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What proportions of different transport modes do e-scooters replace? A meta-analysis

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ABSTRACT

This paper presents a meta-analysis of stand-up e-scooters' mode replacement, based on outcomes from one hundred studies and dataset collections. The material includes scientific publications and grey literature from Europe, North America and Oceania. We aggregate the various replaced transport modes into three groups: private motorized vehicles, public transport and active transport. The mode replacement outcomes are survey-based, primarily directed towards e-scooter users. The mode replacement question is either about what mode would have been used on the last trip if the e-scooter were not available or about general changes in trip frequency of other modes after starting using e-scooter. Site-specific characteristics are added to the characteristics of the surveys. Meta-regressions show that the proportions of replaced private motorized vehicles and public transport are primarily associated with the proportions of these modes in the cities' transport/commuting at the outset. Active transport represents the largest proportion of modes replaced by the e-scooter, but with less explained variation with respect to site-specific characteristics. We derive quality-corrected meta-analytic estimates of e-scooter mode replacement proportions from a subset of the meta-data.

1. Introduction

Stand-up/standing e-scooters have been introduced and proliferated in many parts of the World since their appearance in the last decade; often as shared vehicles supplied by multi-national enterprises (Hardt and Bogenberger, 2019; Fearnley, 2020). A relatively large supply of e-scooters in major urban areas, with dockless (free flowing) access and online payment systems, have provided a new desired transport mode for some; and a new element of discomfort and obstruction for others (Tuncer et al., 2020; Gibson et al., 2021; Mitropoulos et al., 2023). The overall external net effects, or life cycle effects, from the increasing mode shift to e-scooter, are not obviously positive (Lazer, 2023). What transport modes e-scooters replace will have considerable impact on this net effect (Mitropoulos et al., 2023).

The body of literature presenting estimates of e-scooters' mode-replacement shares have become quite extensive over a period of just about seven years. In the last few years, review studies of e-scooter usage have also appeared (ITF, 2020; Fearnley, 2020; Badia and Jenelius, 2023; Mitropoulos et al., 2023; Wang et al., 2023). The review studies assert that e-scooters first and foremost replace walking (Mitropoulos et al., 2023; Wang et al., 2023), but also cycling and public transport (Badia and Jenelius, 2023). For the replacement of cars and other private motorized vehicles, it is indicated that this share is higher in North America than in, e.g., Europe (ITF, 2020; Fearnley, 2020; Wang et al., 2023). However, to date, no studies have formally analysed systematic variations in mode substitution towards e-scooter. In our paper, therefore, we extend the assessed body of mode replacement outcomes into a meta-analysis.

We aggregate the various replaced transport modes into three groups: private motorized vehicles (PMV), public transport (PT) and active transport (AT). Using meta-regression, we estimate whether characteristics of the cities and the outcomes/study contexts can explain variation in mode replacement proportions. The analysis takes into account that part of the replacement outcomes originates from studies that have produced multiple outcomes. We include only survey-based mode replacement outcomes, the majority of these comprising e-scooter users' retrospective assessments (Wang et al., 2023). Most surveys have been based on asking what mode would have been applied on the last (most recent) trip if the e-scooter were not available; in some surveys, respondents have been asked about general changes in trip usage frequency of various other modes after starting using e-scooter.

At the outset we have 307 e-scooter mode replacement outcomes

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from 100 studies. Most of the 100 studies include e-scooter replacement estimates for all three classes of transport modes: 307 PMV, 295 PT, and 298 AT replacements. We apply about 80 % (244) of this material in meta-regression of case-area characteristics and survey-features, including all three mode class replacements. From this material we retain only the 212 outcomes based on last-trip mode-replacement question in a corrected meta-analytic estimate of mode-replacements, for PMV, PT and AT, in European and non-European cities. To our knowledge this is a first meta-analysis of e-scooters' mode replacement. It provides relevant input to the assessment of whether the growth of e-scooter usage improves transport's effect on GHG emissions, road safety, or other aspects of transport and city liveability (Mitropoulos et al., 2023; Wang et al., 2023).

2. Data and methods

2.1. Literature search approach – study inclusion criteria

Literature on survey-based e-scooter mode replacement was searched via Web of Science and Google Scholar, using the search words: "e-scooter", "substitution", "replacement", "walk", "cycling", "bicycle", "bike", "car", "automobile", "motorized", "ridehailing", "ridesharing" and variations of these keywords (e.g. with and without hyphen; truncations). Additionally, outcomes from the grey literature have been identified in reports, newsletters and industry outlets. Some studies were subsequently found via reference lists, i.e., snowballing. A last addendum of outcomes comprises confidential data sets from three international e-scooter rental sharing companies' own user surveys. Afterwards, also "micromobility" was applied as a search word, on its own, without identifying more outcomes. Our search was, with some exceptions, limited to English and Scandinavian languages, covering Europe, North America and Oceania. All the non-confidential studies, reporting survey-based outcomes that were considered for meta-analysis, are listed in the Supplementary Material, S1.

The central tendency measure from the studies that we apply is the estimated proportions of replaced transport modes. We aggregate the various sets of specified modes into three principal groups: the replaced proportions of travel by i) *private motorized vehicles* (PMV), including private car, shared car, ridehailing/taxi, as well as MC/moped/scooter; ii) *public transport* (PT), primarily rail-based and bus/coach; and iii) *active transport* (AT) modes, i.e., walking and cycling, private and shared bicycles, also including pedelec e-bikes.

In meta-analysis literature, the central tendency estimate is often referred to as an "effect size" or an "outcome" (Borenstein et al., 2009; Harrer et al., 2021). In a narrow sense "effect size" refers to a measured effect of an intervention, but the term is often applied more broadly, as any central tendency input to meta-analysis (Harrer et al., 2021). We will apply "effect size" and "outcome" interchangeably as terms for the mode replacement proportions.

E-scooters, or "electrically powered stand-up scooters", appeared as a new mode in 2015, in China, and started to diverge across the World from early 2017, primarily as a rental sharing product (Hardt and Bogenberger, 2019; Fearnley, 2020; Weschke et al., 2022). We do not delve into the impact of public interventions on e-scooter usage and mode replacement, whether encouraging, direct/restrict or banning e-scooter sharing supply (Badia and Jenelius, 2023; Berretta, 2023; Liao et al., 2024).

2.2. More outcomes (effect-sizes) than studies

Table 1 provides an overview of the survey-based material providing outcomes of e-scooter-replaced PMV, PT, and AT proportions. The table also includes characteristics of the case areas (sites) and characteristics of the outcomes/studies. The material shown is split with respect to the three covered continents: North America, Oceania, and Europe. We did not find survey-based studies reporting e-scooter mode replacement effect sizes from other continents.

Considering the three upper rows in Table 1, the simple average of AT replacement proportion (by e-scooter) is close to 50 %, across continents. The mean proportions of PMV replacement and PT replacement are both close to 20 % in outcomes from Europe, with higher PMV replacement and lower PT replacement in the two other continents.

The characteristics of the case areas, where the mode replacement effect sizes originate, have mostly been added from external web-based sources, like Wikipedia (e.g., city populations and metro/tram figures, also including their Mode share entry[1]). There is considerable variation in the outcomes regarding site-specific features like area size (the inner/urban city area or the built-up area of a larger agglomeration, region or country), population density, and availability of rail-based public transport (metro / subway or tram / light rail). For some case-area characteristics there are also relatively large differences between the continents, in particular the length of metro/tram lines relative to the population and the modal shares in commuting. All the 144 case areas are listed in the Supplementary Material, S2.

When it comes to characteristics of the outcomes/surveys, we also find considerable differences in the material from the three continents. A much larger share of the outcomes from Europe are based on reports from e-scooter rental sharing companies; and the confidential outcomes only stem from Europe. The share of outcomes from peer-review studies or PhD theses is relatively low from all continents. The European studies have a much higher variation in sample size behind each outcome; and the data of the European studies are more recent. Moreover, there are more outcomes per European study than per non-European study, on average. The study with most outcomes, 44, is among the confidential sources; the second place is shared by Arup/NatCen (2022), including 30 outcomes from different cities in England, and another confidential source with 30 outcomes from Europe. The most common measurement of replaced modes was based on questions about the last trip (Wang et al., 2023). Shared e-scooters dominate in the set of replacement outcomes; private scooters are represented in only a handful of outcomes from Europe (Table 1).

2.3. Data processing – outcome removal based on area type or sample size

The meta-data summarized in Table 1 includes some outcomes that are based on sampling from large, diversified regions, even entire countries. Before meta-regression we remove such effects sizes that are not based on more clearly delimitated city areas. Moreover, we also remove some effect sizes that stem from sample sizes that we consider "too small" or "implausibly large".

The considerations about an accepted sample size interval for the outcome was partly based on inspecting the distribution of sample sizes, of the 307 outcomes, and truncating outliers (shown in figures in the Supplementary Material, S1). The upper truncation level will only remove four outcomes, from a study with considerably more outcomes (and reducing the maximum sample size from nearly 400,000 to under 100,000). As the four outcomes are clear outliers, we consider it preposterous to include them; they would have had an overly strong statistical weight in the meta-analysis. For the lower level, we fix the minimum sample size at 30, a rule-of-thumb figure for assuming large sample properties (De Veaux et al., 2021). However, although 30 observations will yield a relatively decent probability of including replacement of a mode that has a replacement proportion of only 0.1 (as PT in North America and Oceania), more specific rules can be proposed for proportions, e.g., that the proportion times the sample size is at least 10 (Lock et al., 2021). That would imply that 30 is sufficient for e-scooter mode replacement proportions larger than about 0.3, but not for lower proportions (0.1 would require 100, following that calculation rule).

[1] https://en.wikipedia.org/wiki/Modal_share

Table 1
Descriptive statistics of 307 outcomes from 100 survey-based studies of e-scooter mode-replacement, in North America, Oceania and Europe.

Variable	North America, n = 60 (43 studies)				Oceania, n = 10 (6 studies)				Europe, n = 237 (51 studies)			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Proportion of e-scooter trips that replace PMV (outcome)	0.41	0.16	0.02	0.80	0.23	0.1	0.07	0.44	0.19	0.1	0.03	0.52
Proportion of e-scooter trips that replace PT (outcome) (n = 51/9/233)	0.10	0.06	0.01	0.28	0.09	0.05	0.04	0.22	0.22	0.12	0.00	0.58
Proportion of e-scooter trips that replace AT (outcome) (n = 53/9/236)	0.45	0.15	0.11	0.81	0.57	0.09	0.44	0.72	0.50	0.11	0.21	0.82
Share stating non-travel (induced demand) (n = 34/8/164)	0.07	0.05	0.01	0.2	0.09	0.06	0.03	0.19	0.04	0.05	0.00	0.25
Population of outcome site, in millions	4.0	7.4	0.04	48	1.1	1.5	0.22	5	2.6	11.4	0.02	83
Size of outcome site, in square km	2799	5881	3	38,585	1479	3023	295	9992	1040	5045	10	37,000
Population density, at outcome site	2159	2315	615	18341	1347	993	146	2702	4565	4995	203	30,066
The outcome site has metro and/or tram - dummy= 1	0.78	0.42	0	1	0.10	0.32	0	1	0.58	0.49	0	1
The length (km) of metro/tram lines, at outcome site	113	207	0	1313	122	384	0	1215	151	445	0	3369
Km of metro/tram lines relative to area size, at outcome site	0.23	1.11	0	8.56	0.01	0.04	0	0.12	0.46	0.89	0	5.29
The outcome site has municipality-supported bike rental system - dummy= 1	0.63	0.49	0	1	0	0	0	0	0.67	0.47	0	1
The proportion, in the outcome site, commuting by PMV	0.78	0.15	0.28	0.97	0.73	0.14	0.50	0.87	0.50	0.19	0.20	0.87
The proportion, in the outcome site, commuting by PT	0.12	0.1	0.01	0.6	0.13	0.08	0.04	0.23	0.21	0.14	0.01	0.59
The proportion, in the outcome site, commuting by AT	0.07	0.05	0.01	0.23	0.09	0.04	0.05	0.17	0.27	0.13	0.02	0.50
Area level of the outcome site is a city - dummy= 1	0.78	0.42	0	1	1	0	1	1	0.81	0.39	0	1
Outcome replacement question about alternative mode on “last trip” instead of e-scooter (not modes replaced by e-scooter “in general”) - dummy= 1	0.70	0.46	0	1	1	0	1	1	0.91	0.28	0	1
Only shared e-scooter usage (not private or mixed) assessed for the outcome - dummy= 1	0.72	0.45	0	1	0.60	0.52	0	1	0.82	0.39	0	1
Only private (not shared or mixed) e-scooter usage assessed for the outcome - dummy= 1	0	0	0	0	0	0	0	0	0.03	0.18	0	1
Outcome sample consisting of e-scooter rental share company-registered users - dummy= 1	0.22	0.42	0	1	0.2	0.42	0	1	0.75	0.44	0	1
Outcome from e-scooter rental share company - dummy= 1	0	0	0	0	0	0	0	0	0.59	0.49	0	1
Outcome from confidential e-scooter rental share company - dummy= 1	0	0	0	0	0	0	0	0	0.54	0.5	0	1
Outcome from peer-review publication or PhD thesis - dummy= 1	0.27	0.45	0	1	0	0	0	0	0.08	0.28	0	1
Female share in outcome sample (n = 30/5/137)	0.37	0.09	0	1	0.42	0.09	0	1	0.31	0.11	0	1
Age> 30 share in outcome sample (n = 25/4/88)	0.62	0.16	0	1	0.64	0.1	1	1	0.45	0.1	0	1
Data collection year	2019		2018	2023	2020		2018	2022	2021		2018	2022
Outcome sample size (n = 53/9/235)	1598	1863	13	7965	1206	1472	97	3872	6940	32,313	13	393,981
No. of outcomes per study	1.4		1	5	1.7		1	3	4.6		1	44

Note: The number of outcomes per study (in the last row) can be considered an aggregate of three dependent proportions of transport mode (group)s replacement outcomes. E.g., from one-outcome studies, we retrieve three replacement outcomes: PMV, PT, and AT. The category PMV includes all *private motorized* two and four-wheeled *vehicles* (private car, shared car, ridehailing/taxi, MC/moped/scooter); PT comprises primarily land-based *public transport* (rail-based and bus/coach); AT refers to *active transport*, walking and cycling (both private and shared bicycles, including pedelec e-bikes).

Outcomes lacking information about sample size are also excluded from the meta-regression, for many of these only PMV replacement was reported, which by itself yields a reason for excluding the outcome. Implementing these restrictions on available outcomes from the literature will reduce the set for meta-regression to 244 × 3 outcomes from 82 studies (in 112 city areas).

In addition to replacement of existing modes, a new mode like the e-scooter is expected to also yield induced travel (Bai et al., 2021; Mitropoulos et al., 2023; Wang et al., 2023). In several outcomes, a category of “would not travel if the e-scooter were not available” was reported together with alternative modes, for e-scooter users that were asked about non-availability of e-scooter on their last e-scooter trip. Induced demand is important in a transport-economic assessment of e-scooter usage, but the inclusion of the "would not have travelled" category is limited and beyond the mode replacement scope of this paper. In our analyses, we include only mode *replacement*, aggregated to the three categories, PMV, PT and AT. Leaving out the share of induced demand, we normalize the sum of the three mode replacement categories to 1, to achieve the desired outcome-uniformity in meta-analysis (Nelson and Kennedy, 2009).

Some of the listed variables in Table 1 can be highly correlated. We test for correlation before heading to the meta-regression and, after variable transformations, we retest selected variables (moderators) in specific meta-regression models. In addition, we test for multicollinearity in weighted least squares models (Tabachnick and Fidell, 2021). Another way to circumvent correlation and potential multicollinearity problems is to unite two variables into one, as we do for rail-based public transport. Initial modelling of e-scooter mode replacement showed that the coefficients of metro (subway) and tram (light rail) existence/length were close, indicating very similar association with mode replacement.

Regarding the modal shares for travel to work, these are also normalized to 1 before meta-analysis; the normalization will remove categories like "work from home". The three commuting mode groups mirror our grouping of replaced modes by the e-scooter: PMV, PT and AT.

2.4. Quality assessment of the survey-based mode replacement measurement

Wang et al. (2023) present an assessment of the survey-based questions that have been applied to measure e-scooter mode replacement. These can be aggregated into two classes:

I. The largest part of outcomes from the literature are based on counterfactual information regarding the *last trip* by e-scooter (Table 1), the alternative mode that would have been used in case the e-scooter were not available.
II. In about 30 % of the outcomes from North America and nearly ten percent of the outcomes from Europe, the mode replacement has been measured by questions about e-scooter mode replacement *in general*. Such questions may, for example, ask about a listing of modes that the e-scooter has replaced (in general); or listing modes and ask about increase/decrease in their use following the usage of e-scooter.

Wang et al. (2023) consider that more research on the measurement effect from using I or II may be warranted. We provide such testing, applying a dummy set to 1 for outcomes based on measuring mode replacement "in general". Wang et al. (2023, p. 9) do consider that "asking respondents to report counterfactual information for the last trip helps reduce the eventual recall bias that would be otherwise associated with the use of alternative survey questions". We think this assessment can be strengthened; such that for retrospective counterfactual measures, questions about mode replacement *in general* are inferior to questions about the alternative mode on the *last trip*. While the response regarding substituted mode on *last trip* might be slightly influenced by the listing of mode alternatives (often with an added "would not have made the trip, if e-scooter were not available), the listing of mode alternatives for replacement *in general* may have an overly strong effect on the resulting mode-replacement distribution. The aggregated replacement of PMV, PT and AT, will easily depend on how many modes under each of the three were listed. There is potentially a long list of PMV, and there are various modes of PT, but for AT perhaps only two types of bicycle modes (private and shared), while walk is only walk. The *last trip* question is also more consistent with other travel-survey based approaches to the measurement of modal usage and other travel behaviour, in that the most recent trip behaviour forms the base for measurement to reduce recall bias (Hoogendoorn-Lansera et al., 2015; Wang et al., 2023). We will therefore consider the coefficient of the dummy for general mode replacement questions as a measure of methodological bias, in the meta-regression.

2.5. More about the meta-analytic approach

A point of departure in the standard meta-analysis approach is the weighing of effect sizes, or outcomes (θ), by their variance. As variances or standard errors of estimates are not always reported in single studies, we follow the (second-best) approach of weighing each value outcome by the square root of the outcome (study) sample size (Hunter and Schmidt, 1990; Hedges et al., 2010).

If we, at the outset, can assume a variation between outcomes/studies in the proportions of replaced modes by e-scooters, driven by both site-specific and outcome/study-specific characteristics, a between-study, or between-outcome, variance ought to be added (Borenstein et al., 2009; Nakagawa et al., 2017). With studies on transport mode shift to e-scooters that are carried out in different locations with varying transport mode access and usage, we do consider a model with between-outcome variance (random effects model) more appropriate than the special case with no between-outcome variance (fixed-effect model). The heterogeneity of our meta-data, the variation in transport mode shares replaced, across outcomes and areas, will be verified in our modelling and tests (see Supplementary Material, S1, that also includes publication bias testing).

We add an error component (ζ_k) to the model of effect sizes (outcomes), k; the between-outcome variance $\left(\tau^2 = Var(\zeta)\right)$ is added to the denominator of the statistical weight. (Thus, $\tau = St.dev.(\zeta)$). The random-effects meta-regression model can be formulated as:

$$\widehat{\theta}_k = \beta_0 + \beta_1 x_{1k} + \ldots + \beta_n x_{nk} + \zeta_k + \varepsilon_k \tag{1}$$

where $x_1 \ldots x_n$ are moderators (case area and/or survey variables) and ε_k is the sampling error. The random effects model can be considered a two-level model (Harrer et al., 2021), where $\theta_k = \beta_0 + \beta_1 x_{1k} + \ldots + \beta_n x_{nk} + \zeta_k$ is level 1 (the e-scooter replacement estimates) and $\widehat{\theta}_k = \theta_k + \varepsilon_k$ is level 2 (the outcome "sub-group" level). The sampling error ($\varepsilon_k = \widehat{\theta}_k - \theta_k$) has an expected value of 0 (with $Var(\varepsilon_k) = s_k^2$, the sampling error variance, and thus, s_k the standard deviation of the sampling error).

Some of the studies include several outcomes; we might then expect correlation between outcomes from the same study. A multilevel/three-level modelling or a robust variance modelling are both appropriate for handling studies with several outcomes (Van den Noortgate and Onghena, 2003; Moeyaert et al., 2017). The three-level meta-regression model can be formulated as:

$$\widehat{\theta}_{ij} = \beta_0 + \beta_1 x_{1,ij} + \ldots + \beta_n x_{n,ij} + \zeta_{(3)j} + \zeta_{(2)ij} + \varepsilon_{ij} \tag{2}$$

with an additional within-cluster (within-study) heterogeneity ($\zeta_{(2)ij}$, at level 2) to a between-cluster (between-study) heterogeneity ($\zeta_{(3)j}$, at level 3). The subscript ij indicates an outcome i nested in cluster j. That also implies a within-cluster variance $\left(Var(\zeta_{(2)}) = \tau_{(2)}^2\right)$ in addition to the between-outcome variance $\left(Var(\zeta_{(3)}) = \tau_{(3)}^2\right)$. The multilevel (three-level) model as well as the (two-level) random effects model have fixed slope coefficients; they are random intercept models (Harrer et al., 2021).

In robust variance estimation (RVE), standard errors are calculated by averaging products of the regression residuals (Pustejovsky and Tipton, 2021). We apply the correlated effects modelling:

$$\widehat{\theta}_{ij} = \beta_0 + \beta_1 x_{1,ij} + \ldots + \beta_n x_{n,ij} + u_j + \varepsilon_{ij} \tag{3}$$

where u_j is the between-study heterogeneity (and $Var(u) = \tau^2$). The variance of the sampling error is estimated as the average of outcome sampling variances in the study ($s_j^2 = 1/q_j \sum_{i=1}^{q_j} s_{ij}^2$), where q refers to the number of outcomes in the study. Moreover, the correlated effects model of RVE fixes a covariance of outcome errors, $Cov(\varepsilon_{hj}, \varepsilon_{ij}) = \rho s_j^2$, where ρ is the correlation between two outcomes within a study ($h \neq i$). This model is simplified by assuming that the outcomes in a study have similar sampling error variance ($s_{ij}^2 \approx s_j^2$) and that the correlation of outcome pairs are similar, such that ρ can be fixed to a single value (Pustejovsky and Tipton, 2021).

All three types of models, specified in Eqs. (1)–(3), will be applied to our meta-dataset. The multilevel model (2) and the RVE model (3) are also termed hierarchical models, as they take into account the cluster structure of the meta-data, that some studies include several outcomes. The level of heterogeneity and the multilevel/hierarchical structure will be assessed by formal tests (Borenstein et al., 2009; Harrer et al., 2021). In modelling e-scooter replacement proportions, of three transport mode categories, we follow the advice of applying logit-transformation of these proportions (p) in the meta-regression, i.e., $\theta = p/1 - p$ (Harrer et al., 2021). We also logit-transform moderators that represent proportions, including PMV, PT and AT shares in commuting as well as the shares of female respondents and respondents older than 30 years in the output samples. Other scale variables are ln-transformed. The logit-transformed e-scooter replacement proportions, from the meta-regression, can be transformed back by use of the exponential function (e), i.e., $\hat{p} = 1/1 + e(-\hat{\theta})$.

2.6. Meta-regression – modelling approach and moderators

As shown in Table 1, there are considerable differences between e-scooter replacement outcomes from the three continental areas. The AT replacement levels are fairly similar, but the PMV and PT replacements differ. We put the relatively small Oceanian sub-group together with the North American sub-group, in a "non-European" group. We test for continental model differences by interacting explanatory variables with the (Non-European / European) continental dummy variable.

The outcome meta-data from the three continents, displayed in Table 1, also show differences in the distribution of study features and study site characteristics. Hence, we assess whether explanatory variables co-vary similarly across the continental outcome groups. Table 1 provides the shortlist of available moderators in meta-regression models of e-scooter mode replacements. We will present parsimonious models, including those study features and study site characteristics that show the strongest statistical association with the PMV, PT, and AT replacement.

3. Results

3.1. Meta-regression – explaining variation across e-scooter mode replacement outcomes; case-area and survey moderators

Tables 2a-2c show the meta-regression results for, respectively, (the logits of) PMV, PT and AT proportions replaced by e-scooter. All three specifications described above are included: random effects (1), multilevel (2) and RVE (3). These models are applied to the 244 × 3 mode replacement outcomes (based on delimited sample sizes) from 82 studies in 112 city areas. The moderators in the meta-regressions comprise both case-area features and characteristics of the surveys or the survey samples. The models are parsimonious, including only moderators that co-vary significantly at the 10 %-level in at least one of the three model specifications.

The outcome site-specific moderators (from Table 1) that were retained in the meta-regressions of e-scooter mode replacements comprise: (the logit of) the mode class commuting proportions

Table 2a
Meta-regression, explaining variation in e-scooter replacement of the logit of the proportion of private motorized vehicle (PMV) trips.

	Random effects (1)	Multilevel (2)	RVE (3)
Intercept	−3.181*** (0.591)	−2.586*** (0.641)	−2.806** (1.280)
Ln_density	0.257*** (0.063)	0.174** (0.064)	0.218 (0.127)
Eur_ln_density	−0.044� (0.024)	−0.081** (0.029)	−0.100*** (0.033)
Logit_pmv_commuting	0.345*** (0.045)	0.221*** (0.045)	0.238** (0.098)
Lnyear	0.251 (0.184)	0.411� (0.236)	0.437 (0.265)
Logit_agex30	0.205� (0.115)	0.146 (0.140)	0.124 (0.120)
Escooter_users	−0.346* (0.144)	−0.260 (0.164)	−0.354** (0.167)
General_trip	0.769*** (0.177)	0.797*** (0.196)	0.606*** (0.206)
Eur_general_trip	−0.655** (0.234)	−0.529� (0.276)	−0.300 (0.320)
R^2 (amount of heterogeneity accounted for)	53.5 %		-
F (test of moderators)	31.29 ($p < 0.0001$)	15.98 ($p < 0.0001$)	
BIC	466.3	401.1	
AIC	431.7	363.1	
logLik	−205.9	−170.5	
QE (test for residual heterogeneity)	17,186.4 ($p < 0.0001$)		
Single outcome variance share, sampling error (level 1)		0.63 %	
Within-study variance share (level 2)		28.18 %	
Between-study variance share (level 3)		71.19 %	
Anova test of three levels vs. two levels	70.65 ($p < 0.0001$)		
I^2 (residual heterogeneity / unaccounted variability)	99.0 %	99.4 %	98.1 %
τ^2 (between-studies variance)	0.2847		0.2451
H^2 (unaccounted variability / sampling variability)	96.5		
No. of clusters (studies)		82	82
No. of outcomes	244	244	244

Note: Standard errors in parentheses; significance levels: *** < 0.001, ** < 0.01, * < 0.05, � < 0.1. The regression models are estimated in R, packages meta, metafor and robumeta (Schwarzer et al., 2015; Viechtbauer, 2010; Fisher et al., 2023); all models are mixed effects models based on REML, the restricted maximum-likelihood estimator (Harrer et al., 2021).

(Logit_pmv_commuting, Logit_pt_commuting, Logit_at_commuting), (the log of) the outcome area (Ln_area), (the log of) the population density at outcome site (Ln_density), and (the log of) the metro/tram line length relative to outcome area size (Ln_rail_index). In addition, three interactions with the European continent dummy were retained: Eur_ln_area, Eur_ln_density, and Eur_ln_rail_index. The outcome survey-specific moderators retained were: (the log of) the outcome data collection year (Lnyear), a general trip (not the last trip) replacement question dummy (General_trip), a dummy for only e-scooter users in outcome data (Escooter_users), a dummy for confidential (e-scooter rental share) company outcomes (Company_report), (the logit of) the female share in the outcome data (Logit_femalex), (the logit of) the age above 30 share in the outcome data (Logit_agex30). In addition, two interactions with the European continent dummy were retained: Eur_general_trip and Eur_escooter_users.

At the outset, all included logit- and ln-transformed scale variables, as well as dummies, in the meta-regression, have a pairwise Pearson coefficient below |.5|. However, the interaction of these variables with the continent dummy (Europe=1) yields higher correlation levels, up to

|.75|, and one beyond |.8|. We have checked variance inflator factors (VIF) applying weighted least square, that did show VIF values above 4, in the models of all three replaced modes, as displayed in Supplementary Material S3. However, as we found no other strong indications of multicollinearity problems, (like coefficient sign shifts or inflated standard errors). Thus, we have retained the eight moderators in the models for PMV, PT, as well as AT replacement, in spite of the VIF values and relatively strong pairwise correlations; these are still congruent with thresholds proposed in the literature (Harrell, 2015; Tabachnick and Fidell, 2021). In the RVE model, we fix the correlation between outcome pairs (ρ) to 0.5; we find no substantial impact from changing this value.

For all three mode-replacement meta-regressions (Tables 2a–c), all formal tests reject homogeneity. Thus, a random effects model is clearly preferred to a fixed effects model (Borenstein et al., 2009). The QE test of heterogeneity is influenced by the number of outcomes, but not the I^2 test, for which a size above 75 % indicates strong heterogeneity (Higgins et al., 2003). The I^2 test is however influenced by the precision level of the outcomes; it is the amount of variability beyond what is caused by sampling error. Tau-squared (τ^2) is not influenced by neither the number of outcomes nor their precision; τ^2 is significantly different from zero in random effects models, for PMV, PT and AT. (In the random effects model, τ^2 is a between-*outcome* variance; it does not take into account that some outcomes come from the same study, like hierarchical models do.) Finally, H^2 is considerably higher than 1 in all models, for all three mode replacements, which also indicates strong heterogeneity (Harrer et al., 2021).

Furthermore, a multilevel/hierarchical structure is strongly supported by the Anova (likelihood ratio) test, comparing the log-likelihood of the multilevel model vs. the random effects model. Thus, a multilevel/hierarchical model is clearly preferred to a (two-level) random effects model (Harrer et al., 2021). We will therefore put more weight on the results from the hierarchical models (2 and 3). Thus, when both the multilevel model and the RVE model show that coefficients are not different from 0 at the 10 % significance level, we weigh that result more strongly than the statistical significance in the random effects coefficients (1). The R^2 of the random effects model, together with the F values of the random effects and multilevel models (1 and 2), still indicate that the moderators yield models that fit relatively well to the mode replacement outcomes (Tables 2a-2c).

The strongest case-area moderator of (the logit of the proportion of) PMV trips replaced by e-scooter is the logit of the PMV share in commuting (Logit_pmv_commuting), with a significantly positive relationship in all models (1−3). The natural log of the population density of the case-area (Ln_density) shows a significantly positive relationship in some models, but not in the RVE. A significantly lower density effect in the European part of the PMV replacement outcomes is however found in all three models. Regarding survey-specific moderators, all models show a strong positive bias on PMV replacement figures from using general questions about e-scooter mode replacement (General_trips) instead of a question about the last trip. Surveys that were strictly limited to samples of existing e-scooter users (Escooter_users) tend to yield lower PMV replacement estimates, but not in the multilevel model (2). A reduced e-scooter user effect on PMV replacement shares in the European part of the outcomes has weak statistical significance in the hierarchical models (2 and 3). The age of the survey participants, the logit of the survey sample share above 30 years (Logit_agex30), and the log of the survey year (Lnyear, where 2017 was set to 1) showed no strong association with the log of the proportion of PMV trips replaced by e-scooter (Table 2a).

Regarding (the log of the proportion of) PT trips replaced by e-scooter, the logit of the PT share in commuting (Logit_pt_commuting) shows a significantly positive relationship in all models (1−3). The log of the case-area size and the log of the rail index (the km length of metro and tram lines with respect to the city area square km size) show positive association with the share of PT trip replacement by e-scooter in the European part of the outcomes (Eur_ln_area and Eur_ln_rail_index). Among survey-specific moderators as well, a significantly positive association is limited to the European part of the outcomes; a positive bias from using general questions about e-scooter mode replacement (Eur_general_trips) and survey samples including only e-scooter users (Eur_escooter_users). The logit of the survey sample share above 30 years (Logit_agex30) shows a significantly negative association with the logit of replaced PT trips. The negative association with the logit of survey sample share of females (Logit_femalex) has weak statistical significance in the hierarchical models (2 and 3). The association between outcomes from e-scooter sharing company reports (Company_reports) and the logit of replaced PT trips is even weaker (Table 2b).

When comes to (the logit of the proportion of) AT trips replaced by e-scooter, the logit of the AT share in commuting (Logit_at_commuting) shows a significantly positive relationship in all models (1−3). The log of the rail index (Ln_rail_index) shows a significantly negative association with the share of e-scooter replacement of AT. Regarding survey-

Table 2b
Meta-regression, explaining variation in e-scooter replacement of the logit of the proportion of public transport (PT) trips.

	Random effects (1)	Multilevel (2)	RVE (3)
Intercept	−1.852*** (0.138)	−1.786*** (0.132)	−1.905*** (0.174)
Eur_ln_area	0.091** (0.035)	0.056� (0.030)	0.127*** (0.037)
Eur_ln_rail_index	0.067*** (0.014)	0.049*** (0.012)	0.071*** (0.024)
Logit_pt_commuting	0.245*** (0.047)	0.243*** (0.042)	0.233*** (0.079)
Logit_femalex	−0.121** (0.047)	−0.072� (0.037)	−0.121 (0.068)
Logit_agex30	−0.191� (0.100)	−0.251* (0.109)	−0.239** (0.111)
Company_report	0.206* (0.088)	0.202 (0.155)	0.208 (0.153)
Eur_escooter_users	0.466** (0.171)	0.585*** (0.169)	0.418** (0.144)
Eur_general_trip	0.518*** (0.145)	0.514** (0.166)	0.384* (0.203)
R^2 (amount of heterogeneity accounted for)	68.3 %		
F (test of moderators)	54.65 ($p < 0.0001$)	41.66 ($p < 0.0001$)	
BIC	431.9	371.8	
AIC	397.3	333.8	
logLik	−188.7	−155.9	
QE (test for residual heterogeneity)	8971.8 ($p < 0.0001$)		
Single outcome variance share, sampling error (level 1)		1.26 %	
Within-study variance share (level 2)		40.88 %	
Between-study variance share (level 3)		57.86 %	
Anova test of three levels vs. two levels	65.56 ($p < 0.0001$)		
I^2 (residual heterogeneity / unaccounted variability)	98.3 %	98.8 %	95.4 %
τ^2 (between-studies variance)	0.2242		0.1786
H^2 (unaccounted variability / sampling variability)	57.6		
No. of clusters (studies)		82	82
No. of outcomes	244	244	244

Note: Standard errors in parentheses; significance levels: *** <0.001, ** <0.01, * <0.05, � <0.1. The regression models are estimated in R, packages meta, metafor and robumeta (Schwarzer et al., 2015; Viechtbauer, 2010; Fisher et al., 2023); all models are mixed effects models based on REML, the restricted maximum-likelihood estimator (Harrer et al., 2021).

specific moderators, all models show a strong negative bias on AT replacement figures from using general questions about e-scooter mode replacement (General_trips) instead of a question about the last trip. A weakening of this association in the European part of the outcomes is not statistically significant in the RVE model (3). There is a negative association between the log of replaced AT trips and survey samples including only e-scooter users (Escooter_users); this is however more or less fully offset in the European part (Eur_escooter_users). The logit of the share above 30 years (Logit_agex30), and the log of the survey year (Lnyear) showed no significantly negative association with the logit of the proportion of AT trips replaced by e-scooter in the hierarchical models (Table 2c).

Table 2c
Meta-regression, explaining variation in e-scooter replacement of the logit of the proportion of active transport (AT) trips.

	Random effects (1)	Multilevel (2)	RVE (3)
Intercept	0.567* (0.225)	0.426 (0.276)	0.689* (0.342)
Ln_rail_index	−0.044*** (0.009)	−0.039*** (0.008)	−0.062*** (0.020)
Logit_at_commuting	0.128*** (0.038)	0.082* (0.037)	0.208*** (0.072)
Lnyear	−0.275* (0.135)	−0.249 (0.177)	−0.371 (0.217)
Logit_agex30	−0.210* (0.083)	−0.149 (0.100)	−0.108 (0.108)
Escooter_users	0.370** (0.126)	0.286� (0.149)	0.340* (0.167)
Eur_escooter_users	−0.363** (0.132)	−0.323* (0.154)	−0.329* (0.183)
General_trip	−0.896*** (0.133)	−0.842*** (0.151)	−0.755*** (0.213)
Eur_general_trip	0.459** (0.166)	0.494* (0.199)	0.374 (0.250)
R^2 (amount of heterogeneity accounted for)	35.7 %		
F (test of moderators)	15.69 ($p < 0.0001$)	8.99 ($p < 0.0001$)	
BIC	332.3	282.2	
AIC	297.7	244.2	
logLik	−138.8	−111.1	
QE (test for residual heterogeneity)	14510.1 ($p < 0.0001$)		
Single outcome variance share, sampling error (level 1)		2.99 %	
Within-study variance share (level 2)		27.66 %	
Between-study variance share (level 3)		69.36 %	
Anova test of three levels vs. two levels	55.5 ($p < 0.0001$)		
I^2 (residual heterogeneity / unaccounted variability)	98.7 %	97.1 %	98.1 %
τ^2 (between-studies variance)	0.1652		0.2064
H^2 (unaccounted variability / sampling variability)	75.6		
No. of clusters (studies)		82	82
No. of outcomes	244	244	244

Note: Standard errors in parentheses; significance levels: *** <0.001, ** <0.01, * <0.05, � <0.1. The regression models are estimated in R, packages meta, metafor and robumeta (Schwarzer et al., 2015; Viechtbauer, 2010; Fisher et al., 2023); all models are mixed effects models based on REML, the restricted maximum-likelihood estimator (Harrer et al., 2021).

3.2. Meta-regression of outcomes based on “last trip” replacement questions; case-area moderators

Tables 3a-3c present meta-regression models of the subset of 212 × 3 mode replacement outcomes, from 62 studies in 101 city areas, that were based on *last-trip* e-scooter replacement questions. We expect that removing the outcomes based on using questions about e-scooter mode-replacement in general will reduce bias (Wang et al., 2023). Enhanced outcome precision will not remove heterogeneity, however, as heterogeneity in the e-scooter mode replacement outcomes is also driven by case-area features. We have retained only these case-area features in the meta-regression models in Tables 3a-3c.

For all three mode replacements, the (logit of the) mode share in commuting explains the variation in the specific mode replacement, with positive coefficient signs. Overall, e-scooter PMV and PT replacement are better explained by our included case-area features than the AT replacement. E-scooter PMV replacement increases in the log of density, but less in the case-areas in the European continent. E-scooter PT replacement increases in the log of the area size and in the log of the rail index, but only in the European continent. E-scooter AT replacement decreases in the log of the rail index (Tables 3a-3c). It is to be remarked that the coefficients of a few moderators are statistically insignificant in either the multilevel model or the RVE model (but not similarly in both, see Ln_density in the PMV replacement in Table 3a and Logit_at_commuting in Table 3c).

Table 3a
Meta-regression, predicting e-scooter replacement of PMV trips.

	Random effects (1)	Multilevel (2)	RVE (3)
Intercept	−3.054*** (0.445)	−2.115*** (0.463)	−2.095 (1.236)
Ln_density	0.247*** (0.059)	0.160** (0.060)	0.149 (0.146)
Eur_ln_density	−0.049** (0.015)	−0.079*** (0.022)	−0.074** (0.026)
Logit_pmv_commuting	0.406*** (0.045)	0.241*** (0.046)	0.313*** (0.107)
R^2 (amount of heterogeneity accounted for)	47.4 %		
F (test of moderators)	54.1 ($p < 0.0001$)	26.1 ($p < 0.0001$)	
BIC	376.9	325.5	
AIC	360.2	305.4	
logLik	−175.1	−146.7	
QE (test for residual heterogeneity)	14999.5 ($p < 0.0001$)		
Single outcome variance share, sampling error (level 1)		1.38 %	
Within-study variance share (level 2)		14.08 %	
Between-study variance share (level 3)		84.54 %	
Anova test of three levels vs. two levels	95.5 ($p < 0.0001$)		
I^2 (residual heterogeneity / unaccounted variability)	98.9 %	98.6 %	97.5 %
τ^2 (between-studies variance)	0.2562		0.1789
H^2 (unaccounted variability / sampling variability)	90.7		
No. of clusters (studies)		62	62
No. of outcomes	212	212	212

Note: Standard errors in parentheses; significance levels: *** <0.001, ** <0.01, * <0.05, � <0.1. The regression models are estimated in R, packages meta, metafor and robumeta (Schwarzer et al., 2015; Viechtbauer, 2010; Fisher et al., 2023); all models are mixed effects models based on REML, the restricted maximum-likelihood estimator (Harrer et al., 2021).

Table 3b
Meta-regression, predicting e-scooter replacement of PT trips.

	Random effects (1)	Multilevel (2)	RVE (3)
Intercept	−1.852*** (0.138)	−1.786*** (0.132)	−1.905*** (0.174)
Eur_ln_area	0.091** (0.035)	0.056� (0.030)	0.127*** (0.037)
Eur_ln_rail_index	0.067*** (0.014)	0.049*** (0.012)	0.071*** (0.024)
Logit_pt_commuting	0.245*** (0.047)	0.243*** (0.042)	0.233*** (0.079)
R^2 (amount of heterogeneity accounted for)	68.3 %	-	-
F (test of moderators)	54.65 ($p < 0.0001$)	41.66 ($p < 0.0001$)	-
BIC	431.9	371.8	-
AIC	397.3	333.8	-
logLik	−188.7	−155.9	-
QE (test for residual heterogeneity)	8971.8 ($p < 0.0001$)		-
Single outcome variance share, sampling error (level 1)	-	1.26 %	-
Within-study variance share (level 2)	-	40.88 %	-
Between-study variance share (level 3)	-	57.86 %	-
Anova test of three levels vs. two levels	65.56 ($p < 0.0001$)		-
I^2 (residual heterogeneity / unaccounted variability)	98.3 %	98.8 %	95.43
τ^2 (between-studies variance)	0.2242	-	0.1786
H^2 (unaccounted variability / sampling variability)	57.6	-	-
No. of clusters (studies)	-	82	82
No. of outcomes	244	244	244

Note: Standard errors in parentheses; significance levels: *** < 0.001, ** < 0.01, * < 0.05, � < 0.1. The regression models are estimated in R, packages meta, metafor and robumeta (Schwarzer et al., 2015; Viechtbauer, 2010; Fisher et al., 2023); all models are mixed effects models based on REML, the restricted maximum-likelihood estimator (Harrer et al., 2021).

Table 3c
Meta-regression, predicting e-scooter replacement of AT trips.

	Random effects (1)	Multilevel (2)	RVE (3)
Intercept	0.169** (0.056)	0.088 (0.083)	0.196** (0.093)
Ln_rail_index	−0.051*** (0.012)	−0.053*** (0.011)	−0.059** (0.027)
Logit_at_commuting	0.068* (0.029)	0.051 (0.033)	0.117** (0.046)
R^2 (amount of heterogeneity accounted for)	7.9 %		
F (test of moderators)	10.2 ($p < 0.0001$)	12.2 ($p < 0.0001$)	
BIC	256.6	208.6	
AIC	243.2	191.9	
logLik	−117.6	−91.0	
QE (test for residual heterogeneity)	14782.2 ($p < 0.0001$)		
Single outcome variance share, sampling error (level 1)		2.99 %	
Within-study variance share (level 2)		27.66 %	
Between-study variance share (level 3)		69.36 %	
Anova test of three levels vs. two levels	57.97 ($p < 0.0001$)		
I^2 (residual heterogeneity / unaccounted variability)	98.7 %	97.1 %	97.6 %
τ^2 (between-studies variance)	0.1524		0.1444
H^2 (unaccounted variability / sampling variability)	77.4		
No. of clusters (studies)		62	62
No. of outcomes	212	212	212

Note: Standard errors in parentheses; significance levels: *** <0.001, ** <0.01, * <0.05, � <0.1. The regression models are estimated in R, packages meta, metafor and robumeta (Schwarzer et al., 2015; Viechtbauer, 2010; Fisher et al., 2023); all models are mixed effects models based on REML, the restricted maximum-likelihood estimator (Harrer et al., 2021).

Table 4 presents an overview of the resulting estimates of e-scooter mode replacement based on the models in Tables 3a-3c (n = 212). We present separate estimates for the European and non-European continent parts of the meta-data, as well as a few cities, for illustrative purposes. We also include the simple averages of e-scooter mode replacements (the sum of PMV, PT and AT replacement normalised to 1). The simple averages from the outcomes, whether at continent or city level, do not represent a criterion, these are just simple averages of outcome estimates; still, they provide a measure for comparison against the model-based point estimates.

As expected, the meta-regression estimates at the continent level matches fairly well the simple averages of outcomes, based on the 212 outcomes from surveys using “last trip” replacement measurement. Although case-area features explain a considerable part of the distribution in PMV and PT replacement (Tables 3a-3b), there is additional heterogeneity in single city figures, such that model-based estimates may be more dispersed from the outcome averages from the city (Table 4).

4. Discussion and conclusions

Our study adds to the corpus of e-scooter mode replacement studies and the recent literature reviews (Badia and Jenelius, 2023; Mitropoulos et al., 2023; Wang et al., 2023), by introducing formal meta-analysis and meta-regression. The number of included effect-sizes, or outcomes, was relatively large; 307 in total, 244 applied in meta-regression, and 212 applied for deriving “best estimates” from the available meta-data. The number of e-scooter mode replacement outcomes can be multiplied by three, as we analysed three proportions: private motorized vehicles (PMV, primarily cars), public transport (PT) and active transport (AT). The data did not enable differentiation with respect to travel purpose, such that all travel purposes are added together. Our meta-regression enabled an assessment of what case-area characteristics and survey features that explain the variation in the published outcomes of e-scooter transport mode replacement. To our knowledge this is a first meta-analysis and meta-regression of what transport modes that e-scooters replace.

Our overall meta-regression results are consistent with observations from former reviews, that e-scooters transport mode replacement to a large extent is governed by the transport mode distribution at the outset (Badia and Jenelius, 2023; Wang et al., 2023). In areas where the share of commuting by PMV is higher, e-scooters’ PMV replacement is higher; and likewise for PT replacement and AT replacement. This also explains the main part of the difference in the subset of replacement outcomes from European vs. the non-European subset. What is similar in the outcomes from European and non-European studies is that more than half of the transport mode replacement by e-scooters is AT replacement. The e-scooter replacement of AT can be considerably larger than the relative share of AT in daily travel, in particular the e-scooter replacement of walking (Badia and Jenelius, 2023; Mitropoulos et al., 2023; Wang et al., 2023). In the meta-regression, the e-scooter replacement of AT, however, was not as well explained as the replacements of PMV and PT. This might partly be explained by AT replacement being more stable around 0.5, compared to the lower and more fluctuating PMV and PT

Table 4
Average e-scooter mode-replacement proportions from subset of 212 outcomes, with meta-regression estimates.

	PMV replacement				PT replacement				AT replacement			
	Average value in included outcomes	Meta-regression estimates			Average value in included outcomes	Meta-regression estimates			Average value in included outcomes	Meta-regression estimates		
		Random effects	Multilevel	RVE		Random effects	Multilevel	RVE		Random effects	Multilevel	RVE
Non-Europe	0.36	0.36 (0.35)	0.37 (0.36)	0.39 (0.37)	0.09	0.10 (0.09)	0.10 (0.10)	0.09 (0.09)	0.55	0.54 (0.51)	0.52 (0.51)	0.52 (0.49)
Europe	0.20	0.20 (0.20)	0.20 (0.19)	0.19 (0.19)	0.24	0.27 (0.27)	0.25 (0.23)	0.28 (0.27)	0.56	0.53 (0.54)	0.55 (0.52)	0.54 (0.53)
Denver CO	0.32	0.37 (0.36)	0.38 (0.37)	0.40 (0.38)	0.07	0.08 (0.08)	0.09 (0.09)	0.08 (0.07)	0.61	0.55 (0.53)	0.54 (0.53)	0.52 (0.50)
Liverpool	0.36	0.23 (0.23)	0.21 (0.21)	0.21 (0.21)	0.11	0.21 (0.21)	0.19 (0.19)	0.22 (0.21)	0.53	0.57 (0.57)	0.59 (0.57)	0.57 (0.55)
Frankfurt	0.19	0.17 (0.17)	0.19 (0.18)	0.18 (0.17)	0.37	0.3 (0.30)	0.28 (0.26)	0.31 (0.31)	0.44	0.52 (0.52)	0.53 (0.51)	0.51 (0.50)

Note: The averages in the outcomes, 40 from non-European cities and 172 from European cities, as well as three from Liverpool, two from Frankfurt, and one from Denver, are normalised to 1 (the sum of replaced PMV, PT and AT). For the meta-regression estimates, based on the models in Tables 3a-3c, the proportion to the left is the normalised estimate and the proportion in the parentheses are the original model estimates.

replacement proportions. Still, the results in Table 3c might indicate that we have not identified site-specific features that could explain the e-scooter's AT replacement, when removing outcomes with survey features that we consider a source of bias ("general trips" replacement question).

The associations of mode replacement with other case-area features might not be that obvious. Regarding the positive association between residential density and PMV replacement, when controlling for the PMV proportion in commuting, it might partly cover non-commuting travel and that increasing density lowers the odds of choosing the car among alternative modes (see, e.g., Brownstone and Golob, 2009). The association is found to be significantly smaller in European subset of the outcomes, comprising cities with higher density on average than the non-European subset. The PT replacement is found to be higher in cities that are larger in square km size, in the European subset, which is less easy to explain, but might also mask relationships in PT usage in non-commuting. Likewise, for the positive association between PT replacement and the rail index (metro/tram line kms divided by the sq. km area size), in the European subset, that although controlling for PT shares in commuting, a higher rail index might mirror higher PT quality and usage in non-commuting (see, e.g., Utsunomiya and Shibayama, 2021). For AT replacement, there is a negative association with the rail index, possibly indicating that trip combinations or chains between AT and PT compete better against e-scooter alternatives. However, we find that there is a scope for more investigations into the associations between built environment and transport infrastructure at the one hand and e-scooter mode replacement at the other.

We expected that survey characteristics could explain some variation in the e-scooter mode replacement outcomes, in particular the mode replacement question, differentiating between specific questions about alternative mode to e-scooter in the last trip and less specific ("general") questions about a listing of what modes the e-scooter usage had replaced (or would replace) in general (Wang et al., 2023). We found that the latter, asking general questions (in our "general trip" dummy), bias PMV replacement upwards and AT replacement downwards. One simple explanation about these bias directions is that far more PMV modes are listed than AT modes (see, e.g., Weber et al., 1988). Use of "general trip" measurements (instead of "last trip") might still vary in terms of how large bias they can be expected to yield. We have not carried out in-depth analysis of this potential variation, primarily due to "general trip" only constituting about 13 % of the (244) outcomes. One obvious element is whether the stated general change in one specific mode ("more", "less", "no change", etc.), due to the e-scooter, is applied directly into quantified replacement proportions, or whether it is re-adjusted to the initial mode distribution. The latter can be expected to yield less biased results. If outcomes based on "general trip" will grow, irrespective of the bias assessment, the bias variation, due to initial mode-distribution adjustment or other approaches, might be investigated in future meta-regression.

We also have to point out that the mode replacement measurement becomes more ambiguous when the sum of replaced mode shares surpasses 1; we have just applied simple normalization to 1. In any case, the measurement question was found to be far more decisive than the type of outcome provider; we found no significant impacts on e-scooter mode replacement, neither from the confidential subset of outcomes nor from the grey literature in general (using dummies in the regression models, see Supplement S4). Another moderator tested was a dummy for outcomes based on private e-scooters' mode replacement; we found no significant impact, but private e-scooters' share in published outcomes was very small.

We found that outcomes based on only e-scooter users, in general users of shared e-scooters, had lower PMV replacement and higher AT replacement. In the European subset, however, they had lower AT replacement and higher PT replacement. Possibly samples of e-scooter users (representing more than 70 % of all 307 outcomes) can be considered as providing more reliable mode replacement responses, although the replacement question is retrospective and counterfactual for them as well as for the non-users (Wang et al., 2023). However, while non-users clearly provide hypothetical assessments, the e-scooter users can anchor their answer in actual behaviour.

We found only weak associations between mode replacement and female shares and age above 30 shares in the outcome surveys; and for quite many outcomes we lacked information about these shares. It is however not unlikely that actual variation in e-scooter usage, with respect to age and gender distribution, will have an impact on the mode replacement (Fearnley, 2022). The time trend in our analysis is also relatively weak; as the meta-data covers the period from 2018 to 2023, there is a COVID-19 period in the middle or later part, with mode usage restrictions that will vary in scope and duration across areas, hampering the assessment of possible e-scooter mode replacement over time. In general, PT was partly restricted in many of the included cities in the meta-data during the pandemic, thus we might hypothesise that the impact would primarily materialise as relatively lower PT replacement and relatively higher private mode (PMV and AT) replacement. However, the continent with the largest share of outcomes from 2020 and 2021, Europe, is the continent with highest PT replacement. If what we have found for the above-mentioned time period remains stable over a longer time of growth in e-scooter usage, we might get development patterns like those we have drawn in Supplement S5. It can be expected from our results that cities that already have reached strong sustainable transport results in terms of the shares travelling by AT or PT, will primarily obtain less usage of AT and PT after the introduction of shared e-scooters in their downtown areas. Based on the meta-analysis of published e-scooter mode replacement estimates, it seems overly optimistic to present the introduction of shared e-scooters as a measure to reduce travelling by car, or PMV, especially in European cities.

Considering the estimated e-scooter replacement proportions, we find ca. 37 % PMV, 10 % PT and 53 % AT, in the non-European subset of the meta-dataset; in the European subset, we find ca. 20 % PMV, 25 % PT and 55 % AT. These estimates are closest to those from the multilevel models. Our meta-analysis has been based on using *trips* as measurement scale, as this was the predominant measurement applied in the available literature on e-scooter mode replacement. However, as indicated by Fearnley (2022) and by Meroux et al. (2023), the e-scooter mode replacement pattern using distance (km) as the measurement scale can be different; replaced PMV trips can be longer on average than the replaced AT trips. Meroux et al. (2023) derived a factor of 1.08, for the e-scooter replacement of car-based trip distances vs. trips, based on data from four US cities. If we apply this factor to PMV as well as to PT, in the European as well as in the non-European subset, we can adjust the e-scooter mode replacement rates, in km travelled, to 39 %, 10 % and 51 %, respectively for PMV, PT and AT, in the non-European subset, and to 21 %, 26 % and 53 %, in the European subset. The km-based replacement proportions are the most relevant measurements for calculations of changes in greenhouse gas emissions, health/injury risk change, etc., due to mode changes (de Bortoli and Christoforou, 2020; Meroux et al., 2023; Schröder et al., 2023).

In the available literature, there are few outcomes that assess or compare e-scooter mode replacement under different regulatory frameworks or varying methods of deployment of shared e-scooters. But this literature is growing, e.g., investigating the potential impact of policies that target interaction of e-scooter with other modes, primarily PT (Luo et al., 2021; Ziedan et al., 2021a; 2021b; Liao et al., 2024). Much of this literature is, however, based on trip data, which is not directly applicable for the assessment of e-scooter mode replacement (e.g., Kalakoni et al., 2024; Li et al., 2024).

Heineke et al. (2023) assessed e-scooter regulation measures in 100 larger cities worldwide, differentiating their regulation policy in four archetypes, ranging from "no regulation" (29 %), "open regulate environment" (23 %), "tender regulated" (13 %), and "banned" (35 %). The latter group comprises Chinese cities and Paris and Barcelona in Europe. The other three groups would cover other cities in our meta-dataset. Adding and classifying regulatory elements for all 144 case areas, for the relevant period of the outcomes survey collection, was considered beyond the scope of our meta-analysis. Future meta-regressions might enable taking such policy-elements into account, together with more case-area characteristics than we included.

There are also other outcome variations that future meta-analyses can handle better with new studies, e.g., the mode replacement of privately owned versus shared e-scooters. Our meta-regression has still added evidence to the mode-replacement sizes and to the associations with case-area characteristics as well as outcome survey features. Some major findings in our meta-regression verify what was already alluded in former reviews (Badia and Jenelius, 2023; Mitropoulos et al., 2023; Wang et al., 2023), that the e-scooter tends to replace primarily the modes that are most used at the outset, and in nearly any case, mostly replacing active transport (AT). In general, our meta-regression models include various important site-specific features, that do explain part of the e-scooter mode replacement, but new research could extend the scope into, e.g., more built environment variables, perhaps also weather/climate, as well as the above-mentioned regulatory elements and transport policy issues. Beyond the mode replacement issue, meta-analysis of e-scooter induced demand is also a possibility for future research.

CRediT authorship contribution statement

Knut Veisten: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Nils Fearnley:** Writing – review & editing, Writing – original draft, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

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Declaration of Competing Interest

We declare no conflict of interest.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jcmr.2025.100082.

Data availability

The data that has been used is confidential.

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