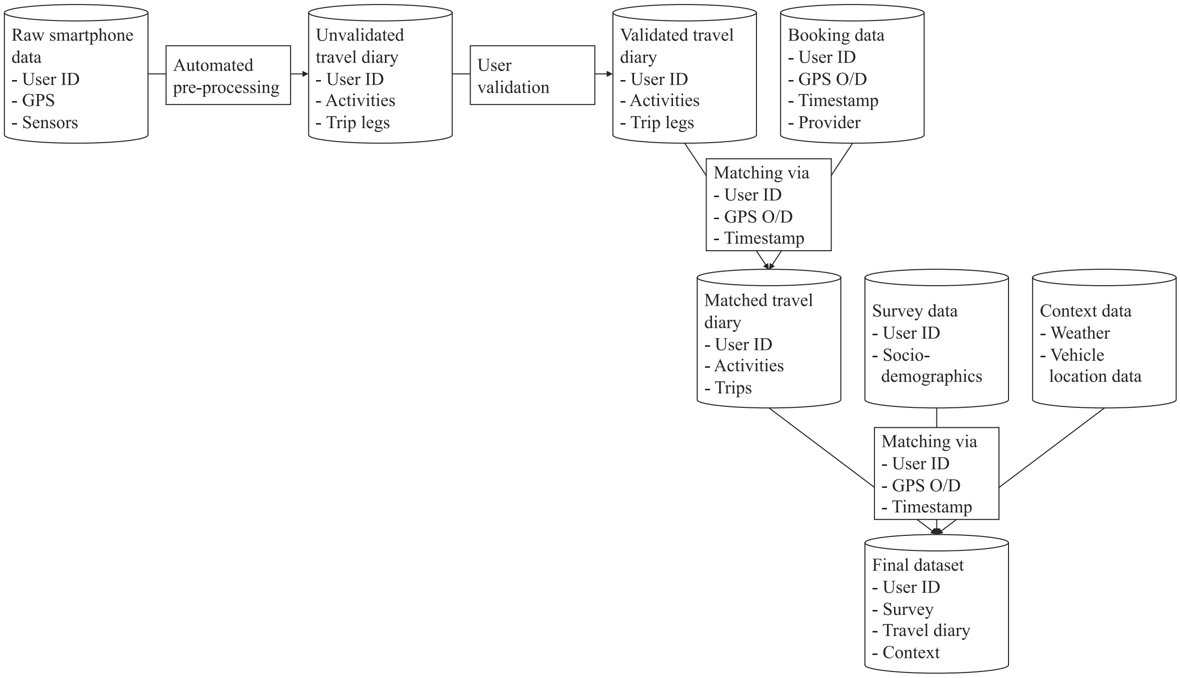

Fig. 3. Data integration flow chart.

3.2.2. GPS tracks

The smartphone app 'MyWay' (available in app stores) was used for GPS tracking. The app passively collects raw smartphone data (GPS traces, sensor data), identifies trips and infers the transport mode used based on a comparison with public transport timetables, acceleration and travel speed, and past user mode choice. Each day, the app presents users with a summary of their realized trip legs and allows retrospective editing of transport modes. Fig. 2 gives a visual impression of the user interface. Overall, we collected 65 716 trips for 540 respondents with this method, which further divide into 17 004 public transport trips, 16 211 car trips, 15 393 walking trips, 14 246 bike trips, 2 537 e-bike trips, and 345 e-scooter trips.

3.2.3. Booking records

We further received booking records for all shared micro-mobility trips booked by our participants during the study duration through a new intermodal journey planning app 'yumuv' (available in app stores), which was launched by Swiss Federal Railways in June 2020. Matching these booking records with the GPS tracks allowed us to differentiate private from shared micro-mobility trips. Out of the total of 2 537 e-bike trips, 287 had matching booking records and were hence labelled as shared e-bike trips. Out of the total of 345 e-scooter trips, 121 had matching booking records.

3.2.4. Contextual data

Finally, we added contextual data to each trip. This includes weather data (openly available in ten-minute intervals for Zurich), as well as the distance to the next available shared micro-mobility vehicle at the beginning of each trip. In order to compute the latter, Swiss Federal Railways records the locations of all shared micro-mobility vehicles in Zurich in five-minute intervals through the providers' APIs.

3.2.5. Data integration flow

Fig. 3 shows the overall data integration flow. From left to right and from top to bottom, we start with the passively collected raw smartphone data (GPS tracks, sensor data), which the smartphone app 'MyWay' automatically pre-processes towards an 'unvalidated travel diary' using information on past user mode choice, acceleration and travel speeds, as well as public transport timetables. The performance of the app's backend to infer transport modes is exceptionally high (correct inferred mode in 92% of all cases) as results and comparisons from previous papers using the same tracking app in Zurich show (Molloy et al., 2020). The unvalidated travel diary contains trip legs (GPS O/D, timestamp, inferred transport mode) and activities. Each day, the app presents users with a summary of their realized trips and allows retrospective editing of transport modes ('user validation'), which results in the 'validated travel diary'. In a third step, the validated travel diaries are matched with the booking data (via user IDs, GPS O/D and timestamps) to separate shared from private micro-mobility trips ('matching'). Note that we also aggregate trip legs to trips in this step to be able to estimate the mode choice model subsequently. The metric used to identify the main transport mode per trip is distance, i.e. the mode that covers the largest share of the total distance is identified as the main transport mode for the trip. Finally, we integrate the 'matched travel

Table 2
Comparison of survey respondents and recent censuses. All values in %.

	This survey	Census (SE)	Census (MZMV)
Year	2020	2018	2015
N (Zurich municipality only)	540	7808	809
Filtered for age groups	18–65	18–65	18–65
Person-specific attributes			
Age			
18–20	0	3	2
21–30	26	20	16
31–40	38	31	28
41–50	23	22	25
51–60	8	18	21
61–65	5	7	8
Female	46	50	51
Education (tertiary degree)	76	58	49
Full-time employed	81	68	63
PT season ticket ownership			
Nation-wide	19	n/a	16
Local (Zurich)	38	n/a	43
Household-specific attributes			
Monthly income			
4,000 CHF and below	17	n/a	11
4,001 CHF – 8,000 CHF	21	n/a	35
8,001 CHF – 12,000 CHF	23	n/a	26
12,001 CHF – 16,000 CHF	25	n/a	14
16,000 CHF and above	13	n/a	14
Children			
0	73	70	62
1	12	14	17
2 and above	15	15	20
Adults			
1	26	28	15
2	62	56	56
3 and above	12	15	29
Cars			
0	46	n/a	45
1	45	n/a	43
2 and above	9	n/a	11
Bikes			
0	16	n/a	19
1	20	n/a	25
2 and above	63	n/a	56
E-bikes			
0	86	n/a	95
1	10	n/a	4
2 and above	4	n/a	1
E-Scooters			
0	97	n/a	n/a
1	3	n/a	n/a
2 and above	0	n/a	n/a

diary' with the 'survey data' and the 'context data' via user IDs, GPS O/D and timestamps to obtain the final, integrated dataset.

3.3. *Representativeness*

We compare the characteristics of our sample to the latest censuses to investigate its representativeness. The latest available censuses are the 2018 "Strukturdatenerhebung" (SE) and the 2015 mobility census "Mikrozensus Mobilität und Verkehr" (MZMV). While the former is more current, the latter includes substantially more information on mobility-related topics.

Table 2 shows the resulting comparison. Our sample is slightly younger (mean: 38 years) than the respondents of both previous censuses (2015: 42 years, 2018: 41 years)[7]. It further includes slightly fewer females (46%) than previous censuses (2015: 50%, 2018: 51%). The share of respondents holding a tertiary degree (2015: 49%, 2018: 58%, 2020: 76%) and the share of respondents in full-time employment (2015: 63%, 2018: 68%, 2020: 81%) are higher in our sample than in both previous surveys. In line, the mean monthly household income is also higher in our sample than in the previous survey (2015: ~9,000 CHF, 2020: ~10,000 CHF). The household

[7] Note that all surveys are filtered for respondents of age 18+ as this is the required legal minimum age to use shared micro-mobility services in Zurich at the time of writing.

Table 3
Attributes used for model estimation (trip-level statistics).

Attribute	Unit	Min.	1st Qu.	Med.	Mean	3rd Qu.	Max.
Trip-specific attributes							
Distance	km	0.01	1.35	3.01	4.15	5.60	80.28
Access distance[1]							
PT	km	0.01	0.29	0.42	0.45	0.56	4.30
Shared e-bike[2]	km	0.00	0.13	0.22	0.23	0.33	0.50
Shared e-scooter[2]	km	0.00	0.04	0.07	0.09	0.12	0.50
Transfers	count	0.00	0.00	1.00	0.63	1.00	4.00
Elevation	km	−0.47	−0.02	0.00	0.00	0.02	0.47
Morning (6am – 9am)	binary	0.00	0.00	0.00	0.19	0.00	1.00
Night (9 pm – 5am)	binary	0.00	0.00	0.00	0.09	0.00	1.00
Weather							
Precipitation	mm/h	0.00	0.00	0.00	0.16	0.05	6.14
Wind speed	m/s	1.22	3.56	4.73	5.26	6.19	18.68
Person-specific attributes							
PT season ticket (local)	binary	0.00	0.00	0.00	0.40	1.00	1.00
PT season ticket (nation)	binary	0.00	0.00	0.00	0.18	0.00	1.00
PT season ticket (bundle)	binary	0.00	0.00	0.00	0.04	0.00	1.00
Cars in household	count	0.00	0.00	1.00	0.64	1.00	5.00
Bikes in household	count	0.00	1.00	2.00	2.25	3.00	6.00
E-bikes in household	count	0.00	0.00	0.00	0.18	0.00	3.00
E-scooters in household	count	0.00	0.00	0.00	0.03	0.00	2.00
Age	years	19.00	30.00	36.00	37.92	45.00	65.00
Female	binary	0.00	0.00	0.00	0.46	1.00	1.00
University education	binary	0.00	0.00	1.00	0.74	1.00	1.00
Full-time employment	binary	0.00	0.00	1.00	0.69	1.00	1.00

[1] access distance is only defined for public transport and shared micro-mobility services.
[2] when available.

structure exhibits slight differences in the share of single/dual adult households (2015: 71%, 2018: 84%, 2020: 85%) as well as in the share of households without children (2015: 62%, 2018: 70%, 2020: 73%). Households in our sample further owned slightly fewer cars, and slightly more bikes, e-bikes and nation-wide public transport season tickets compared to the 2015 census.

4. Mode choice

In this section, we estimate the mode choice model and present the results.

4.1. Method

We first generate the choice sets by complementing each of the 65 716 observed trips in our GPS tracking data with the data for the non-chosen alternatives. For each observed trip, we calculate the non-chosen alternatives with the agent-based transport simulation software MATSim (Horni et al., 2016). The MATSim Zurich scenario has been used extensively in transport planning research (e.g., Balac et al., 2019; Becker et al., 2020; Hörl et al., 2021; Manser et al., 2020) and provides reliable attribute values for the non-chosen alternatives. Due to reasons described earlier, MATSim is limited to public transport, private cars, private bikes and walking. While we can safely assume that e-bikes and e-scooters are used on the same routes as private bikes (thus, distances of these alternatives are equal), travel times are likely to differ. Thus, we constrain our models to use distance parameters only and exclude travel time parameters.

In addition to trip-specific attributes (distance, access distance, transfers, elevation, time of day), we include weather (precipitation, wind) and a number of binary person-specific attributes that have previously been hypothesized to influence micro-mobility mode choice. These include public transport season ticket ownership (local, nation, bundle[8]), the number of vehicles in the household (cars, bikes, e-bikes, e-scooters), age, gender, university education and employment status. Prices were not included in this choice model as they are heavily correlated with distances for many transport modes such as private cars, shared e-scooters and shared e-bikes, and their inclusion would thus lead to multicollinearity issues. For example, the shared e-bike operator in Zurich charges an unlocking fee of 1 CHF and an additional per-kilometre fee of 1 CHF. Table 3 summarizes all attributes used for subsequent model estimation.

We build on discrete choice theory to develop our mode choice model. In particular, we select a mixed logit model to account for the panel structure of our data as well as for taste heterogeneity in mode choice between individuals (Hensher and Greene, 2003; McFadden and Train, 2000; Train, 2009).

[8] Transport bundles sold in Zurich during the time of study included a local public transport season ticket and a 60-minute monthly allowance for shared micro-mobility services.

In the context of random utility models, choices of individuals can be explained by comparing the relative utility of each alternative and choosing the alternative with the highest utility

$$P_{nit} = \Pr\left(U_{nit} \geq U_{njt}, \forall j \neq i\right) \quad (1)$$

where P_{nit} is the probability of individual n choosing alternative i over alternatives j in choice situation t, U_{nit} is the utility of alternative i for individual n in choice situation t, and U_{njt} is the utility of alternative j for individual n in choice situation t. The utility of alternatives is separated into two parts: a deterministic part, V, and a random part, , such that

$$U_{nit} = V_{nit} + \varepsilon_{nit} \quad (2)$$

The deterministic part V can further be expressed as

$$V_{nit} = \beta_{ni0} + \sum\nolimits_{k=1}^{K} \beta_{ik} x_{nitk} \quad (3)$$

where β_{ni0} is a random alternative-specific constant to capture heterogeneity in mode choice over individuals, β_{ik} is a vector of parameters for K attributes to be estimated, and x_{nitk} is a vector of (observed) explanatory variables. In our case, the explanatory variables include person-specific information (e.g., socio-demographics such as age and gender) as well as trip-specific information (e.g., distance, precipitation). For an overview of all explanatory variables, we refer to Table 3. The final formulation of all utility functions for our models can be found in Appendix 1.

The choice probability for mixed logit models can be expressed as

$$P_{nit} = \int L_{nit}(\beta) f(\beta) d\beta \quad (4)$$

where $L_{nit}(\beta)$ is the logit probability at parameters β , defined as

$$L_{nit}(\beta) = \frac{e^{V_{nit}(\beta)}}{\sum_{j=1}^{J} e^{V_{nit}(\beta)}} \quad (5)$$

and $f(\beta)$ is a density function. For further detail on the mathematical formulation of mixed logit models, we refer to Hensher and Greene (2003), McFadden and Train (2000) as well as Train (2009).

We built and estimated our specific model iteratively (i.e., dropping insignificant and insubstantial variables) to obtain the most parsimonious model possible that simultaneously allows for cross-modal comparisons. For model estimation, we used maximum likelihood with 500 MLHS[9] draws in the R package Apollo (Hess and Palma, 2019). Apollo recognizes the repeated choice nature of panel data and multiplies probabilities across individual choice observations for each individual (Hess and Palma, 2019).

Finally, we set the availabilities. For each person, we verify if each transport mode was used at least once during the three months. If not, we set the availability of the respective transport mode to zero for all trips of that person, i.e. remove it from the choice set for this person. Further, we set the availability of shared e-scooters, shared e-bikes and public transport to zero for each trip where no vehicle was detected within a 500 m radius or no public transport connection was found.

4.2. Results

Table 4 displays the estimation results. The mixed logit model has an excellent fit with an adjusted rho-square value of 0.45. In comparison to the reference mode (walking), trip distance substantially and significantly influences mode choice for all other modes. Precipitation positively influences mode choice for public transport and cars, and negatively for all micro-mobility modes, most so for shared e-bikes and e-scooters. Elevation and wind speed further negatively influence mode choice for non-electric bikes.

One perhaps surprising result concerns the penalty of the access distance for public transport and shared e-bikes and e-scooters. Access distance for shared e-scooters is penalized substantially more (-5.89) than access distance for public transport and shared e-bikes (-2.29 and −2.43, respectively)[10]. Users of shared e-scooters are willing to walk an average of 60 m and a maximum of 210 m to access a vehicle, while users of shared e-bikes are willing to walk an average of 200 m and up to 490 m to access a vehicle. Public transport users are willing to walk even longer (average: 400 m) to reach their preferred stop. We offer three explanations for this behaviour. First, it can be related to the spatial availability of the different services (cf. Fig. 1 and Table 1). The availability and density of shared micro-mobility services is particularly high in the city centre, where most trips are also conducted and where access distances are relatively short. The outer city areas can only be reached with public transport as micro-mobility services are largely absent, hence longer access distances have to be accounted for. Second, shared e-scooters are used for substantially shorter distances than both other modes. Hence, a 200 m access distance relative to the overall trip distance is substantially more for shared e-scooters and thus presents a greater relative burden. Third, shared e-scooters cannot be pre-reserved in Zurich. The longer the access distance, the more uncertainty in availability users face. For public transport real-time information about vehicle locations is available through major trip planning apps (e.g., Google Maps or the city's public transport app) and Zurich's shared e-bikes can be pre-reserved for up to ten minutes.

[9] MLHS draws avoid undesirable correlation patterns that arise when standard Halton sequences are used for several variables (Hess et al., 2006).

[10] Additional saturation effects of the density of shared micro-mobility fleets were not found.

Table 4
Estimation results (mixed logit model).

	PT		Car		Bike		E-Bike (personal)		E-Bike (shared)		E-Scooter (personal)		E-Scooter (shared)	
	Coef.	t.rat.	Coef.	t.rat.	Coef.	t.rat.	Coef.	t.rat.	Coef.	t.rat.	Coef.	t.rat.	Coef.	t.rat.
ASC (μ)	−4.01	−9.04	−6.13	−10.38	−3.80	−9.08	−5.86	−13.77	−6.48	−9.88	−6.49	−8.44	−4.67	−7.90
ASC (σ)	−1.22	−44.62	−1.71	−33.68	−1.79	−42.81	−1.30	−25.54	−1.76	−12.84	0.77	5.70	0.40	3.32
Distance	2.10	23.00	1.95	24.55	1.61	22.08	1.78	22.44	2.25	14.77	1.57	9.02	1.34	9.77
Distance * Distance	−0.04	−23.78	−0.03	−27.90	−0.03	−23.74	−0.03	−15.81	−0.08	−5.29	−0.06	−2.82	−0.02	−1.67
Distance * Precipitation	0.78	3.34	0.74	3.16	−0.77	−3.29	−0.76	−2.41	−4.34	−3.16	−0.63	−0.88	−4.29	−1.64
Distance * Elevation					−0.14	−3.39								
Distance * Wind speed					−0.33	−2.40								
Access distance	−2.29	−29.89							−2.43	−2.02			−5.89	−2.77
PT transfer	−0.64	−23.05												
Morning (6am – 9am)	0.27	5.01	−0.13	−2.28	0.34	6.64	0.44	5.16	−0.04	−0.17	0.71	2.65	0.34	1.19
Night (9pm – 5am)	−0.12	−1.64	−0.04	−0.53	−0.04	−0.54	−0.23	−1.80	−0.20	−0.71	0.86	3.31	0.31	1.05
Vehicles in household			1.25	29.19	0.15	8.47	1.34	19.32			2.36	4.68		
PT season ticket (local)	0.32	4.64												
PT season ticket (nation)	0.99	11.86												
PT season ticket (bundle)	0.87	6.21							−0.11	−0.49			1.84	8.09
Age	0.00	−0.03	0.02	1.83	0.01	1.38	0.01	0.93	0.04	3.00	0.02	1.16	0.00	−0.27
Female	0.15	2.31	−0.39	−5.08	−0.38	−5.51	0.13	1.21	0.78	2.59	0.23	0.68	−0.83	−2.16
University education	−0.03	−0.30	0.28	1.88	0.06	0.58	0.78	5.31	0.08	0.28	−1.78	−6.33	−0.10	−0.28
Full-time employment	−0.24	−2.46	−0.36	−3.51	−0.13	−1.52	0.66	5.31	1.98	8.22	2.48	4.77	0.49	1.45
Number of individuals	540													
Number of observations	65 716													
Adj. Rho-square	0.45													

Table 5
Micro-mobility substitution rates (trip-level and km-level) derived from the mode choice model.

	E-Bike (personal)		E-Bike (shared)		E-Scooter (personal)		E-Scooter (shared)	
Mode	trip	km	trip	km	trip	km	trip	km
Walk	26%	9%	24%	9%	35%	19%	51%	25%
PT	20%	29%	27%	43%	23%	27%	19%	38%
Car	37%	48%	11%	15%	17%	25%	12%	15%
Bike	17%	14%	33%	29%	24%	27%	13%	13%
E-Bike (personal)			3%	5%	2%	1%	1%	2%
E-Bike (shared)	0%	0%			0%	0%	4%	5%
E-Scooter (personal)	0%	0%	0%	0%			0%	0%
E-Scooter (shared)	0%	0%	0%	0%	0%	0%		

Several further parameter estimates show the expected results and are thus only briefly mentioned here. For public transport, season tickets positively influence mode choice while transfers negatively influence mode choice. The transport bundle further positively influences mode choice for shared e-scooters. Vehicle ownership positively influences mode choice for each respective mode. Of the socio-demographic parameter estimates, gender and full-time employment are most significant at the 95% confidence level. Identifying as female positively influences mode choice for public transport and negatively for cars, bikes and shared e-scooters. Full-time employment, in turn, positively influences mode choice for shared and personal e-bikes as well as personal e-scooters, while it negatively influences mode choice for the more established transport modes such as public transport, private cars and bikes.

5. Substitution patterns and environmental implications

In this section, we first utilize the estimated choice model to derive substitution patterns[11] for each micro-mobility mode. Using these substitution patterns, we then calculate net CO_2 emissions.

5.1. Substitution patterns

Methodologically, only a slight adaption to the above choice model is necessary to derive substitution patterns. We take the subsets of trips conducted with e-scooters and e-bikes and set the availability for each mode, when chosen, from one to zero. We then apply our model to the subset of trips with adjusted availabilities to predict the alternative mode choice. Conceptually, this predicted alternative mode is equal to what is commonly described as a substituted mode, i.e. the mode that would have been chosen if the chosen mode had not been available. Using the new predictions, we can calculate average substitution rates for e-scooters and e-bikes on a trip-level and on a km-level. For the trip-level, we divide the number of trips with a particular substituted mode (e.g., public transport) by the total number of trips conducted with the micro-mobility mode (e.g., shared e-scooters):

$$subrate_{triplevel}(mode_{chosen}, mode_{substituted}) = \frac{\sum trips(mode_{substituted})}{\sum trips(mode_{chosen})} \tag{6}$$

where $\sum \boldsymbol{trips}(\boldsymbol{mode})$ denotes the number of trips conducted with a particular mode.

For the km-level, we divide the total distance covered with a particular substituted mode by the total distance covered with the micro-mobility mode:

$$subrate_{kmlevel}(mode_{chosen}, mode_{substituted}) = \frac{\sum distance(mode_{substituted})}{\sum distance(mode_{chosen})} \tag{7}$$

where $\sum \boldsymbol{distance}(\boldsymbol{mode})$ denotes the total distance covered with a particular mode.

The resulting substitution patterns are shown in Table 5. We observe that personal e-bikes replace trips conducted with all four main modes (walk, PT, car, bike), while shared e-bikes replace substantially fewer car trips and more PT and bike trips. E-scooters in general replace substantially more walk trips than e-bikes. In general, the trip-level substitution rates exhibit a higher share of walking trips than the km-level substitution rates. The reason is that walking trips are comparatively short, thus have less impact in distance-based measures.

One of the many advantages of this choice model-based approach to deriving substitution patterns is that precise distance measures

[11] Substitution patterns (or 'substitution rates') can also be elicited with surveys, i.e. by asking participants about their last trip and their alternative mode choice. Indeed, this approach is much more common than the choice model approach developed here. The latter, however, has one key advantage over the former: it allows to calculate precise, distance-based substitution patterns. These are more adequate for estimating environmental implications than trip-based substitution patterns stemming from surveys for three reasons. First, it is substituted distance and not substituted trips that matters when calculating environmental implications. Second, substitution patterns derived from choice models are valid for all trips, not just the ones explicitly asked for, as they build on user preferences. Third, substitution patterns derived from choice models are more reliable than those derived from stated preference surveys, which are prone to biases such as the recall bias or the social desirability bias. Hence, we chose to proceed with the choice model approach instead of detailing the results from survey data, which we also elicited.

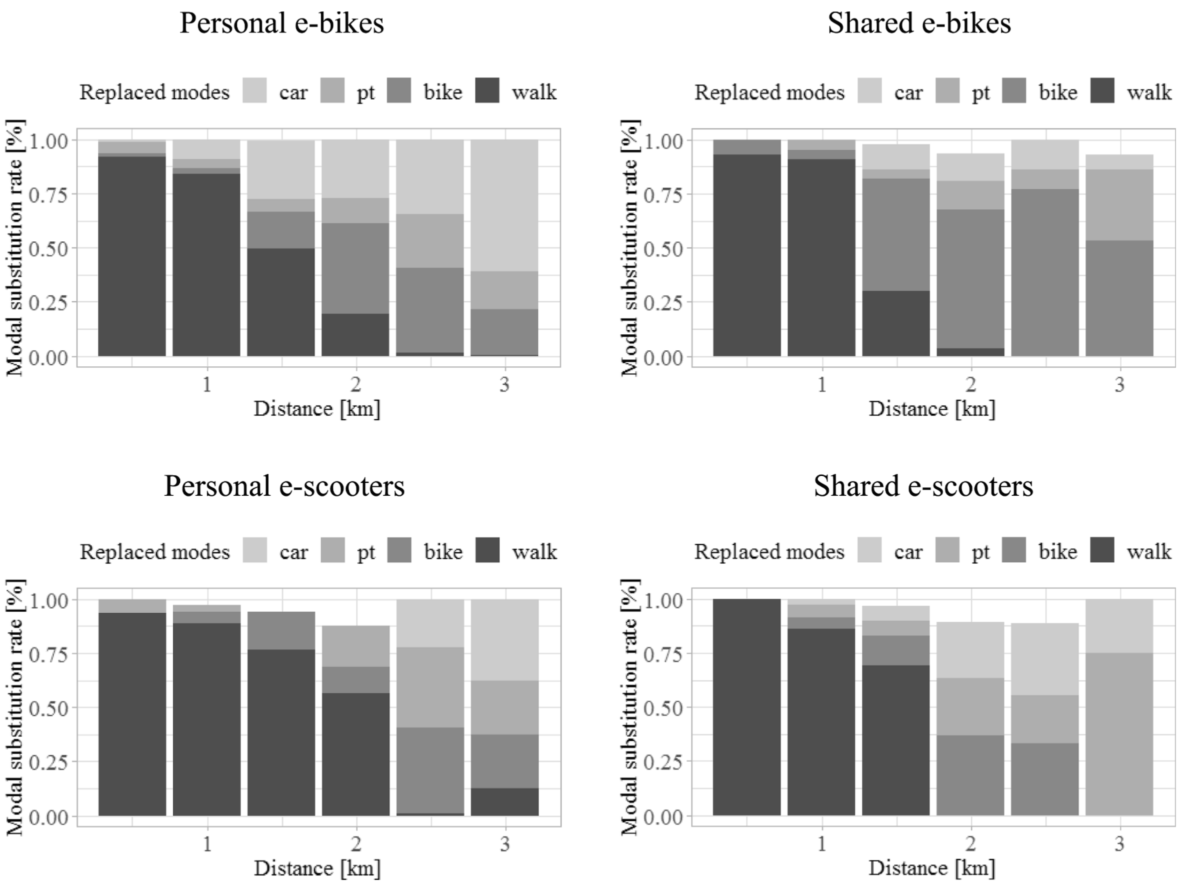

Fig. 4. Substitution rates for micro-mobility modes by distance.

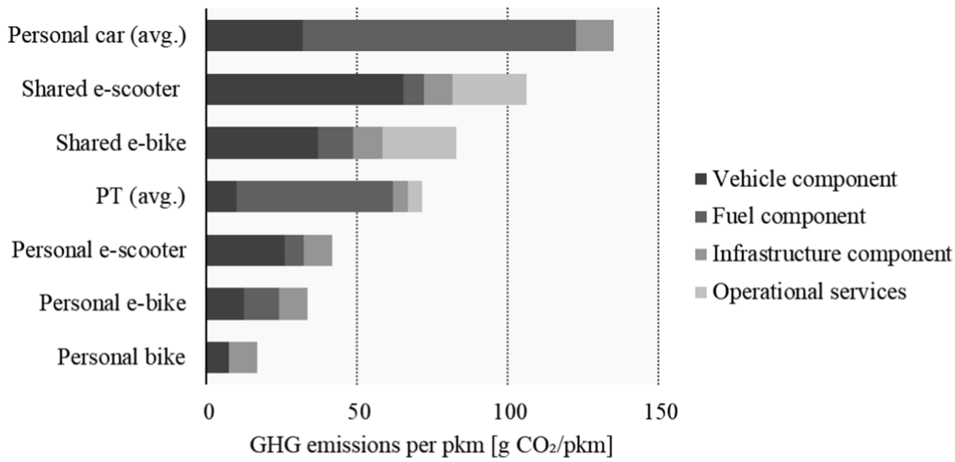

Fig. 5. Life cycle CO_2 emissions per passenger kilometre of selected transport modes (adapted from ITF, 2020).

for each trip are observed. For surveys, these are usually imprecise or simply not available as they are based on participants' memories of recent trips. Fig. 4 displays substitution rates by distance brackets. Two general patterns emerge. For short trips, all micro-mobility modes mostly replace walking. As the distance grows, the shares of replaced public transport, bike and car trips increase. Personal e-bikes, however, replace personal cars substantially more often for longer distances than all other modes.

Table 6
Average micro-mobility net emissions after substitution effects.

Substituted mode	Gross emissions	Substitution patterns (km-level) by micro-mobility mode			
	[g CO_2/pkm]	E-Bike (personal)	E-Bike (shared)	E-Scooter (personal)	E-Scooter (shared)
Walk	0†	9%	9%	19%	25%
PT (avg.)	72†	29%	43%	27%	38%
Car (avg.)	135†	48%	15%	25%	15%
Bike	17†	14%	29%	27%	13%
E-Bike (personal)	34†		5%	1%	2%
E-Bike (shared)	83†	0%		0%	5%
E-Scooter (personal)	42†	0%	0%		0%
E-Scooter (shared)	106†	0%	0%	0%	
Emissions of substituted modes		88	58	58	55
Emissions of micro-mobility mode		34†	83†	42†	106†
Net emissions [g CO_2/pkm]		**−54**	**25**	**−16**	**51**

† Emission calculations drawn from ITF (2020).

5.2. Environmental implications

The impact of a new transport mode on the sustainability of the surrounding transport system depends not only on the replaced modes, but also on their respective emissions. In this subsection, we integrate our findings on substitution patterns with previous findings on gross CO_2 emissions to calculate the net CO_2 emissions of the different micro-mobility modes.

Building on previous work from de Bortoli and Christoforou (2020) and Hollingsworth et al. (2019), the International Transport Forum (ITF, 2020) recently conducted a comprehensive analysis of the life cycle emissions of emerging and more established transport modes. It took into account not only established components of such analyses (e.g., infrastructure wear, vehicle manufacturing, and fuel), but also developed a new component (operational services, e.g. rebalancing) which is a key differentiating characteristic and an emission driver of emerging modes such as shared micro-mobility services. Fig. 5 shows the emissions in g CO_2 per passenger kilometre (pkm) for all modes relevant to this study. Appendix 2 further details the assumptions in terms of lifetime, mileage and occupancy levels.

We integrate these findings on CO_2 emissions with our findings on substitution patterns for shared and personal e-bikes and e-scooters to calculate their 'net emissions':

$$net\ \ emissions\ \ (mode) = gross\ \ emissions\ \ (mode) - \sum_i gross\ \ emissions\ \ (replaced\ \ mode_i) \tag{8}$$

Consider the following (hypothetical) example: a shared e-scooter (106 g CO_2/pkm) replaces public transport[12] (72 g CO_2/pkm) and walking (0 g CO_2 / pkm) in equal amounts (i.e., 50% and 50%). The 'gross emissions' of shared e-scooters are 106 g CO_2 / pkm. The gross emissions of the replaced modes are 36 g CO_2 / pkm (calculate: 50% * 72 g CO_2 / pkm + 50% * 0 g CO_2 / pkm). The resulting net emissions of shared e-scooters are thus 70 g CO_2 / pkm. Positive net emissions can be interpreted as the additional emissions caused per pkm by the new mode. In turn, negative net emissions can be interpreted as the emissions saved per pkm by the new mode.

Table 6 shows the resulting net emissions using the previously derived km-level substitution rates for all four micro-mobility modes. Note that only km-level substitution rates (i.e., not trip-level substitution rates) can be used for this type of analysis as trip-level substitution rates are biased towards short walk trips (see comparison in Table 5). We find that the CO_2 emissions of personal e-bikes (34 g CO_2/pkm) and personal e-scooters (42 g CO_2/pkm) are lower than the average CO_2 emissions of the modes they replace (88 g CO_2 / pkm and 58 g CO_2 / pkm, respectively). Shared e-bikes and shared e-scooters exhibit the opposite pattern: their CO_2 emissions are higher than the average CO_2 emissions of the modes they replace. Hence, from a short-term mode choice perspective and under current conditions, only personal e-bikes and e-scooters contribute to making transport more sustainable, while shared e-bikes and e-scooters actually emit more CO_2 than the transport modes they replace. All values can be regarded as lower limits as a certain share of trips can be assumed to be induced (i.e., not replacing previous trips), further adding to CO_2 emissions.

It is also very reasonable to assume that the public transport system runs "fixed", regardless of who switches to/from public transport, and hence that 0 g CO_2/pkm should be applied to trips with public transport. Following this logic, the net CO_2 emissions of all micro-mobility modes increase to –33 g CO_2/pkm for personal e-bikes, 56 g CO_2/pkm for shared e-bikes, 3 g CO_2/pkm for personal e-scooters and 79 g CO_2/pkm for shared e-scooters.

Finally, we know that substitution patterns vary with trip distance (cf. Fig. 4). Hence, net emissions will differ by distance bracket. Fig. 6 visualizes this relationship. We find that net emissions for personal e-bikes and e-scooters are positive for short distances as they predominantly replace walking for short trips. For longer distances, they replace cars and public transport substantially more often, resulting in overall negative net emissions. Net emissions of shared e-bikes and e-scooters are positive regardless of the distance

[12] It can also be argued that the public transport system is "fixed" regardless of who switches to/from public transport and hence 0 CO_2 emissions should be applied. We show the differences between the two ways of treating CO_2 emissions from public transport in our application further below.

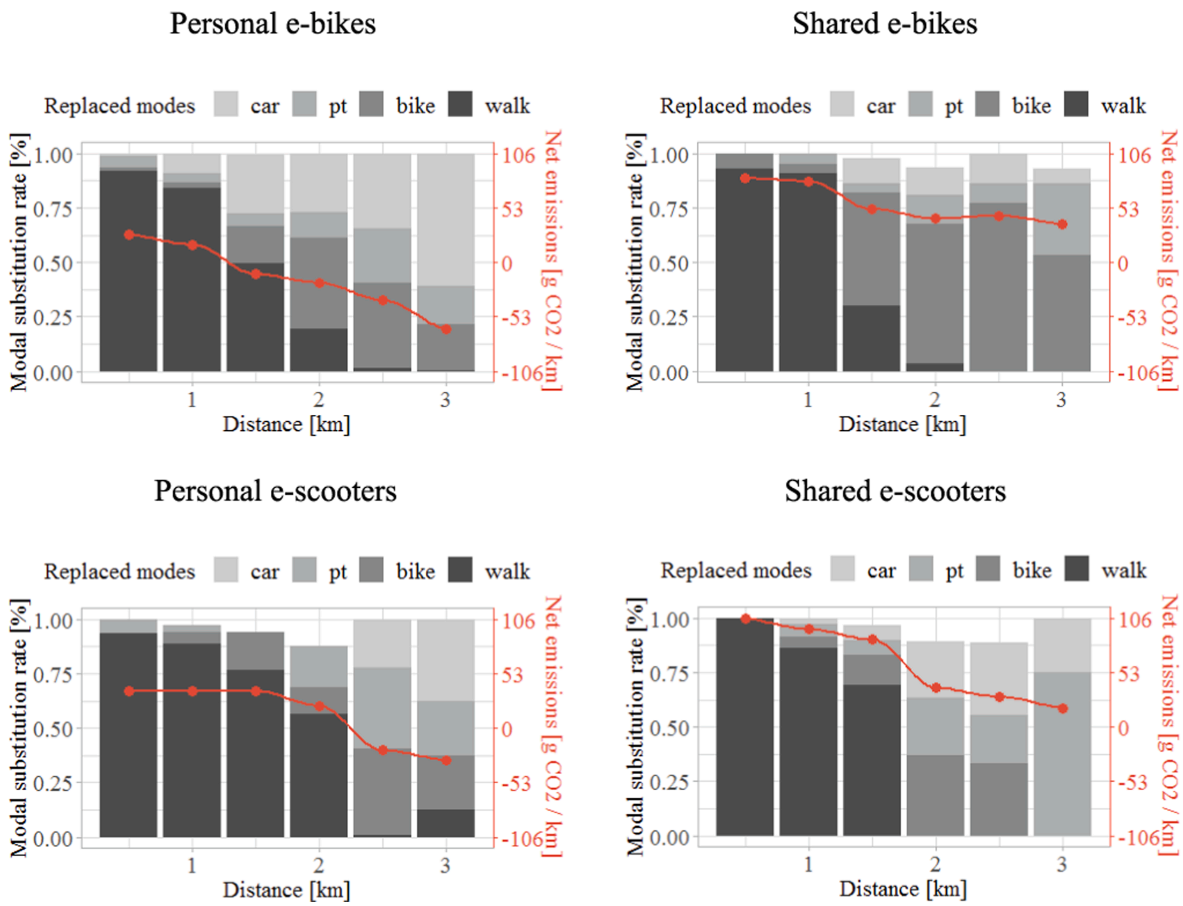

Fig. 6. Replaced modes (stacked bars) and resulting per-kilometre net emissions (dots/line) for micro-mobility modes by distance.

bracket and highest for short distances.

6. Contributions and conclusions

This is the first study to collect revealed preference data for and to estimate a comprehensive mode choice model between several shared and personal micro-mobility modes (e-bikes, e-scooters) and more established transport modes (public transport, car, bike, walk). Our contributions to research, policy and practice are threefold.

First, our results build the foundation to incorporate micro-mobility into transport network simulations to understand and to forecast their impact at system level and under varying policy scenarios. All else equal, the choice model reveals that trip distance, precipitation and access distance are fundamental to shared micro-mobility mode choice. Users are willing to walk between ~ 60 m and ~ 200 m to access shared e-scooters and shared e-bikes, respectively. Pre-booking functionality decreases the disutility of larger access distances. These results are not only useful to researchers and practitioners aiming to extend transport network simulations, but can also inform service provider's decisions on how to optimize their vehicle repositioning schemes.

Second, we demonstrate how choice models can be used to derive distance-based substitution patterns. Distance-based substitution patterns are more adequate for estimating environmental implications than common trip-based substitution patterns that are elicited through surveys for several reasons. First, it is substituted distance and not substituted trips that matters when calculating environmental implications. Second, substitution patterns derived from choice models are valid for all trips, not just the ones explicitly asked for, as they build on user preferences. Third, substitution patterns derived from choice models are more reliable than those derived from stated preference surveys, which are prone to biases such as the recall bias or the social desirability bias. This methodological contribution will gain in relevance as further new mobility services are introduced and their environmental implications will need to be assessed.

Third, our results yield direct policy implications for cities aiming to reduce transport-related CO_2 emissions. We show that personal e-bikes and e-scooters emit less CO_2 than the transport modes they replace, while shared e-bikes and e-scooters emit more CO_2 than the transport modes they replace. This finding challenges a common vision in transport that 'sharing is caring' for the environment. For micro-mobility, the relationship indeed appears to be reverse. On the one hand, city administrations can use these insights to justify public subsidies for personal e-bike/e-scooter sales and investments in bike lanes to increase their mode share further.

On the other hand, our results suggest caution when admitting and licensing shared micro-mobility providers. City administrations can collaborate with and require providers to improve the two main sources of CO_2 emissions of shared micro-mobility (operational services and vehicle manufacturing) while safeguarding their potential to improve transit catchment areas and to ease peak-time transit occupancy (e.g., Bieliński et al., 2021; de Bortoli and Christoforou, 2020; ITF, 2020). While shared e-bikes and e-scooters might increase CO_2 emissions in the short-term, they could help spark sustainable mobility transitions in the long-term if usage leads to ownership. While first evidence from a trial with cargo cycles in Germany points in this direction (Narayanan et al., 2021), more longitudinal studies are clearly needed to establish this relationship.

Finally, we acknowledge that this study has limitations. First, we used average values for life-cycle CO_2 emissions from a study conducted by the International Transport Forum (2020). While this study is the most comprehensive one of this type known to the authors, it only produces average values. In reality, variability exists for different vehicle types and fleet configurations. Hence, our results can be regarded as an approximation only and future work could conduct a sensitivity analysis around average values and/or consider more specific values for local CO_2 emissions. Second, despite all efforts in recruiting a truly random sample, the socio-demographics of our participants show some deviations from previous surveys which limit the representativeness of the survey and thus the results of this article. Third, although COVID-19 incidence rates were comparatively low in Switzerland during the time of study[13], travel behaviour was still affected. Most of all, public transport usage remained lower than usual (Molloy et al., 2021). Our study thus potentially over-estimates public transport substitution by other modes.

Author contribution

Daniel J. Reck: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Henry Martin:** Data pre-processing. **Kay W. Axhausen:** Conceptualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

We specify the utility functions for the mixed logit model using the abbreviations as follows:

Modes

WA Walk
PT Public transport
CA Car
BI Bike
PEB Personal e-bike
SEB Shared e-bike
PES Personal e-scooter
SES Shared e-scooter

Attributes

DI Trip distance
AD Access distance
TR Transfers
EL Elevation
MO Morning
NI Night
PR Precipitation
WI Wind
PTL PT season ticket (local)
PTC PT season ticket (nation)

[13] The 7-day incidence rate per 100,000 inhabitants ranged between 1.4 on 1 June and 27.0 on 1 October. In comparison, the highest rate was reported on 11 November (666.3).

PTB PT season ticket (bundle)
HHC Cars in household
HHB Bikes in household
HHE E-bikes in household
HHS E-scooters in household
UE University education
FT Full-time employment
AG Age
FE Female

Utility functions

$$U_{WA} = ASC_{WA} + \varepsilon$$

$$U_{PT} = ASC_{PT} + \beta_{PT_{DI}}{}^{*}DI + \beta_{PT_{DI2}}{}^{*}DI^2 + \beta_{PT_{PRDI}}{}^{*}PR^{*}DI + \beta_{PT_{AD}}{}^{*}AD + \beta_{PT_{TR}}{}^{*}TR + \beta_{PT_{PTB}}{}^{*}PTB + \beta_{PT_{PTL}}{}^{*}PTL + \beta_{PT_{PTC}}{}^{*}PTC + \beta_{PT_{MO}}{}^{*} MO + \beta_{PT_{NI}}{}^{*}NI + \beta_{PT_{AG}}{}^{*}AG + \beta_{PT_{FE}}{}^{*}FE + \beta_{PT_{UE}}{}^{*}UE + \beta_{PT_{FT}}{}^{*}FT + \varepsilon$$

$$U_{CA} = ASC_{CA} + \beta_{CA_{DI}}{}^{*}DI + \beta_{CA_{DI2}}{}^{*}DI^2 + \beta_{CA_{PRDI}}{}^{*}PR^{*}DI + \beta_{CA_{HHC}}{}^{*}HHC + \beta_{CA_{MO}}{}^{*} MO + \beta_{CA_{NI}}{}^{*}NI + \beta_{CA_{AG}}{}^{*}AG + \beta_{CA_{FE}}{}^{*}FE + \beta_{CA_{UE}}{}^{*}UE + \beta_{CA_{FT}}{}^{*}FT + \varepsilon$$

$$U_{BI} = ASC_{BI} + \beta_{BI_{DI}}{}^{*}DI + \beta_{BI_{DI2}}{}^{*}DI^2 + \beta_{BI_{PRDI}}{}^{*}PR^{*}DI + \beta_{BI_{HHB}}{}^{*}HHB + \beta_{BI_{WI}}{}^{*} WI^{*}DI + \beta_{BI_{EL}}{}^{*}EL^{*}DI + \beta_{BI_{MO}}{}^{*}MO + \beta_{BI_{NI}}{}^{*}NI + \beta_{BI_{AG}}{}^{*}AG + \beta_{BI_{FE}}{}^{*} FE + \beta_{BI_{UE}}{}^{*}UE + \beta_{BI_{FT}}{}^{*}FT + \varepsilon$$

$$U_{PEB} = ASC_{PEB} + \beta_{PEB_{DI}}{}^{*}DI + \beta_{PEB_{DI2}}{}^{*}DI^2 + \beta_{PEB_{PRDI}}{}^{*}PR^{*}DI + \beta_{PEB_{HHE}}{}^{*}HHE + \beta_{PEB_{MO}}{}^{*}MO + \beta_{PEB_{NI}}{}^{*}NI + \beta_{PEB_{AG}}{}^{*}AG + \beta_{PEB_{FE}}{}^{*}FE + \beta_{PEB_{UE}}{}^{*}UE + \beta_{PEB_{FT}}{}^{*}FT + \varepsilon$$

$$U_{SEB} = ASC_{SEB} + \beta_{SEB_{DI}}{}^{*}DI + \beta_{SEB_{DI2}}{}^{*}DI^2 + \beta_{SEB_{PRDI}}{}^{*}PR^{*}DI + \beta_{SEB_{PTB}}{}^{*}PTB + \beta_{SEB_{AD}}{}^{*}AD + \beta_{SEB_{MO}}{}^{*}MO + \beta_{SEB_{NI}}{}^{*}NI + \beta_{SEB_{AG}}{}^{*}AG + \beta_{SEB_{FE}}{}^{*}FE + \beta_{SEB_{UE}}{}^{*}UE + \beta_{SEB_{FT}}{}^{*}FT + \varepsilon$$

$$U_{PES} = ASC_{PES} + \beta_{PES_{DI}}{}^{*}DI + \beta_{PES_{DI2}}{}^{*}DI^2 + \beta_{PES_{PRDI}}{}^{*}PR^{*}DI + \beta_{PES_{HHS}}{}^{*}HHS + \beta_{PES_{MO}}{}^{*}MO + \beta_{PES_{NI}}{}^{*}NI + \beta_{PES_{AG}}{}^{*}AG + \beta_{PES_{FE}}{}^{*}FE + \beta_{PES_{UE}}{}^{*}UE + \beta_{PES_{FT}}{}^{*}FT + \varepsilon$$

$$U_{SES} = ASC_{SES} + \beta_{SES_{DI}}{}^{*}DI + \beta_{SES_{DI2}}{}^{*}DI^2 + \beta_{SES_{PRDI}}{}^{*}PR^{*}DI + \beta_{SES_{PTB}}{}^{*}PTB + \beta_{SES_{AD}}{}^{*}AD + \beta_{SES_{MO}}{}^{*}MO + \beta_{SES_{NI}}{}^{*}NI + \beta_{SES_{AG}}{}^{*}AG + \beta_{SES_{FE}}{}^{*}FE + \beta_{SES_{UE}}{}^{*}UE + \beta_{SES_{FT}}{}^{*}FT + \varepsilon$$

Note that all alternative specific constants are random to account for taste heterogeneity in mode choice between individuals.

Appendix B

In this study, we use CO_2 emissions calculated by the International Transport Forum (ITF, 2020). The report and a detailed excel file with all calculations are available online (accessed 1 October 2021):

- Report: https://www.itf-oecd.org/sites/default/files/docs/environmental-performance-new-mobility.pdf
- Excel: https://www.itf-oecd.org/sites/default/files/life-cycle-assessment-calculations-2020.xlsx

From the Excel file, we extract the following details on each transport modes' characteristics (Table 7):

Table 7
Transport mode characteristics (extracted from ITF, 2020).

		Bike (personal)	E-Bike (personal)	E-Scooter (personal)	PT (avg.)	E-Bike (shared)	E-Scooter (shared)	Car (avg.) (personal)
Lifetime	year	5.6	5.6	3.0	25.0	1.9	1.9	15.0
Annual mileage	km	2400	2400	2200	55,000	2900	2900	12,100
Average occupancy	person	1.0	1.0	1.0	103.5	1.0	1.0	1.5
Life-cycle mileage	pkm	13,440	13,440	6600	142,312,500	5510	5510	272,250
Life-cycle CO_2 emissions	kg	228	455	276	10,225,710	458	587	36,850
CO_2 emissions	g/pkm	17	34	42	72	83	107	135

References

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.

Balac, M., Becker, H., Ciari, F., Axhausen, K.W., 2019. Modeling competing free-floating carsharing operators - A case study for Zurich, Switzerland. Transport. Res. Part C: Emerg. Technol. 98, 101–117.

Becker, H., Balac, M., Ciari, F., Axhausen, K.W., 2020. Assessing the welfare impacts of shared mobility and Mobility as a Service (MaaS). Transport. Res. Part A: Policy Pract. 131, 228–243.

de Bortoli, A., Christoforou, Z., 2020. Consequential LCA for territorial and multimodal transportation policies: method and application to the free-floating e-scooter disruption in Paris. J. Cleaner Prod. 273, 122898. https://doi.org/10.1016/j.jclepro.2020.122898.

Bieliński, T., Kwapisz, A., Ważna, A., 2021. Electric bike-sharing services mode substitution for driving, public transit, and cycling. Transport. Res. Part D: Transp. Environ. 96, 102883. https://doi.org/10.1016/j.trd.2021.102883.

Bigazzi, A., Wong, K., 2020. Electric bicycle mode substitution for driving, public transit, conventional cycling, and walking. Transport. Res. Part D: Transp. Environ. 85, 102412. https://doi.org/10.1016/j.trd.2020.102412.

Bourne, J.E., Cooper, A.R., Kelly, P., Kinnear, F.J., England, C., Leary, S., Page, A., 2020. The impact of e-cycling on travel behaviour: A scoping review. J. Transport & Health 19, 100910. https://doi.org/10.1016/j.jth.2020.100910.

Campbell, A.A., Cherry, C.R., Ryerson, M.S., Yang, X., 2016. Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. Transport. Res. Part C: Emerg. Technol. 67, 399–414.

Caspi, O.r., Smart, M.J., Noland, R.B., 2020. Spatial associations of dockless shared e-scooter usage. Transport. Res. Part D: Transp. Environ. 86, 102396. https://doi.org/10.1016/j.trd.2020.102396.

Christoforou, Z., de Bortoli, A., Gioldasis, C., Seidowsky, R., 2021. Who is using e-scooters and how? Evidence from Paris. Transport. Res. Part D: Transp. Environ. 92, 102708. https://doi.org/10.1016/j.trd.2021.102708.

Du, Y., Deng, F., Liao, F., 2019. A model framework for discovering the spatio-temporal usage patterns of public free-floating bike-sharing system. Transport. Res. Part C: Emerg. Technol. 103, 39–55.

El-Assi, W., Salah Mahmoud, M., Nurul Habib, K., 2017. Effects of built environment and weather on bike sharing demand: a station level analysis of commercial bike sharing in Toronto. Transportation 44 (3), 589–613.

Fearnley, N., Johnsson, E., Berge, S.H., 2020. Patterns of E-Scooter Use in Combination with Public Transport. Transp. Find.

Fishman, E., Washington, S., Haworth, N., 2013. Bike share: a synthesis of the literature. Transp. Rev. 33 (2), 148–165.

Fishman, E., Washington, S., Haworth, N., 2014. Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia. Transport. Res. Part D: Transp. Environ. 31, 13–20.

Fishman, E., 2016. Bikeshare: A review of recent literature. Transp. Rev. 36 (1), 92–113.

Fukushige, T., Fitch, D.T., Handy, S., 2021. Factors influencing dock-less E-bike-share mode substitution: Evidence from Sacramento, California. Transport. Res. Part D: Transp. Environ. 99, 102990.

Gebhart, K., Noland, R.B., 2014. The impact of weather conditions on bikeshare trips in Washington, DC. Transportation 41 (6), 1205–1225.

Guidon, S., Becker, H., Dediu, H., Axhausen, K.W., 2019. Electric bicycle-sharing: a new competitor in the urban transportation market? An empirical analysis of transaction data. Transp. Res. Rec. 2673 (4), 15–26.

Guidon, S., Reck, D.J., Axhausen, K., 2020. Expanding a(n) (electric) bicycle-sharing system to a new city: Prediction of demand with spatial regression and random forests. J. Transp. Geogr. 84, 102692. https://doi.org/10.1016/j.jtrangeo.2020.102692.

Hawa, L., Cui, B., Sun, L., El-Geneidy, A., 2021. Scoot over: Determinants of shared electric scooter presence in Washington D.C. Case Studies on Transp. Policy 9 (2), 418–430.

He, Y.i., Song, Z., Liu, Z., Sze, N.N., 2019. Factors influencing electric bike share ridership: analysis of Park City, Utah. Transport. Res. Rec. 2673 (5), 12–22.

Hensher, D.A., Greene, W.H., 2003. The mixed logit model: the state of practice. Transportation 30 (2), 133–176.

Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. J. Choice Model. 32, 100170. https://doi.org/10.1016/j.jocm.2019.100170.

Hess, S., Train, K.E., Polak, J.W., 2006. On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit model for vehicle choice. Transport. Res. Part B: Methodol. 40 (2), 147–163.

Hörl, S., Becker, F., Axhausen, K.W., 2021. Simulation of price, customer behaviour and system impact for a cost-covering automated taxi system in Zurich. Transport. Res. Part C: Emerg. Technol. 123, 102974. https://doi.org/10.1016/j.trc.2021.102974.

Hollingsworth, J., Copeland, B., Johnson, J.X., 2019. Are e-scooters polluters? The environmental impacts of shared dockless electric scooters. Environ. Res. Lett. 14 (8), 084031. https://doi.org/10.1088/1748-9326/ab2da8.

Horni, A., Nagel, K., Axhausen, K.W., 2016. The multi-agent transport simulation MATSim. Ubiquity Press, London.

ITF, 2020. Good to Go? Assessing the Environmental Performance of New Mobility, International Transport Forum, Paris.

Kroesen, M., 2017. To what extent do e-bikes substitute travel by other modes? Evidence from the Netherlands. Transport. Res. Part D: Transp. Environ. 53, 377–387.

Laa, B., Leth, U., 2020. Survey of E-scooter users in Vienna: Who they are and how they ride. J. Transp. Geogr. 89, 102874. https://doi.org/10.1016/j.jtrangeo.2020.102874.

Lazarus, J., Pourquier, J.C., Feng, F., Hammel, H., Shaheen, S., 2020. Micromobility evolution and expansion: Understanding how docked and dockless bikesharing models complement and compete - A case study of San Francisco. J. Transp. Geogr. 84, 102620. https://doi.org/10.1016/j.jtrangeo.2019.102620.

Li, A., Gao, K., Zhao, P., Qu, X., Axhausen, K.W., 2021. High-resolution assessment of environmental benefits of dockless bike-sharing systems based on transaction data. J. Cleaner Prod. 296, 126423. https://doi.org/10.1016/j.jclepro.2021.126423.

MacArthur, J., Dill, J., Person, M., 2014. Electric bikes in North America: Results of an online survey. Transp. Res. Rec. 2468 (1), 123–130.

Manser, P., Becker, H., Hörl, S., Axhausen, K.W., 2020. Designing a large-scale public transport network using agent-based microsimulation. Transport. Res. Part A: Policy Pract. 137, 1–15.

Mathew, J.K., Liu, M., Seeder, S., Li, H., Bullock, D.M., 2019. Analysis of E-scooter trips and their temporal usage patterns. Inst. Transport. Eng. ITE J. 89 (6), 44–49.

McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. J. Appl. Econ. 15 (5), 447–470.

McKenzie, G., 2019. Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, DC. J. Transp. Geogr. 78, 19–28.

Molloy, J., Castro Fernández, A., Götschi, T., Schoeman, B., Tchervenkov, C., Tomic, U., Hintermann, B., Axhausen, K.W., 2020. A national-scale mobility pricing experiment using GPS tracking and online surveys in Switzerland: Response rates and survey method results. *Arbeitsberichte Verkehrs-und Raumplanung*, 1555.

Molloy, J., Schatzmann, T., Schoeman, B., Tchervenkov, C., Hintermann, B., Axhausen, K.W., 2021. Observed impacts of the Covid-19 first wave on travel behaviour in Switzerland based on a large GPS panel. Transp. Policy 104, 43–51.

NACTO, 2020. Shared micromobility in the US: 2019. National Association of City Transportation Officials, New York.

Narayanan, S., Gruber, J., Liedtke, G., Antoniou, C., 2021. Purchase intention and actual purchase of cargo cycles: Influencing factors and policy insights. Preprint submitted to Transport. Res. Part A: Policy and Pract.

Noland, R.B., 2019. Trip patterns and revenue of shared e-scooters in Louisville. Kentucky, Transport Findings, April.

Noland, R.B., 2021. Scootin' in the rain: Does weather affect micromobility? Transport. Res. Part A: Policy Pract. 149, 114–123.

Ortúzar, J.d.D., Willumsen, L.G., 2011. Modelling Transport. John Wiley & Sons, New York.

Reck, Daniel J., Haitao, He, Guidon, Sergio, Axhausen, Kay W., 2021a. Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland. Transport. Res. Part C: Emerg. Technol. 124, 102947. https://doi.org/10.1016/j.trc.2020.102947.

Reck, D.J., Guidon, S., Axhausen, K.W., 2021b. Modelling shared e-scooters: A spatial regression approach. In: Paper presented at the 9th Symposium of the European Association for Research in Transportation (hEART), Lyon, February.

Reck, Daniel J., Axhausen, Kay W., 2021. Who uses shared micro-mobility services? Empirical evidence from Zurich, Switzerland. Transport. Res. Part D: Transp. Environ. 94, 102803. https://doi.org/10.1016/j.trd.2021.102803.
Ricci, Miriam, 2015. Bike sharing: A review of evidence on impacts and processes of implementation and operation. Res. Transport. Bus. Manage. 15, 28–38.
Sanders, Rebecca L., Branion-Calles, Michael, Nelson, Trisalyn A., 2020. To scoot or not to scoot: Findings from a recent survey about the benefits and barriers of using E-scooters for riders and non-riders. Transport. Res. Part A: Policy. Pract. 139, 217–227.
Schmid, B., Axhausen, K.W., 2019. Predicting response rates of all and recruited respondents: A first attempt. Transp. Find.
Shaheen, S., Cohen, A., 2019. Shared Micromobility Policy Toolkit: Docked and Dockless Bike and Scooter Sharing. UC Berkeley Transportation Sustainability Research Center, Richmond, CA. Retrieved from https://escholarshiorg/uc/item/00k897b5. Accessed on 27 September 2020.
Shaheen, S.A., Zhang, H., Martin, E., Guzman, S., 2011. Hangzhou public bicycle: Understanding early adoption and behavioural response to bike sharing in Hangzhou, China. In: Paper presented at the 90th Annual Meeting of the Transportation Research Board, Washington, DC, January.
Shen, Yu, Zhang, Xiaohu, Zhao, Jinhua, 2018. Understanding the usage of dockless bike sharing in Singapore. Int. J. Sustain. Transport. 12 (9), 686–700.
Söderberg f.k.a Andersson, A.S., Adell, E., Hiselius, L.W., 2021. What is the substitution effect of e-bikes? A randomised controlled trial. Transport. Res. Part D: Transp. Environ., 90, 102648.
Sun, Qi, Feng, Tao, Kemperman, Astrid, Spahn, Andreas, 2020. Modal shift implications of e-bike use in the Netherlands: Moving towards sustainability? Transport. Res. Part D: Transp. Environ. 78, 102202. https://doi.org/10.1016/j.trd.2019.102202.
Teixeira, J.F., Silva, C., Moura e Sá, F., 2021. Empirical evidence on the impacts of bikesharing: a literature review. Transp. Rev., 41(3), 329-351.
Train, K.E., 2009. Discrete choice methods with simulation. Cambridge University Press.
Wang, K., Qian, X., Circella, G., Lee, Y., Malik, J., Fitch, D.T., 2021. What Mobility Modes Do Shared E-Scooters Displace? A Review of Recent Research Findings. Paper presented at the 100th Annual Meeting of the Transportation Research Board, Washington, DC, January.
Younes, Hannah, Zou, Zhenpeng, Wu, Jiahui, Baiocchi, Giovanni, 2020. Comparing the temporal determinants of dockless scooter-share and station-based bike-share in Washington, DC. Transport. Res. Part A: Policy Pract. 134, 308–320.
Zhu, Rui, Zhang, Xiaohu, Kondor, Dániel, Santi, Paolo, Ratti, Carlo, 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.
Zuniga-Garcia, N., Machemehl, R., 2020. Dockless electric scooters and transit use in an urban/university environment. In: Paper presented at the 99th Annual Meeting of the Transportation Research Board, Washington, DC, January.