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Real-world and traffic-adjusted physical activity levels of micromobility modes in Barcelona

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ABSTRACT

Introduction: The goal of this study is to assess the level of physical activity associated with the use of different micromobility modes in the context of the city of Barcelona, considering both real-world and traffic-adjusted conditions.

Methods: The study used GPS and accelerometer devices to obtain objective measurements from 502 trips taken, including 128 trips by electric scooter users, 308 trips by conventional shared bike users, and 66 trips taken by electric shared bicycle users.

Results: The analysis confirmed that a notable disparity exists between the various modes of micromobility used in the city and the physical activity levels their usage entails.

Conclusions: Our findings highlight the importance of recognizing conventional and electric bikes as active modes of transport that may provide greater health benefits than e-scooters.

1. Introduction and literature review

Micromobility modes of transport have seen a significant increase in popularity in recent years. This trend has been driven by a variety of functional and non-functional factors (Bretones and Marquet, 2022), including concerns about the environment and traffic congestion (de Bortoli, 2021; McQueen et al., 2021), as well as the emergence of new technologies that make these modes of transportation more accessible and convenient (Milakis et al., 2020). One area of particular interest is the relationship between micromobility and physical activity (PA), as in the context of expanding urbanization and the associated increase in sedentary lifestyles, micromobility modes have emerged as potential solutions to these challenges. Understanding how these modes influence PA levels is crucial as PA entails direct benefits for health, reducing the risk of developing cardiovascular and respiratory diseases, type 2 diabetes, and some types of cancer, and diminishing the risk of all-cause mortality (Berntsen et al., 2017; Castro et al., 2019; Boris Gojanovic et al., 2011a, b; Sanders et al., 2022; Woodcock et al., 2011, 2014). Moreover, while there is a consensus that traditional active mobility involves physical effort to initiate movement, exemplified by activities like walking and cycling, our study endeavours to scrutinize these conventional classifications within the context of micromobility. This inquiry arises from the ongoing debate surrounding whether micromobility modes, including e-cycling and e-scootering, align with the traditional definitions of active transportation and what implications this classification might carry for overall PA levels.

Micromobility encompasses a range of small, lightweight vehicles powered by humans or electricity, including bicycles, e-bikes, e-scooters, and similar electrically powered modes of transportation, for both shared and private use. Research suggests that using

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micromobility modes for transportation can lead to increased PA, especially when cycling (Boris Gojanovic et al., 2011a, b; Otero et al., 2018; Peterman et al., 2016; Raustorp and Koglin, 2019). Additionally, research has shown that e-bikes can also promote PA (Castro et al., 2019; Chabanas et al., 2019; Fyhri and Fearnley, 2015; B Gojanovic et al., 2011a, b; Sundfør and Fyhri, 2017; Wild and Woodward, 2019). However, the current body of literature on e-scooters, while growing, is still relatively limited compared to bicycles and e-bikes. As e-scooters fall within the category of micromobility and share characteristics with e-bikes, including electric propulsion, it is plausible that they may provide some form of PA engagement, although the extent and nature of this engagement remain to be fully understood. Hence, the current debate is centred on accurately quantifying the PA generated by various micromobility modes, particularly e-scooter use, and comparing these activity levels with those achieved through previous modes of transportation (Glenn et al., 2020; Sanders et al., 2022).

Previous research on the relationship between micromobility and PA has primarily relied on self-reported measures, such as questionnaires and surveys. While these methods provide valuable information on the socioeconomic context of micromobility users and their self-reported PA levels (Troiano et al., 2014), they also have limitations, including potential reporting biases, variability in perception, and issues with reliability and validity (Matthews et al., 2012; Shephard, 2003; Sylvia et al., 2014). Self-reporting often requires individuals to reflect on past experiences, which can be influenced by inherent memory limitations or the tendency for selective recall. This means that respondents may bring diverse and potentially nuanced personal perceptions to their responses, contributing to variability in reported data. To overcome some of these limitations, recent studies have begun to use accelerometers and GPS as more objective and precise measures, as these devices have helped enhance human movement monitoring, particularly in everyday life (Batista Ferrer et al., 2018; Chaix et al., 2019; Duncan et al., 2016; Marquet et al., 2020; Plasqui et al., 2013; Rowlands, 2018; White et al., 2019). Accelerometers can provide simple ratios of time spent in active or sedentary modes, while also being able to categorize the data according to the intensity of the activity (such as light or moderate exercise) or estimate distance travelled (such as steps), On the other hand, GPS devices can pinpoint a location within a few meters at any given time, as well as generate mobility indicators that describe an individual's daily mobility patterns. However, when it comes to distinguishing transportation-related activities like walking or cycling, the combination of GPS and accelerometer is more useful than using each sensor separately. Indeed, when distinguishing between active and passive modes of transportation, the performance of transport mode detection is improved when GPS data, such as speed, is added to accelerometer data (Brondeel et al., 2015; Ellis et al., 2014; Lee and Kwan, 2018). Therefore, these wearable devices accurately measure daily PA, energy expenditure and are valid and reliable predictors of total PA.

In the context of transportation, energy expenditure is often reported as the number of Metabolic Equivalents of Tasks (METs) per minute or MET-minutes per day (Castro et al., 2019; B Gojanovic et al., 2011a, b; Tao et al., 2020; Wilson et al., 2020). This allows for a direct comparison of the energy expenditure of different modes of transportation and can provide insight into the potential health benefits of different modes. The Compendium of Physical Activities provides data on the energy expenditure of various activities and transportation modes, including cycling and scootering (Ainsworth et al., 2011). However, it is important to note that the values provided in the Compendium are based on laboratory settings and may not accurately reflect the energy expenditure of these activities in real-life conditions (Ainsworth et al., 2011; Allahbakhshi et al., 2019). Factors such as terrain, weather, and personal characteristics can all affect energy expenditure (Cusack, 2021; Langford et al., 2017; McGinn et al., 2007), and therefore, it is important to assess PA levels under real-life conditions to obtain a more accurate understanding of the impact of these modes on energy expenditure and overall PA levels (Allahbakhshi et al., 2019, 2020; Awais et al., 2015). Similarly, while most previous studies have sought to generate objective PA gained per minute of a trip in a micromobility mode, we also need to consider that travel behaviours in each mode of transport are significantly different from each other (Arias-Molinares et al., 2023; Cubells et al., 2023; Rayaprolu and Venigalla, 2020; Roig-Costa et al., 2021; Şengül and Mostofi, 2021). Thus, resulting PA levels will likely differ when analysing PA data standardized by a minute of use, or analysing total PA gained from typical micromobility use.

Therefore, the primary aim of this research is to assess the PA (in METs) associated with the use of different micromobility modes in the context of the city of Barcelona both in real-world and traffic-adjusted conditions. Indeed, this study offers a deeper understanding of the potential differences between biking and scootering. By using objective measures from both accelerometer and GPS devices, this study aims to provide a more accurate understanding of the matter, providing valuable insights into the latent health benefits in terms of PA of using micromobility modes for transportation, which can help inform policies and interventions aimed at promoting active transportation.

The paper is organized as follows. Section 2 introduces the study case, data and methods used, while Section 3 presents the results obtained. Section 4 is dedicated to the discussion of the results and the limitations of the study. Finally, conclusions and further implications are drawn in Section 5.

2. Methods and data

2.1. Study setting

The study took place in the municipality of Barcelona, a densely populated urban area with mixed land use and a continuous, compact layout (Marquet and Miralles-Guasch, 2018). The urban environment of Barcelona makes it a popular location for micromobility usage and is representative of traditional European cities with dense, compact urban areas where these new modes of transportation compete for public space with pedestrians, cyclists, and cars (Esztergár-Kiss and Lopez Lizarraga, 2021). In fact, in 2021 bicycle trips accounted for a total of 144,950, and e-scooter trips for 37,621 (representing a 3.3 and 0.9% of total trips, respectively) (IERMB, 2021). Our analysis focused on conventional and electric bicycles from the public bike-sharing system along with privately owned e-scooters. The dock-based bicycle sharing system, Bicing, has over 100,000 registered users and a fleet of 7000 bikes

(Soriguera and Jiménez-Meroño, 2020). Unlike Bicing, the municipality does not offer an e-scooter sharing platform and does not allow private e-scooter companies to operate within city limits, meaning all e-scooter users in Barcelona use their privately owned vehicles (Fig. 1).

2.2. *Overview of the data collection methodology*

The NEWMOB study conducted in 2020 surveyed 902 micromobility users in Barcelona, Spain. The study aimed to understand the travel behaviour and impact of COVID-19 on micromobility adoption. The survey was conducted between September 15th to October 1st using 8 pollsters that were distributed in strategic points of the city of Barcelona during working days between 9 a.m. and 8 p.m. Through a Computer Assisted Personal Interviewing (CAPI) technique, private e-scooter and bike sharing (both in conventional and electric modalities) users were randomly intercepted and asked to answer a questionnaire that took 10–15 min. Eligible participants had to be living or working in Barcelona and were over 16 years old due to the minimum age requirement for driving an electric scooter and using the public bike sharing system. The sample consisted of 326 electric scooter users, 251 moped scooter users, 217 traditional bike users, and 108 electric bike users. The questionnaire covered socio-demographic characteristics, transport usage, multimodality, and use of public space and mobility (further information is available at (Roig-Costa et al., 2021)).

From this initial sample, a subsample of participants was further selected to participate in a tracking study using dedicated GPS and accelerometer devices. We randomly selected a representative subsample from the baseline survey ending up with 65 e-scooters, 74 conventional bikers, and 37 e-bike users. Participants in the study first signed an informed consent and then completed a baseline questionnaire covering their demographics, self-reported health, and PA habits. They were then provided with an accelerometer device (GT3X-BT; ActiGraph LLC, Pensacola, FL, USA) and a GPS device (BT-Q1000×; QStarz, Taiwan, R.O.C.). The devices were to be worn all day, except during activities like showering, swimming, contact sports, and night-time sleeping. Participants were also asked to fill out a daily travel diary, sent via smartphone messages at the end of each day, to help with cross-checking their trips and interpreting accelerometer-recorded PA levels. To analyse daily mobility patterns, we excluded participants who did not wear the devices for a minimum of 8 h in one of the seven days it was given to them. This resulted in a sample of 39 eligible users, and 502 trips. The study aimed to collect a sufficiently large number of trips for each micromobility mode, prioritizing data accuracy over sample size. Ensuring that the trips were accurately associated with their respective modes was crucial to the study's reliability and validity.

2.3. *Accelerometer and GPS data processing*

Accelerometer data were analysed using Actilife software. The data were summarized into 15-s intervals and any periods of 60 min or more with zero values were considered as "non-wear" and were excluded from analysis. For analysing mode and PA during commuting, participants had to provide at least one day (8 h) of valid accelerometer and GPS data from a working day. Likewise, the GPS devices were set to record the participants' location every 15 s. The GPS data were processed using the Human Activity Behaviour Identification Tool and Data Unification System (HABITUS) software. HABITUS applies a heuristic algorithm to identify trips from GPS trajectories and determine their mode of transportation by calculating the distance and speed between sequential GPS points (Berjisian and Bigazzi, 2022). This software classifies trips with a 90th percentile speed ranging from $\geq$10 km/h to $<$25 km/h as "micromobility trips." For this research, only micromobility trips were considered in the analysis. Because the HABITUS software is unable to differentiate between e-scooter and bicycle trips, travel diaries were used to help identify the specific mode of transportation for each micromobility trip. These travel diaries were designed to have information regarding the number of trips and the micromobility mode used for each of the participants, daily. They were sent to the participants every day through WhatsApp or Email (in accordance with their preferences) to be filled (see Annex 1). They gave self-reported information about trips that complemented the objective data coming from accelerometers.

Fig. 1. Barcelona dock-based bicycle sharing system and private e-scooter.

Accelerometer and GPS data were combined for every 15-s epoch. The merged data were imported into ArcGis Pro software (Esri, Redlands, California, USA) where trips that had taken place outside the limits of Barcelona municipality were visually identified and removed. We also filtered out trips that were either too short (less than 2 min) or too long (more than 2 h, n = 176) or had an average speed above 60 km/h (n = 32). After the data cleaning process, 502 routes remained.

Once valid trips were identified, we first decided to express the intensity of PA as Metabolic Equivalents of Task (METs) to enhance comparability between different studies. MET is a unit that measures the energy consumption rate during PA (Mendes et al., 2018). One MET is equal to the amount of energy expended while sitting at rest, calculated as oxygen uptake per kilogram of body mass per minute (3.5 ml/O2/kg/min) (Hills et al., 2014). The total amount of METs per route was calculated by using the Freedson equation (METS/min = 1.439008 + 0.000795 × count/min (vertical axis)) (Freedson et al., 1998). The average MET/minute corresponding to each trip was obtained by dividing the overall estimated number of METs by the total minutes of the trip. Additionally, the PA data were summarized into minutes spent for each trip identified, and in terms of total minutes of sedentary, light, moderate, vigorous, and very vigorous activity levels. We applied Troiano et al. (2008) set of cut points commonly used to define PA intensities (Sedentary: <100 cpm; Light: 100–1951 cpm; Moderate: 1952–5724 cpm; Vigorous: 5725–9498; Very vigorous: >9488).

2.4. Data analysis

The sample characteristics were assessed based on age, gender, occupation, education, and Body Mass Index (BMI) category (Table 1). Participants were asked to self-report which mode of micromobility they primarily used. This information was then used to categorize the participants into bike, e-bike, or e-scooter habitual users. Apart from employing descriptive statistics, bivariate analysis was applied to characterize the attributes of trips (average time, distance, speed), the average gained METs, and the average time spent in each PA intensity (Table 2). In addition, we assessed differences in total METs and MET/minute in relation to transport mode, gender, and age (Table 3).

To evaluate energy expenditure (METs) across various micromobility modes and uses, we differentiated between two distinct measurements: (1) capturing all PA from the start to the end of the trip, inclusive of sedentary time (e.g., at intersections, traffic lights, etc.), and (2) focusing solely on trip segments during which the user was actively engaged, thereby excluding sedentary time. We designated the first metric as 'Real-World Energy Expenditure' (RWE) and the second as 'Traffic-Adjusted Energy Expenditure' (TAE).

Real-World Energy Expenditure (RWE) offers a comprehensive assessment of the PA experienced by micromobility users in Barcelona. However, this metric is heavily influenced by factors such as local street layout, driving conditions, and available infrastructure, which may not accurately reflect the typical PA associated with micromobility use. Consequently, we introduce the 'Traffic-Adjusted Energy Expenditure' (TAE) measurement to account for stops and driving conditions imposed by the local context. This alternative measure more precisely estimates the PA generated by micromobility while in motion, making it a more suitable metric for inter-city comparisons. We further categorize both measurements into Total METs and METs per minute. This differentiation is crucial because energy expenditure depends not only on the type of micromobility employed but also on the specific trip characteristics, such as distance. Given that previous studies have established distinct trip features for various micromobility modes, it is essential to evaluate energy expenditure by examining both the entire trip and by stratifying PA on a per-minute basis.

In summary, the combination of measurement types - Real-World Energy Expenditure (RWE) and Traffic-Adjusted Energy

Table 1
Sociodemographic characteristics of the sample.

Sample characteristics (n = 39)	Overall	Electric scooter	Conventional shared bike	Electric shared bike
N	*39*	*11*	*20*	*8*
Demographics				
Male	25 (64.10%)[a]	6 (54.55%)	14 (70.00%)	5 (62.50%)
Age, years (mean (SD))	31.03 (11.12)	30.36 (8.96)	29.80 (12.17)	35.00 (11.46)
Age, years				
16-24	13 (33.33%)	3 (27.27%)	9 (45.00%)	1 (12.50%)
25-34	14 (35.90%)	5 (45.45%)	6 (30.00%)	3 (37.50%)
35-44	7 (17.95%)	2 (18.18%)	2 (10.00%)	3 (37.50%)
45+	5 (12.82%)	1 (9.09%)	3 (15.00%)	1 (12.50%)
Education level				
< High school	3 (7.69%)	1 (9.09%)	2 (10.00%)	–
High school	17 (43.59%)	6 (54.55%)	7 (35.00%)	4 (50.00%)
College	19 (48.72%)	4 (36.36%)	11 (55.00%)	4 (50.00%)
Professional status				
Student	5 (12.82%)	–	5 (25.00%)	–
Active	33 (84.62%)	10 (90.91%)	15 (75.00%)	8 (100.00%)
Retired	1 (2.56%)	1 (9.09%)	–	–
BMI index (kg·m^2)				
Mean (SD)	23.68 (3.18)	25.36 (4.11)	22.88 (2.42)	23.36 (2.90)
Regular weight (18.5–25)	29 (74.36%)	6 (54.55%)	17 (85.00%)	6 (75.00%)
Overweight (25–30)	9 (23.08%)	4 (36.36%)	3 (15.00%)	2 (25.00%)
Obesity (≥30)	1 (2.56%)	1 (9.09%)	–	–

[a] Results are presented as n (%).

Table 2
Objectively measured physical activity by micromobility mode of transport.

	All	Conventional shared bike	Electric shared bike	Electric scooter	
	N = 502	N = 308	N = 66	N = 128	
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	p-value[a]
RWE - Average METs	2.47 (1.06)	2.66 (1.15)	2.55 (1.08)	1.98 (0.53)	<0.001
TAE - Average METs	2.65 (1.06)	2.81 (1.16)	2.75 (1.09)	2.20 (0.56)	<0.001
Average distance (kilometres)	2.28 (2.13)	2.37 (2.21)	2.46 (2.52)	1.96 (1.64)	0.138
Average time (minutes)	11.87 (9.29)	12.38 (9.98)	12.12 (8.39)	10.51 (7.84)	0.157
Average speed (km/h)	11.46 (6.81)	11.42 (6.88)	12.17 (8.72)	11.17 (5.41)	0.618
Average active time (minutes)	9.30 (8.27)	10.43 (9.16)	9.52 (7.13)	6.47 (5.44)	<0.001
Average time in sedentary activity (minutes)	2.57 (2.93)	1.95 (2.25)	2.61 (2.69)	4.05 (3.85)	<0.001
Average time in light activity (minutes)	6.44 (6.30)	6.97 (7.18)	6.23 (5.37)	5.26 (3.90)	0.034
Average time in MVPA activity (minutes)	2.86 (4.92)	3.45 (5.36)	3.28 (5.31)	1.21 (2.79)	<0.001

SD: Standard Deviation; MVPA: Moderate to Vigorous Physical Activity.
[a] Derived from Analysis of Variance (Anova) statistics.

Table 3
Total METs and MET/minute.

	RWE	TAE	RWE	TAE
	Total METs[a]	Total METs	MET/minute	MET/minute
Transport Mode				
Conventional bike	34.23 (15.07) *	31.23 (15.30)	2.66 (0.35)	2.83 (0.37)
Electric bike	32.95 (14.28)	29.37 (14.14)	2.59 (0.39)	2.78 (0.39)
Electric scooter	19.44 (9.04)	14.10 (7.92)	2.02 (0.30)	2.24 (0.33)
Gender				
Male	31.23 (16.66)	27.84 (16.91)	2.53 (0.43)	2.73 (0.44)
Female	27.23 (10.42)	22.75 (11.01)	2.34 (0.44)	2.52 (0.43)
Age				
16–24	25.76 (7.80)	21.70 (8.05)	2.46 (0.40)	2.67 (0.43)
25–34	25.57 (11.95)	22.08 (12.23)	2.40 (0.46)	2.59 (0.46)
35–44	37.34 (21.40)	33.74 (21.90)	2.54 (0.57)	2.70 (0.57)
45+	41.55 (18.24)	37.44 (19.64)	2.54 (0.35)	2.72 (0.32)

[a] Results are presented as Mean (Standard Deviation).

Expenditure (TAE) - along with measurement characteristics - Total METs and METs per minute - generates a comprehensive set of four distinct metrics for assessing the PA generated by micromobility usage. The definitions, advantages, and practical applications of each measure are concisely presented in Fig. 2.

To examine the relationship between micromobility modes used in a trip and the total METs and METs per minute generated, while controlling for key sociodemographic characteristics, we utilized multilevel linear mixed-effects models built with the R package "lme4" (Bates et al., 2015). These models incorporated user-specific and trip-specific random effects to account for any unobserved heterogeneity (refer to Tables 4 and 5), as MLME modelling allows us to incorporate the hierarchical structure of our data, where PA measurements are nested within specific routes and individual user profiles.

Also, to facilitate the interpretation of the models, we calculated and graphed the marginal effects using the R package "ggeffects" (Lüdecke, 2018). This approach allowed us to predict the total MET and MET/minute per trip for each transport category, with all other variables held at their average values (refer to Fig. 3). Additionally, we assessed these values in terms of gender to investigate significant differences between male and female users, and to determine which modes may accentuate these differences (Figs. 4 and 5). The decision to include gender-specific figures in the analysis was based on a preliminary descriptive examination of the data presented in Table 3, indicating potential differences in physical activity levels. Given these findings, we deemed it relevant to present gender-specific results aligning with existing research in the field of transport and micromobility, which emphasizes the importance of considering gender differences when conducting analyses (Beecham and Wood, 2014; Campisi et al., 2021; Cubells et al., 2023; Frings et al., 2012; Haynes et al., 2019).

3. Results

3.1. Descriptive characteristics

The final data set consisted of 502 trips that belonged to 39 individuals distributed between 11 electric scooter users (128 trips), 20 conventional shared bike users (308 trips), and 8 electric shared bike users (66 trips). The characteristics of the study population are outlined in Table 1. The participants, on average, were 31 years old and of regular weight (mean BMI of 23.68 kg/m2), with 23% considered overweight. Over half of the participants were men (64%) and had completed high school (44%) or college/university

	Total METs	MET/minute
Real World Energy Expenditure (RWE)	Total energy expenditure accumulated in a single trip and real world driving conditions for a specific micromobility mode.	Energy expenditure per minute accumulated in a single trip and real world driving conditions for a specific micromobility mode.
	Pros • Comprehensive measure of overall PA intensity during the entire trip. ***Useful for*** • Providing a more detailed understanding of patterns of physical activity throughout the trip, such as how much time is spent in different activity intensities.	***Pros*** • Provides a more precise measure of the intensity of physical activity by accounting for the duration of the trip. • Less prone to measurement errors associated with averaging the intensity of all activities throughout the trip. ***Useful for*** • Comparing the relative intensity of trips when using different modes.
	Useful measure to compare WITHIN cities.	
Traffic Adjusted Energy Expenditure (TAE)	Total energy expenditure accumulated in a single trip when accounting only for active phases of the trip, excluding traffic light stops or other sedentary phases of the trip, for a specific micromobility mode.	Energy expenditure per minute accumulated in a single trip when accounting only for active phases of the trip, excluding traffic light stops or other sedentary phases of the trip, for a specific micromobility mode.
	Pros • Provides a more precise estimate of the actual physical activity that occurs during the active part of the trip. ***Useful for*** • Comparing the overall physical activity intensity of different trips or modes of transportation.	***Pros*** • Provides a precise measure of the active part and intensity of the physical activity, on a per-minute basis. • Help standardize the measurement of physical activity across different studies and populations, allowing for more meaningful comparisons. ***Useful for*** • Quantifying the health benefits of physical activity during a trip.
	Useful measure to compare BETWEEN cities/urban environments.	

Fig. 2. Definition, benefits, and utility of using Total METs and MET/minute under the two scenarios proposed.

Table 4
Fit Linear Mix Effects Models: Linear associations of Mode Used with Total METs.

	Model 1				Model 2			
	RWE - Total MET				TAE - Total MET			
	Coeff.	Std. Err.	t value	P > |z|	Coeff.	Std. Err.	t value	P > |z|
Transport Mode								
Electric scooter (REF)								
Conventional bike	18.293	5.845	3.129	**0.005**[b]	21.785	5.968	3.650	**0.000**[a]
Electric bike	12.825	7.179	1.786	0.108	16.615	7.302	2.275	**0.050**[c]
Age								
16-24 (REF)								
25–34	3.574	6.186	0.578	0.697	2.728	6.336	0.431	0.634
35–44	16.395	7.484	2.191	0.054	13.782	7.668	1.797	**0.042**[c]
45 +	11.517	7.876	1.462	0.247	11.453	8.099	1.414	0.253
Gender								
Female (REF)								
Male	1.22	5.238	0.233	0.786	0.678	5.359	0.126	0.682

[a] $p < 0.001$.
[b] $p < 0.01$.
[c] $p < 0.05$.

education (49%), being almost 85% of the participants employed. Both conventional and electric shared bike users were more likely to be men (70 and 63% respectively) and highly educated (55 and 50% respectively). On the other hand, electric scooter users were more likely to have a lower education level, i.e., high school (55%), and to present overweight or even obesity levels (45%). In terms of age, the e-scooter and the conventional shared bike are more used for younger population groups (under 35 years old), while the shared e-bike is mainly for individuals between 25 and 45 years old. Regarding professional status, almost all our sample was working at the time of the analysis.

3.2. *Physical activity analysis*

For the aims of the statistical analyses, a summary of objectively measured energy expenditure, distance, time, and speed of overall

Table 5
Fit Linear Mix Effects Models: Linear associations of Mode Used with METs per minute.

	Model 3 RWE – MET/minute Coeff.	Model 4 TAE – MET/minute Std. Err.	t value	P > |z |	Coeff.	Std. Err.	t value	P > |z |
Transport Mode rowhead								
Electric scooter (REF)								
Conventional bike	0.831	0.161	5.154	0.000[a]	0.626	0.139	4.514	0.000[a]
Electric bike	0.776	0.199	3.902	0.001[a]	0.578	0.170	3.401	0.000[a]
Age rowhead								
16-24 (REF)								
25–34	0.005	0.170	0.029	0.365	0.127	0.147	0.865	0.387
35–44	0.143	0.206	0.693	0.173	0.186	0.178	1.044	0.297
45 +	−0.011	0.216	−0.051	0.604	0.031	0.188	0.163	0.871
Gender rowhead								
Female (REF)								
Male	0.075	0.144	0.520	0.370	0.081	0.124	0.648	0.517

[a] $p < 0.001$.

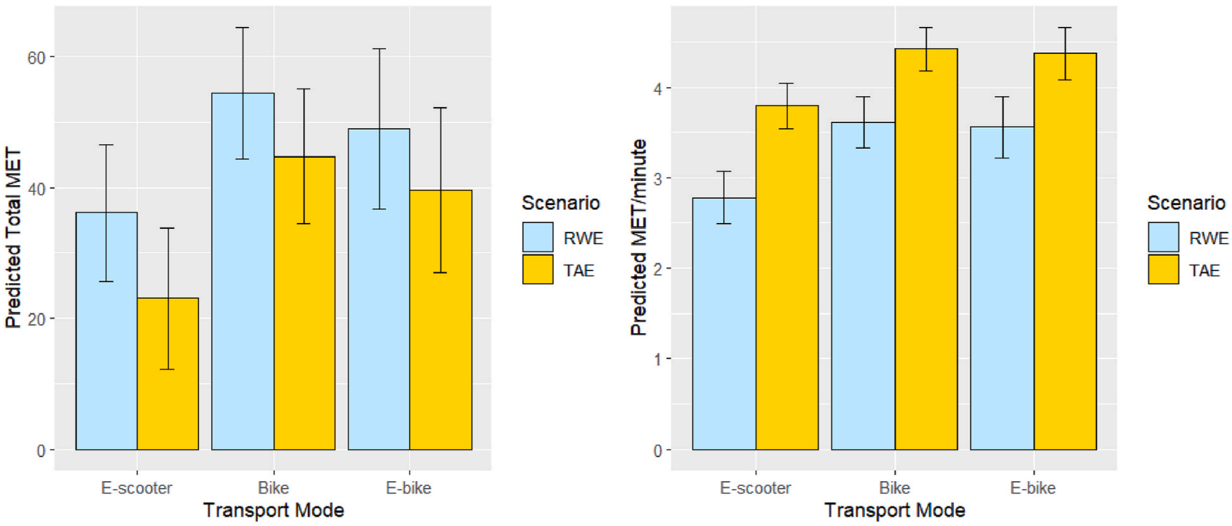

Fig. 3. Predicted Total METs and MET/minute for both scenarios, RWE and TAE.

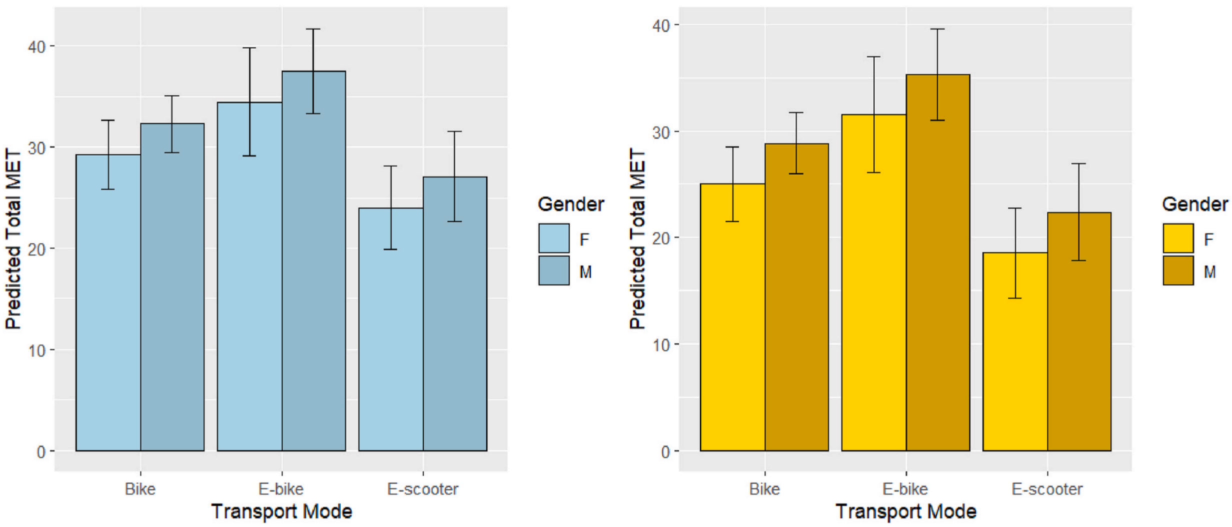

Fig. 4. Predicted Total METs by gender, for both scenarios, RWE (left) and TAE (right).

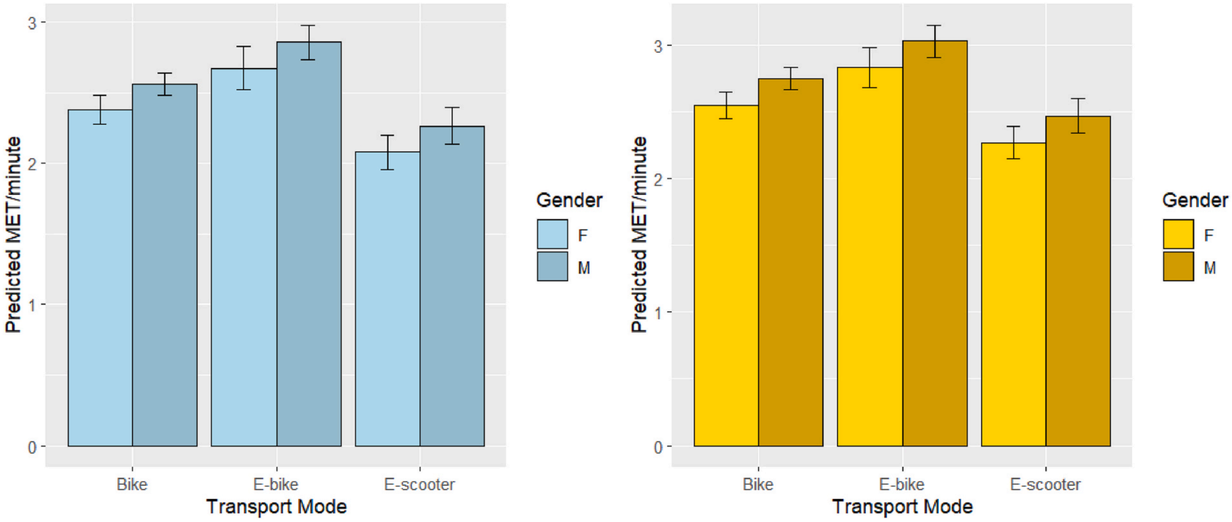

Fig. 5. Predicted MET/minute by gender, for both scenarios, RWE (left) and TAE (right).

sample trips and per mode of transport is presented in Table 2.

On average, a single trip taken in a micromobility mode generates 2.47 METs in Real World Energy (RWE) conditions, while generating 2.65 in Traffic-Adjusted conditions (TAE). Under the RWE scenario, the conventional bike is the micromobility mode presenting the highest RWE MET values (2.66) as opposed to the e-scooter which presents the lowest ones (1.98). Also, the electric bike presents an average MET value that is close to the conventional one (2.55). Similar results are found under the TAE scenario but with overall higher values. It is also important to note that the differences in averaged MET values between modes is found as statistically significant (<0.001).

Regarding other basic characteristics, in terms of distance, micromobility trips are on average of 2.28 km long, not presenting a substantial difference between modes, yet e-scooter trips are the shortest ones. Regarding total time, we can see that the average time per trip is of 12 min, with again no significant variations between modes. Indeed, as distance and time define speed, results show that the average speed is around 11.5 km/h. These three factors present high standard deviations, suggesting that there is a wide range of variation in these variables across the sample.

Additionally, it is interesting to see how the total time of trips is distributed between sedentary and active time, and more specifically, between sedentary, light, and moderate-to-vigorous (MVPA) physical intensity. Remarkably, only in the case of e-scooter trips do we find sedentary time to be almost as high (4.05 min) as light active time (5.26 min), while for both bike and e-bike trips a major part of the time is associated with light activity (6.97 and 6.23 min, respectively). Also, the difference between MVPA minutes is significant when comparing bike and e-bike (3.45 and 3.28 min, respectively) with e-scooter (1.21 min), with bike trips entailing at least on average 3 min of this intense PA.

Table 3 shows the average total METs and METs per minute of trips now incorporating not just the mode of transport but other sociodemographic characteristics of interest such as gender and age. In terms of mode of transport, trips done by conventional bike present the higher PA expenditure both per trip and per minute, followed by the e-bike and the e-scooter. Regarding gender, men present slightly higher METs in all cases. In terms of age, results are somewhat different between total METs and METs per minute. Total METs (both including and excluding sedentary activity) are higher for individuals older than 35 years old, whilst METs per minute are similar in all age groups.

3.3. Multivariate analysis

Table 4 explores the relationship between the different micromobility modes used and average total METs per trip, for the two scenarios previously mentioned, RWE and TAE. Because Model 1 and Model 2 do not adjust by the length of the trip, observed differences might be caused by a combination of different physical energy expenditures inherent to each mode of transport in combination with travel behaviour patterns regarding types and lengths of routes chosen in each mode of transport. For instance, a lengthy e-bike journey may result in a comparable PA outcome as a shorter conventional bicycle trip, even though the energy expenditure per kilometre on a conventional bicycle is likely to be greater.

The models in this table also account for the influence of age and gender. Model 1 finds the Total METs of trips made by conventional bikes to be significantly higher than those trips that were made using an e-scooter (coefficient = 18.293, $p = 0.005$). While the association was not found significant, the direction and magnitude of coefficients also suggest that e-bikes were generating higher Total METs than e-scooters although, predictably, those differences were smaller than those observed for conventional bike trips. In Model 2, which excludes sedentary activity, the Total METs were in this case positively associated with the use of both conventional (coefficient = 21.785, $p < 0.001$) and electric bikes (coefficient = 16.615, $p = 0.050$) indicating similar directions and magnitudes of coefficients that situate conventional bike as the most active micromobility mode, being followed by electric bike and e-scooter respectively.

In the below table (Table 5), models are presented to show the associations between the micromobility mode used and METs per minute, accounting for the above-mentioned sociodemographic characteristics. For this second case, in both scenarios (with and without sedentary activity) METs/minute are positively associated with the use of the conventional bike (coefficient = 0.831, $p < 0.001$ for Model 3; coefficient = 0.626, $p < 0.001$ for Model 4) and electric bike (coefficient = 0.776, $p = 0.001$ for Model 3; coefficient = 0.578, $p < 0.001$ for Model 4), as compared to the e-scooter that acts as the reference group.

Additionally, to understand the impact of the mode of transport chosen on the outcome variable (METs/minute), we estimated the margin effects to calculate predicted values, allowing us to assess the effect of a unit change in each predictor on the outcome, holding all other variables constant. In Fig. 3 we see the predicted values in terms of Total METs for both scenarios analysed on the left bar plot. In this case, an expected increment of 50.66% is expected for using the bike rather than the e-scooter, and 11.17% if using the e-bike under the RWE scenario. These expected increases are even higher when just considering the active time (TAE scenario), being an increment of 94.70% for the e-scooter, and 13.05% for the e-bike. Also in Fig. 3, we have the predicted values now in terms of MET per minute (right graph). In this case, a minute on a conventional bike causes 28.06% more PA than a minute on an e-scooter. For the e-bike, the difference is smaller, being 1.40% less PA per minute.

When estimating Total METs for both RWE and TAE scenarios, in terms of gender (Fig. 4), men present higher estimated values than women, with similar increases for the three modes, being 12.80% for e-scooters, 10.50% for bikes and 8.90% for e-bikes under the RWE scenario; and 20.58% for e-scooters, 15.26% for bikes, and 12.12% for e-bikes, under the TAE scenario. Therefore, e-scooter male users are the ones presenting a higher increment in expected Total METs per trip, as compared to women.

In Fig. 5, the same outcomes are found, now regarding estimated MET/minute. Under the first scenario (RWE), males can expect higher MET/minute than women by all modes, concretely, an increment of 8.65% for e-scooters, 7.56% for bikes, and 7.12% for e-bikes. The same happens under the second scenario presented (TAE), where the percentual increases are as follows: 8.81% for e-scooters, 7.84% for bikes, and 7.07% for e-bikes.

4. Discussion

The goal of this study was to assess the level of PA related to different modes of micromobility in Barcelona, considering both real-world scenarios and traffic-adjusted conditions. To achieve this, we used GPS and accelerometer devices to obtain objective measurements. The final data set included 502 trips taken by 39 people, including 128 trips taken by electric scooter users, 308 trips taken by conventional shared bike users, and 66 trips taken by electric shared bike users. Under Real World Energy (RWE) conditions, a micromobility trip generated an average of 2.47 METs, while in Traffic-Adjusted Energy (TAE) conditions, it generated 2.65 METs. As expected, conventional bikes presented the highest MET values, while e-scooters had the lowest. E-scooter trips resulted in 2.20 METs (in the TAE scenario), which is below the value that is assigned to automobile driving by the 2011 Compendium (Ainsworth et al., 2011). This is consistent with Sanders et al. (2022) most recent research, which found that e-scooter trips were approximately as active as auto trips.

When trying to understand micromobility PA, however, it is important to acknowledge the distinct travel patterns associated with different micromobility modes in terms of distance and frequency of use. Our findings reveal that, on average, e-scooter trips are shorter (1.96 km) compared to the mean distance covered by other micromobility modes (2.28 km), as other studies suggest (Liao and Correia, 2022; Reck et al., 2021). The observed relationship between e-scooters and shorter trips can be attributed to two primary factors: (1) the characteristics of the built environment in Barcelona, which facilitates a high prevalence of short-distance trips (Marquet and Miralles-Guasch, 2015), and (2) the interconnectivity between e-scooter usage and walking, as both modes cater to similar travel distances, Reck et al. (2022) study showing how e-scooters tend to replace a significantly higher number of walking trips when compared to e-bikes, for instance.

In the multivariate analyses, the Total METs of trips taken by conventional bicycles were significantly higher than those made using e-scooters. Results suggested that e-bikes also generated higher Total METs than e-scooters although the association was not found significant. When focusing on the active phase of the trip, both conventional and electric bikes were also found to generate more Total METs. This indicates that conventional bikes are the most active micromobility mode, followed by electric bikes and e-scooters, respectively. Similar results were found when we stratified the analysis in terms of METs per minute to account for possible trip-structure differences between modes. Our findings reinforce the idea that both conventional and electric bikes need to be considered active modes of transport that may provide greater health benefits than e-scooters.

In terms of how PA levels are generated during the trip itself, our analysis reveals a clear difference between e-scooter trips and bike and e-bike trips, with e-scooter showing intermittent PA peaks interspersed with extended sedentary periods, while bikes and e-bikes both exhibited a more uniform distribution of PA throughout the journey without pronounced fluctuations in intensity. While both travel modes may generate equivalent overall PA per trip, the more spread-out distribution of PA observed in cycling trips is likely to offer superior cardiovascular and metabolic benefits, as it promotes sustained aerobic exercise, facilitates beneficial metabolic adaptations and might reduce the risk of overexertion and injury (Garber et al., 2011; Holtermann et al., 2018).

On the aggregate, our results position both conventional and electric bikes as active modes of transport that can provide significant public health benefits. At the same time, we provide further evidence for e-scooters not to be considered active travel modes, as they not only generate lower overall PA (Glenn et al., 2020; Sanders et al., 2022) but also exhibit a highly inconstant in-trip distribution of PA, reliant on sporadic exertion peaks, which may be less beneficial for cardiovascular and metabolic health.

When trying to precisely quantify these PA differences by using margin effects our analysis revealed an expected increment of almost 51% Total METs when using a bike as opposed to an e-scooter under the RWE scenario. When we controlled for sedentary trip sections and accounted only for the active stages of the trip (TAE scenario), the expected increments were even greater, with Total METs gained from a bike trip being almost double than those generated by e-scooter use. Our analysis also indicated that a minute of riding a conventional bike is associated with 28% more PA than a minute of riding an e-scooter. Conversely, the difference between a minute of riding an e-bike versus an e-scooter was smaller, with 1.4% less PA per minute.

When stratifying by gender, PA gained by male participants was higher in all cases, and measurement types. This is likely because, as previous literature has found, men are more inclined towards adopting risky and fast riding practices and tend to exhibit less compliance with rules (Cubells et al., 2023; Gioldasis et al., 2021; Lind et al., 2021), while women have traditionally been found to develop risk-averse attitudes when riding micromobility modes (Graystone et al., 2022; Prati et al., 2019).

These findings have significant implications for policymakers and transport policy experts, particularly regarding initiatives that aim to plan for health and PA. Our study is among the first to use device-based measures of PA and tracking to estimate accurate PA levels for three different micromobility modes. Previous research had used self-reported measures to underscore the importance of the choice of transport mode on PA levels, emphasizing the critical role of active micromobility modes such as conventional and electric bicycles (Castro et al., 2019; Dons et al., 2018; Hajna et al., 2019; Miller et al., 2015; Raza et al., 2020; Vich et al., 2019; Wild and Woodward, 2019).

Our findings underscore the importance of recognizing conventional and electric bicycles as the primary active micromobility modes, despite the growing popularity of e-scooters worldwide. The relatively low PA associated with e-scooter use is even more worrisome given the fact that in cities such as Barcelona the majority of new e-scooter users replace walking (Felipe-Falgas et al., 2022), effectively substituting an active mode of transportation for a more sedentary one. Considering these findings, we recommend that transport planners prioritize promoting modal shifts toward cycling and electric cycling since any shift from walking or biking to e-scootering would result in a net loss of PA.

The analysis of e-scooters and other micromobility modes' specific impacts is heavily influenced by their intended use and the types of transportation they replace. While e-scooters may provide a net benefit in situations where they replace more sedentary modes, such as private vehicles, this is not necessarily true in dense and compact cities like Barcelona. In these environments, short trips well-suited for e-scooters are often already served by active transport modes like walking and biking, making it less likely that e-scooters will offer significant advantages over existing options. This aligns with the findings of several studies that have consistently demonstrated e-scooters' tendency to replace walking trips (Christoforou et al., 2021; de Bortoli and Christoforou, 2020; Fearnley et al., 2020; James et al., 2019; Laa and Leth, 2020; Mitropoulos et al., 2023; Nikiforiadis et al., 2021; Reck et al., 2022).

Therefore, only by considering the modal replacement can we accurately assess the impact of these modes on public health. With active travel being a crucial source of PA and having a substantial influence on health outcomes, such as cardiovascular health, weight management, mental health, cognitive function, and chronic diseases, policymakers should differentiate between active micromobility modes - bikes and e-bikes - and those that tend to be more sedentary than their most common alternatives - e-scooters. To maximize the public health benefits of promoting micromobility modes, it is crucial that a significant proportion of new micromobility users effectively replace car usage with e-scooter or bike sharing. Thus, policymakers can incentivize the adoption of these micromobility modes by investing in infrastructure, such as bike lanes and parking, and creating a regulatory framework that supports bike and e-bike sharing programs. Education and outreach campaigns can also encourage the public to replace car usage with micromobility modes. By taking these policy actions, cities and municipalities can create a supportive environment that makes it easier for individuals to adopt micromobility modes, leading to improved public health outcomes and reduced risk of chronic diseases.

4.1. Limitations

This study is subject to certain limitations that must be acknowledged. Firstly, the sample size utilized in the analysis is limited and may be subject to bias, as those who agreed to participate may not represent the average adult population in terms of their general health conditions and PA levels. Second, the classification of trips according to the mode(s) of transport employed was based on self-reported data from travel diaries, which may be less reliable than objective identification. Similarly, BMI scores were calculated using self-reported height and weight data. Thirdly, it is important to exercise caution when interpreting the results of the multivariate models presented, as they have been standardized on a per-minute basis, and thus, the theoretical differences may not align with the actual daily usage patterns of these modes of transportation. Nonetheless, accurately assessing the total energy expenditure per minute of each mode is still valuable as it provides the capability to construct hypothetical scenarios based on possible alterations to current mobility practices. Fourthly, several factors differentiate private and shared micromobility modes, potentially affecting their usage patterns and, consequently, their associated PA levels. In the context of Barcelona, there may be potential variations in trip characteristics, particularly distance, influenced by factors such as the distribution of Bicing stations in the case of the public bicycle system. Unlike privately-owned e-scooter trips, which are often door-to-door and may encompass the entire trip, trips made using Bicing are conditioned by the availability and location of Bicing stations. Likewise, we acknowledge that trips involving Bicing may inherently provide users with additional PA due to walking to and from the stations. To account for these variations, control variables were incorporated into the analysis. However, it is important to recognise that these differences between private and shared modes introduce complexity into the analysis, and the study's findings should be interpreted within this specific urban context. And, finally, it is worth noting that hip-worn accelerometers may not be as accurate as other methods when assessing PA specifically related to cycling or electric scooter use, as these activities involve complex body movements that may not be captured as effectively by a device worn on the hip. For assessing PA associated with cycling, thigh-worn accelerometers may provide a more accurate measurement of PA. However, these devices may be less effective at measuring other types of PA, such as e-scootering. Although hip-worn accelerometers have wide-ranging applicability, easy data processing, cost-effectiveness, and accessibility, as indicated by other transport and health studies (Brondeel et al., 2015; Kerr et al., 2016; Voss et al., 2016), their limitations in assessing PA related to micromobility use must be acknowledged and considered as an opportunity for further research advancement in this field.

To enhance comprehension of the subject matter, future investigations should employ larger participant cohorts to bolster the veracity of the results. Moreover, it is vital to acknowledge that innovative research endeavours in these domains can broaden the horizons of knowledge and contribute to the formulation of more precise and effective measurement instruments in the future. Lastly, further studies ought to be conducted in other urban and semi-urban regions where micromobility is gaining prominence in modal share, to validate the conclusions suggested in this investigation.

5. Conclusions

The goal of the present study was to assess the level of PA related to different modes of micromobility in Barcelona, considering both real-world scenarios and traffic-adjusted conditions. The study used GPS and accelerometer devices to obtain objective measurements from 502 trips taken, including 128 trips taken by electric scooter users, 308 trips taken by conventional shared bike users, and 66 trips taken by electric shared bike users.

The analysis suggests the presence of potential differences among various modes of micromobility used in the city of Barcelona and the associated PA levels. Shared bicycles and electric bicycles are associated with higher MET values, while the use of electric scooters cannot be regarded as an active mode of transportation, as e-scooter users accumulate fewer METs per trip. By stratifying results using different measurements including real-world conditions and active-only portions of the trips we are also able to understand how these PA values will translate in other geographic contexts or under different driving conditions. The study highlights the significant impact that the mode of transportation can have on PA levels, with biking offering the greatest potential for increasing trip METs. Overall, results reinforce the idea that not all micromobility modes should be treated equally when addressing public health expected outcomes, as our models clearly define conventional bikes and electric bikes as net generators of PA. Micromobility management policies should thus differentiate between modes to avoid unexpected negative outcomes. However, it is important to acknowledge that our findings should be interpreted with caution due to the limitations imposed by our sample size. While our results provide preliminary insights into potential disparities there is need for further research with larger and more representative samples to draw more definitive conclusions regarding PA levels across different micromobility modes.

CRediT authorship contribution statement

Alexandra Bretones: Conceptualization. Alexandra Bretones: Conceptualization, Methodology, Formal analysis, Investigation, Visualization, Writing – original draft. Carme Miralles-Guasch: Funding acquisition, Supervision, Writing – review & editing. Oriol Marquet: Conceptualization, Funding acquisition, Supervision, Writing – review & editing.

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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.

Annex 1. Daily Travel Diaries

Q1. How many trips have you made today on a micromobility mode (shared bike/shared e-bike/e-scooter? Also consider the trip back home.

Q2. Could you tell us the start time of these trips? Could you also tell us the reason?

	Micromobility mode	Start time	Trip purpose
Trip 1			*
Trip 2			

(*continued on next page*)

(*continued*)

	Micromobility mode	Start time	Trip purpose
Trip 3			
Trip 4			
Trip 5			
Trip 6			
Trip 7			
…			

*Options to choose → Go to work or studies or work arrangements/Visit family or friends/Accompany or care for people/Everyday purchases (food)/Non-everyday purchases/Leisure, fun, shows, cinemas, restaurants/Participate in sports activities/Back home.

References

Ainsworth, B.E., Haskell, W.L., Herrmann, S.D., Meckes, N., Bassett, D.R.J., Tudor-Locke, C., Greer, J.L., Vezina, J., Whitt-Glover, M.C., Leon, A.S., 2011. 2011 Compendium of physical activities: a second update of codes and MET values. Med. Sci. Sports Exerc. 43, 1575–1581. https://doi.org/10.1249/MSS.0b013e31821ece12.

Allahbakhshi, H., Conrow, L., Naimi, B., Weibel, R., 2020. Using accelerometer and GPS data for real-life physical activity type detection. Sensors 20, 588. https://doi.org/10.3390/s20030588.

Allahbakhshi, H., Hinrichs, T., Huang, H., Weibel, R., 2019. The key factors in physical activity type detection using real-life data: a systematic review. Front. Physiol. 10.

Arias-Molinares, D., García-Palomares, J.C., Romanillos, G., Gutiérrez, J., 2023. Uncovering spatiotemporal micromobility patterns through the lens of space–time cubes and GIS tools. J. Geogr. Syst. 25, 403–427. https://doi.org/10.1007/s10109-023-00418-9.

Awais, M., Mellone, S., Chiari, L., 2015. Physical activity classification meets daily life: review on existing methodologies and open challenges. In: 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Presented at the 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. EMBC), pp. 5050–5053. https://doi.org/10.1109/EMBC.2015.7319526.

Bates, D., Mächler, M., Bolker, B.M., Walker, S.C., 2015. Fitting linear mixed-effects models using lme4. J. Stat. Software 67. https://doi.org/10.18637/jss.v067.i01.

Batista Ferrer, H., Cooper, A., Audrey, S., 2018. Associations of mode of travel to work with physical activity, and individual, interpersonal, organisational, and environmental characteristics. J. Transport Health 9, 45–55. https://doi.org/10.1016/J.JTH.2018.01.009.

Beecham, R., Wood, J., 2014. Exploring gendered cycling behaviours within a large-scale behavioural data-set. Transport. Plann. Technol. 37, 83–97. https://doi.org/10.1080/03081060.2013.844903.

Berjisian, E., Bigazzi, A., 2022. Evaluation of methods to distinguish trips from activities in walking and cycling GPS data. Transport. Res. C Emerg. Technol. 137, 103588 https://doi.org/10.1016/j.trc.2022.103588.

Berntsen, S., Malnes, L., Langåker, A., Bere, E., 2017. Physical activity when riding an electric assisted bicycle. Int. J. Behav. Nutr. Phys. Activ. 14 https://doi.org/10.1186/S12966-017-0513-Z.

Bretones, A., Marquet, O., 2022. Sociopsychological factors associated with the adoption and usage of electric micromobility. A literature review. Transport Pol. 127, 230–249. https://doi.org/10.1016/j.tranpol.2022.09.008.

Brondeel, R., Pannier, B., Chaix, B., 2015. Using GPS, GIS, and accelerometer data to predict transportation modes. Med. Sci. Sports Exerc. 47, 2669–2675. https://doi.org/10.1249/mss.0000000000000704.

Campisi, T., Skoufas, A., Kaltsidis, A., Basbas, S., 2021. Gender equality and E-scooters: mind the gap! A statistical analysis of the sicily region. Italy. SOCIAL SCIENCES-BASEL 10. https://doi.org/10.3390/socsci10100403.

Castro, A., Gaupp-Berghausen, M., Dons, E., Standaert, A., Laeremans, M., Clark, A., Anaya-Boig, E., Cole-Hunter, T., Avila-Palencia, I., Rojas-Rueda, D., Nieuwenhuijsen, M., Gerike, R., Panis, L.I., de Nazelle, A., Brand, C., Raser, E., Kahlmeier, S., Götschi, T., 2019. Physical activity of electric bicycle users compared to conventional bicycle users and non-cyclists: insights based on health and transport data from an online survey in seven European cities. Transp. Res. Interdiscip. Perspect. 1, 100017 https://doi.org/10.1016/j.trip.2019.100017.

Chabanas, B., Praznoczy, C., Duclos, M., 2019. Commuter e-bike use is associated with increased total physical activity over time. Eur. J. Publ. Health 29, ckz187.092. https://doi.org/10.1093/eurpub/ckz187.092.

Chaix, B., Benmarhnia, T., Kestens, Y., Brondeel, R., Perchoux, C., Gerber, P., Duncan, D.T., 2019. Combining sensor tracking with a GPS-based mobility survey to better measure physical activity in trips: public transport generates walking. Int. J. Behav. Nutr. Phys. Activ. 16, 1–13. https://doi.org/10.1186/s12966-019-0841-2.

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

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. Transport Geogr. 106, 103502 https://doi.org/10.1016/j.jtrangeo.2022.103502.

Cusack, M., 2021. Individual, social, and environmental factors associated with active transportation commuting during the COVID-19 pandemic. J. Transport Health 22, 101089. https://doi.org/10.1016/j.jth.2021.101089.

de Bortoli, A., 2021. Environmental performance of shared micromobility and personal alternatives using integrated modal LCA. Transport. Res. Transport Environ. 93 https://doi.org/10.1016/j.trd.2021.102743.

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. Clean. Prod. 273 https://doi.org/10.1016/j.jclepro.2020.122898.

Dons, E., Rojas-Rueda, D., Anaya-Boig, E., Avila-Palencia, I., Brand, C., Cole-Hunter, T., de Nazelle, A., Eriksson, U., Gaupp-Berghausen, M., Gerike, R., Kahlmeier, S., Laeremans, M., Mueller, N., Nawrot, T., Nieuwenhuijsen, M.J., Orjuela, J.P., Racioppi, F., Raser, E., Standaert, A., Int Panis, L., Götschi, T., 2018. Transport mode choice and body mass index: cross-sectional and longitudinal evidence from a European-wide study. Environ. Int. 119, 109–116. https://doi.org/10.1016/j.envint.2018.06.023.

Duncan, D.T., Méline, J., Kestens, Y., Day, K., Elbel, B., Trasande, L., Chaix, B., 2016. Walk score, transportation mode choice, and walking among French adults: a GPS, accelerometer, and mobility survey study. Int. J. Environ. Res. Publ. Health 13, 1–14. https://doi.org/10.3390/IJERPH13060611.

Ellis, K., Godbole, S., Marshall, S., Lanckriet, G., Staudenmayer, J., Kerr, J., 2014. Identifying active travel behaviors in challenging environments using GPS, accelerometers, and machine learning algorithms. Front. Public Health 2.

Esztergár-Kiss, D., Lopez Lizarraga, J.C., 2021. Exploring user requirements and service features of e-micromobility in five European cities. CASE STUDIES ON TRANSPORT POLICY 9, 1531–1541. https://doi.org/10.1016/j.cstp.2021.08.003.

Fearnley, N., Johnsson, E., Berge, S.H., 2020. Patterns of E-Scooter Use in Combination with Public Transport. Findings. https://doi.org/10.32866/001c.13707.

Felipe-Falgas, P., Madrid-Lopez, C., Marquet, O., 2022. Assessing environmental performance of micromobility using LCA and self-reported modal change: the case of shared E-bikes, E-scooters, and E-mopeds in Barcelona. Sustainability 14, 4139. https://doi.org/10.3390/su14074139.

Freedson, P.S., Melanson, E., Sirard, J., 1998. Calibration of the computer science and applications, inc. accelerometer. Med. Sci. Sports Exerc. 30, 777–781.
Frings, D., Rose, A., Ridley, A.M., 2012. Bicyclist fatalities involving heavy goods vehicles: gender differences in risk perception, behavioral choices, and training. Traffic Inj. Prev. 13, 493–498. https://doi.org/10.1080/15389588.2012.664796.
Fyhri, A., Fearnley, N., 2015. Effects of e-bikes on bicycle use and mode share. Transport. Res. Transport Environ. 36, 45–52. https://doi.org/10.1016/j.trd.2015.02.005.
Garber, C.E., Blissmer, B., Deschenes, M.R., Franklin, B.A., Lamonte, M.J., Lee, I.-M., Nieman, D.C., Swain, D.P., 2011. Quantity and quality of exercise for developing and maintaining cardiorespiratory, musculoskeletal, and neuromotor fitness in apparently healthy adults: guidance for prescribing exercise. Med. Sci. Sports Exerc. 43, 1334. https://doi.org/10.1249/MSS.0b013e318213fefb.
Gioldasis, C., Christoforou, Z., Seidowsky, R., 2021. Risk-taking behaviors of e-scooter users: a survey in Paris. Accid. Anal. Prev. 163, 106427.
Glenn, J., Bluth, M., Christianson, M., Pressley, J., Taylor, A., Macfarlane, G.S., Chaney, R.A., 2020. Considering the potential health impacts of electric scooters: an analysis of user reported behaviors in provo, Utah. Int. J. Environ. Res. Publ. Health 17, 1–15. https://doi.org/10.3390/ijerph17176344.
Gojanovic, Boris, Welker, J., Daucourt, C., Gremion, G., 2011a. The electric bike: a new way towards a better health for people and environment. Med. Sci. Sports Exerc. 43, 455. https://doi.org/10.1249/01.MSS.0000401256.52713.20.
Gojanovic, B., Welker, J., Iglesias, K., Daucourt, C., Gremion, G., 2011b. Electric bicycles as a new active transportation modality to promote health. Med. Sci. Sports Exerc. 43, 2204–2210. https://doi.org/10.1249/MSS.0b013e31821cbdc8.
Graystone, M., Mitra, R., Hess, P.M., 2022. Gendered perceptions of cycling safety and on-street bicycle infrastructure: bridging the gap. Transport. Res. Transport Environ. 105 https://doi.org/10.1016/j.trd.2022.103237.
Hajna, S., White, T., Panter, J., Brage, S., Wijndaele, K., Woodcock, J., Ogilvie, D., Imamura, F., Griffin, S.J., 2019. Driving status, travel modes and accelerometer-assessed physical activity in younger, middle-aged and older adults: a prospective study of 90 810 UK Biobank participants. Int. J. Epidemiol. 48, 1175–1186. https://doi.org/10.1093/IJE/DYZ065.
Haynes, E., Green, J., Garside, R., Kelly, M.P., Guell, C., 2019. Gender and active travel: a qualitative data synthesis informed by machine learning. Int. J. Behav. Nutr. Phys. Activ. 16, 135. https://doi.org/10.1186/s12966-019-0904-4.
Hills, A.P., Mokhtar, N., Byrne, N.M., 2014. Assessment of physical activity and energy expenditure: an overview of objective measures. Front. Nutr. 1.
Holtermann, A., Krause, N., Beek, A.J. van der, Straker, L., 2018. The physical activity paradox: six reasons why occupational physical activity (OPA) does not confer the cardiovascular health benefits that leisure time physical activity does. Br. J. Sports Med. 52, 149–150. https://doi.org/10.1136/bjsports-2017-097965.
IERMB, 2021. EMEF-2021_Informe-Resum-Executiu.pdf.
James, O., Swiderski, J.I., Hicks, J., Teoman, D., Buehler, R., 2019. Pedestrians and E-scooters: an initial look at E-scooter parking and perceptions by riders and non-riders. Sustainability 11, 5591. https://doi.org/10.3390/su11205591.
Kerr, J., Patterson, R.E., Ellis, K., Godbole, S., Johnson, E., Lanckriet, G., Staudenmayer, J., 2016. Objective assessment of physical activity: classifiers for public health. Med. Sci. Sports Exerc. 48, 951. https://doi.org/10.1249/MSS.0000000000000841.
Laa, B., Leth, U., 2020. Survey of E-scooter users in Vienna: Who they are and how they ride. J. Transport Geogr. 89 https://doi.org/10.1016/j.jtrangeo.2020.102874.
Langford, B.C., Cherry, C.R., Bassett, D.R., Fitzhugh, E.C., Dhakal, N., 2017. Comparing physical activity of pedal-assist electric bikes with walking and conventional bicycles. J. Transport Health 6, 463–473. https://doi.org/10.1016/j.jth.2017.06.002.
Lee, K., Kwan, M.-P., 2018. Automatic physical activity and in-vehicle status classification based on GPS and accelerometer data: a hierarchical classification approach using machine learning techniques. Trans. GIS 22, 1522–1549. https://doi.org/10.1111/tgis.12485.
Liao, F., Correia, G., 2022. Electric carsharing and micromobility: a literature review on their usage pattern, demand, and potential impacts. International Journal of Sustainable Transportation 16, 269–286. https://doi.org/10.1080/15568318.2020.1861394.
Lind, A., Honey-Rosés, J., Corbera, E., 2021. Rule compliance and desire lines in Barcelona's cycling network. Transportation Letters 13, 728–737. https://doi.org/10.1080/19427867.2020.1803542.
Lüdecke, D., 2018. Ggeffects: tidy data frames of marginal effects from regression models. J. Open Source Softw. 3, 772. https://doi.org/10.21105/joss.00772.
Marquet, O., MacIejewska, M., Delclòs-Alió, X., Vich, G., Schipperijn, J., Miralles-Guasch, C., 2020. Physical activity benefits of attending a senior center depend largely on age and gender: a study using GPS and accelerometry data. BMC Geriatr. 20, 1–10. https://doi.org/10.1186/s12877-020-01527-6.
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/ASSET/IMAGES/LARGE/10.1177_0969776417703158-FIG2.JPEG.
Marquet, O., Miralles-Guasch, C., 2015. The Walkable city and the importance of the proximity environments for Barcelona's everyday mobility. Cities 42, 258–266. https://doi.org/10.1016/j.cities.2014.10.012.
Matthews, C.E., Moore, S.C., George, S.M., Sampson, J., Bowles, H.R., 2012. Improving self-reports of active and sedentary behaviors in large epidemiologic studies. Exerc. Sport Sci. Rev. 40, 118–126. https://doi.org/10.1097/JES.0B013E31825B34A0.
McGinn, A.P., Evenson, K.R., Herring, A.H., Huston, S.L., 2007. The relationship between leisure, walking, and transportation activity with the natural environment. Health Place 13, 588–602. https://doi.org/10.1016/j.healthplace.2006.07.002.
McQueen, M., Abou-Zeid, G., MacArthur, J., Clifton, K., 2021. Transportation transformation: is micromobility making a macro impact on sustainability? J. Plann. Lit. 36, 46–61. https://doi.org/10.1177/0885412220972696.
Mendes, M. de A., Silva, I. da, Ramires, V., Reichert, F., Martins, R., Ferreira, R., Tomasi, E., 2018. Metabolic equivalent of task (METs) thresholds as an indicator of physical activity intensity. PLoS One 13, e0200701. https://doi.org/10.1371/journal.pone.0200701.
Milakis, D., Gedhardt, L., Ehebrecht, D., Lenz, B., 2020. Is micro-mobility sustainable? An overview of implications for accessibility, air pollution, safety, physical activity and subjective wellbeing. Handbook of Sustainable Transport 180–189. https://doi.org/10.4337/9781789900477.00030.
Miller, H.J., Tribby, C.P., Brown, B.B., Smith, K.R., Werner, C.M., Wolf, J., Wilson, L., Oliveira, M.G.S., 2015. Public transit generates new physical activity: evidence from individual GPS and accelerometer data before and after light rail construction in a neighborhood of Salt Lake City, Utah, USA. Health Place 36, 8–17. https://doi.org/10.1016/J.HEALTHPLACE.2015.08.005.
Mitropoulos, L., Stavropoulou, E., Tzouras, P., Karolemeas, C., Kepaptsoglou, K., 2023. E-scooter micromobility systems: review of attributes and impacts. Transp. Res. Interdiscip. Perspect. 21, 100888 https://doi.org/10.1016/j.trip.2023.100888.
Nikiforiadis, A., Paschalidis, E., Stamatiadis, N., Raptopoulou, A., Kostareli, A., Basbas, S., 2021. Analysis of attitudes and engagement of shared e-scooter users. Transport. Res. Transport Environ. 94, 102790 https://doi.org/10.1016/j.trd.2021.102790.
Otero, I., Nieuwenhuijsen, M.J., Rojas-Rueda, D., 2018. Health impacts of bike sharing systems in Europe. Environ. Int. 115, 387–394. https://doi.org/10.1016/j.envint.2018.04.014.
Peterman, J.E., Morris, K.L., Kram, R., Byrnes, W.C., 2016. Pedelecs as a physically active transportation mode. Eur. J. Appl. Physiol. 116, 1565–1573. https://doi.org/10.1007/s00421-016-3408-9.
Plasqui, G., Bonomi, A.G., Westerterp, K.R., 2013. Daily physical activity assessment with accelerometers: new insights and validation studies. Obes. Rev. 14, 451–462. https://doi.org/10.1111/OBR.12021.
Prati, G., Fraboni, F., De Angelis, M., Pietrantoni, L., Johnson, D., Shires, J., 2019. Gender differences in cycling patterns and attitudes towards cycling in a sample of European regular cyclists. J. Transport Geogr. 78, 1–7. https://doi.org/10.1016/j.jtrangeo.2019.05.006.
Raustorp, J., Koglin, T., 2019. The potential for active commuting by bicycle and its possible effects on public health. J. Transport Health 13, 72–77. https://doi.org/10.1016/j.jth.2019.03.012.
Rayaprolu, S., Venigalla, M., 2020. Motivations and mode-choice behavior of micromobility users in Washington, DC. Journal of Modern Mobility Systems 1, 110–118. https://doi.org/10.13021/jmms.2020.2894.
Raza, W., Krachler, B., Forsberg, B., Sommar, J.N., 2020. Health benefits of leisure time and commuting physical activity: a meta-analysis of effects on morbidity. J. Transport Health 18, 100873. https://doi.org/10.1016/J.JTH.2020.100873.

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

Reck, D.J., Martin, H., Axhausen, K.W., 2022. Mode choice, substitution patterns and environmental impacts of shared and personal micro-mobility. Transport. Res. Transport Environ. 102, 103134 https://doi.org/10.1016/j.trd.2021.103134.

Roig-Costa, O., Gómez-Varo, I., Cubells, J., Marquet, O., 2021. La movilidad post pandemia: perfiles y usos de la micromovilidad en Barcelona. Revista Transporte y Territorio 25, 72–96. https://doi.org/10.34096/rtt.i25.10958.

Rowlands, A.V., 2018. Moving forward with accelerometer-assessed physical activity: two strategies to ensure meaningful, interpretable, and comparable measures. Pediatr. Exerc. Sci. 30, 450–456. https://doi.org/10.1123/PES.2018-0201.

Sanders, R.L., da Silva Brum-Bastos, V., Nelson, T.A., 2022. Insights from a pilot investigating the impacts of shared E-scooter use on physical activity using a single-case design methodology. J. Transport Health 25, 101379. https://doi.org/10.1016/J.JTH.2022.101379.

Şengül, B., Mostofi, H., 2021. Impacts of E-micromobility on the sustainability of urban transportation—a systematic review. Appl. Sci. 11, 5851. https://doi.org/10.3390/app11135851.

Shephard, R.J., 2003. Limits to the measurement of habitual physical activity by questionnaires. Br. J. Sports Med. 37, 197–206. https://doi.org/10.1136/BJSM.37.3.197.

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.

Sundfør, H.B., Fyhri, A., 2017. A push for public health: the effect of e-bikes on physical activity levels. BMC Publ. Health 17, 809. https://doi.org/10.1186/s12889-017-4817-3.

Sylvia, L.G., Bernstein, E.E., Hubbard, J.L., Keating, L., Anderson, E.J., 2014. Practical guide to measuring physical activity. J. Acad. Nutr. Diet. 114, 199–208. https://doi.org/10.1016/J.JAND.2013.09.018.

Tao, T., Wu, X., Cao, J., Fan, Y., Das, K., Ramaswami, A., 2020. Exploring the nonlinear relationship between the built environment and active travel in the twin cities. Journal of Planning Education and Research 0739456X20915765. https://doi.org/10.1177/0739456X20915765.

Troiano, R.P., Berrigan, D., Dodd, K.W., Mâsse, L.C., Tilert, T., Mcdowell, M., 2008. Physical activity in the United States measured by accelerometer. Med. Sci. Sports Exerc. 40, 181. https://doi.org/10.1249/mss.0b013e31815a51b3.

Troiano, R.P., McClain, J.J., Brychta, R.J., Chen, K.Y., 2014. Evolution of accelerometer methods for physical activity research. Br. J. Sports Med. 48, 1019–1023. https://doi.org/10.1136/BJSPORTS-2014-093546.

Vich, G., Marquet, O., Miralles-Guasch, C., 2019. "Is there any time left for walking?" Physical activity implications of suburban commuting in the Barcelona metropolitan region. Geografisk Tidsskrift - Danish Journal of Geography 119, 136–145. https://doi.org/10.1080/00167223.2019.1589386.

Voss, C., Sims-Gould, J., Ashe, M.C., McKay, H.A., Pugh, C., Winters, M., 2016. Public transit use and physical activity in community-dwelling older adults: combining GPS and accelerometry to assess transportation-related physical activity. Journal of Transport & Health, Special Issue: Public Transport and Health 3, 191–199. https://doi.org/10.1016/j.jth.2016.02.011.

White, T., Westgate, K., Hollidge, S., Venables, M., Olivier, P., Wareham, N., Brage, S., 2019. Estimating energy expenditure from wrist and thigh accelerometry in free-living adults: a doubly labelled water study. Int. J. Obes. 43, 2333–2342. https://doi.org/10.1038/S41366-019-0352-X.

Wild, K., Woodward, A., 2019. Why are cyclists the happiest commuters? Health, pleasure and the e-bike. J. Transport Health 14, 100569. https://doi.org/10.1016/j.jth.2019.05.008.

Wilson, O.W.A., Elliott, L.D., Duffey, M., Papalia, Z., Bopp, M., 2020. The contribution of active travel to meeting physical activity recommendations among college students. J. Transport Health 18, 100890. https://doi.org/10.1016/j.jth.2020.100890.

Woodcock, J., Franco, O.H., Orsini, N., Roberts, I., 2011. Non-vigorous physical activity and all-cause mortality: systematic review and meta-analysis of cohort studies. Int. J. Epidemiol. 40, 121–138. https://doi.org/10.1093/ije/dyq104.

Woodcock, J., Tainio, M., Cheshire, J., O'Brien, O., Goodman, A., 2014. Health effects of the London bicycle sharing system: health impact modelling study. BMJ 348. https://doi.org/10.1136/BMJ.G425.