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Interventions reducing car usage: Systematic review and meta-analysis

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ABSTRACT

This systematic literature review aimed to investigate the extent to which transport-related interventions induced a reduction in car use. Both qualitative synthesis and *meta*-analysis were employed. The synthesis included 31 original studies, while the *meta*-analysis included 21. Of the qualitatively synthesised studies, 74 % demonstrated that interventions were effective in reducing car use. The pooled estimates of the effects showed a significant reduction in car usage with a mean effect size of Hedges' g = -0.117 (p = 0.024). The effect strongly varies across the studies due to considerable heterogeneity (I^2 = .98, with a 95 % prediction interval from −0.589 to 0.355). At the moderator level, no significant differences were identified in the mean effect sizes for any subgroups, and the key factors could not be distinguished. The current body of evidence highlights that transport-related interventions can significantly influence car usage reduction, while literature suggests that this may benefit environment and society.

1 Background

To meet the overarching goal of sustainable development, transport policies and interventions should, among other things, mitigate risks posed by the growing use of motorized individual transport. These risks include global risks related to climate change caused by releasing greenhouse gases into the atmosphere, as well as social risks resulting from noise, road congestion, traffic injuries, social

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inequalities, and physical inactivity, which can contribute to obesity and other health problems. Reducing car usage by shifting from car to transport modes such as walking, cycling or public transport, may mitigate traffic congestion, improve air quality, decrease greenhouse gas emissions or help to achieve daily physical activity level recommended by WHO (International Transport Forum, 2023). However, reducing car usage requires changes in transport behaviours of society, which is difficult and long-lasting (Wohlwill and Weisman, 1981).

While there is a lot of research on the effects of transport-related interventions on changing transport behaviour, they often adopt a selective perspective. Ogilvie et al. (2004) pioneered a comprehensive assessment of interventions effectively shifting populations from cars to walking and cycling, estimating a potential 5 % reduction in car use within motivated groups. Later, Scheepers et al. (2014) systematically summarised the evidence on the effectiveness of transport interventions published until 2014. They evaluated interventions utilizing physical, legal, economic, or communicative tools to stimulate a shift from car to active transport (walking, cycling). The effectiveness of transport interventions, in general, are rarely the subject of *meta*-analysis. They are only available for narrowed-down research questions regarding, e.g., the built environment (Ewing and Cervero, 2010), particular intervention types (Fujii et al., 2009) or social groups (Cerin et al., 2017). A broader, though not yet comprehensive, approach to such an evaluation was proposed by Möser and Bamberg (2008) who analysed the effect of soft transport interventions on car use. The term ‘soft’ refers to interventions that aim to affect people’s perceptions and attitudes, affecting decision-making and transport behaviour (Möser and Bamberg, 2008; Semenescu et al., 2020). Their review concluded that soft transport interventions effectively increase the proportion of non-car use by 7 % on average (a corresponding mean effect size of Cohen’s $h = .15$ was obtained). More recently, Semenescu et al. (2020) summarised all of the available evidence on the effect of soft transport interventions published in the preceding 30-year period. The results were very similar to Möser and Bamberg’s (2008) and accounted for a 7 % reduction in car use on average and a mean effect size of Hedges’ $g = .163$.

To the best of our knowledge, there are no *meta*-analyses covering a broad spectrum of interventions comparable to the range of studies included in Scheepers et al.’s (2014) review and therefore covering both hard (i.e. including infrastructure investments, traffic engineering, or control measures), soft, and mixed (a combination of hard and soft) interventions. Because transport-related

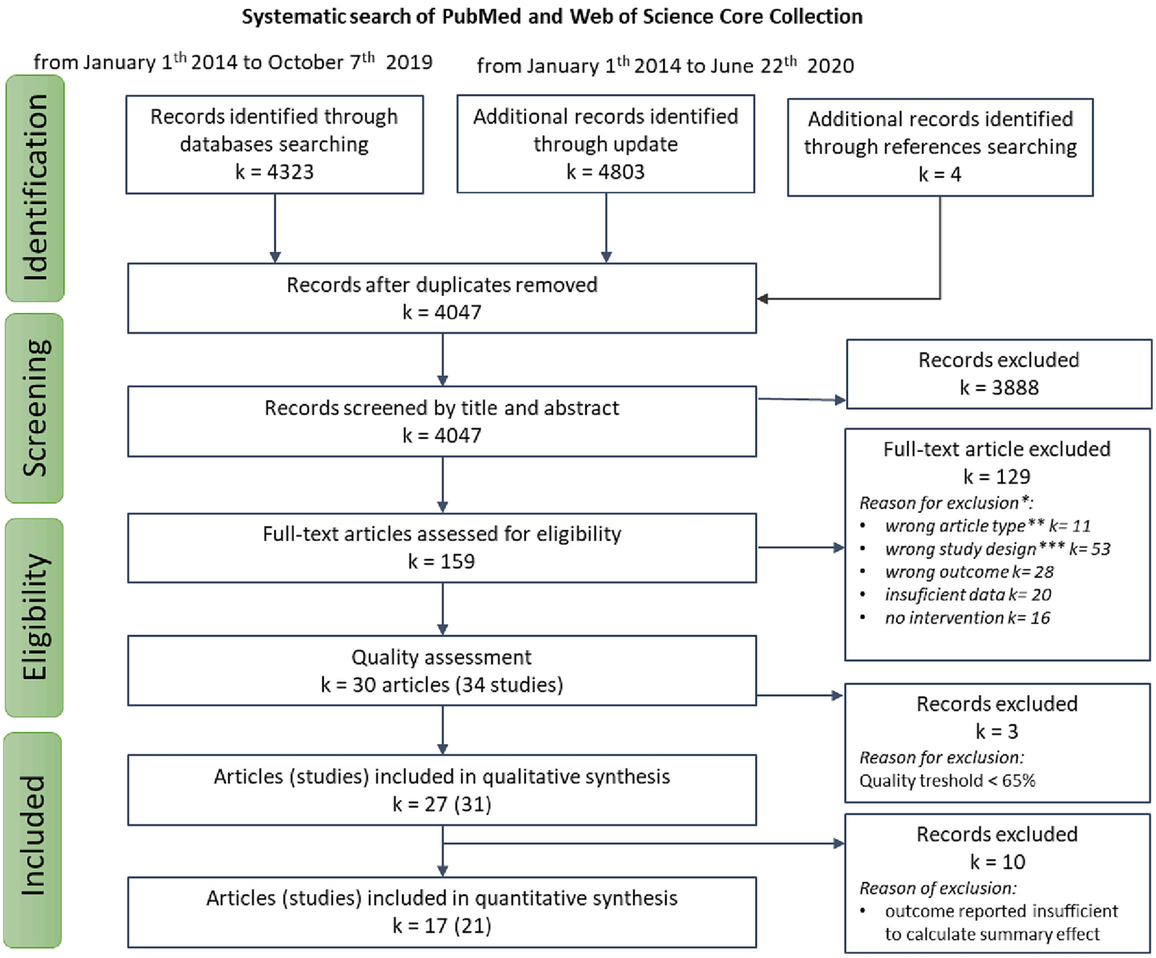

Fig. 1. Flow chart for study selection.

interventions are increasingly being implemented and evaluated, many studies have come out since Scheepers, and therefore, there is a need to update the published evidence. Accordingly, this study aims to synthetise and *meta*-analyse evidence published since 2014, building upon Scheepers et al. (2014) while addressing questions: To what extent transport-related interventions are effective in inducing car reduction? and, Which interventions are the most effective in reducing car usage? These insights hold significance for the development of policy interventions such as travel demand management, and Sustainable Urban Mobility Plans (Okraszewska et al., 2018).

For the purposes of this paper, 'intervention' is defined as "any policy, program, or environmental change (physical and/or social) used to promote specific health behaviours or goals" (Lakerveld et al., 2020).

2 Methods

Two research methods were used to address the defined research questions. A systematic literature review was conducted to provide a comprehensive and unbiased summary of the available evidence concerning the interventions employed and their effectiveness. Furthermore, a *meta*-analysis was performed to combine the results of multiple studies, offering a more precise estimation of the intervention effects. This review was structured according to the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) guidelines (Page et al., 2021) and its corresponding protocol was registered with the International Prospective Register of Systematic Reviews (PROSPERO) under registration number #CRD42020156636.

2.1. Search strategy

A systematic database search was undertaken in October 2019 and updated in June 2020.The search included original studies published from January 2014 to June 2020 and the research strategy proposed by Scheepers et al. (2014) was largely adopted.

The search procedure was executed across two prominent electronic databases:: PubMed and Web of Science Core Collection. The quest involved the utilization of both controlled terms (MesH in PubMed) and free text terms. In particular, the terms 'active travel', 'motorised travel', 'mode shift', 'intervention' and their synonyms were searched. Previous systematic reviews and *meta*-analyses covering a similar research focus were used as a basis for determining these terms (Möser and Bamberg, 2008; Scheepers et al., 2014; Semenescu et al., 2020). A search filter was used to limit the results to adults. No language restrictions were applied. The complete search strategy for the PubMed and Web of Science Core Collection databases can be found in Appendix A. An additional manual search was conducted through references of systematic reviews and *meta*-analyses that have been published since 2014.

All articles underwent initial screening based on their titles and abstracts, a process executed by two researchers to determine their eligibility for further assessment (see Fig. 1). Inter-rater reliability was evaluated using Cohen's Kappa, a statistical measure. Any discrepancies between the raters were resolved through discussions aimed at achieving consensus. In instances where an agreement could not be reached, a fourth researcher was consulted, in accordance with the approach recommended by Higgins and Green (2011). The full texts were obtained for the eligible articles and screened independently by two raters.

2.2. Eligibility criteria

The review included original, peer-reviewed experimental and quasi-experimental studies that investigated the effectiveness of transport-related interventions promoting a shift from car use to walking, cycling or public transport.

Included in the review were studies exclusively focusing on general adult population. Eligibility criteria necessitated the studies to provide quantitative outcomes indicating changes in car usage (increase, decrease/, or no change). Such outcomes included parameters like travel time or distance, number of trips, frequency of trips, or the proportion of trips by car. The scope exclusively considered actual behavioral changes, whether reported by participants themselves or objectively measured (e.g., through accelerometers or trip counts).

2.3. Quality assessment

'Standard quality assessment criterion for evaluating primary research papers' (Kmet et al., 2004) was used to evaluate the quality of selected studies. Two independent assessors evaluated the studies against 14 specific criteria: objective or question description, study design, subject selection method and description, random allocation description, blinding of investigators or subjects, exposure and outcome measure(s), sample size, analysis description and appropriateness, variance estimation, confounding control, results presentation, and conclusion support. Each criterion received a score ranging from 0 to 2 points (0 points for non-compliance with the criterion, 1 point for partial compliance, and 2 points for complete fulfillment). Any disputes were resolved through discussion and mutual consensus. For each study, a summary score was calculated and represented on a scale from 0 to 100 %. Studies were deemed eligible if they achieved a minimum score of 65 %, which indicated they were from moderate-to-high quality. This threshold was selected as an intermediary between the liberal threshold of 55 % and the conservative threshold of 75 %, as suggested by Kmet et al. (2004). A comparable approach was employed by Stanczykiewicz et al. (2019) in their own review.

2.4. Data extraction and coding

Descriptive data were extracted from each study: (i) study characteristics: first author, year of publication, study location, study

Table 1
Moderator groups and subgroups used in *meta*-analysis.

Moderator group	Subgroup	Description and examples
Intervention class (based on Möser and Bamberg (2008))	Hard	Interventions including infrastructure improvements, traffic engineering and control measures or pricing
	Soft	Interventions using social marketing techniques to influence transport behaviour and attitudes, e.g., travel awareness programs, workplace travel plans, cycling promotion campaigns
	Mixed	Interventions combining hard and soft measures, e.g., new PT line complemented with a promotional campaign
Tools used (based on Scheepers et al. (2014))	Physical	Interventions providing infrastructure improvements, new transport facilities or equipment
	Communicative	Interventions providing targeted materials or tools aimed at a direct change of individuals' behaviour
	Economic	Interventions using subsidies, rewards or penalties to enhance the use or resignation of transport modes
	Combined	Interventions using a combination of two or more types of tools
Intervention type	Car restrictions	restricted car traffic zones, introduction of paid parking instead of free parking
	PT infrastructure	Interventions providing new or changed transport infrastructure, e.g., new tram or rail line
	W/C infrastructure	Interventions providing new or changed walking and/or cycling infrastructure, e.g., new walking and cycling trails
	PT services	Interventions providing new or changed PT services, e.g., introduction of fare-free public transport
	W/C services	Interventions providing new or changed walking and/or cycling services, e.g., introduction of a bike-sharing system
	Social strategies	Interventions including educational and promotional activities, e.g., travel awareness campaigns, bicycle trainings
Level of intervention	Population-level	In which the participants were exposed to the intervention by living in its proximity; the intervention was not targeted at individuals but at, for example, people living in the district where a new PT connection was opened
	Individual-level	Interventions were addressed to individuals to shape their behaviour; the participants were directly involved in the intervention and its evaluation
Data collection method	Self-reported	Data was collected using questionnaires and/or travel diaries
	Objective	Data was collected using counts, or participants were asked to wear pedometers or accelerometers
	Self-reported + objective	A combination of self-reported and objective data collection methods was used
Study design	Experiment	Study participants were randomly assigned to the intervention and control groups
	Quasi-experiment	Study participants were not randomly assigned to the intervention and control groups
Quasi-experimental design (based on Fujii et al. (2009))	Non-controlled	Only the intervention group is evaluated; the measurements take place before and after the intervention
	Only post-control	Intervention and control groups are compared only after the intervention
	Pre-/ post-control	Intervention and control groups are evaluated both before and after the intervention

W/C = walking and/or cycling; PT = public transport.

design, ascertainment of outcome indicators, and measurement time points, (ii) study participants: sample size, distribution of age, gender; (iii) intervention: aim, design, entity that initiated or commissioned the intervention; (iv) tools used: legal, economic, communicative, physical; (v) method of evaluation; (vi) statistical characteristics: covariables included, sensitivity analyses performed; and (vii) reported outcomes and their significance. Data extraction from each article was performed independently by pairs of researchers. In the event of a lack of consensus, a third researcher was engaged to reach an agreement, following the approach recommended by Higgins and Green (2011). A summary of the included studies is presented in Table 3.

For the purposes of the *meta*-analysis, data were coded based on the adopted set of sub-groups (described in Table 1), representing different levels of moderators, further included in moderator analysis (described in Section 2.6.2).

Table 2
Categories used to capture the direction and significance of the effect.

Code	Effect direction & significance	Effect description
–	significant-decrease	There was a statistically significant decrease in car usage
–	non-significant-decrease	Car usage decreased but the effect was not statistically significant
0-	decrease-untested	Car usage decreased, but the result was not tested for significance
0+	increase-untested	Car usage increased, but the result was not tested for significance
+	non-significant-increase	Car usage increased but the effect was not statistically significant
++	significant-increase	There was a statistically significant increase in car usage
X	inconclusive	The study did not allow for unambiguous conclusions
No	no effect	Car usage remained unchanged

Table 3
Characteristics of articles and studies included in the qualitative synthesis.

No	Author (Year)	Country	Study design	Follow-up period	Data collection	Sample size	Population	Tools used	Intervention		Effect
									Class	Type	
1.	Aittasalo (2019)	FI	pre-post (phase 1)RCT (phase 2)	n.r.	questionnairesaccelerometerstravel diary	n = 900 (phase 1) IG: n = 422 (phase 2)CG: n = 208 (phase 2)	employees	communicativephysical	mixed	1) environmental improvements2) social and behavioural strategies	**0-** **0-**
2.	Aldred (2019)	GB	natural experiment	1 year	travel diaries questionnaires	IG: n = 750CG: n = 962	general population	physical	hard	Cities-wide infrastructure changes improving W/C environment	–
3.	Anderson (2016)	SE	pre-post	1 year	questionnaires	IG: n = 547CG: n = 625	car owners	economics communicativephysical	mixed	congestion charge scheme	—-
4.	Audrey (2019)	GB	RCT	1 year	accelerometers GPS receiverstravel diaries questionnaires	IG: n = 221CG: n = 256	employees	communicative	soft	behavioural intervention	**No**
5.	Bamberg (2017)	DE	RCT	–	questionnaires	IG: n = 288 CG: n = 18	new residents	communicative	soft	personal travel planning campaign	—-
6.	Cats(2017)	EST	pre-post	1 year	questionnairestravel diary	n = 1500 households	general population	economics	hard	free–fare public transport	**0-**
7.	Charles (2015)	AU	pre-post	n.r.	observationsquestionnairespedestrian and bicycle counters	BL_IG: n = 34,549 BL_CG: n = 34,549 FUP_IG: n = 42,232 FUP_CG: n = 42,232	studentsstaff	physical	hard	new pedestrian bridge	—-
8.	De Kruijf (2018)	NL	longitudinal	1 month	questionnaires	n = 547	studentsstaff	economics	hard	monetary incentives to use e-bikes	**0-**
9.	Foley (2017)	GB	natural experiment	8 years	questionnaires	n = 365	general population	physical	hard	motorway extension	**X**
10.	Friman (2019)	SE	pre-post	4 months	questionnaires	BL: n = 401FUP: n = 190	employees	economicscommunicative	mixed	temporary free public transport	–
11.	Geng (2016)	CN	controlled trial	1–2 months	questionnaires	IG: 191CG: 201	general population	communicative	soft	behavioural intervention	–
12.	Heinen (2015)	GB	quasi-experimental	3 years	travel diaries questionnaires	n = 466	employees	physical	hard	new busway + a service path for W/C	–
13.	Heinen (2016)	GB	quasi-experimental	3 years	questionnaires	BL: n = 1164 FUP: n = 500	employees	physical	hard	new busway + a service path for W/C	–
14.	Hong (2016)	USA	pre-post	5 months	questionnaires	IG: n = 101 CG: n = 103	general population	economicsphysical	hard	new light rail transit line	**X**
15.	Hsieh (2017)	TW	RCT	–	questionnaires	IG1: n = 53 IG2: n = 57 CG: n = 53	general population	communicative	soft	personalised travel plans: 1) action plans2) coping plans	+ —-

(*continued on next page*)

Table 3 (*continued*)

No	Author (Year)	Country	Study design	Follow-up period	Data collection	Sample size	Population	Tools used	Intervention		Effect
									Class	Type	
16.	Knott (2019)	GB	natural experimental	1 year	questionnairestravel diary	n = 884	employees	economicsphysical	mixed	1) from free parking to paid or no parking2) from paid parking to no parking	—- —-
17.	Ma (2017)	AU	natural experimental	1 year	GPS device	IG: n = 245 CG: n = 96	general population	communicative	soft	individualised marketing program	—-
18.	Molina (2015)	ES	pre-post	8 months	questionnaires	n = 173	students	communicativephysical	mixed	public bike-sharing program	**X**
19.	Ogilvie (2016)	UK	quasi-experimental	3 years	questionnaires	BL: n = 1,143FUP: n = 470	general population	physical	hard	new busway + a service path for W/C	—
20.	Piras (2018)	IT	quasi-experimental	2 years	questionnaires	IG: n = 133 CG: n = 29	general population	communicativephysical	mixed	new light railway line + travel behaviour change program	**0-**
21.	Rodriguez (2014)	US	natural experimental		questionnaires	N = 292 IG: n = 189 CG: n = 103	students	communicative	soft	Smart Moves Apartment Finder Map	—
22.	Ruiz(2018)	ES	quasi-experimental	1 year	questionnaires	BL_IG: n = 85 BL_CG: n = 80FUP: n = 118	drivers	communicative	soft	travel behaviour change program	**0-**
23.	Song (2017)	GB	quasi-experimental	2 years	questionnaires	BL: n = 3,496FUP n = 1,906	general population	physical	hard	development/ improvement of walking and cycling routes	**0-**
24.	Spears (2017)	US	quasi-experimental	6 months	questionnaires	IG: n = 126 CG: n = 77	general population	physical	hard	new light rail line	**X**
25.	Sun(2020)	CN	natural experimental	1 year	questionnaires	BL: n = 5,436FUP: n = 1,770	general population	physical	hard	first metro line	+
26.	Termida (2016)	SE	longitudinal	7 months	travel diary	FUP1: n = 91	residents	physical	hard	new tram line	**X**
27.	Xie(2016)	CN	pre-post	3 years	travel diary	n = 7,585	general population	physical	hard	1) one tram line2) two additional tram lines	— —

W/C = walking and/or cycling, PT = public transport, n.r. = not reported, BL = baseline, FUP = follow-up period, IG = intervention group, CG = control group, GPS = Global Positioning System; RCT = Randomised controlled trial; Effect category: "–" = significant-decrease; "-" = non-significant-decrease; "0-" = decrease-untested; "X" = inconclusive; "No" = no effect; "0+" = increase-untested; "+" = non-significant-increase; "++" = significant-increase.

2.5. Data synthesis

Systematic review

In the descriptive analysis, the approach proposed by Żukowska et al. (2022) was used, and the strength of the evidence of the intervention effect was described based on eight pre-determined categories indicating the association between the intervention and modal shift as well as the quality of the study and the significance of the results (see Table 2).

Meta-analysis

Studies were not included in the *meta*-analysis if they did not report sufficient indicators (such as standard deviation or other information from which it can be obtained, e.g. confidence intervals or p-value, as suggested by Higgins and Green (2011)) and were rejected from further analysis. The change in car usage was selected as a primary effect measure. Even if different outcomes reported it (i.e., travelled time or distance, number, frequency, or proportion of trips), the outcomes were included in the same *meta*-analysis as reliable car usage reduction measures, like in the approach of Semenescu et al. (2020) and in accordance with the *meta*-analysis guidelines (Borenstein et al., 2011). Because studies use different scales for reporting intervention effects, they cannot be compared directly. For this reason we used Hedges' g, a standardised effect size measure, which is the ratio of raw difference in samples' means and pooled standard deviation (Borenstein et al., 2011). A reduction in car usage was reported in each study as a negative value, and an increase in car usage as a positive value. Thus, a negative summary effect value means that the intervention effectively reduced car usage. The standardised studies outcomes, along with overall outcome, were summarized in forest plot, a graph commonly used to present results of *meta*-analysis. For each study, the plot represents standardised effect size (represented by point) and 95 % confidence interval (represented usually by horizontal line). The summary outcome is usually plotted as a diamond with vertical diagonal representing mean effect size and the lateral points indicating confidence interval boundaries. The mean effect size is considered as small if lower than $|0.2|$, large if exceeds $|0.8|$, and moderate between these thresholds, a classification adopted from Cohen (1988).

Because the studies, their settings and context, strongly differ between each other, the random-effects model was applied. The model accounts for these differences by assuming that (in opposite to fixed-effects model) studies do not share the common effect size, but there is a distribution of true effect sizes, coming from random (between-study) variance (Borenstein et al., 2010). Summary effect size is calculated as a weighted mean, where weight assigned to each study is calculated as an inverse of study's total variance, which is a sum of within-study variance and between-study variances (for further references we refer the reader to (Borenstein et al., 2010)). To further assess the variability, the heterogeneity of studies was assessed using Q-test and I^2 statistics. Q-test is a statistical test commonly used in *meta*-analyses to check for heterogeneity among included studies, I^2 index allows to quantify the extent of heterogeneity; given in percents, the I^2 index represents the share of between-study variance in total variation (Huedo-Medina et al., 2006). We additionally calculated prediction interval to assess for effect sizes variation, as suggested by Borenstein et al. (2017). Given in the same scale as original outcome, a 95 % prediction interval informs about the expected range of true effect sizes for 95 % of comparable future studies. For effect size representing mean difference, prediction interval can be simply computed as mean effect size ± doubled standard deviation of true effect sizes (Borenstein et al., 2017).

To further assess and explain studies heterogeneity, and identify factors affecting interventions' effectiveness, we performed moderation analysis. The method allows to judge whether the effect size variation among studies is related to, e.g., intervention type, study design or the evaluated outcome (so called 'moderators'), i.e. whether these factors explain effect size differences. In our study we calculated the mean effect sizes separately in subgroups representing the respective moderator level and assessed, using the Q-test statistic, whether there are statistically significant between-group differences (Huedo-Medina et al., 2006).

The common issue in *meta*-analyses is the risk of publication bias, which may result from the selective publication of studies with statistically significant findings (Müller et al., 2013). The occurrence of the bias may lead to nonrepresentative share of studies depending on effect direction or significance, and, in result, biased conclusions coming from *meta*-analysis. For this reason, it should be carefully inspected (Shi et al., 2019). To account for this issue, we used two methods: the funnel plot visual inspection and the Egger test. A funnel plot is a scatter plot representing study's standardised effect size (x-axis) against its precision (y-axis), commonly measured by standard error of estimation. Because usually higher precision is achieved in larger studies, the studies on the bottom of the plot (at smaller precision) should be scattered more widely, narrowing symmetrically (i.e., getting closer to mean effect) towards the top of plot. If, visually assessed, asymmetry in funnel plot occurs, it indicates that there is a likelihood of publication bias. Egger test is a statistical test based on linear regression (standardised effect size vs. precision) that allows for quantitative assessment of funnel plot asymmetry. In case of no publication bias, the regression intercept should be zero, therefore, the statistically significant test result indicates the existence of the asymmetry meaning the likelihood of publication bias (Borenstein et al., 2011).

In case of more complex studies, incorporating multiple intervention groups, time points or outcomes, we followed the guidelines by Borenstein et al. (2011). The following assumptions were adopted for *meta*-analysing the studies: (1) if multiple outcomes representing the same effect were reported in the study, a combined effect size was calculated assuming their dependence; similarly, if outcomes based on self-reported information and objective measurements were reported in one study, a combined effect size was calculated; in such case the combined effect size is calculated as arithmetic average of the effect sizes; (2) if the studies included more than one intervention group, or results were reported separately for population segments or trip motivations, these were treated as independent samples in the analysis and the combined study-level effect size was calculated as weighted average of the effect sizes; (3) if effect sizes were reported for multiple post-intervention timepoints (follow-up periods), only the earliest one was considered, which is in line with the *meta*-analysis guidelines (Borenstein et al., 2011). Wherever pre-post correlation was required and not reported in the study, the approach suggested by Higgins and Green (2011) was followed, i.e. the correlation coefficient was adopted from similar studies (see (Fujii et al., 2009; Semenescu et al., 2020)).

In our *meta*-analysis we computed all statistics using the Comprehensive Meta-Analysis software, version 3.0 (Borenstein et al., 2013).

3. Results

Fig. 1 presents a flow diagram illustrating the process of articles search and review. Out of the initial 9,126 articles identified in the two stages, 5,079 were duplicates, 3,888 were excluded based on title or abstract, and 159 underwent the full-text review. Ultimately, this selection process provided 34 eligible studies from 30 publications for further processing. The exclusion criteria encompassed various factors, including incorrect article type, inappropriate study design, incongruent outcome, inadequate data, and absence of intervention.

According to a classification introduced by Landis and Koch (1977), a moderate agreement between the researchers was achieved with a Cohen's Kappa of 0.55 ÷ 0.83. The quality of the included studies was scored between 59.1 and 95.8 %. The most common criteria that reduced the rating were non-existent or insufficient description of the research question or objective(s), ambiguous outcome, and, in relevant cases, lack or insufficient definition of the exposure measure(s), analytic methods, or estimation of variances. Overall, $k = 34$ studies were evaluated, of which $k = 3$ were below the 65 % threshold and were excluded from the analyses. The systematic review included a total of 31 studies from 27 articles, and the *meta*-analysis included 21 studies from 17 articles.

3.1. Systematic review

The studies (Table 3) enrolled 188,870 participants, and the sample size between studies ranged between 80 and 153,562. All studies included interventions targeted at adult populations. Overall, 15 studies (48 %) were targeted at general population, whereas seven (23 %) enrolled employees, four (13 %) academic society, and five (16 %) users of specific transport modes (car, public transport, pedestrians). Across the original studies, there was a slight predominance in favour of quasi-experimental studies ($k = 18$, 58 %) over experimental ones ($k = 13$, 42 %). Across the first group nine studies applied pre-post study designs, two were of correlational, longitudinal designs and across the latter group only six were randomised controlled trials. Regarding the assessment of transport behaviours, all studies ($k = 31$, 100 %) relied on the self-report method (questionnaires or travel diary), whereas four (13 %) studies also used objective methods (accelerometer, GPS, counts, observation). The evaluated studies covered different classes of interventions: eight studies (26 %) focused on soft interventions based on mainly communicative tools, 15 (48 %) studies referred to hard interventions using physical, economic, or legal means, and eight studies (26 %) represented a mixed approach. The studies were conducted in 15 different countries across four continents: Europe ($k = 20$), North America ($k = 3$), Asia ($k = 6$), Australia ($k = 2$).

Of the 31 studies analysed, 23 (74 %) confirmed that the intervention was effective in reducing car usage. However, in most of them, the effect was either statistically non-significant ($k = 9$) or was not tested for significance ($k = 7$). In seven studies, a statistically significant decrease in car usage was found. These interventions include three hard interventions (Charles-Edwards et al., 2014; Knott et al., 2019), one mixed intervention (Andersson and Nässén, 2016) and three soft interventions (Bamberg and Rees, 2017; Hsieh et al., 2017; Ma et al., 2017). The interventions producing a statistically significant decrease in car usage were as follow: restrictive actions in the field of parking policy (Knott et al., 2019), personalised transport planning campaigns (Bamberg and Rees, 2017; Hsieh et al., 2017; Ma et al., 2017), congestion charge scheme (Andersson and Nässén, 2016), and development of pedestrian infrastructure (Charles-Edwards et al., 2014).

Two studies (Hsieh et al., 2017; Sun et al., 2020) reported an increase in car usage, though the effect was not statistically significant. The main results of the study by Hsieh et al. (2017) indicate that implementation of 'action plans' alone non-significantly increased car usage, while a combined 'action-plus-coping plans' were effective in car usage reduction. Sun et al. (2020) showed that the introduction of a new metro line prompted bus users to switch modes and attracted pedestrians and bikers while the amount of car and e-bike usage remained essentially unchanged. The study by Piras et al. (2018), in turn, suggested that a new railway line supported by a

Table 4
Effectiveness of intervention in predefined classes.

Effect		Intervention Class					
		hard		soft		mixed	
Code	Effect direction & significance	nr	[%]	nr	[%]	nr	[%]
–	significant-decrease	3		3		1	
–	non-significant-decrease	3	71%	1	75%	3	83%
0–	decrease-untested	6		2		1	
0+	increase-untested	4	24%	0	0%	1	17%
+	non-significant-increase	1		1		0	
++	significant-increase	0	6%	0	13%	0	0%
X	inconclusive	0		0		0	
No	no effect	0	0%	1	13%	0	0%

travel behaviour change program may reduce the number of car journeys. However, generalising conclusions is difficult in this case due to a lack of information on the significance of the results. The other three studies (Termida et al., 2016; Hong et al., 2016; Spears et al., 2016) on the effectiveness of new railway lines produced inconclusive results. Thus, the question on the impact of rail investments on car use remains unresolved.

When it comes to the studies that analysed the impact of improving the environment for pedestrians and cyclists, all the studies reported decreases in car usage. In the case of one study (Charles-Edwards et al., 2014), the effect was statistically significant; three studies (Aldred et al., 2019; Heinen et al., 2015; Heinen and Ogilvie, 2016) reported a shift from cars to active transport, but the effect was not significant; one study (Song et al., 2017) reported a decrease in car usage, but no analytic methods were used to test the effect for significance. Moreover, Song et al. (2017) suggested that infrastructure for pedestrians and bikers alone may be insufficient to enhance active travel, i.e. passive exposure to the intervention was not directly related to a shift between transport modes used.

The results of five articles were coded as inconclusive (Termida et al., 2016; Foley et al., 2017; Hong et al., 2016; Molina-García et al., 2015; Spears et al., 2016). Only in one study (Audrey et al., 2019), there was no effect reported, car usage remained unchanged.

The effectiveness results obtained were also examined through the lens of intervention classification. Each of the intervention class we employed demonstrated a substantial level of positive effect across merged significance classes. Specifically, hard interventions exhibited a rate of 71 % decrease in car usage, soft interventions demonstrated 75 %, and mixed interventions showcased an even higher rate of 83 %. Notably, inconclusive results were absent in the case of soft interventions, while they were observed in 24 % of hard interventions and 17 % of mixed interventions. Additionally, certain interventions were evaluated as increasing a car usage across merged significance classes accounting for 6 % of hard interventions and 13 % of soft interventions (see Table 4).

3.2. Meta-Analysis

The *meta*-analysed studies reported different outcomes: travel time (k = 3), frequency of trips (k = 2), trip proportion (k = 12) or a combination of two or more outcomes representing the same effect size (k = 4). The studies investigated either the hard (k = 10), soft (k = 7) or mixed interventions (k = 4) and used either physical (k = 7), communicative (k = 5), or economic (k = 1) tools, or a combination of different tools in one intervention (k = 8). Considering the type of intervention, the studies evaluated either population-level interventions (k = 13; the interventions included new public transport infrastructure, new public transport services, new walking or cycling infrastructure, or the introduction of car restrictions) or individual-level interventions (k = 8; the interventions included new walking or cycling services, social and behavioural strategies). Regarding study design, the studies were based on natural experiments (k = 13) and quasi-experimental studies (k = 8). Across the latter group, six of eight studies were based on the non-controlled design and based only on pre- and post-comparisons. Most of the studies used self-reported instruments only – questionnaires and/or travel diaries (k = 17). Only four studies used objective data collection methods (traffic counts, accelerometers) in

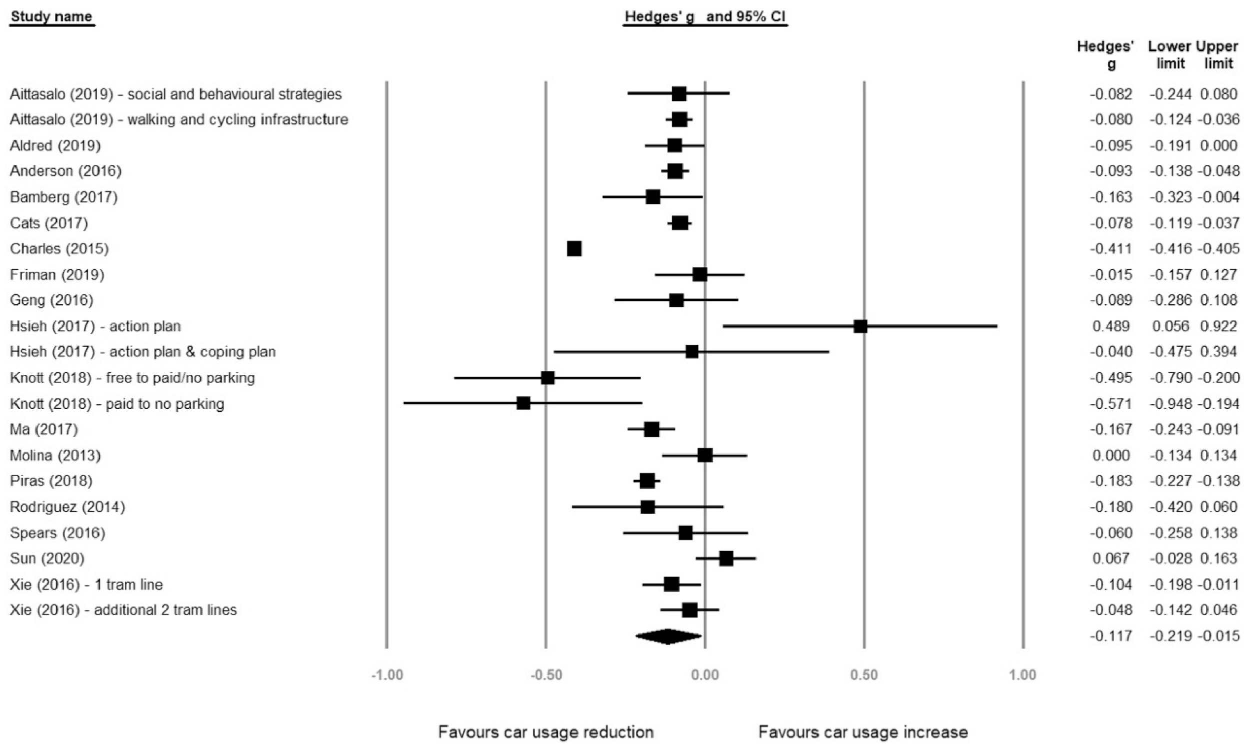

Fig. 2. Forest plot of effect size of transport-related interventions on car usage reduction.

addition to self-reported instruments. The follow-up period lasted from 1 to 108 months (13.6 months on average).

Across the 21 original studies, 11 (52 %) indicated a significant car usage reduction in result of the intervention, and only in one study (5 %) indicated a significant increase in car usage (see the forest plot in Fig. 2). The mean effect size was found to be significant with Hedges' g below.20 (g = -.117, 95 % CI [-.219, −.015], Z = -2.26, p = .024), suggesting that implementation of interventions enhancing to use active transport modes or public transport leads to car usage reduction, but the effect is small (Cohen, 1988). The mean effect significantly varies across the studies (Q(20) = 1082.03, p < .01), which justifies the use of random-effects model. And, almost all of the variability in effect estimates (I^2 = .98) may be explained by the heterogeneity of the studies (Higgins and Thompson, 2002). The estimated 95 % prediction interval was −.589 to.355, which allows us to generalise that the true effect size in 95 % of comparable future studies will fall in this interval.

Table 5 shows the results of the moderation analysis. The results yielded no significant differences between the mean effect sizes obtained for any moderator subgroups – the between group difference measured by Q statistic was not statistically significant in any group of moderators.

How the results change if the quasi-experimental studies with the weakest non-controlled design are excluded from the analysis was also tested. The summary effect is lower than in the case of including the studies but still significant with Hedges' g = -.097, 95 % CI [-.15, −.04] and a lower heterogeneity of the studies is observed (I^2 = 62 %).

To assess for publication bias, we built a funnel plot and conducted Egger's test. The plot was visually checked for asymmetry. While the distribution of studies on the plot (Fig. 3) seems to be asymmetrical to a low extent, the Egger's test results (intercept: 6.01, p < .001) implicate a publication bias. Assessment of the magnitude of the bias is prevented by the observed strong heterogeneity of the studies (Shi et al., 2019).

4. Discussion

The purpose of this study was to investigate the effectiveness of interventions designed to induce car use reduction and to explore the key factors that may influence their effectiveness. We adopted a comprehensive, integrative approach that incorporates the available evidence on a wide variety of transport interventions aimed at reducing car usage in favour of walking, cycling or public transport and assessed them qualitatively and quantitatively. The results from the systematic review are complemented with findings

Table 5
Moderation analysis of studied interventions.

Variable	k	Hedges' g (95 % CI)	Z	p	Q (p)	I^2
Mean effect size	21	−.117 (−.219, −.015)	−2.258	.024	1082.03 (.000)	98.2
Intervention class	Between-group difference: Q(2) = 0.678, p = 0.713					
Hard	10	−.166 (−.322, −.010)	−2.089	.037	688.71 (.000)	98.7
Mixed	4	−.093 (−.172, −.014)	−2.296	.022	14.03 (.003)	78.6
Soft	7	−.111 (−.201, −.021)	−2.428	.015	9.72 (.137)	38.3
Intervention class	Between-group difference: Q(2) = 1.269, p = .736					
Physical	7	−.157 (−.357,.042)	−1.550	.121	245.83 (.000)	97.6
Economic	1	−.078 (−.119, −.037)	−3.745	.000	n.a.	n.a.
Communicative	5	−.077 (−.229,.075)	−.988	.015	9.72 (.137)	38.3
Combined	8	−.110 (−.166, −.053)	−3.820	.000	23.83 (.001)	70.63
Intervention type	Between-group difference: Q(5) = 4.583, p = .469					
Car restrictions	3	−.353 (−.704, −.003)	−1.975	.048	9.166 (.057)	56.4
PT infrastructure	6	−.128 (−.303,.047)	−1.429	.153	300.29 (.000)	98.3
PT services	2	−.073 (−.112, −.034)	−3.656	.000	.70 (.403)	.0
Social strategies	7	−.111 (−.201, −.021)	−2.428	.015	9.73 (.137)	38.3
W/C infrastructure	2	−.083 (−.123, −.043)	−4.062	.000	.08 (.000)	.0
W/C services	1	.000 (−.134,.134)	.000	1	n.a.*	n.a.*
Level of intervention	Between-group difference: Q(1) = .590, p = .442					
Individual	8	−.094 (−.177, −.011)	−2.227	.026	12.14 (.096)	42.4
Population	13	−.147 (−.274, −.020)	−2.269	.023	972.52 (.000)	98.8
Outcome	Between-group difference: Q(3) = 3.339, p = .342					
Multiple	4	−.045 (−.266,.176)	−.400	.689	8.87 (.031)	66.2
Proportion of trips	12	−.172 (−.301, −.043)	−2.622	.009	859.48 (.000)	98.7
Time	3	−.030 (−.151,.090)	−.494	.622	6.06 (.048)	67.0
Trip frequency	2	−.030 (−.146,.085)	−.516	.606	.13 (.717)	.0
Data collection	Between-group difference: Q(1) = .690, p = .406					
Self-reported only	17	−.088 (−.137, −.040)	−3.597	.000	52.27 (.000)	69.4
Additional counts	4	−.189 (−.408,.030)	−1.690	.091	265.04 (.000)	98.9
Study design	Between-group difference: Q(1) = .225, p = .635					
Experiment	13	−.091 (−.155, −.028)	−2.811	.005	32.37 (.001)	62.9
Quasi-experiment	8	−.130 (−.280,.019)	−1.707	.088	627.62 (.000)	98.9
only post-control	1	−.060 (−.258,.138)	−.594	.552	n.a.*	n.a.*
pre-/post-control	1	−.167 (−.243, −.091)	−4.307	.000	n.a.*	n.a.*
non-controlled	6	−.134 (−.309,.040)	−1.508	.132	581.80 (.000)	99.1
Mean effect size excluding TPP studies	15	−.103 (−.172, −.034)	−2.913	.004	37.08 (.000)	64.9

* n.a. = not applicable, W/C = walking and/or cycling, PT = public transport.

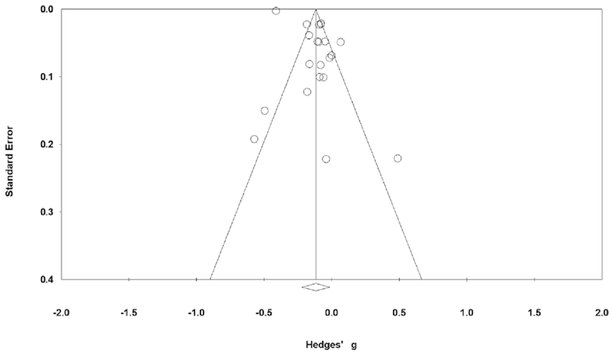

Fig. 3. Funnel plot of the *meta*-analysis.

from the *meta*-analysis. In addition, moderator analysis was conducted. This paper updates the review by Scheepers et al. (2014) with studies published in the years 2014–2020.

4.1. Discussion of findings

The results of systematic review largely confirm the findings of Scheepers et al. (2014). A car usage reduction was confirmed by 74 % of studies, while only one study (Sun et al., 2020) found an opposite effect; and five studies were inconclusive. Scheepers et al. (2014) categorized the results by grouping interventions into four categories: work-place-based interventions, architectural and urbanistic adjustments, population-wide interventions, and bicycle-renting systems.

In our own study, we compared the analysed interventions across eight predefined categories, which illuminate the relationship between interventions and car reduction. Additionally, we evaluated the quality of the studies and the significance of their outcomes. As the applied approach did not unveil distinct patterns indicating the dependence of intervention type on their effectiveness, we introduced an additional method that entails comparing the effectiveness of intervention classes: hard, soft, and mixed interventions. This supplementary analysis addresses concerns about generalizability and offers an extra perspective on the effectiveness of various intervention types.

Comparing the effectiveness of individual intervention classes is challenging due to uneven numerical representation of classes and the variation in targets, tools, measures, and circumstances. Soft interventions concentrate on changing attitudes and behaviours through psychological and social methods, whereas hard interventions involve physical changes to infrastructure and policy regulations. Often, a combination of both soft and hard interventions is necessary to effectively encourage car reduction in favour of more sustainable and active modes of transportation.

With the *meta*-analysis results, we can confirm the findings from the systematic review. We found that the interventions significantly affected a reduction in car usage but with a total effect of a small magnitude (Hedges' g = -.117). Regarding intervention class, our results suggest that both hard, mixed, and soft transport interventions significantly reduce car usage, although the difference between particular intervention classes (soft, hard, mixed) was not found to be statistically significant. The summary effect for soft transport interventions is comparable to the effect obtained by other researchers (Fujii et al., 2009; Möser and Bamberg, 2008; Semenescu et al., 2020). The convergence of the results is surprising given the different assumptions and eligibility criteria adopted in these *meta*-analyses. At the same time, even if the effect is small, the effectiveness of soft transport interventions is repeatedly confirmed. We argue that even small effect sizes are relevant, as the reach and exposure are large and at the population level, this really matters.

Our results suggest that the effect of population-level interventions is higher than the effect of individual-level interventions (however, the difference between the two levels is not significant at $p < .05$). Interestingly, the literature presents contrasting opinions. For instance, according to Stappers et al. (2018), the effectiveness of small, individual-level interventions is usually higher than population-level interventions. Mayne et al. (2015) evaluating the efficacy of policy on obesity-related outcomes report that most active transportation interventions targeted at individuals had positive affect, while in the case of infrastructural improvements targeted at the general population, a positive effect was obtained in approximately half of the interventions. However, comparing interventions of different levels is challenging. First, in the case of individual-level interventions, the participants are directly affected by the intervention (e.g., they are given free public transport tickets), and the intervention is designed to affect an individual's behaviour. If the participants are not randomly selected, there is a high risk that they may be more prone to changing their transport behaviour due to their existing attitudes and beliefs. In the case of population-level interventions, the participants are only exposed to the intervention and not directly involved (e.g., they live near the new tram line), and for this reason, the treatment group is probably very heterogeneous, and thus, the results of the intervention may be visible to a lesser extent than in the case of an individual-level approach, even if the intervention is in fact more effective. However, even though it is beyond the scope of our paper, it needs to be noted here that both individual-level (influencing beliefs and attitudes) and population-level (e.g., environmental) factors are important in the context of changing transport behaviours to more sustainable (see, e.g., Bauman et al. (2012)) and are mutually related (e.g., a cycling promotion campaign will not be effective without access to safe and efficient cycling infrastructure). No matter whether and how the interventions were grouped (e.g., by intervention type, level or how the study was designed), the effect strongly varies across the studies and high heterogeneity exists. None of the hypothesised moderator effects was confirmed. For example, the effectiveness of hard public transport infrastructure investment was not significantly different from the effectiveness of a promotion campaign. However, there is a risk that the high heterogeneity that we observe within the studies makes it impossible to find a significant difference between the moderator subgroups, even if a difference does exist, i.e., the high heterogeneity decreases the precision of the pooled effect so that the confidence intervals are larger and more likely to overlap (Hedges and Pigott, 2004). And the lack of observation between the heterogeneity of the subgroups hinders making inferences from moderator analysis. However, if we only look at the magnitude of the effect sizes, hard interventions with a larger mean effect size seem to be more effective than mixed or soft interventions. Among the different types of interventions, car restrictions produce the most substantial, significant effect compared to other intervention types with a moderate magnitude of summary effect, while for the other types of interventions, the effect was either small or absent. This is an interesting result and may suggest that interventions targeted directly at car users may be more effective. Nevertheless, making such inferences requires further scientific support.

4.2. Limitations and challenges related to available evidence

In their article, Scheepers et al. (2014) highlighted a prevailing issue concerning the quality of studies. Our own experience confirms that transportation studies tend to exhibit low methodological quality in general. In the course of our research, even after the full-text screening phase, 129 papers had to be excluded (see Fig. 1) due to reasons that ideally should have been discernible during the abstract review stage. An in-depth analysis of the reasons underlying the recurrent challenges in upholding high methodological quality in transport research could indeed serve as a separate topic for an article and literature review. We argue that there are several factors specific to transportation research that may play a key role. These factors include complexity of transport interventions and policies, complex context of real-world, ethical and logistic constraints, data availability and quality, longitudinal nature of transport interventions and policies, variability in human behaviour, interdisciplinary nature, lack of transport' studies dedicated standards, funds and resources limitations. Complexity of interventions makes it challenging to design rigorous experimental or controlled studies that isolate the effects of a single intervention. Additionally, the control in real-world settings over variables is limited. This can introduce confounding factors that are difficult to account for in the study design. Human behaviour is a key element in transportation studies, and it can be highly variable and influenced by a range of factors, making it difficult to control for all potential confounders. Implementing certain interventions (like changing road infrastructure) on a large scale for experimental purposes is not feasible. Transportation studies often rely on data from various sources, such as surveys, traffic monitoring systems, and observational data. The quality, accuracy, and consistency of the data sources can impact the validity of study findings. Evaluating the long-term impacts of transportation interventions requires extended study periods and follow-up, which might be resource-intensive and challenging to sustain. Many interventions also require significant funding.

The quality assessment conducted within this research highlighted low quality of multiple studies. Based on the adopted quality assessment criteria, we excluded studies with the weakest quality and studies reporting insufficient information. However, we decided not to reject non-controlled, quasi-experimental studies. Since this design is widely used by transportation researchers (see, e.g., Möser & Bamberg (2008)), such rejection would result in a considerable reduction in the number of analysed studies. One needs to be aware that when the investigation is not controlled, the intervention effect cannot be isolated from the influence of unknown extraneous factors, generating threats to its internal validity (Fujii et al., 2009). To account for the possible effect of external factors on the results in the case of non-controlled studies, we evaluated the summary effect excluding their results. This resulted in a slightly lower but statistically significant summary effect indicating a reduction in car usage as a result of intervention.

Another issue related to the studies is how the data were collected. All of the studies used self-reported instruments for data collection, while objective assessment measures were also used in only four studies. On the one hand, the validity of self-reported data may be questionable due to the possible response bias (Rosenman et al., 2011), but on the other hand, subjective data collection measures are often supported by dedicated applications or devices (e.g. accelerometers). The awareness of being observed may lead to biased responses and thus to distort the effect of the intervention.

4.3. Strength and limitations of our research

Since the publication of Scheepers et al. (2014), there has been a lot of new evidence on effectiveness of transport interventions. In our research we updated their review but also incorporated new methods and integrative, qualitative plus quantitative, approach. First, we applied a systematic review to the new evidence, using new method to classify intervention effects that was developed by co-authors of this manuscript. Second, by incorporating *meta*-analysis and quantitative approach, we were able to get more insight into the effectiveness of transport-related interventions, i.e., we could assess and compare studies numerical outcomes, not possible to obtain using solely a systematic review. Because many studies do not report enough information or the outcomes are poorly described to be included in *meta*-analysis, we believe that the integrative approach that we employed allowed us to answer the research question posed in the most comprehensive way.

Since every review is at risk of bias from multiple sources (Drucker et al., 2016), in our research we tried to avoid or address the risks adopting strict assumptions in particular stages of the research. Based on the strict eligibility criteria adopted in PROSPERO and then in our review, with a high degree of certainty we can say that we avoided citation bias, multiple publication bias, and language bias. With the *meta*-analysis assumptions, outcome reporting bias was also addressed. Since we only searched two databases, the possibility that we may have missed some important studies is highly probable. To mitigate this risk, we undertook dual protective actions. Firstly, we choose WoS and Pubmed as databases covering topics connected with transport-related interventions and their impact on environment and society, and their mutual relation. Moreover, we searched through the references of related systematic reviews and *meta*-analyses. In accordance with the adopted search strategy, the research did not account for grey literature and unpublished works, and therefore publication bias could have been an issue. The risk of publication bias was also recognised in the results of the conducted *meta*-analysis, which may affect the generalizability of the findings. However, its magnitude cannot be assessed due to the large heterogeneity of the included studies. On the other hand, Scheepers et al. (2014), based on earlier works, argued that the results show that no matter the type of study analysed, the effects are obtained in the same direction (i.e., a shift from cars to active transport).

5. Conclusion

Altogether, our findings point out that the current state of evidence allows us to confirm previous results that transport interventions aimed at reducing in car usage in favour of other, more sustainable, transport modes (Möser and Bamberg, 2008; Ogilvie et al., 2007; Semenescu et al., 2020) have the potential to change transport patterns to be more sustainable and thus benefit health through increased physical activity levels. But, at the same time, our research shows that it is not only the intervention characteristics and setting, but also the methodology and how the outcomes are measured that influence the estimated effect.

Nevertheless, further research is necessary to improve our understanding of the potential of transport interventions. Because many existing studies are not properly validated and/or are the subject of biases that may have a non-negligible impact on their reliability and validity, more in-depth, high-quality research is needed. Therefore, further evidence is required to be able to clearly indicate the interventions that are the most effective at reducing car usage and the most helpful for achieving specific transport policy objectives.

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CRediT authorship contribution statement

Romanika Okraszewska: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Data curation, Conceptualization. **Aleksandra Romanowska:** Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Formal analysis, Conceptualization. **Dana Clarissa Laetsch:** Data curation. **Anna Gobis:** Data curation. **Lucia A. Reisch:** Data curation. **Carlijn B.M. Kamphuis:** . **Jeroen Lakerveld:** Supervision. **Piotr Krajewski:** Data curation. **Anna Banik:** Data curation. **Nicolette R. den Braver:** Writing – review & editing, Data curation. **Sarah Forberger:** Data curation. **Hermann Brenner:** Supervision. **Joanna Żukowska:** Funding acquisition.

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.

Data availability

We have shared the link to our data at the Attach File step.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2024.104217.

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