Why public transport interventions work or not? A meta-analysis based on the behaviour change wheel model

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Abstract

Public transportation promotion policies are vital for reducing carbon emissions, improving public health, and fostering sustainable urban development. However, assessing their effectiveness is challenging due to inconsistent research findings and methodologies stemming from varied classification criteria. Additionally, existing meta-analyses often fail to explain why certain policies are more effective, primarily due to a lack of theoretical frameworks underlying these policies. This uncertainty can lead to the misallocation of financial resources, diminished public trust in policy initiatives, reduced overall policy impact, and the persistence of inefficient urban growth patterns. Therefore, there is an urgent need to develop a clear and unified classification framework for evaluating public transport policies, which would standardize future research and meta-analyses, thereby promoting deeper insights and advancements in this field. To address the research gap, our study pioneers the use of the Behaviour Change Wheel (BCW) to analyze public transport policies. Originally developed for public health and environmental protection, the BCW enhances policy design by systematically integrating factors that drive individual behavior change. This framework breaks down interventions into three layers: policy, intervention strategies, and the Capability-Opportunity-Motivation-Behaviour (COM-B) model. Within the BCW, the intervention strategies layer encompasses targeted actions that directly influence behaviors, while the COM-B layer identifies and addresses the key factors—capability, opportunity, and motivation—that drive or impede these behaviors. Existing research has extensively evaluated the impact of public transportation promotion policies using the Behaviour Change Wheel (BCW) framework, which comprises three dimensions: policy, intervention strategies, and the Capability-Opportunity-Motivation-Behaviour (COM-B) model. The policy layer categorizes these policies into six types: **1) Guidance; 2) Environmental and social planning; 3) Service provision; 4) Fiscal; 5) Communication and marketing; 6) Regulations,** which are further broken down into specific strategies within the intervention layer and analyzed for their effects on individuals' capabilities, opportunities, and motivations in the COM-B layer. By conducting a meta-analysis across all three layers, this study aims to provide a deeper understanding of policy effectiveness, particularly in explaining why certain interventions are more effective than others.To deepen the analysis of policy effectiveness, this study conducted a meta-analysis within the BCW framework, synthesizing data from 24 high-quality studies across 16 countries with over 5.59 million data points. We systematically coded each policy into the BCW's three layers and performed stratified subgroup analyses to investigate the causal effects and mechanisms of six public transportation policy categories in promoting transit adoption. The key findings are as follows:

1. The overall meta analysis effect size of public transport policies is 0.5165. Within the policy layer, only guidance policies surpass this average; in the intervention strategies layer, incentivization, coercion & restrictions, modelling, and enablement demonstrate effect sizes above the average; within the COM-B layer, social opportunity and automatic motivation show effect sizes that exceed the mean.
2. Guidance policies are the most effective in promoting public transit adoption (n=12, d=0.881), including incentivization, education, and coercion & restriction interventions. They work well because they enhance reflective motivation (n=7, d=0.3418), automatic motivation (n=5, d=0.9034), and physical opportunities (n=5, d=0.4102), providing strong support for behavioral change.

3. Environmental and social planning policies are least effective policies (n=17, d=0.2093), including environmental restructuring interventions. These measures mainly improve physical opportunities through environmental changes (n=16, d=0.4102), but their limited impact on motivation makes it harder to sustain long-term behavior change.

4. Service provision policies provide substantial long-term benefits (n=21, long term d= 0.5285), which combine environmental restructuring and enablement interventions. These approaches strengthen automatic and reflective motivation (n=7, long term d= 0.6998; n=11, long term d=0.4148) and physical opportunities (n=17, long term d=0.438), leading to both immediate behavior changes and sustained public transit adoption.

Keyword: Public Transit; Behavior Change Wheel; Policy Intervention; Meta-Analysis;

1.Introduction

Public transportation interventions are essential for reducing carbon emissions, improving public health, and promoting sustainable urban development (C40 Cities, 2021; Doru, 2021; Bibri et al., 2020). In recent years, the number of studies on various public transportation interventions has been steadily increasing, signifing the academic community's growing focus on optimizing public transportation system interventions and promoting sustainable travel modes (Bamberg et al., 2021)2015(Pluntk, 2013;Gaerling et al., 2022;Zeiske et al., 2021). However, the effectiveness of these interventions presents significant challenges, as current research often lacks consistency in findings and methodologies due to the varying criteria used to classify interventions. Even existing meta-analyses fail to explain why a particular intervention is effective, due to a lack of theoretical basis for the mechanisms through which these interventions operate. Therefore, this underscores the need for a more systematic approach to evaluate these measures.

A significant challenge in current public transportation research is the absence of a clear theoretical framework and standardized classification for intervention measures. Existing studies attempt to categorize interventions into two categories (Bamberg et al., 2011; Graham-Rowe et al., 2011; Steg, 2003): "hard" interventions aim to change transportation behavior by modifying the physical environment (e.g., building bicycle lanes) and through legal or economic policies (e.g., congestion pricing); "soft" interventions aim at influencing people's beliefs, attitudes, values, and norms (Steg, 2003, p. 190) , which rely on persuasion, incentives, information provision, etc (Möser & Bamberg, 2008). However, these classifications often lack consistent theoretical support, leading to blurred boundaries between categories,. For example, policies like introducing car-sharing schemes, which including both infrastructure and promotion, may simultaneously fall into both "hard" and "soft" interventions (Berg et al., 2019). The current binary classification system complicates the systematic understanding and evaluation of intervention effects, hinders the development of a unified framework for assessing their effectiveness, and obstructs the integration and application of research findings in policy design. Consequently, there is an urgent need to establish a clear and unified classification framework for intervention measures. Such a framework would provide standardized guidance for future public transportation research and meta-analyses, fostering deeper insights and advancements in this field.

A significant body of existing studies has focused on classifying and evaluating the effectiveness of different public transportation policies. However, these studies often fall short in explaining why certain policies are more effective than others. While some research has attempted to employ methods such as SEM, ITS, and targeted learning to shed light on policy mechanisms(Niu & Zhang, 2023; Thorhauge et al., 2019; Y. Zhang et al., 2025), these approaches are often empirical and subjective, subject to contextual changes. Our perspective is that to understand the true mechanisms behind policy effectiveness, it is crucial to recognize that a single policy can be implemented through a variety of interventions, each driven by distinct subjective motivations, which can lead to varying outcomes depending on the contextual backdrop. Thus, to offer more applicable policy recommendations, we have to analyze both the objective interventions and the subjective motivations behind policies. Additionally, we find that many existing studies focus solely on the immediate effectiveness of policies, neglecting their long-term impacts, which may evolve or accumulate over time and require a temporal perspective for a more comprehensive analysis.

The Behaviour Change Wheel (BCW) offers a solution by providing a comprehensive framework that dissects interventions into three interconnected layers: policy, intervention strategies, and the Capability-Opportunity-Motivation-Behaviour (COM-B) model. Originally applied in public health and environmental protection, BCW helps in understanding and designing effective policies by systematically integrating the factors driving individual behavior change. By breaking down each intervention policy into specific strategies and examining how these strategies influence individuals' capabilities, opportunities, and motivations, BCW facilitates a deeper analysis of why certain interventions are effective. This framework thus bridges the gap in existing research, providing a more nuanced understanding of the mechanisms through which public transportation policies can achieve their intended outcomes.

In this study, we aim to apply the Behaviour Change Wheel (BCW) framework to clearly demonstrate how public transport interventions achieve their effects and conduct a meta-analysis within this framework. The primary goal of this approach is to address key questions left unanswered by existing research:

1. Do the seven types of policies—Regulation, Service Provision, Communication and Marketing, Environmental and Social Planning, Guidelines, Fiscal Measures, and Legislation—effectively influence individuals' travel behavior and encourage greater use of public transportation?
2. What explains the varying effectiveness of these policies, considering the different intervention strategies and the underlying motivations driving them?
3. How do the effects of these policies differ when implemented in the short term versus the long term, and what mechanisms account for these differences?

The paper is structured as follows. Section 2 presents a literature review, discussing existing studies on the effectiveness of public transport interventions and defining the Behaviour Change Wheel while exploring its application in understanding the mechanisms behind public transport interventions. Section 3 outlines the methodology used for our meta-analysis, along with details of our data cleaning, coding, and analysis processes. In Section 4, we present the results of the meta analysis, providing a detailed explanation of the specific processes involved in various public transport interventions. Finally, Section 5 discusses the implications of our findings for policymakers.

2.**Literature Review**

2.1 Effectiveness of Public Transport Interventions

Public transportation interventions play a crucial role in promoting sustainable urban development and improving residents' travel behaviors. In existing studies, public transportation interventions are generally categorized into several types:1 built environment improvement, including.......2)... (such as infrastructure upgrades and transportation network optimization), soft interventions (such as public education and behavior guidance), incentive measures (such as economic incentives and subsidies), and planning policies (such as land use policies and traffic control) (Bamberg et al., 2021)2015(Pluntk, 2013;Gaerling et al., 2022;Zeiske et al., 2021). These classification methods vary across studies but share a common goal of increasing public transportation usage and reducing reliance on private vehicles.

The effectiveness of different intervention types varies significantly in evaluation. For example, built environment improvements can substantially enhance the attractiveness of public transportation, but their effectiveness often depends on long-term implementation and substantial financial investment(Kärmeniemi et al., 2018). Soft interventions and incentive measures are more flexible, but their effectiveness may vary depending on the target audience (Semenescu et al., 2020). Additionally, the effectiveness of planning policies is often closely linked to the enforcement strength and consistency of local governments. Therefore, when evaluating the effectiveness of public transportation interventions, it is essential to carefully distinguish and analyze the effects of different types of interventions (Tirachini & Cats, 2020)2020.

In recent years, many studies have employed meta-analysis to synthesize and evaluate the effectiveness of various public transportation interventions on travel behavior. These analytical methods integrate results from multiple studies to provide quantitative support for the overall effectiveness of different interventions. However, while meta-analyses can reveal which interventions are generally more effective, they often fail to explore why these interventions work and struggle to uncover the underlying mechanisms. Particularly due to the diversity of research methods and data sources, meta-analysis results often lack consistency in explaining the effectiveness of interventions (Pluntk, 2013; Gaerling et al., 2022; Zeiske et al., 2021).

2.2 Application of the BCW in Understanding Public Transport Intervention

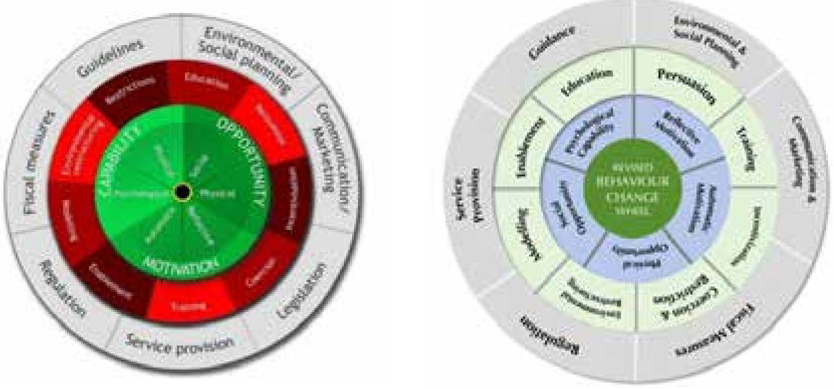
To better understand the mechanisms through which public transportation interventions achieve their effects, it is necessary to introduce a framework that can systematically analyze these measures. In this context, the Behaviour Change Wheel (BCW), a comprehensive framework for analyzing behavioral interventions, offers a new perspective for understanding and optimizing the effectiveness of public transportation interventions (Bamberg et al., 2021)2015.

The Behaviour Change Wheel (BCW) is a comprehensive behavioral intervention analysis framework proposed by Michie et al. in 2011, aimed at unifying and simplifying interdisciplinary theories of behavior change. The BCW model integrates 19 different behavior analysis frameworks and uses the Capability-Opportunity-Motivation-Behavior (COM-B) model to systematically identify and design effective behavioral interventions. The structure of BCW consists of three layers: the core layer, which is the COM-B model; the intervention strategy layer; and the policy layer (Michie et al., 2011)but it is not clear how well they serve this purpose. This paper evaluates these frameworks, and develops and evaluates a new framework aimed at overcoming their limitations. A systematic search of electronic databases and consultation with behaviour change experts were used to identify frameworks of behaviour change interventions. These were evaluated according to three criteria: comprehensiveness, coherence, and a clear link to an overarching model of behaviour. A new framework was developed to meet these criteria. The reliability with which it could be applied was examined in two domains of behaviour change: tobacco control and obesity. Nineteen frameworks were identified covering nine intervention functions and seven policy categories that could enable those interventions. None of the frameworks reviewed covered the full range of intervention functions or policies, and only a minority met the criteria of coherence or linkage to a model of behaviour. At the centre of a proposed new framework is a 'behaviour system' involving three essential conditions: capability, opportunity, and motivation (what we term the 'COM-B system'. Currently, the BCW has been widely applied in various fields, including public health (e.g., smoking cessation and obesity prevention), environmental protection (e.g., reducing plastic waste), and healthcare (Belanger-Gravel, 2019; Gould et al., 2017) Coupe et al., 2021). These application cases demonstrate that the BCW has broad applicability and practicality in understanding and designing behavioral interventions.

Although the BCW has been successfully applied in multiple fields, its application in public transportation interventions remains relatively limited. However, with the onset of the COVID-19 pandemic, the potential of the BCW in transportation behavior analysis has gradually emerged. For example, Wells et al. (2022) utilized the BCW model to analyze post-pandemic traveler behavior in selecting distant destinations, finding that improving transportation facilities and providing value-based social information effectively changed travel behavior . Similarly, Krusche et al. (2022) used the BCW to analyze the barriers and facilitators of public transportation use among UK residents to identify more effective communication strategies that could enhance public confidence in using public transportation.

2.3 BCW in Public intervention policy research

The BCW model, with its three-layer structure, provides a systematic analytical tool for understanding the specific pathways through which public transportation interventions exert their effects. First, the COM-B model helps identify how interventions influence individuals' capabilities, opportunities, and motivations, thereby guiding behavior change. Second, the intervention strategy layer offers nine strategies targeting different behavioral influences, which can be used to design more effective public transportation interventions. Finally, the policy layer provides the necessary policy support and environmental conditions for implementing these strategies (Michie et al., 2011)but it is not clear how well they serve this purpose. This paper evaluates these frameworks, and develops and evaluates a new framework aimed at overcoming their limitations. A systematic search of electronic databases and consultation with behaviour change experts were used to identify frameworks of behaviour change interventions. These were evaluated according to three criteria: comprehensiveness, coherence, and a clear link to an overarching model of behaviour. A new framework was developed to meet these criteria. The reliability with which it could be applied was examined in two domains of behaviour change: tobacco control and obesity. Nineteen frameworks were identified covering nine intervention functions and seven policy categories that could enable those interventions. None of the frameworks reviewed covered the full range of intervention functions or policies, and only a minority met the criteria of coherence or linkage to a model of behaviour. At the centre of a proposed new framework is a 'behaviour system' involving three essential conditions: capability, opportunity, and motivation (what we term the 'COM-B system'. By utilizing the BCW model, researchers and policymakers can gain deeper insights into and optimize the effectiveness of public transportation interventions. This enables the design of more targeted and effective strategies that increase public transportation usage and ultimately achieve sustainable urban transportation systems.



a. The original Behavior Change Wheel **b.** the modified Behavior Change Wheel in this study

Fig. 1 The framework of Behavior Change Wheel

3.Method

This study conducted a systematic review and meta-analysis following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (see Fig. 2), to evaluate the effectiveness of interventions designed to promote public transportation use. Strict inclusion, exclusion criteria, and a structured team-based review process ensured the reliability of study selection and the inclusion of high-quality evidence. The research procedure involved developing a search strategy, selecting relevant databases, defining screening criteria, reviewing and selecting studies, extracting and coding eligible data, and performing the meta-analysis.

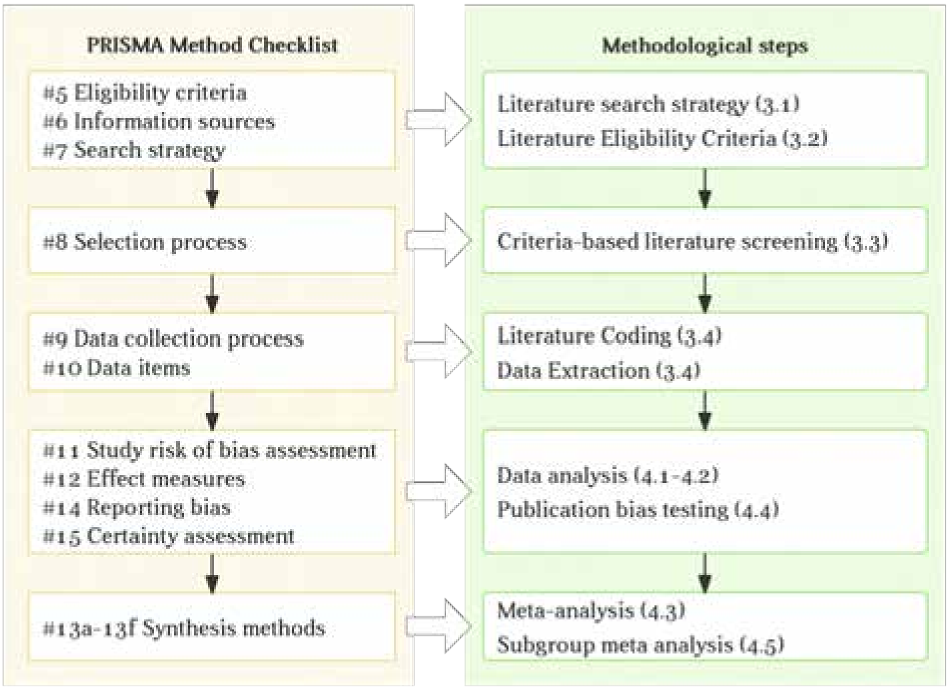


Fig. 2 PRIMA Checklist

3.1 Literature Search Method

The literature search primarily focuses on interventions aimed at promoting public transportation use. The search strategy incorporated key terms (see Supplemental Material Table S1) related to

- public transport modes (e.g., “public transport”, “bus”, “metro”, “rail”, “BRT”).
- intervention behaviors (e.g., “reduce”, “decrease”, “incentive”, “promote”).
- intervention types (e.g., “built environment”, “policy”, “program”).
- study designs (e.g., “natural experiment”, “quasi-experiment”).

The main databases are Scopus, Web of Science, and the Transportation Research Information Service (TRIS). Additionally, reference lists of included studies were manually screened (snowballing) to identify potentially relevant research missed by the database search.

3.2 Eligibility Criteria

Studies retrieved from the search were screened based on the following pre-defined inclusion and exclusion criteria:

(1) Publication Period: Studies published between 2000 and 2023.
(2) Language: Studies published in English.
(3) Publication Type: Peer-reviewed quantitative studies. Reviews, qualitative studies, and preprints were excluded.
(4) Research Field: Studies within behavioral science, transportation, mobility, urban planning, human geography, social sciences, urban studies, or geographic information systems. Studies from unrelated fields (e.g., biology, medicine, chemistry, physics) were excluded.

(5) Study Focus: Studies examining individual public transportation behavior (e.g., bus, BRT, subway, light rail).

(6) Study Design: Studies employing natural or quasi-experimental designs to assess interventions influencing the shift from non-use to regular use of public transport.

(7) Participants: Studies involving general population samples. Studies focusing on specific subgroups (e.g., children, women, students, elderly) were excluded.

(8) Intervention Type: Studies evaluating interventions explicitly designed to promote public transportation use. Studies where public transport use was an indirect outcome (e.g., impact of ride-sharing services like Uber) or where intervention effects were confounded by uncontrolled variables were excluded.

(9) Outcomes: Quantitative studies reporting outcomes related to actual public transport usage (e.g., mode share, frequency, trip duration), based on objective or self-reported data. Studies measuring only behavioral intentions or relying on hypothetical scenarios were excluded.

(10) Data Availability: Studies providing sufficient data to calculate effect sizes, including pre- and post-intervention means and standard deviations (SDs), or values convertible to SDs (e.g., 95% confidence intervals (CIs), standard errors (SEs), p-values, t-values), following Higgins et al. (2019). Studies were excluded if necessary data remained unobtainable after contacting authors for missing data.

3.3 Literature Screening Process

The initial search yielded 11,918 records. After removing 6,824 duplicates using Endnote, 5,094 records remained. Two researchers independently screened titles and abstracts based on criteria 3-5, resulting in 179 potentially relevant studies for full-text review.

These 179 full texts were then independently assessed by the same two researchers against all eligibility criteria (1-10). Disagreements were resolved through discussion with a third researcher. Ultimately, 24 studies (reporting 38 independent effect sizes) met all criteria and were included in the meta-analysis. Key reasons for exclusion at the full-text stage were: non-intervention studies (n=85), inappropriate statistical models (n=37), insufficient data for effect size calculation (n=28), and inaccessible full texts (n=5). The detailed screening process is illustrated in Fig. 3.

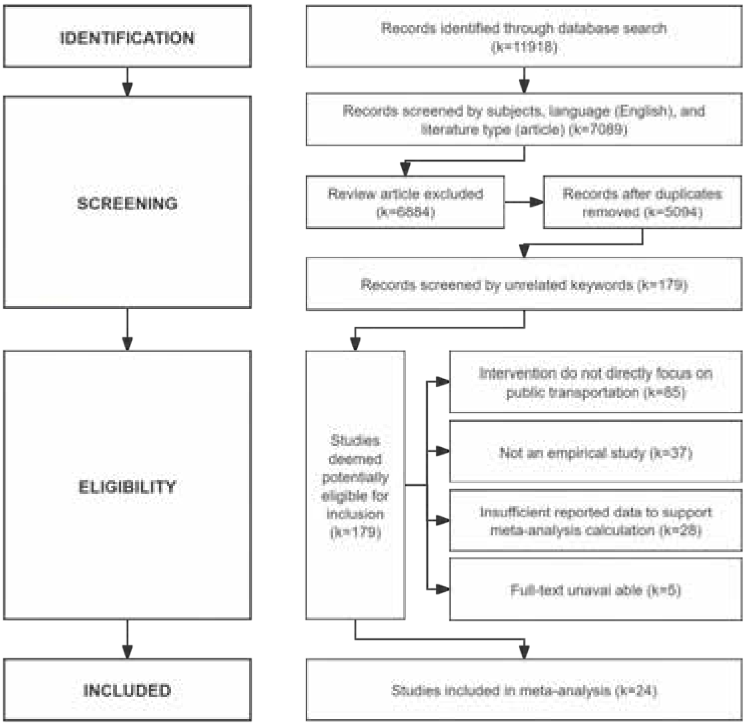


Fig. 3 Literature screening process and details

3.4 Data Extraction and Coding

We developed and employed a standardized form (details in Supplemental Material Table S2) to extract and code data from the 24 included studies (representing 38 effect sizes). Key information extracted included:

(1) Basic Study Information: Authors, publication year, source.

(2) Study Characteristics: Study Design, location (country/city), target transport mode, intervention duration (short-term: ≤180 days; long-term: >180 days), intervention start/end years, sample characteristics (unit of analysis, sample size, presence of self-selection).

(3) Intervention Description: Detailed account of the intervention implemented.

(4) Outcome Measures: Specific public transport behavior outcomes (e.g., ridership, frequency, share), measurement methods (objective/self-reported), data type (e.g., count, survey).

(5) Quantitative Results: Data required for effect size calculation (e.g., sample sizes, means, standard deviations, or convertible statistics like CIs, SEs, p-values, t-values).

(6) BCW Coding: Each intervention was classified according to the Behaviour Change Wheel (BCW) framework, including policy category, intervention function(s), and relevant COM-B components (Capability, Opportunity, Motivation). Detailed coding rules are in Supplemental Material Tables S3-S5.

Two researchers independently performed data extraction and coding. Discrepancies were resolved through discussion to ensure accuracy and consistency. Effect sizes (Cohen's d) and their standard errors (SE) were calculated or converted using the Campbell Collaboration's online tool (Wilson, 2023), following the methods recommended by Higgins (Higgins et al., 2019).

3.5 Meta-Analysis Strategy

This study performed a random-effects meta-analysis, assuming variability in true effect sizes across studies due to the diversity of interventions, contexts, and designs. The analysis strategy included:

(1) Handling Multiple Outcomes: If a study reported multiple related outcomes for one intervention, effect sizes were calculated for each and treated as independent comparisons in the analysis. Sensitivity analyses were conducted where potential dependencies existed.

(2) Handling Multiple Time Points: If a study reported outcomes at multiple post-intervention time points, effect sizes were calculated separately for the earliest (short-term) and latest (long-term) measurements.

(3) Sample Size Allocation: If intervention and control group sample sizes were not reported separately, the total sample size was divided equally between the groups.

(4) Heterogeneity Assessment: Cochran's Q test assessed statistical significance of heterogeneity, while the I^2 statistic quantified its magnitude (interpreting <25% as low, 25%-75% as moderate, and >75% as high heterogeneity)

(5) Moderator Effect Analysis: Subgroup analyses and meta-regression explored the influence of pre-specified moderators (e.g., BCW classifications, intervention duration, sample characteristics, location) on effect size variability.

(6) Publication Bias Assessment: We visually inspected funnel plot symmetry and used Egger's regression test to quantitatively assess potential publication bias.

All meta-analyses were conducted using the 'metafor' package in R software.

4.Results

4.1 Search Result

The literature search initially yielded 11,918 records across the selected databases (Fig. 3). After removing duplicates, 5,094 records remained for title and abstract screening, from which 179 studies were selected for full-text review. Following the application of all eligibility criteria and excluding five articles where the full text could not be accessed, 24 studies were deemed relevant. These 24 studies reported a total of 38 independent effect sizes, which formed the basis for this meta-analysis.

4.2 Study Characteristics

Key characteristics were extracted from the 38 included effect sizes (derived from the 24 studies), as detailed in Supplemental Material Table S6. Publication years ranged from 2002 to 2023, with a majority (60.5%) published between 2020 and 2023. Geographically, studies originated primarily from the United States (n=15 effect sizes) and China (n=5), with others from the Netherlands (n=5), Singapore (n=4), Italy (n=2), and Japan (n=2). Interventions targeted buses (n=18), Bus Rapid Transit (BRT) (n=6), subways (n=5), and light rail (n=9).

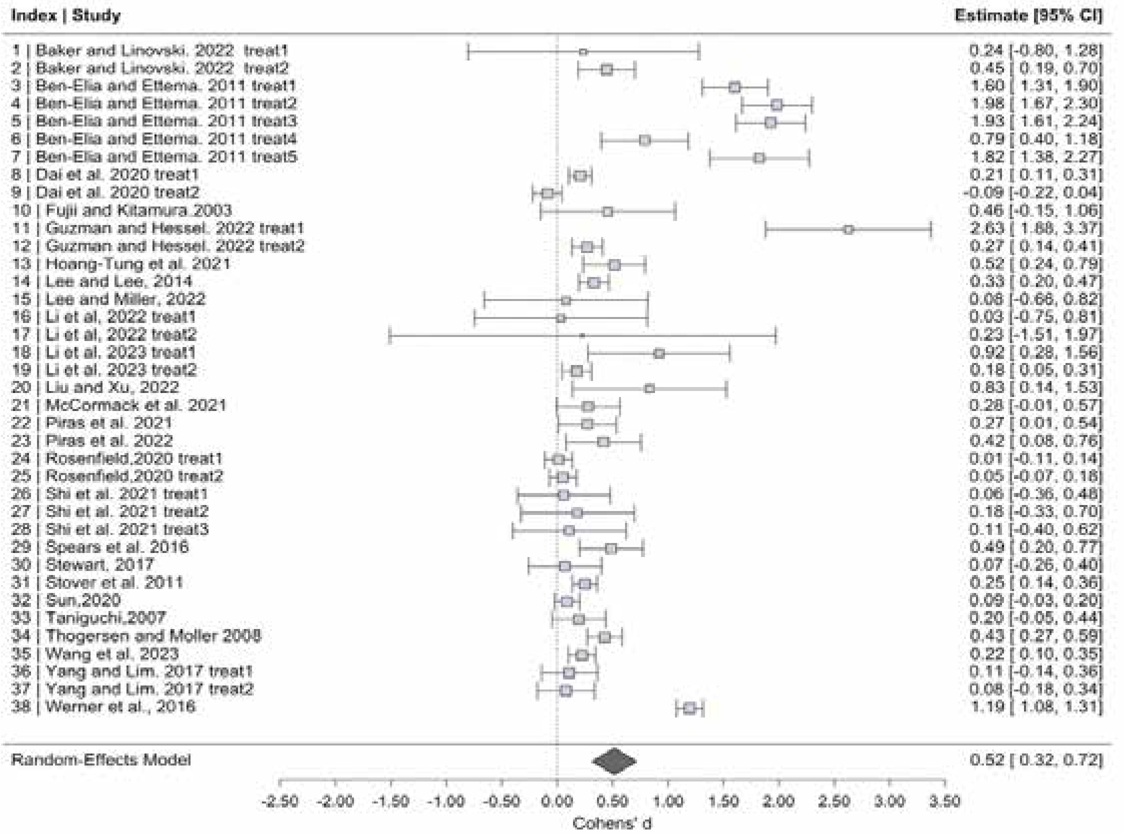
All included studies utilized experimental or quasi-experimental designs. Data sources varied, including travel big data (n=11), surveys (n=20), and statistical yearbooks (n=7).

Most interventions were classified as long-term, lasting over 180 days (57.9%), although intervention durations varied significantly, ranging from a single day to 15 years. The unit of analysis was typically the individual (n=22), but some studies analyzed effects at the level of roads/stations (n=11) or cities (n=5). Sample sizes were predominantly medium (n=20) or large (n=11), with fewer small samples (n=7). Baseline sample sizes ranged from 2 to 270,000, and follow-up samples ranged from 4,000 to 140,000. Most studies (n=27) employed designs that minimized self-selection bias. Control groups consisted of participants not exposed to the specific public transport intervention under investigation, while treatment groups received the intervention. Supplemental Material Table S7 provides a summary of the interventions.

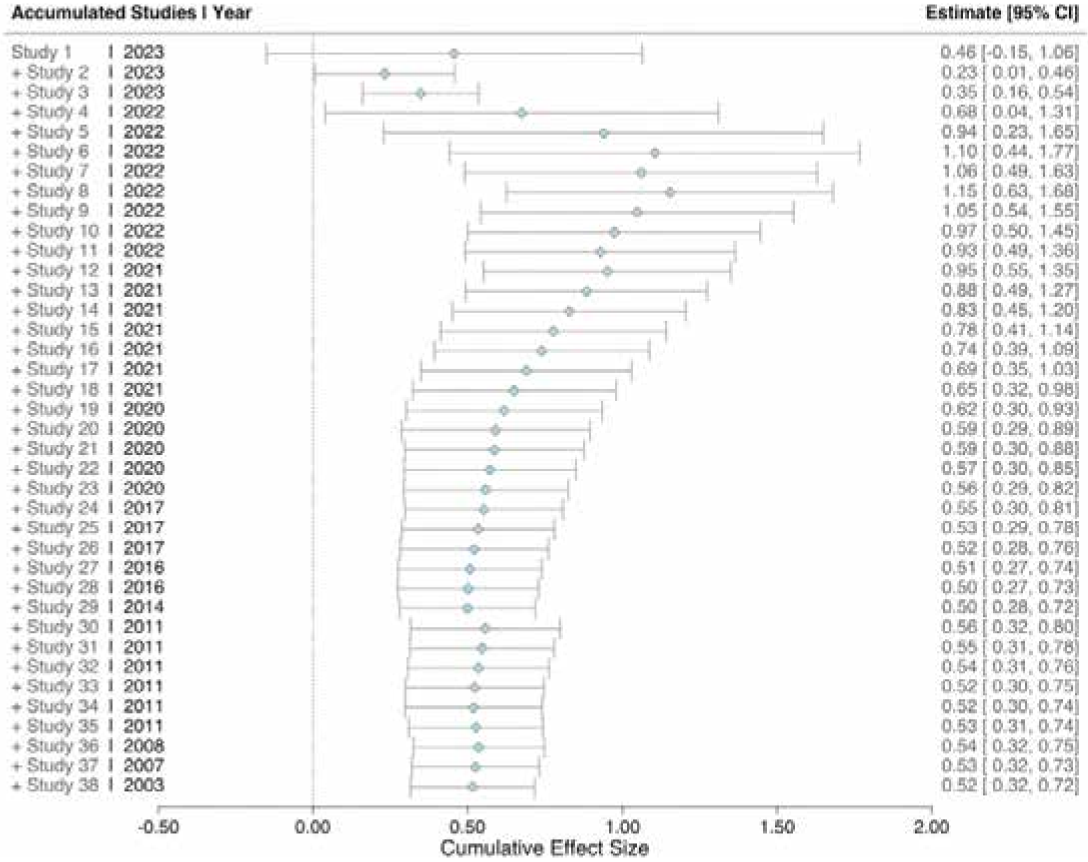
The primary outcome measure across studies was public transport usage frequency or ridership, although some also reported changes in total trips, distance, or mode share (Hoang-Tung et al., 2021; Li et al., 2023a; McCormack et al., 2021). Effect sizes (Cohen's d) and standard errors were calculated for each study outcome. Supplemental Material Table S8 summarizes sample sizes, results, and effect characteristics for each included effect size.
Overall, interventions generally showed a positive effect on public transport usage. However, some studies reported non-significant findings (Marshall Baker & Linovski, 2022), and the magnitude of effects varied considerably across interventions. No studies reported negative (suppressive) effects, likely because all included studies focused on promoting public transport. This variability underscores the importance of investigating potential moderators of intervention effectiveness.

4.3 Meta Analysis and Moderators

We used Cohen's d as the standardized effect size metric to quantify the impact of interventions on public transportation behavior. Positive Cohen's d values indicate that the intervention promoted public transport use. Conventionally, effect sizes are interpreted as small (d < 0.2), moderate (0.2 ≤ d < 0.8), or large (d ≥ 0.8). Given the substantial expected heterogeneity across the diverse interventions, study designs, contexts, and measurement approaches, we employed a random-effects model for synthesizing the 38 independent effect sizes.



a. Forest Plot of Meta Analysis



b. Cumulative Forest Plot

Fig 4. Results of General Meta-Analysis

The meta-analysis included 38 effect sizes from 24 studies, encompassing a total of 756,328 participants. Using a random-effects model, the overall summary effect size was moderate and statistically significant (Cohen's d = 0.5165, 95% CI [0.3158, 0.7172], z = 5.0437, p < 0.0001). This indicates that, on average, interventions effectively promoted public transportation use.

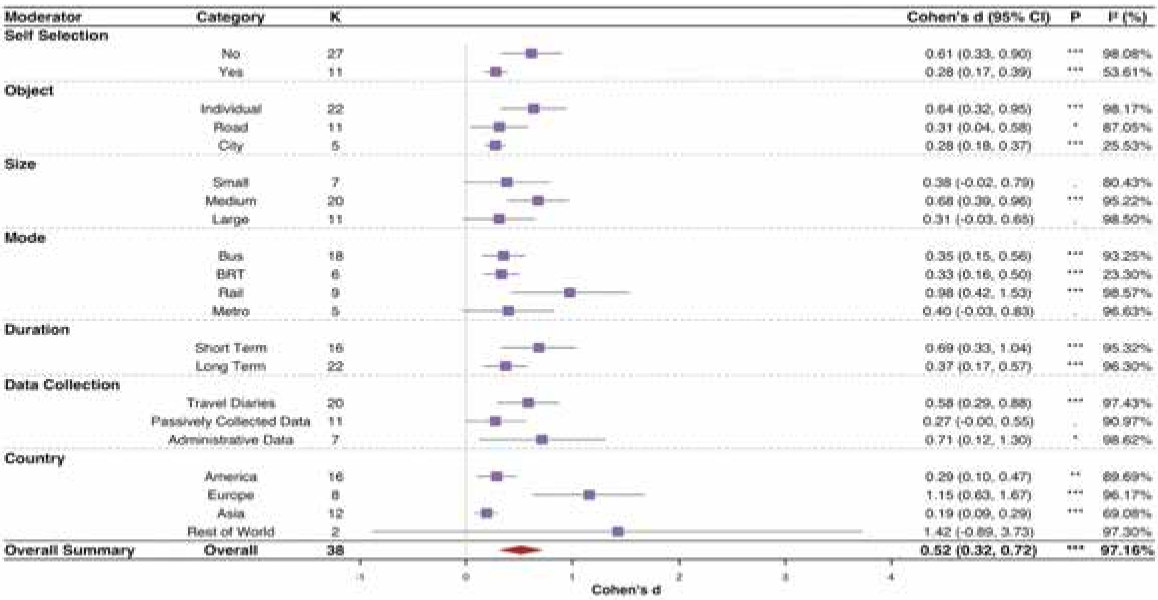


Fig. 5 Moderators of the impact of interventions on public transport travel

Table 1. Moderators of the impact of interventions on public transport travel

Moderator	Category	k	Cohen_d	se	CI	P_Val	I2
Self Selection	No	27	0.6147	0.6147	[0.3336,0.8957]	***	98.08%
	Yes	11	0.2787	0.2787	[0.1709,0.3865]	***	53.61%
Object	Individual	22	0.636	0.6360	[0.3245,0.9474]	***	98.17%
	Road	11	0.3123	0.3123	[0.0404,0.5842]	*	87.05%
	City	5	0.2751	0.2751	[0.1839,0.3664]	***	25.53%
Size	Small	7	0.3834	0.3834	[-0.0223,0.7891]	.	80.43%
	Medium	20	0.6774	0.6774	[0.3912,0.9635]	***	95.22%
	Large	11	0.3104	0.3104	[-0.0312,0.652]	.	98.50%
Mode	Bus	18	0.3518	0.3518	[0.1478,0.5558]	***	93.25%
	BRT	6	0.3313	0.3313	[0.1649,0.4977]	***	23.30%
	Rail	9	0.9768	0.9768	[0.4248,1.5287]	***	98.57%
	Metro	5	0.3975	0.3975	[-0.0337,0.8288]	.	96.63%
Duration	Short Term	16	0.6856	0.6856	[0.3334,1.0379]	***	95.32%
	Long Term	22	0.3718	0.3718	[0.1686,0.575]	***	96.30%
Data Collection	Travel Diaries	20	0.5845	0.5845	[0.2936,0.8754]	***	97.43%
	Passively Collected Data	11	0.2748	0.2748	[-0.0035,0.5531]	.	90.97%
	Administrative Data	7	0.7132	0.7132	[0.1228,1.3036]	*	98.62%
Country	America	16	0.2868	0.2868	[0.102,0.4715]	**	89.69%
	Europe	8	1.1498	1.1498	[0.6298,1.6698]	***	96.17%
	Asia	12	0.1923	0.1923	[0.0902,0.2945]	***	69.08%
	Rest of World	2	1.42	1.4200	[-0.887,3.7269]		97.30%
Total		38	0.5165	0.1024	[0.3158, 0.7172]	***	97.16%

However, significant heterogeneity was detected across studies ($Q(37) = 706.93$, $p < 0.0001$; $I^2 = 97.16\%$), indicating substantial true variation in intervention effects beyond sampling error (Semenescu et al., 2020). This high heterogeneity necessitated moderator analyses to explore potential sources of variation.

We examined several pre-specified moderators related to study characteristics (Table 1). Significant differences in effect sizes were found based on the unit of analysis: interventions showed larger effects when measured at the individual level ($d = 0.636$, $n = 22$) compared to the road/station ($d = 0.312$, $n = 11$) or city level ($d = 0.275$, $n = 5$). Effect sizes were notably larger in studies with medium sample sizes ($d = 0.677$, $n = 20$) compared to those with large ($d = 0.310$, $n = 11$) or small samples ($d = 0.383$, $n = 7$). Data collection method also moderated effects: studies using statistical yearbook data reported the largest average effect ($d = 0.713$, $n = 7$), followed by survey data ($d = 0.584$, $n = 20$), while studies using objective measurements (e.g., smart card data) showed smaller effects ($d = 0.275$, $n = 11$). Studies avoiding self-selected samples reported larger effects ($d = 0.615$, $n = 27$) than those with potentially self-selected participants ($d = 0.279$, $n = 11$), suggesting self-selection bias may attenuate observed effects. Regional differences were observed, with interventions appearing generally more effective in Europe, Africa, and South America compared to North America and Asia. Effects also varied by transport mode, with light rail interventions showing the strongest effects compared to bus, subway, or BRT interventions.

High heterogeneity persisted within several moderator subgroups, particularly for studies using individual or city samples, medium sample sizes, statistical data, non-self-selected samples, and long-term interventions. The duration of the intervention emerged as a key factor related to heterogeneity; long-term interventions exhibited higher variability than short-term ones. Furthermore, cumulative meta-analysis suggested a trend of decreasing effect sizes over time (Fig. 4b), potentially indicating that initial intervention impacts may diminish as the duration increases.

4.4 Publication Bias

We assessed potential publication bias using a funnel plot (Fig. 5) and Egger's regression test. The funnel plot visually relates study effect sizes to their precision. A symmetrical plot suggests low risk of bias, while asymmetry can indicate missing studies (often those with non-significant or small effects). Our funnel plot displayed some asymmetry, with studies clustering more densely on the right side (positive effects), particularly in the lower precision (bottom) part of the plot. This could suggest potential publication bias against non-significant or negative findings, or it might reflect the true distribution of effects given that all included interventions aimed to promote public transport use, coupled with the high heterogeneity observed.

Egger's regression test was performed to quantitatively assess funnel plot asymmetry. The result was not statistically significant ($t = 1.8661$, $p > 0.05$ [based on t-value and df=36]; intercept $b = 0.1310$, 95% CI [-0.1297, 0.3916]). Therefore, Egger's test did not provide significant evidence of publication bias. The observed asymmetry in the funnel plot is more likely attributable to the substantial heterogeneity among the included studies rather than systematic publication bias.

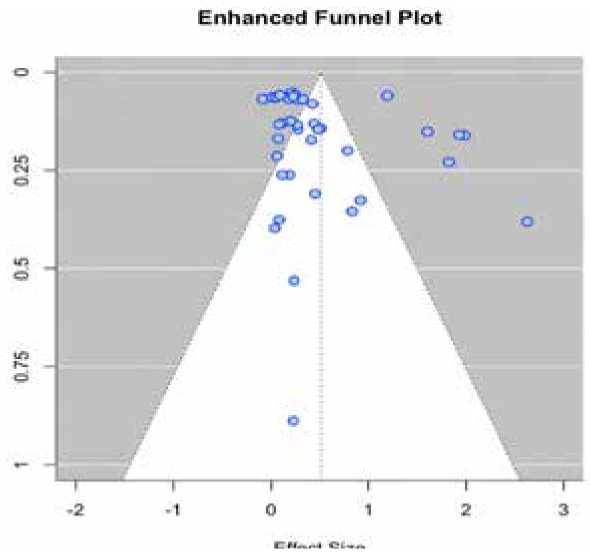


Fig. 6 Funnel plot of publication bias

4.5 Intervention and BCW

We coded the interventions from the 38 included effect sizes according to the three layers of the BCW framework: policy categories, intervention functions, and COM-B components (details in Supplemental Material Table S3-S5). Subgroup analyses were conducted based on these BCW classifications to evaluate differential effects on public transportation behavior (Table 2). Following common meta-analytic practice, subgroup analyses are reported only for categories containing three or more independent effect sizes(Leong et al., 2023).

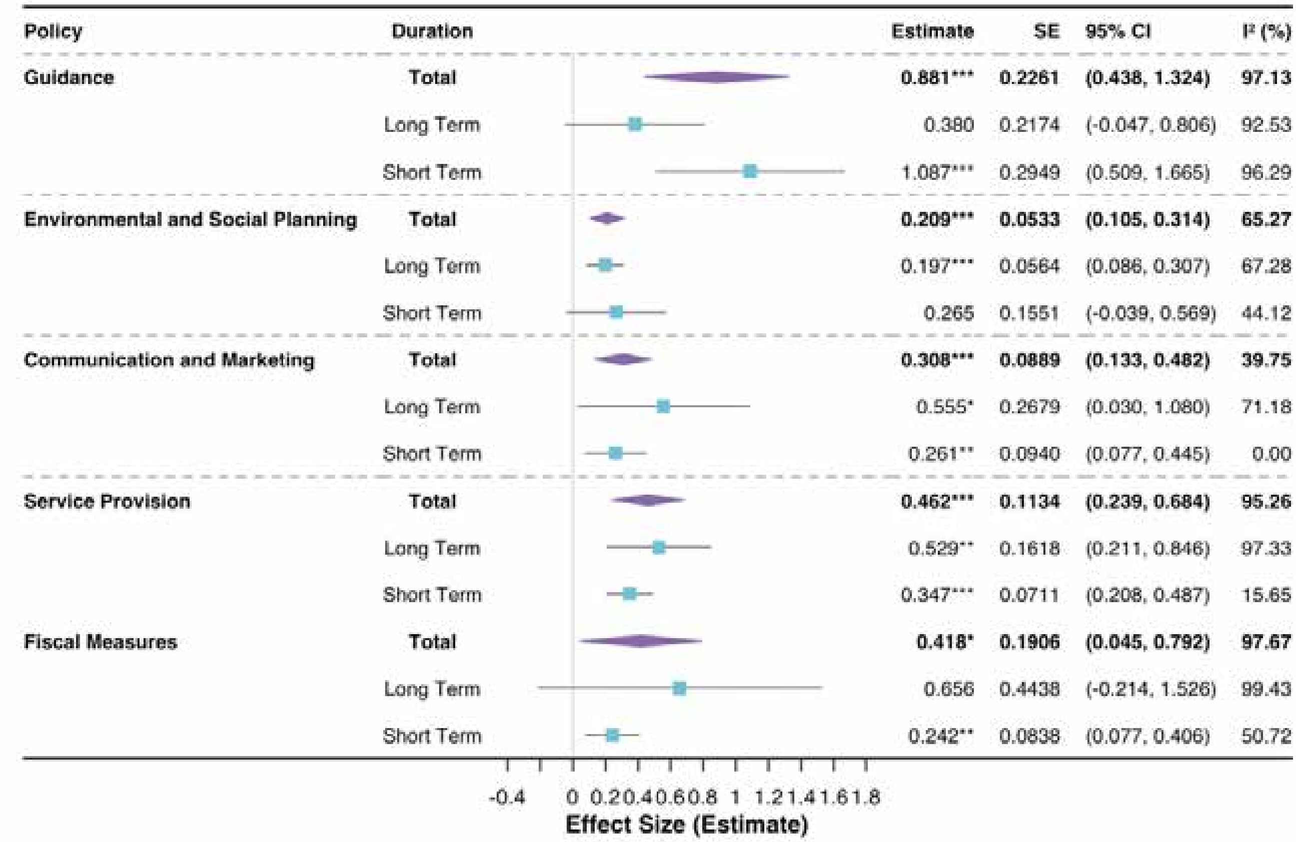
4.5.1 Policy Categories

At the policy level, representing macro-level strategies, interventions most frequently involved Service Provision (e.g., real-time bus information; n=19), Environmental and Social Planning (e.g., new subway lines; n=16), and Guidance (e.g., bus riding guides; n=12). Subgroup analysis revealed significant differences in effectiveness, with Guidance policies showing the largest positive effect ($d = 0.881$, $n=12$, $I^2 = 95.3\%$), while Environmental and Social Planning policies showed the smallest effect ($d = 0.209$, $n=16$, I^2 high). Service Provision ($d = 0.462$, $n=19$, $I^2 = 97.7\%$) and Fiscal policies (e.g., monthly passes; $d = 0.418$, $n=10$, I^2 high) also yielded moderate positive effects. Communication/Marketing and Regulation policies were excluded from subgroup analysis due to insufficient studies (n<3). High heterogeneity was observed within most policy categories. Intervention duration significantly moderated policy effects: Guidance policies were most effective in the short-term (≤ 80 days; d = 1.087, n=8), whereas Communication/Marketing (d = 0.555, n=3) and Service Provision (d = 0.529, n=14) demonstrated substantial positive effects over the long-term (> 180 days). Although Fiscal policies showed positive long-term effects (d=0.656, n=5), this was not statistically significant. Notably, Guidance policies had significantly stronger short-term effects compared to their long-term impact (d=0.380, n=4), while Communication/Marketing effects appeared stronger long-term (short-term d=0.261, n=3). Heterogeneity remained high within policy subgroups across both short- and long-term durations, particularly for Guidance, Service Provision, and Fiscal policies.

Table 2. Effect sizes of interventions categorized by the BCW framework

Subgroup		Duration	Estimate	CI	pval
Policy					
	Guidance	Total	0.881	[0.4379,1.3241]	***
		Long term	0.3796	[-0.0466,0.8058]	.
		Short term	1.0872	[0.5093,1.6651]	***
	Environmental & Social Planning	Total	0.2093	[0.1048,0.3139]	***
		Long term	0.1968	[0.0862,0.3073]	***
		Short term	0.2653	[-0.0388,0.5694]	.
	Communication and Marketing	Total	0.3077	[0.1334,0.4821]	***
		Long term	0.5547	[0.0297,1.0798]	*
		Short term	0.261	[0.0768,0.4453]	**
	Service Provision	Total	0.4615	[0.2393,0.6838]	***
		Long term	0.5285	[0.2113,0.8457]	**
		Short term	0.3473	[0.208,0.4867]	***
	Fiscal Measures	Total	0.4275	[-0.0102,0.8652]	.
		Long term	0.6561	[-0.2136,1.5259]	
		short term	0.1492	[0.0077,0.2907]	*
Intervention		Total			
	Education	Total	0.2595	[0.0928,0.4262]	**
		Long term	0.3796	[-0.0466,0.8058]	.
		Short term	0.2729	[0.1151,0.4307]	***
	Persuasion	Total	0.2729	[0.1151,0.4307]	***
		Short term	0.2729	[0.1151,0.4307]	***
	Incentivization	Total	0.9719	[0.454,1.4897]	***
		Long term	0.9451	[-0.6312,2.5214]	
		Short term	0.9959	[0.4499,1.5418]	***
	Restriction & Coercion	Total	1.1118	[0.5637,1.6599]	***

		Short term	1.3968	[0.8273,1.9663]	***
	Environmental Restriction	Total	0.3177	[0.1538,0.4816]	***
		Long term	0.34	[0.1435,0.5365]	***
		Short term	0.26	[0.0137,0.5064]	*
	Modeling	Total	0.5547	[0.0297,1.0798]	*
		Long term	0.5547	[0.0297,1.0798]	*
	Enablement	Total	0.5756	[0.0916,1.0597]	*
		Long term	0.6634	[-0.1462,1.4731]	
		Short term	0.4291	[0.2911,0.5671]	***
COM-B		Total			
	Psychological Capability	Total	0.2459	[0.114,0.3777]	***
		Long term	0.2613	[-0.033,0.5556]	.
		Short term	0.3361	[0.2144,0.4578]	***
	Social Opportunity	Total	0.5547	[0.0297,1.0798]	*
		Long term	0.5547	[0.0297,1.0798]	*
	Physical Opportunity	Total	0.4102	[0.2018,0.6186]	***
		Long term	0.4388	[0.1781,0.6996]	***
		Short term	0.3697	[0.1598,0.5797]	***
	Automatic Motivation	Total	0.9034	[0.4495,1.3573]	***
		Long term	0.6998	[-0.2017,1.6012]	
		Short term	1.0168	[0.4838,1.5498]	***
	Reflective Motivation	Total	0.3418	[0.1783,0.5053]	***
		Long term	0.4148	[0.1765,0.6532]	***
		Short term	0.2372	[0.0916,0.3828]	**



Policy	Duration	Estimate	SE	95% CI	I² (%)
Guidance	**Total**	**0.881*****	**0.2261**	**(0.438, 1.324)**	**97.13**
	Long Term	0.380	0.2174	(-0.047, 0.806)	92.53
	Short Term	1.087***	0.2949	(0.509, 1.665)	96.29
Environmental and Social Planning	**Total**	**0.209*****	**0.0533**	**(0.105, 0.314)**	**65.27**
	Long Term	0.197***	0.0564	(0.086, 0.307)	67.28
	Short Term	0.265	0.1551	(-0.039, 0.569)	44.12
Communication and Marketing	**Total**	**0.308*****	**0.0889**	**(0.133, 0.482)**	**39.75**
	Long Term	0.555*	0.2679	(0.030, 1.080)	71.18
	Short Term	0.261**	0.0940	(0.077, 0.445)	0.00
Service Provision	**Total**	**0.462*****	**0.1134**	**(0.239, 0.684)**	**95.26**
	Long Term	0.529**	0.1618	(0.211, 0.846)	97.33
	Short Term	0.347***	0.0711	(0.208, 0.487)	15.65
Fiscal Measures	**Total**	**0.418***	**0.1906**	**(0.045, 0.792)**	**97.67**
	Long Term	0.656	0.4438	(-0.214, 1.526)	99.43
	Short Term	0.242**	0.0838	(0.077, 0.406)	50.72

Fig. 7 Sub-group analysis of Policy Layer

4.5.2 Intervention Functions

Examining intervention functions, which describe the specific implementation mechanisms, we found Environmental Restructuring (e.g., building new lines; n=20), Incentivisation (e.g., free rides; n=12), and Enablement (e.g., passenger assistance; n=9) were the most common, while Persuasion (n=3) and Modelling (n=3) were least frequent. Subgroup analysis showed statistically significant positive effects for all functions with sufficient data. Coercion and Restriction yielded the largest effect (d = 1.11, n=8, I^2 = 97.9%), closely followed by Incentivisation (d = 0.93, n=13, I^2 = 98.1%). Conversely, Education (d = 0.084, n≥3, I^2 = 99%) and Persuasion (d = 0.27, n=3, I^2=?) showed the smallest effects. Training interventions were too few for analysis (n<3). High heterogeneity was prevalent within most function categories. In the short-term, Coercion/Restriction (d = 1.40, n=6) and Incentivisation (d = 0.94, n=10) were most effective. For long-term interventions, Modelling produced significant positive effects (d = 0.55, n=3); Incentivisation (d = 0.95, n=3) and Enablement (d = 0.66, n=6) also showed strong positive effects, although these were not statistically significant in the long-term subgroup analysis. Effect sizes for most functions were broadly similar across durations, often slightly larger long-term. Heterogeneity remained high within function subgroups and generally increased for long-term interventions compared to short-term ones.

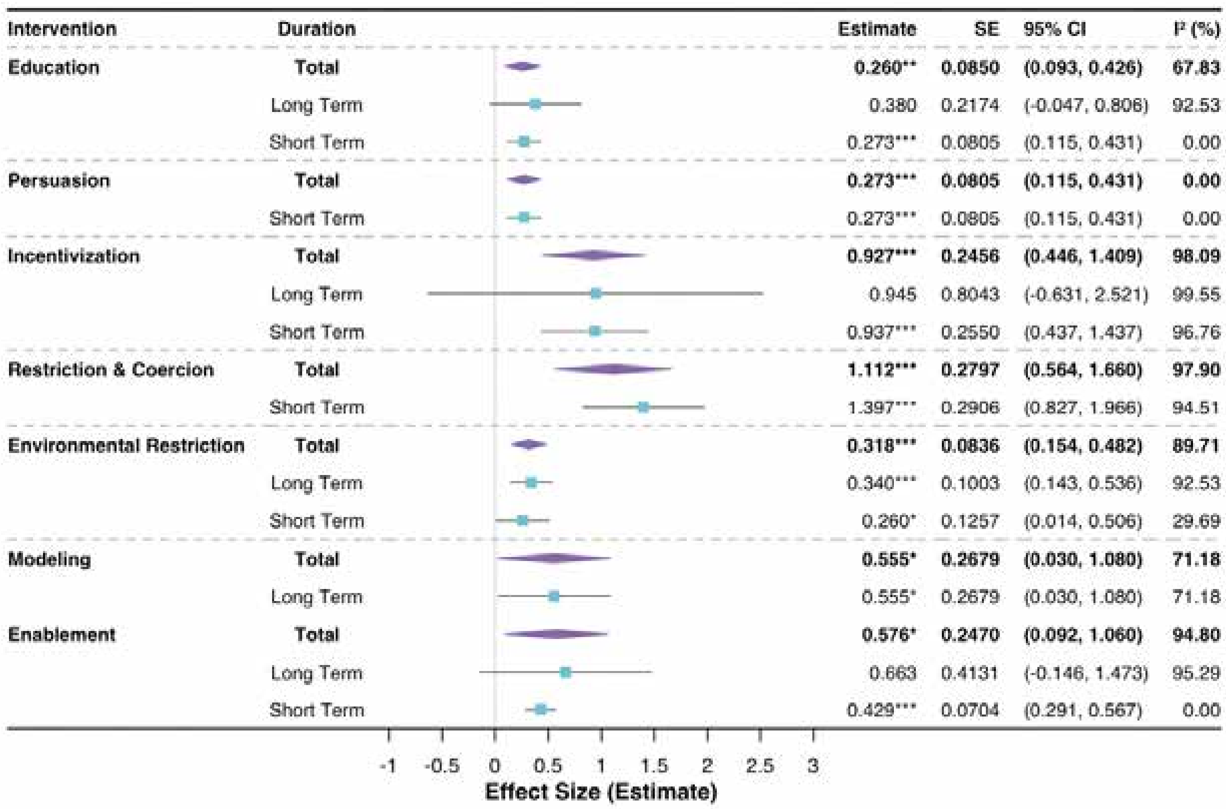


Fig. 8 Sub-group analysis of Intervention Layer

4.5.3 COM-B Components

Finally, analyzing interventions based on the target COM-B components (Capability, Opportunity, Motivation), we found Physical Opportunity (e.g., adding stations; n=23) and Reflective Motivation (e.g., promotional posters; n=17) were most frequently addressed, while Social Opportunity (e.g., school travel projects; n=3) was targeted least often. Subgroup analysis indicated that targeting Automatic Motivation yielded the largest overall effect (d = 0.87, n=15, I^2 = 97.6%), followed by targeting Social Opportunity (d = 0.55, n=3, I^2 = 71.2%). Targeting Psychological Capability (e.g., providing information to reduce perceived complexity) was least effective (d = 0.20, n=9, I^2 = 58.6%). High heterogeneity was observed within the Automatic Motivation subgroup. Considering duration, targeting Automatic Motivation showed the strongest short-term effect (d = 0.96, n=10), while targeting Reflective Motivation had a smaller short-term effect (d = 0.17, n=5). For long-term interventions, targeting Social Opportunity was most effective and showed relatively low heterogeneity (d = 0.55, n=3). Targeting Automatic Motivation also produced a large long-term effect (d = 0.70, n=5), though this was not statistically significant in the long-term subgroup. Interventions targeting Psychological Capability had similarly small effects in both short-term (d=?) and long-term analyses (d = 0.26, n=5). Comparing durations, the effect of targeting Automatic Motivation appeared slightly attenuated long-term, whereas the effect of targeting Reflective Motivation was substantially larger long-term (d = 0.41, n=12) compared to short-term (d = 0.16, n=5). As with other BCW layers, heterogeneity within COM-B subgroups was generally higher for long-term interventions compared to short-term ones.

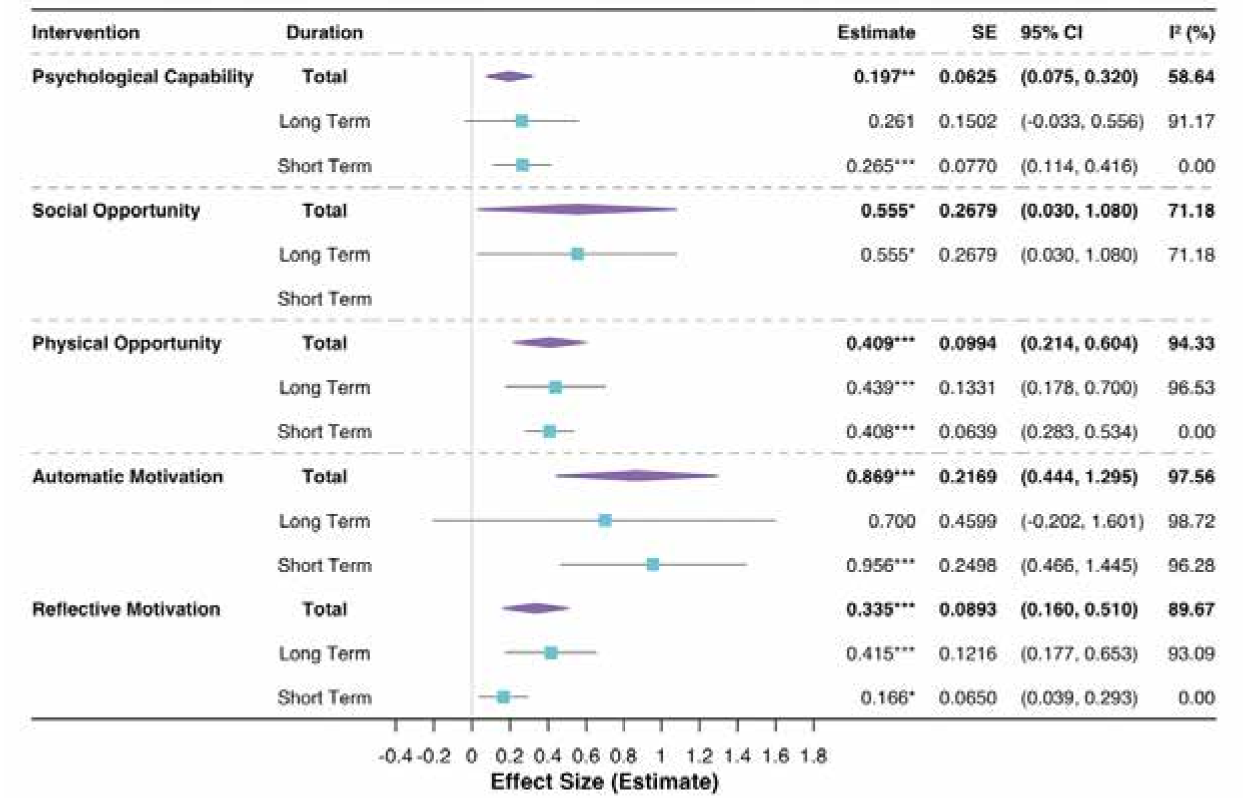


Fig. 9 Sub-group analysis of COM-B Layer

5.Discussion

This study presents a meta-analysis evaluating interventions aimed at promoting public transportation use, employing the Behaviour Change Wheel (BCW) framework to classify these interventions and elucidate the mechanisms underlying their effectiveness. By analyzing how different interventions, categorized by the BCW, influence travel behavior, we sought to understand why certain approaches are more successful than others. Our findings offer a structured understanding of intervention mechanisms, providing theoretical and practical insights for developing more effective future public transport policies.

Synthesizing data from 38 effect sizes across 24 studies and 16 countries, our meta-analysis revealed a statistically significant, moderate positive overall effect of interventions on public transportation usage (Cohen's d = 0.5165, $p < 0.0001$). This general finding aligns with previous research indicating that various interventions can successfully promote public transport adoption(Aravind et al., 2024; L. Zhang et al., 2019). However, the analysis also uncovered substantial heterogeneity ($I^2 = 97.16\%$), signifying considerable variability in intervention effectiveness across different contexts, populations, and intervention designs. This variability is exemplified by contrasting findings, such as the large effect reported for ticket discounts by Guzman & Hessel (2022; d ≈ 2.63) compared to the negligible effect of transport card subsidies found by Rosenfield et al. (2020; d ≈ 0.01). (Guzman & Hessel, 2022; Rosenfield et al., 2020). Such discrepancies underscore the necessity of delving deeper into the specific conditions and mechanisms—as facilitated by the BCW framework—that determine why and when interventions succeed or fail.

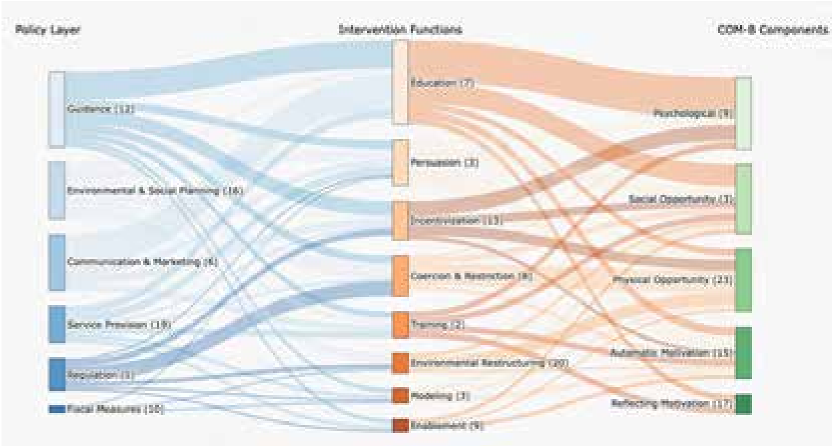


Fig. 10 Distribution of included studies within the BCW framework

To elucidate the mechanisms linking public transportation policies to behavior change, this study employed the Behaviour Change Wheel (BCW) model. We developed a novel three-level analytical framework categorizing interventions by ‘policy category’, ‘intervention function’, and ‘COM-B component’ (Capability, Opportunity, Motivation). This approach reveals how macro-level policy tools translate into impacts on individual travel decisions. Our analysis suggests a hierarchical pathway: policy categories establish strategic direction, implemented via specific intervention functions, which ultimately drive behavior change by influencing individuals’ capabilities, opportunities, or motivations (COM-B). The interplay between these levels explains not only the key factors influencing behavior but also the causal pathways and necessary conditions for intervention effectiveness. Thus, policy success hinges on the synergy between the chosen intervention functions and their alignment with relevant COM-B targets.

Applying this BCW framework, we mapped the distribution of intervention types across the included effect sizes (Fig. 7). This revealed distinct patterns: Environmental and Social Planning (n=16 coded instances) and Service Provision (n=19) were the predominant policy categories. These typically relied on Environmental Restructuring (n=20) and Incentivisation (n=13) as core intervention functions, primarily targeting Physical Opportunity (n=23) and Reflective Motivation (n=17). This pattern supports a dual-pathway mechanism for behavior change, emphasizing improvements in infrastructure accessibility (Physical Opportunity) and influencing conscious decision-making through incentives (Reflective Motivation). The strong association observed between Physical Opportunity and Environmental Restructuring interventions (representing 43.5% of all coded connections) highlights the focus on infrastructure optimization within these policy types. In contrast, Guidance policies exhibited more complex pathways, often combining multiple functions (e.g., Education, n=7; Persuasion, n=3) to influence Automatic Motivation (n=15), underscoring the role of cognitive approaches in reshaping habits. The scarcity of interventions classified under Regulation (n=1) or Training (n=2) suggests potential gaps in research and practice regarding institutional constraints and skills development.

Significant variations exist in the effectiveness and pathways of different policy interventions. Our meta-analysis identified Guidance policies as the most effective overall (d = 0.881), significantly exceeding the average effect size (d = 0.5165). This aligns with findings from included studies where strategies like rewarding commuters (Ben-Elia & Ettema, 2011) or establishing pilot low-carbon cities (Li et al., 2023b) substantially increased public transport use, consistent also with related literature (Zarabi et al., 2024). The BCW analysis helps explain this high effectiveness: Guidance policies often integrate multiple intervention functions, such as Incentivization, Education, and Coercion/Restriction. This multi-pronged approach simultaneously targets Reflective Motivation (e.g., changing attitudes via education), Automatic Motivation (e.g., fostering habits via incentives/restrictions), and Physical Opportunities (e.g., providing convenient information), thereby removing barriers while strengthening drivers for behavior change (Bamberg et al., 2007). Their success likely stems from this ability to influence both conscious deliberation and automatic habits, potentially creating feedback loops that reinforce habit formation, perhaps through mechanisms related to reward processing (Schultz, 2015). This aligns with their strong short-term effects (d = 1.087). However, the diminished long-term impact (d = 0.380) may reflect processes like hedonic adaptation or diminishing marginal utility over time (Loewenstein & Ubel, 2008).

Our analysis revealed that Environmental and Social Planning policies, despite their frequent implementation, yielded the weakest overall effect on promoting public transport use (d = 0.209), significantly below the average intervention effect. Illustrative examples include the negligible impacts observed following the opening of Singapore's CCL Circle Line (Dai et al., 2020) or the introduction of Washington State's RapidRide BRT service replacing traditional buses (Cohen's d = 0.0705, SE = 0.1683)(Stewart et al., 2017). The BCW framework clarifies this finding: these policies predominantly utilize Environmental Restructuring functions to enhance Physical Opportunity (e.g., adding infrastructure). While seemingly contradictory to studies highlighting the positive effects of environmental changes (Nagaraja, 2002; Wu et al., 2023) , our BCW-informed analysis suggests these interventions often fail because they neglect the motivational components of the COM-B model. This creates an "infrastructure-motivation gap," where improved physical access does not translate into a willingness to change established travel behaviors (Chen et al., 2022). The insufficient focus on motivation likely also explains why the long-term effects of these policies were weaker (d = 0.197) than their short-term effects (d = 0.265). This aligns with theoretical perspectives suggesting that interventions lacking cognitive engagement may be ineffective (Sunstein, 2017) and highlights that overcoming ingrained preferences often requires more than infrastructure improvements alone, especially considering external factors like the rise of ride-hailing or remote work (Erhardt et al., 2022). Therefore, relying solely on physical infrastructure enhancements typical of Environmental and Social Planning policies appears insufficient to bridge the "infrastructure-motivation gap" and drive substantial shifts towards public transport. Achieving synergistic effects and promoting sustained behavior change likely requires complementing these structural interventions with strategies that actively engage cognitive and motivational factors, such as targeted incentives or behavioral guidance.

Furthermore, this study highlights intervention duration as a critical moderator of policy effectiveness, revealing distinct temporal patterns consistent with dual-process theories distinguishing immediate responses from considered intentions (Kahneman, 2002). Guidance policies, particularly those employing Coercion/Restriction or Incentivization functions, exhibited significantly stronger short-term effects (d = 1.087) compared to their long-term impact (d = 0.380). This suggests such approaches can induce rapid behavioral shifts, but their effects may decay without sustained reinforcement. Conversely, Service Provision policies demonstrated the most substantial and enduring positive effects over the long term (d = 0.529). This resonates with research indicating that consistent improvements in service quality and accessibility foster sustained public transport use (Hynes et al., 2018; Zarabi et al., 2024). Interventions like providing updated bus information pamphlets (Taniguchi & Fujii, 2007), or enhancing station accessibility and payment systems (Lee & Miller, 2022) function akin to "fluency nudges" (Ölander & Thøgersen, 2014), simplifying the user experience and gradually reshaping preferences. These policies typically combine Environmental Restructuring and Enablement functions, addressing not only Physical Opportunity but also enhancing information access (Capability) and convenience (Motivation). By targeting multiple COM-B components, they foster positive experiences that, consistent with the Theory of Planned Behavior (Ajzen, 1991), can solidify attitudes and intentions, leading to more lasting behavior change.

Our analysis consistently highlights the centrality of COM-B components in driving behavior change. Evaluating the pathways from policy through intervention functions to COM-B targets reveals significant differences in effectiveness based on which behavioral determinants are addressed. Using COM-B components as moderators confirms that interventions targeting Motivation (both automatic, d ≈ 0.90, and reflective, d ≈ 0.34) yield the largest effects. In contrast, interventions focusing primarily on Physical Opportunity or Psychological Capability demonstrated weaker impacts (pooled effect d≈0.25). This underscores that while enhancing opportunities (e.g., via infrastructure) is necessary, effectively stimulating motivational drivers is crucial for promoting behavior change. Furthermore, intervention functions that directly influence motivation, such as Incentivization, Modelling, and Enablement, appear particularly effective precisely because they successfully engage these motivational levers.

This study also examined the moderating influence of contextual factors on intervention effectiveness. Findings indicate that effectiveness is significantly shaped by multiple contextual dimensions. The level of analysis emerged as a key factor, with interventions targeting individuals (d ≈ 0.64) showing larger effects than those at the road/station (d ≈ 0.31) or city level (d ≈ 0.28), reflecting potential "proximity effects" where interventions closer to the individual decision-maker are more impactful. However, city-level analyses exhibited greater stability (lower I^2), suggesting policy-level interventions might possess greater cross-context robustness. Measurement method also mattered significantly: effect sizes derived from administrative census data were largest (d ≈ 0.71) but showed extreme heterogeneity (I^2 > 98%), possibly reflecting variations in data protocols.

Critically, objective travel data yielded significantly smaller effect sizes ($d \approx 0.27$) compared to self-reported data ($d \approx 0.58$; $\Delta d \approx 0.31$, $p < 0.01$). This likely reflects social desirability bias in self-reports (Paulhus & Reid, 1991), suggesting that evaluations relying solely on subjective measures may systematically overestimate intervention impacts. Geographic characteristics showed complex relationships; for instance, mid-sized cities appeared to be effective intervention contexts ($d \approx 0.68$), potentially due to a balance of social norms and resources. Higher effects were observed in Europe compared to Asia ($d \approx 1.15$ vs. 0.19), possibly reflecting cultural or policy environment differences. The intervention duration effect was confirmed, with short-term interventions ($d \approx 0.69$) outperforming long-term ones ($d \approx 0.37$), potentially hinting at behavioral inertia and suggesting the value of intermittent reinforcement strategies. Finally, transport mode mattered: interventions involving rail systems showed larger effects ($d \approx 0.98$) than other modes, possibly due to their structured nature, although the diminished effect for mature metro systems ($d \approx 0.40$) suggests a potential threshold effect where excessive system rigidity might limit further intervention impact. Collectively, these findings emphasize the crucial role of context in shaping intervention outcomes, necessitating customized strategies.

These findings yield important practical implications for public transportation policy. First, policymakers should move beyond single-strategy approaches towards integrated, multi-layered intervention systems. Such systems should strategically combine enhancements to Physical Opportunity (e.g., infrastructure via Environmental/ Social Planning) with efforts to stimulate and sustain Motivation (e.g., via Guidance, Communication/Marketing, Service Provision). For instance, new infrastructure should be paired with informational campaigns, seamless payment systems, and potentially targeted incentives to bridge the “infrastructure-motivation gap.” Second, strategies must be temporally aligned with policy goals. For rapid behavioral shifts, approaches like incentives or restrictions (often under Guidance policies) may be prioritized due to their strong short-term effects. However, fostering sustainable habits requires a longer-term focus on enhancing Service Provision and Enablement, continuously improving the travel experience and system efficiency. Third, given the identified synergy between opportunity and motivation, and the risk of solely focusing on infrastructure, initiatives must strategically balance investments in both physical and psychological domains to maximize resource efficiency and policy impact. Finally, intervention design must be context-sensitive, tailoring approaches based on factors like city size, cultural context, existing transport system characteristics, and target population characteristics to optimize effectiveness.

This research offers several novel contributions. Primarily, by systematically applying the BCW framework, it provides an integrated theoretical lens for analyzing diverse public transportation interventions, decomposing them into policy categories, intervention functions, and target COM-B components to clarify their operational logic. Second, moving beyond typical meta-analyses focused on overall effects or broad categories, this study delves into the underlying mechanisms driving intervention success or failure. It quantifies effectiveness differences (e.g., Guidance vs. Environmental Planning policies) and, crucially, offers explanations grounded in behavioral theory for why these differences exist, particularly emphasizing the distinct roles of opportunity and motivation. Third, through rigorous coding and detailed subgroup analyses, the study provides robust empirical evidence supporting these mechanistic explanations. Overall, this comprehensive framework bridges behavioral science theory and empirical policy evaluation, offering a theoretically sound basis for designing more sophisticated and effective public transportation strategies.

Despite these contributions, the study has limitations that warrant caution in interpretation. First, the substantial heterogeneity observed ($I^2 > 97\%$ in some analyses) indicates that intervention effects are influenced by numerous unmeasured factors, including specific study designs, implementation fidelity, local contexts, and concurrent events. While moderator analyses explained some variance, considerable heterogeneity remains, highlighting the need for future research employing more controlled designs or focusing on more homogeneous intervention types. Second, our inclusion criteria (English-language, quantitative studies, 2000-2023) may introduce publication and selection biases, potentially omitting relevant findings. Future syntheses could broaden inclusion criteria. Third, reliance on Cohen’s d as the primary effect size metric, while standard, simplifies complex behavioral shifts; future work could benefit from incorporating richer, multi-dimensional outcomes or mixed-methods data. Finally, while the BCW framework is comprehensive for behavioral analysis, it inherently focuses less on broader external factors (e.g., political dynamics, macroeconomic trends) that undoubtedly influence public transport use. Future research employing mixed methods and expanding geographic/temporal scope could further enrich understanding of intervention effectiveness and mechanisms within these wider systems.

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6.Conclusion

This study systematically evaluated the impact and underlying mechanisms of public transportation interventions using a novel three-level analytical model based on the Behaviour Change Wheel (BCW) framework. By synthesizing evidence on the short- and long-term effects of different policy categories, we draw the following main conclusions:

First, Guidance policies demonstrate the largest overall positive effect on promoting public transport use. These interventions, often employing education, promotion, and social norm strategies, effectively enhance awareness and positive attitudes, leading to significant short-term increases in ridership. By fostering understanding of environmental and economic benefits and shaping social norms, they contribute to reinforcing positive attitudes and building a foundation for longer-term behavior change. However, our analysis suggests that the impact of Guidance policies may diminish over time if not complemented by other sustained strategies, highlighting the need for integrated approaches rather than relying solely on guidance for long-term sustainability.

Second, Environmental and Social Planning policies, while crucial for improving the physical environment and accessibility of public transport through infrastructure development, exhibit limited effectiveness in driving sustained behavior change independently. This underscores the challenge of the "infrastructure-motivation gap," where structural improvements alone often fail to overcome ingrained travel habits. To achieve lasting impacts and enhance transportation sustainability, these policies must be integrated with interventions that actively engage motivational and capability factors, such as targeted incentives or behavioral guidance strategies.

Third, Service Provision policies demonstrate significant positive effects, particularly notable for their lasting impact over the long term. These policies succeed by not only enhancing Physical Opportunity but also by providing ongoing support, convenience, and technological innovations that address other key behavioral determinants. From a COM-B perspective, effective Service Provision often targets multiple components—including Opportunity, Motivation, and Capability—thereby comprehensively supporting the adoption and maintenance of public transport use.

In conclusion, achieving sustainable public transportation systems requires comprehensive, integrated strategies that leverage the strengths of different policy approaches. Effective interventions should combine the motivational impetus often provided by Guidance policies, the essential infrastructure improvements from Environmental and Social Planning, and the sustained, multi-faceted support offered by well-designed Service Provision. Utilizing frameworks like the BCW to understand these mechanisms allows for the design of more targeted, efficient, and ultimately more effective policies. Such evidence-informed policy design is crucial for promoting public transport use and contributing to the development of greener, healthier, and more livable urban environments. Continued research, expanding methodological approaches and scope, will be vital for further refining our understanding and fostering adaptive, resilient public transportation systems.

Supplemental Material

Table S1 Search strategy

Table S2 Standardized Form of Extracting and Coding data

Table S3 Definitions of policy categories as described by the Behaviour Change Wheel

Policy category	Definition	Public Transport Examples
Guidelines	The development and dissemination of documents that make recommendations for action in response to defined situations	Orientation documents issued in the programme (e.g. some pilot zones)
Environmental and social planning	Architecture, urban and rural planning, object and location design, and planning for housing, social care, employment, equality, benefits, security and education	Construction, improvement of public transportation routes
Communications and marketing	Mass media campaigns, digital marketing campaigns, and correspondence	Leafleting, SMS, large screen publicity, etc.
Service provision	Provision of any kinds of service or material resource and aids, whether they be structured or ad hoc, financed or unpaid	Fare subsidies, new lines, etc.
Regulation	Development and implementation of rules regarding behaviour that instruct the behaviour and possibly provide rewards and punishments for conforming	temporary incentives in MRT(a full rebate of subway fare)
Fiscal measures	Use of taxation and tax relief	public transit tax credit

Table S4 Definitions of intervention types as described by the Behavior Change Wheel

Intervention type	Definition	Public Transport Examples
Environmental restructuring	Changing the physical or social context	construct new metro line
Education	Increasing knowledge or understanding	Promote information on health/public transportation/environment;
Persuasion	Using communication to induce positive or negative feelings or stimulate action	Providing public transit information through communication and lectures
Incentivization	Creating an expectation of reward	Free tickets, subsidies, differential pricing policies
Coercion and Restriction	Creating an expectation of punishment or cost or use of rules to reduce opportunities to engage in target behaviors	Increase in gasoline pricesΔRestrictions on automobile travel
Training	Imparting skills	Emerging transit software use through training
Modelling	Providing an example for people to aspire to or imitate	Workplace mobility management program
Enablement	Increasing means/ reducing barriers to increase capability (beyond education and training) or opportunity (beyond environmental restructuring)	Simplifying ticket purchasing by smartcard system

Table S5 Components of the COM-B model

	COM-B model component	Definition	Public Transport Examples
C	Physical capability	Physical skill, strength, or stamina	?
	Psychological capability	Knowledge or psychological skills, strength, or stamina to engage in the necessary mental processes	Real-time Information System; Mobile apps and GPS trackers to provide motivations and advice
O	Physical opportunity	Opportunity afforded by the environment involving time, resources, locations, cues, and physical ‘affordance’	BCT, Integrated Mass Transit System, new railway, new metro line, entrance of Uber
	Social opportunity	Opportunity afforded by interpersonal influences, social cues and cultural norms that influence the way that we think about things, e.g. the words and concepts that make up our language	Workplace pt programme
M	Reflective motivation	Reflective processes involving plans (self-conscious intentions) and evaluations (beliefs about what is good and bad)	Use of mobile apps and GPS trackers to provide motivation and advice
	Automatic motivation	Automatic processes involving emotional reactions, desires (wants and needs), impulses, inhibitions, drive states and reflex responses	Temporary incentives in MRT (a full rebate of subway fare)

Table S6 Key characteristics of Studies

Index	study	country	Start Year	Duration	Duration Type	Data Source	Experimental group Sample size	Control group sample size	Total sample size	Self-Selection	Sample Type	Sample Type	Size	Travel Mode
1	Baker and Linovski. 2022 treat1	USA	2012	2555	long	Passively collected data	4	32	36	non-self-selection	Road	Midium		BRT
2	Baker and Linovski. 2022 treat2	USA	2012	2555	long	Passively collected data	121	121	242	non-self-selection	Road	Midium		BRT
3	Ben-Elia and Ettema. 2011 treat1	Netherland	2006	91	short	Travel Diaries	232	232	232	non-self-selection	individual	Midium		Rail
4	Ben-Elia and Ettema. 2011 treat2	Netherland	2006	91	short	Travel Diaries	232	232	232	non-self-selection	individual	Midium		Rail
5	Ben-Elia and Ettema. 2011 treat3	Netherland	2006	91	short	Travel Diaries	232	232	232	non-self-selection	individual	Midium		Rail
6	Ben-Elia and Ettema. 2011 treat4	Netherland	2006	91	short	Travel Diaries	108	108	108	non-self-selection	individual	Midium		Rail
7	Ben-Elia and Ettema. 2011 treat5	Netherland	2006	91	short	Travel Diaries	108	108	108	non-self-selection	individual	Midium		Rail
8	Dai et al. 2020 treat1	Singapore	2009	1095	long	Travel Diaries	1122	1122	2244	non-self-selection	individual	Large		Rail
9	Dai et al. 2020 treat2	Singapore	2009	1095	long	Travel Diaries	1122	1122	2244	non-self-selection	individual	Large		Rail
10	Fujii and Kitamura.2003	Japan	2002	30	short	Travel Diaries	23	20	43	selfselection	individual	Small		Bus
11	Guzman and Hessel. 2022 treat1	Colombia	2013	2190	long	administrative data	144697	271046	361744	non-self-selection	individual	Large		Bus
12	Guzman and Hessel. 2022 treat2	Colombia	2013	2190	long	administrative data	144697	271046	361744	non-self-selection	individual	Large		Bus
13	Hoang-Tung et al. 2021	Vietnam	2016	540	long	Travel Diaries	501	501	501	selfselection	individual	Midium		BRT
14	Lee and Lee, 2014	USA	2002	3285	long	administrative data	7197	7197	7197	non-self-selection	City	Large		Bus
15	Lee and Miller, 2022	USA	2018	365	long	Passively collected data	952	952	952	non-self-selection	Road	Large		BRT
16	Li et al, 2022 treat1	USA	2017	730	long	Passively collected data	18	11	29	non-self-selection	Road	Small		Bus
17	Li et al, 2022 treat2	USA	2017	730	long	Passively collected data	9	2	11	non-self-selection	Road	Small		Bus
18	Li et al. 2023 treat1	China	2010	2190	long	administrative data	571	2874	3445	non-self-selection	City	Midium		Bus
19	Li et al. 2023 treat2	China	2010	2190	long	administrative data	571	2874	3445	non-self-selection	City	Midium		Bus
20	Liu and Xu, 2022	China	2010	2190	long	administrative data	600	3105	3705	non-self-selection	City	Midium		Bus
21	McCormack et al. 2021	Canada	2018	365	long	Travel Diaries	80	116	196	selfselection	individual	Midium		BRT
22	Piras et al. 2021	Italy	2019	1	short	Travel Diaries	116	109	225	selfselection	individual	Midium		Bus
23	Piras et al. 2022	Italy	2019	1	short	Travel Diaries	59	83	142	selfselection	individual	Midium		Rail
24	Rosenfield,2020 treat1	USA	2016	240	long	Passively collected data	481	494	975	non-self-selection	individual	Large		Bus

25	Rosenfield,2020 treat2	USA	2016	240	long	Passively collected data	489	494	983	non-self-selection	individual	Large	Bus
26	Shi et al. 2021 treat1	USA	2014	180	short	Passively collected data	34	62	96	non-self-selection	Road	Small	Bus
27	Shi et al. 2021 treat2	USA	2014	180	short	Passively collected data	18	78	96	non-self-selection	Road	Small	Bus
28	Shi et al. 2021 treat3	USA	2014	180	short	Passively collected data	17	79	96	non-self-selection	Road	Small	Bus
29	Spears et al. 2016	USA	2012	180	short	Travel Diaries	128	79	207	selfselection	individual	Midium	Metro
30	Stewart, 2017	USA	2010	1095	long	Travel Diaries	93	57	150	non-self-selection	Road	Midium	BRT
31	Stover et al. 2011	USA	2004	1770	long	administrative data	631	631	631	non-self-selection	City	Large	Bus
32	Sun,2020	China	2015	365	long	Travel Diaries	833	456	1289	selfselection	individual	Large	Metro
33	Taniguchi,2007	Japan	2004	92	short	Travel Diaries	367	79	446	selfselection	individual	Midium	Bus
34	Thogersen and Moller 2008	Denmark	2002	30	short	Travel Diaries	471	251	722	selfselection	individual	Midium	Bus
35	Wang et al. 2023	China	2004	2555	long	Travel Diaries	524	524	1048	non-self-selection	Road	Large	Rail
36	Yang and Lim. 2017 treat1	Singapore	2015	70	short	Travel Diaries	120	119	239	selfselection	individual	Midium	Metro
37	Yang and Lim. 2017 treat2	Singapore	2015	70	short	Travel Diaries	109	119	228	selfselection	individual	Midium	Metro
38	Werner et al., 2016	USA	2012	365	long	Passively collected data	22	43	65	non-self-selection	Road	Small	Metro

Table S7 summary of the interventions of Studies

Table S8 Coding Results of Studies