Journal of Cycling and Micromobility Research 9 (2026) 100123

Contents lists available at ScienceDirect

Journal of Cycling and Micromobility Research

journal homepage: www.sciencedirect.com/journal/journal-of-cycling-and-micromobility-research

Interventions to increase cycling: A critical assessment of effectiveness

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ARTICLE INFO

Keywords:
Cycling
Policies
Sustainable transport
Incentives
Interventions, rewards

ABSTRACT

Cycling is widely promoted as a sustainable mode of transport, yet evidence on the effectiveness of interventions remains mixed. Existing research often compares interventions by type, with less attention to the behavioural mechanisms through which they are expected to increase cycling. This study addresses this gap through a synthesis of 124 empirical studies evaluating cycling interventions. A rule-based classification framework is used to compare outcomes across heterogeneous study designs and measures, assessing interventions by type, cost, and behavioural mechanisms, and the direction, strength, and confidence of observed cycling outcomes. No-change findings are common, including in higher-confidence studies. Structural interventions such as bike paths and street redesign, often increase cycling on specific routes but do not consistently lead to population-level change, suggesting that some observed increases reflect redistribution of existing cyclists rather than new cycling uptake. Behavioural interventions such as campaigns and training programs frequently improve knowledge, confidence, or skills, but do not reliably translate into sustained cycling behaviour on their own. In contrast, resource and incentive interventions such as e-bike access, subsidies, and bike shares schemes, are most consistently associated with increases in cycling, particularly where they improve practical access to cycling. Other behavioural mechanisms, including motivation, habit formation, and social influence, appear to reinforce change rather than drive it independently. These findings suggest that increasing cycling depends less on influencing decision-making alone and more on changing the conditions that make cycling possible. The study provides a structured approach for comparing diverse evidence and highlights the importance of aligning intervention design with the behavioural mechanisms most likely to support cycling uptake.

1. Introduction

Cycling is increasingly promoted as a central component of sustainable urban mobility strategies, with demonstrated benefits for reducing congestion, air quality, and health (Brand et al., 2021; Oja et al., 2011). Despite these advantages, uptake remains uneven across contexts, reflecting the influence of perceived safety, access to bicycles and supportive infrastructure, land use, and broader socio-cultural and policy conditions (Roaf et al., 2024; Pearson et al., 2025).

In order to increase cycling, a wide range of interventions have been suggested for or introduced by policymakers, city planners, non-governmental organizations, schools, or companies (Dubuy et al., 2013; Giles-Corti et al., 2016; Villa-González et al., 2017; Winters et al., 2017). Even though intervention types have been evaluated in various ways (Giles-Corti et al., 2016; Pearson et al., 2025; Roaf et al., 2024), these may be broadly grouped into three categories: structural interventions that alter the built environment or regulatory context (e.g. Xiao et al., 2023); behavioural interventions that target individual decision-making (e.g., Bopp et al., 2018); and resource and incentive interventions that improve access, reward, or reduce financial and practical constraints (e.g. Fyhri et al., 2017). As shown by Roaf et al. (2024), interventions often combine several of these dimensions.

Evidence regarding the effectiveness of interventions is mixed (Larsen et al., 2024; Ogilvie et al., 2004; Roaf et al., 2024; Yang et al., 2010). While some studies report positive effects, many appear to show limited or no measurable change in cycling behaviour, even where intermediate outcomes improve (Pearson et al., 2025). There are also inconsistencies in contextual variation and methodological challenges, including differences in study design, outcome measures, and the absence of standardized approaches that make it difficult to compare studies. Reviews have for this reason often resulted in generalized conclusions, such that “physical environmental restructure interventions” or “individually tailored behavioural programmes” are the most effective interventions (Pearson et al., 2025: 482).

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https://doi.org/10.1016/j.jcmr.2026.100123
Received 30 April 2026; Received in revised form 16 June 2026; Accepted 24 July 2026
Available online 29 July 2026
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Four recent systematic reviews have synthesized evidence on cycling and active travel interventions based on meta-analyses of intervention effectiveness (Larsen et al., 2024; Pearson et al., 2025; Roaf et al., 2024; Fitch-Polse and Agarwal, 2025). These studies have classified interventions by type, study design, 'benefit', or by behaviour change 'technique'. Less attention has however been paid to the *mechanisms* through which interventions influence behaviour, i.e. capability, opportunity, and motivation as components of the underlying behaviour system (Michie et al., 2011). As a result, it remains unclear which mechanisms are most consistently associated with behavioural change, and under what conditions.

This study addresses this research gap through a structured evidence analysis and synthesis of cycling interventions that goes beyond existing systemic reviews by introducing a rule-based signal classification framework to enable consistent comparison across heterogeneous study designs and outcome measures. This is combined with a behavioural mechanism approach that shifts analysis from intervention types to the pathways through which behaviour change occurs. By integrating these elements, a basis for comparing diverse forms of evidence is developed, allowing to identify the behavioural mechanisms most consistently associated with changes in cycling behaviour.

2. Theoretical background

Transport behaviour is influenced by various factors. While no specific models appear to have been developed for cycling, Schwanen and Lucas' (2011): 25) model of automobile use can be transferred to cycling. It distinguishes personal/internal and external/contextual factors shaping behaviour; the former including early cognitions, perceptions, moral motivations, values, personal norms, attitudes & beliefs, personal intention, and habits; the latter including knowledge and information systems, alternative transport options, the cost of alternatives, and transport policies. Social and cultural norms, as well as past experiences also have relevance (Schwanen and Lucas, 2011). In the context of cycling, skills and fitness (internal) as well as built and natural environment (including weather and topography), also play a role (Henriques-Neto et al., 2020; Martín-López et al., 2025). Zarabi et al. (2025) further distinguish cycling out of choice vs. cycling out of necessity.

From a behavioural point of view, cycling is shaped by a combination of physical, social, and psychological factors. Key determinants have been identified as infrastructure provision, perceived and objective safety, travel distance, convenience, access to bicycles and facilities, and broader cultural and social norms. For example, Pearson et al. (2025) reviewed 106 studies of interventions, finding that infrastructure provision such as protected bike lanes and traffic calming were the most effective to increase cycling, while behavioural programmes and e-bike provision were also effective. Other recent systematic reviews have also concluded that infrastructure measures have the greatest relevance for cycling (Roaf et al., 2024).

Infrastructure and street design influence on safety, route directness, and travel time, have also been associated with cycling uptake (Vera-Villarroel et al., 2016; von Stülpnagel and Binnig, 2022). Safety perceptions are also shaped by wider environmental and traffic conditions, including vehicle speeds and driver behaviour (Kienteka et al., 2014; Gössling et al., 2019). Access-related factors, including bicycle ownership and technologies such as e-bikes, play an important role in enabling participation (Rérat, 2021; Fyhri et al., 2017). Social and cultural influences further shape individual decisions, including norms, identity, and the visibility of cycling within everyday mobility practices (Aldred and Jungnickel, 2014; Sherwin et al., 2014), with variation across socio-demographic groups (Mendoza et al., 2017).

Interventions influence cycling behaviour by modifying these determinants through specific behavioural mechanisms. Rather than directly causing behaviour change, they shape the decision environment and the likelihood that individuals choose to cycle. This perspective aligns with established behavioural frameworks, including the COM-B model, which conceptualises behaviour (B) as a function of capability (C), opportunity (O), and motivation (M) (Michie et al., 2011), as well as related theories emphasising attitudes, social norms, and perceived behavioural control.

Framing interventions in terms of behavioural mechanisms provides a basis for comparing how different interventions influence behaviour across contexts. This approach helps distinguish the visible form of an intervention from the behavioural processes through which it is expected to operate. For example, cycling training programs may represent a single intervention category but produce different results based on the extent to which they activate behaviour change levers in the COM-B model. Training programs might rely on cultivating the skills and confidence of participants through classes (capability), providing biking equipment (opportunity) and/or scheduling organised activities that encourage social interaction (motivation). Conversely, different interventions may promote uptake through similar behaviour mechanisms. For example, bike paths and e-bike subsidies make execution of a behaviour possible by providing opportunities to cycle.

Only one systematic review (Larsen et al., 2024) investigated studies focused on behavioural interventions in the context of commuter cycling. The analysis of 41 papers shows that most studies ($n = 25$) "utilised a personalised travel planning intervention", or a "mobile phone-based platform", while five "evaluated the benefits of a cycling promotion scheme or event", and three studies each "a messaging intervention" and "a workplace challenge". Two studies focused on a "community behaviour change" programme (Ibid.: 395). Larsen et al., (2024) conclude that all intervention types (personalized travel plans; mobile phone-based platforms; messaging) show promise in changing pro-cycling behaviour.

Studies have evaluated intervention types, and where the focus has been on behaviour, study design, sample size, data collection tools, intervention timeframe, or theoretical framework (Larsen et al., 2024). While this approach is useful for organising evidence, it can obscure the pathways through which change occurs, particularly where different intervention types operate through similar mechanisms, or where similar interventions produce different outcomes depending on context and implementation (Ogilvie et al., 2004). As a result, intervention typologies alone provide limited insight into why observed effects differ across studies.

These limitations highlight the need for approaches that move beyond intervention typologies to examine how behavioural mechanisms contribute to observed outcomes. This study responds by integrating a rule-based outcome classification framework with a behavioural mechanism approach, enabling consistent comparison across heterogeneous studies and providing a structured basis for analysing how interventions influence cycling behaviour.

3. Methods

3.1. Study design and approach

This study employs a structured evidence synthesis to examine the effectiveness of interventions aimed at increasing cycling behaviour. The approach builds on established systematic review principles, including elements of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), while extending prior work through a rule-based coding framework designed to improve consistency and comparability across heterogeneous study designs. The review updates and expands an earlier dataset prepared by the authors in 2024 by incorporating newly published studies, refining inclusion criteria, and introducing a standardized method for evaluating behavioural outcomes, intervention types, and underlying mechanisms.

3.2. Information sources, search strategy, and selection

The study sample was constructed through a staged search-and-update process. The first phase of the review was completed in 2024 and consisted of a Web of Science and Google Scholar search of the English-language, peer-reviewed literature. The search focused on studies published from 2013 to 2024 and used combinations of terms related to cycling and intervention, including 'incentive' or 'nudge' or 'intervention' in combination with 'cycling' or 'active mobility'. This yielded a total of n = 303 papers, which were screened against the eligibility criteria described below, to arrive at n = 82.

Because the review process was paused and the cycling intervention literature expanded substantially during the period of 2024–2026, the initial search was subsequently updated using study lists from recent systematic reviews and review articles. Specifically, Pearson et al. (2025), who included n = 106 studies of which n = 23 were identified as potentially relevant studies; Roaf et al. (2024), comprising n = 78 studies, out of which n = 75 were included; and Fitch-Polse and Agarwal (2025), who identified n = 236 studies of which n = 173 were included. Studies published after these reviews that were within the scope of the original search were also sought, of which n = 11 were included. This yielded, with the original review n = 82, n = 364 references, of which n = 38 were removed as duplicates. The n = 326 remaining papers were then screened manually to ensure a consistent focus on empirically evaluated cycling interventions.

Studies were included if they:

- Examined a real-world intervention related to cycling (e.g., infrastructure, programs, policies, or incentives),
- Reported empirical quantitative data, and
- Measured changes in cycling behaviour or cycling-related mode shift.

In this review, cycling behaviour referred to observed or self-reported measures of cycling participation or use. Outcomes of interest included cycling frequency, number of cycling trips, cycling duration, cycling distance, cycling mode share, cyclist counts, bike-share or e-bike use, and uptake of cycling for specific trip purposes such as commuting, school travel, or other transport trips. Cycling-related mode shift referred to reported changes from car use, public transport, walking, or other modes to cycling. Route choice, seasonality, and shifts in trip purpose were not treated as core cycling behaviour outcomes unless reported alongside measurable changes in cycling participation or use. It was not necessary for studies to address behavioural mechanisms to be included in the sample, provided the paper evaluated a cycling intervention and reported a behavioural outcome.

Eligible study designs included randomized controlled trials, quasi-experimental studies, natural experiments, pre–post designs, and observational studies where behavioural change was assessed.

The n = 326 papers were screened manually to ensure a consistent focus on empirically evaluated cycling interventions. Studies were excluded for several reasons, including if they:

- Had sampling limitations, such as very small sample sizes or samples restricted to existing cycling communities (n = 5);
- Focused primarily on safety outcomes, reporting injuries or crash data without assessing changes in cycling behavior (n = 78);
- Lacked original quantitative data about cycling uptake (n = 1);
- Were non–peer-reviewed sources (n = 36), including government reports, Master's theses, and conference papers;
- Did not evaluate a cycling-specific intervention (n = 3), as well as studies unrelated to cycling (n = 19), for example those addressing walking, driver behavior, or aggregate active transport where cycling was not explicitly part of the measured outcome and the intervention was not cycling-relevant;
- Modeled hypothetical interventions without empirical implementation (n = 13);
- Were cross-sectional surveys examining determinants of cycling behavior, such as perceptions, attitudes, confidence, safety concerns, motivation, satisfaction, awareness, and intentions awareness, without directly assessing an intervention (n = 30);
- Were conceptual papers that proposed or refined intervention ideas but did not test them in real-world contexts (n = 6);
- Were complex studies where distinct intervention effects could not be clearly isolated (n = 3);
- Used comparative site studies lacking a before-and-after design such as those comparing cyclist counts across different locations with and without infrastructure (n = 8);

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Following the application of these criteria, a total of 124 studies remained for inclusion in the analysis.

3.3. Data extraction and coding framework

Data were extracted at the study level (one observation per study). The rule-based coding framework (described in further detail in Appendix A) was organised to capture four related dimensions of each study: the characteristics of the intervention, the behavioural mechanisms through which change was expected to occur, the attributes of the study design and context, and the direction and strength of the reported cycling outcome. Intervention characteristics included intervention type, cost, durability, and equity considerations. Study attributes included study design, geography, and assigned confidence level. Outcome coding captured the dominant cycling-related behavioural outcome, its direction of effect and signal strength.

3.3.1. Intervention classification

Interventions were categorized into three primary groups, with further sub-classification to capture variation in approach and implementation:

1. Structural/environmental interventions (STR): Changes to the built environment or regulatory context. Subcategories include:

a) Infrastructure provision (e.g., bike lanes, cycle tracks, greenways),
b) Street redesign (e.g., traffic calming, road space reallocation),
c) Policy and regulatory measures (e.g., cycling strategies, legislation, pricing policies),
d) Transit-related interventions (e.g., integrations with public transport to promote cycling, station access improvements, bike share or storage integration, pass provision), and
e) Land-use changes (e.g., relocation, urban planning decisions affecting travel patterns).

2. Behavioural interventions (BEH): Interventions targeting individual decision-making. Subcategories include:

a) Education and training (e.g., cycling skills programs),
b) Public campaigns and social marketing (e.g. bike month activations)
c) Gamification and digital engagement (e.g., apps, competitions),
d) Behavioural nudges (e.g., messaging, framing, prompts), and
e) Institutional programs (e.g., school- or workplace-based initiatives).

3. Resource and incentive interventions (RES): Interventions improving access or reducing financial barriers. Subcategories include:

a) Bicycle or e-bike provision,
b) Financial subsidies and incentives (e.g., rebates, tax schemes),
c) Public bike share systems, and

d) Access-oriented programs (e.g., earn-a-bike schemes, equipment provision).

Interventions could be coded across multiple categories. In multi-component interventions, a primary (and where relevant secondary) classification was assigned based on the dominant component.

3.3.2. Behavioural mechanisms

Studies were coded according to the primary behavioural mechanism through which change was expected to occur. Eight mechanisms were identified by the authors through repeated engagement with the studies. While coding was not subject to inter-rater review or formal reliability testing, coding rules were developed and tightened iteratively as analysis progressed. This process required the researchers to revisit previously assigned codes as the system was refined. The coding framework was considered stable once further review of the included studies no longer produced new mechanism categories or substantive changes to the coding rules.

1. Motivation and incentives (MOT): Interventions that increase the desirability of cycling through rewards, enjoyment, or perceived benefits (e.g., financial incentives, gamified programs).
2. Convenience / friction reduction (CON): Interventions that reduce effort, time, or logistical barriers associated with cycling (e.g., more direct routes, improved facilities).
3. Information and awareness (INF): Interventions that increase knowledge of cycling options and benefits (e.g., campaigns, travel information).
4. Capability and self-efficacy (CAP): Interventions that build skills, confidence, or perceived ability to cycle (e.g., training programs).
5. Social influence and norms (SOC): Interventions that leverage peer effects, visibility, or group dynamics (e.g., workplace challenges, community programs).
6. Habit formation and prompting (HAB): Interventions that use reminders, cues, or repetition to establish or reinforce cycling behaviour (e.g., app-based prompts, travel planning tools).
7. Access and opportunity (ACC): Interventions that provide the means to cycle (e.g., access to bicycles, equipment, or facilities).
8. Safety and risk reduction (SAF): Interventions that reduce actual or perceived risk (e.g., protected infrastructure, traffic calming, safety measures).

Mechanisms were coded as primary or secondary where multiple pathways were present. In addition, all mechanisms present within each intervention were recorded to reflect the multi-component nature of many interventions. Analyses were conducted using both a single primary mechanism and all mechanisms present. In multi-mechanism analyses, each mechanism was counted independently, such that totals exceed the number of studies.

3.3.3. Cost, durability, and equity

Interventions were classified as low, medium, or high cost based on implementation requirements. Following this classification, behavioural interventions are considered comparatively low cost, resource-based interventions medium cost, and structural interventions high cost. Where multiple components were present, classification is based on the highest-cost element.

Durability was coded based on the temporal scope of measured outcomes, distinguishing between short-term and longer-term effects (approximately one year or more).

Equity coding identified whether studies included demographic or distributional analysis (e.g., by income, gender, age, disability, or race), distinguishing between equity-focused studies, secondary analyses including demographic information, and those without an equity or demographic dimension.

3.3.4. Study design and confidence level

Studies were classified according to a standardized typology reflecting differences in study design and associated causal inference strength: randomized controlled trials (RCT), quasi-experimental (QE), natural experiments (NE), behavioural experiments (EXP), pre–post (PP), and observational (OBS) designs.

A confidence level was then assigned to each coded outcome using a rule-based mapping from study design to causal inference strength (Table 1). RCTs and QE designs were classified as highest confidence, followed by NE, EXP and PP as medium depending on implementation, and OBS studies as lower confidence. Limited adjustments were made where methodological limitations were identified (e.g., small sample size, short follow-up, or risk of bias). A full list of study classifications and assigned confidence ratings is provided in Appendix A.

3.3.5. Outcome coding and signal classification

A rule-based signal coding framework was applied to enable consistent comparison across studies. Each study was coded using a single dominant outcome, prioritised as follows: (1) observed cycling behaviour at the individual or trip level; (2) self-reported cycling behaviour; (3) observed cycling volume, including cyclist counts or bicycle traffic data; and (4) aggregate active transport outcomes where cycling was explicitly included but could not be fully disaggregated.

This hierarchy distinguished between levels of outcome specificity. Bicycle counts were treated as direct measures of observed cycling volume at a given location, route, or network. However, where count data could not distinguish between new cycling uptake, increased cycling by existing cyclists, route redistribution, repeated trips by the same individuals, or shifts from other modes, they were interpreted as evidence of cycling activity rather than definitive evidence of individual-level behaviour change or modal shift. Aggregate active transport outcomes were treated as lower-specificity evidence because walking and cycling could not be separated, but were included only where cycling was explicitly part of the outcome and the intervention was cycling-relevant.

Effects were classified as positive (+), mixed (±), no change (0), or negative (–). Coding was based on observed behavioural change using conservative decision rules. Non-significant or trivial changes (e.g., <5%) were coded as no change. Mixed classifications were used only where genuinely conflicting effects were observed such as increases and decreases across different groups, locations, or time periods.

Signal strength was assigned using pragmatic thresholds to support comparison across heterogeneous outcome measures. These thresholds were not intended to define universal levels of policy importance, since the substantive meaning of a percentage change depends on the outcome, denominator, baseline cycling level, and exposure population. For example, a small percentage-point change in population cycling mode share may represent a meaningful policy effect, whereas a similar percentage change in cycling distance among existing cyclists may be more limited. The thresholds were therefore used as a conservative

Table 1
Study design typology and associated confidence level.

Code	Study type	Key feature	Assigned confidence level
RCT	Randomized controlled trial	Random assignment to intervention/control	High
QE	Quasi-experimental	Non-randomized comparison group	High
NE	Natural experiment	Real-world change, before–after comparison	Medium
EXP	Behavioural experiment	Controlled manipulation of conditions	Medium
PP	Pre–post study	Before–after, no control group	Medium
OBS	Observational	No intervention, correlational	Low

signal-coding tool rather than as absolute judgements of intervention importance.

Where percentage change was reported, effects were classified as:

- Trace: < 5% change
- Small: 5–15%
- Moderate: 15–40%
- Strong: > 40%

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Where percentage change was not reported, equivalent qualitative thresholds were applied based on the reported findings. To avoid inflation of effect size, strength caps were applied for count-based outcomes, subgroup-only effects, mixed results, short-term effects and self-reported-only outcomes. Strong effects (>40%) were reserved for direct cycling behaviour outcomes showing large, consistent, population-level changes. Localised cycling counts, subgroup-specific effects or short-term changes could not be coded as strong even when percentage increases were large.

Confidence ratings were assigned based on study design: high (RCT, QE), moderate (NE, PP), and low (OBS), with limited downgrading where methodological limitations where identified.

The coded dataset enables structured comparison across intervention types, behavioural mechanisms, and study contexts. Signal direction, strength, and confidence were analysed alongside intervention characteristics to identify patterns in effectiveness and implementation. Signal strength was analysed using both primary and all mechanisms present, allowing comparison between dominant behavioural pathways and the combined mechanisms through which interventions operate.

4. Results: outcome signals across the evidence base

The results are presented in two stages. Section 4 first describes the overall evidence base and summarises studies according to coded signal direction, signal strength, and confidence level. It then discusses studies coded as no change, mixed, positive, or negative to clarify how different types of evidence were interpreted. Section 5 then examines the same evidence through the behavioural mechanism framework, comparing outcomes by both primary mechanism and all mechanisms present within multi-component interventions.

4.1. Sample characteristics and overall signal distribution

The final sample included 124 studies spanning a range of intervention types (Appendix A). The vast majority of papers studied projects in the Global North, including Australia and New Zealand (12), Europe (48), North America (33) and the United Kingdom (18). Studies from China (6), Brazil (2) and Colombia (1) were included, along with four studies that were international in scope. Study settings varied in their baseline cycling context. The sample included high-cycling settings, such as the Netherlands, Denmark/Copenhagen, Vancouver (Canada), Cambridge (UK) and Davis (California, USA); moderate or emerging cycling settings, such as London, Toronto, Sydney, Auckland and Bogotá; and lower-cycling, more car-oriented settings, such as Atlanta, Kansas City, Los Angeles and Brisbane. These categories were used only to characterise contextual diversity and were not included as a formal analytical variable.

Structural interventions (STR) and behavioural interventions (BEH) account for the majority of studies, while resource and incentive interventions (RES) are less frequently evaluated (Table 2). Within these categories, infrastructure and street design interventions dominate within STR, while education, campaigns, and behavioural programmes are most common within BEH. Resource and incentive interventions include e-bike provision, subsidy schemes, and financial incentives, but are less frequently represented in the evidence base.

Table 3 summarises findings by signal direction and confidence level.

Table 2
Distribution of studies by primary intervention type.

Intervention Type	Description	Number of Studies	% of Sample
STR	Infrastructure, street design, and transport system changes affecting cycling conditions	47	37.9%
BEH	Education, training, campaigns, and behavioural programmes targeting knowledge, skills, or motivation	49	39.5%
RES	Bicycle and e-bike provision, subsidy schemes, and financial incentives	28	22.6%

Table 3
Distribution of studies by coded signal direction and confidence level.

Signal direction	High	Medium	Low	Total
Positive (+)	17	20	10	47
Mixed (±)	4	3	0	7
No change (0)	41	16	11	68
Negative (–)	0	2	0	2
Total	62	41	21	124

No-effect findings were most common (n = 68), followed by positive effects (n = 47), with relatively few mixed (n = 7) or negative (n = 2) results. This pattern is consistent across confidence levels, with high-confidence studies contributing substantially to both null (n = 41) and positive (n = 17) findings. Overall, the evidence base is heterogeneous, with null findings prevalent even among stronger study designs. Across studies coded as no change, interventions are often associated with changes in intermediate outcomes (e.g., counts, perceptions, or related behaviours) without measurable changes in cycling behaviour at the population level.

4.2. Studies coded as mixed or no change

Structural interventions: Several higher confidence structural interventions (STR), particularly infrastructure provision and street redesign, are associated with increases in cycling counts or use on specific routes, but not consistently with changes in overall cycling behaviour. For example, Skov-Petersen et al. (2017) found substantial increases in cycling volumes following infrastructure upgrades in the Capital Region of Denmark, but only a small share of trips was induced or new to cycling, with most reflecting redistribution from other routes within the network. Similarly, Rissel et al. (2015) reported substantial increases in counts on a new path in Sydney, but no change in cycling frequency among residents. In Hong et al. (2020), some routes in Glasgow showed increases, but there was no significant effect at the aggregate level. Heesch et al. (2016) found increased use of a new corridor in Brisbane, largely among existing cyclists.

Across these studies, increases in cycling volumes are often concentrated on treated routes and do not consistently correspond to increases in population-level cycling. In some cases, infrastructure provision has also shown mixed or null effects at the population level. For example, Evenson et al. (2005) found no increase in cycling following the construction of a multi-use trail.

Behavioural interventions (BEH), including school-based programs, public campaigns, and app-based or gamified interventions, are frequently associated with changes in knowledge, skills, attitudes, or motivation, but not consistently with sustained changes in cycling behaviour. For example, Aranda-Balboa et al., (2022) and Ducheyne et al. (2014) evaluated school-based cycling education and training programs aimed at improving cycling knowledge, skills, and capability among children. Stark et al. (2018) examined an adolescent-focused intervention combining elements of promotion and behavioural support. Other studies include app-based engagement tools and short-term participation initiatives designed to encourage active travel (e.g. Cellina et al., 2019; Bungum et al., 2014).

Across these studies, improvements in intermediate outcomes are common, but sustained changes in cycling behaviour are not. Where increases are observed, they are often short term. For example, Sersli et al. (2019) reported short-term increases following a structured cycling training program that were not sustained, while Bungum et al. (2014) observed temporary changes during a one-day active travel initiative followed by a return to baseline.

Some studies reported increases in active travel or physical activity overall, but no clear or significant cycling-specific change, and were therefore coded as no change under the outcome hierarchy. For example, Chang et al. (2017) reported increases in walking following a transport intervention, while Villa-González et al., (2016) observed increases in active commuting driven primarily by walking, with no significant change in cycling. These findings reflect changes in broader mobility patterns without corresponding changes in cycling behaviour.

A small number of studies report changes in perceived safety, convenience, or cycling conditions without corresponding changes in cycling behaviour. For example, Smith et al. (2020) evaluated school area infrastructure upgrades and reported mixed changes in safety perceptions without corresponding improvements in cycling behaviour. Aittasalo et al. (2019) examined a workplace-based active commuting intervention and observed increased motivation without behavioural change. Lanzendorf et al. (2022) evaluated the reallocation of road space to bicycle lanes and reported improvements in perceived cycling conditions, but no significant change in cycling behaviour.

Some studies show variation in outcomes across contexts or population groups, but do not demonstrate consistent population-level effects. For example, Hong et al. (2020) found increases in cycling along some routes but not others, while Hagen and Tennøy (2021) and Kyriakidis et al. (2023) reported limited or marginal behavioural changes following large-scale street reallocation interventions.

Seven studies were coded as mixed, reflecting variation in cycling behaviour across groups, locations, or contexts, with no consistent overall population-level effect. For example, Merom et al. (2003) found increased cycling among residents living close to a new trail, alongside decreases among those living further away. Other studies show variation by user group, with increases concentrated among those already predisposed to cycle (e.g. Tsirimpa et al. 2019). Structural interventions also show heterogeneous effects across locations (e.g. Xiao et al. 2023).

4.3. Studies coded as positive

Studies coded as positive show variation in effect size, with most reporting trace effects and a smaller number showing small to moderate changes in cycling behaviour. Modest effects are commonly associated with multi-component interventions combining structural (STR) and behavioural (BEH) elements, including area-wide programmes, infrastructure expansion, and national or local campaigns. For example, Goodman et al. (2013) evaluated town-wide cycling investment programmes in England combining infrastructure, promotion, and training, and reported a modest increase in cycling share over time. Pedroso et al. (2016) reported small absolute increases in cycling following infrastructure expansion in Boston, USA, while Nielsen and Haustein (2019) found a modest increase following a national cycling campaign in Denmark. Across these studies, increases in cycling behaviour are detectable but limited in magnitude at the population level.

Resource and incentive interventions (RES) are most consistently associated with positive changes, particularly where they increase access to cycling, with incentives reinforcing these effects. Interventions involving bicycle or e-bike provision, trials, or subsidies are associated with increases in cycling behaviour. For example, Söderberg et al. (2021) provided e-bikes to frequent car users in a randomized controlled trial in Sweden, resulting in increased cycling and reduced car use. Fyhri and Fearnley (2015) and Ton and Duives (2021) provided short-term access to e-bikes in commuter-focused trials in Norway and the Netherlands, leading to increases in cycling frequency and distance. Sundfør and Fyhri (2022) evaluated a public subsidy scheme in Oslo that reduced the cost of e-bike purchase, resulting in increases in cycling trips. Similar effects are observed in real-world programme evaluations, where e-bike rebate and lending schemes increase access to cycling and are associated with increased cycling and partial substitution of car trips, although effects may decline over time while remaining above baseline (e.g. Johnson et al., 2023; Fitch et al., 2022), including in structured workplace programmes that combine access with ongoing behavioural support.

Financial incentive interventions, where monetary rewards are directly tied to cycling behaviour, are also associated with increases in cycling. Máca et al. (2020) tested app-based financial incentives and gamification strategies in a randomized trial in Czech cities, while Ciccone et al. (2021) implemented a field experiment across multiple Norwegian cities using pay-per-kilometre and lottery-based incentives. Both studies reported increases in cycling activity linked to incentive structures. In these cases, effects are closely tied to incentive design and are often strongest in the short term. Hybrid approaches combining financial incentives with improved access to e-bikes show similar patterns, including substantial uptake of e-cycling and partial substitution of car trips, although some of this shift reflects substitution from conventional cycling (e.g. De Kruijf et al., 2018).

Some structural and system-level (STR) interventions that substantially alter accessibility or connectivity are associated with increased cycling behaviour. For example, Frank et al. (2021) evaluated a new urban greenway in Vancouver that improved local connectivity, resulting in increased cycling trips among residents living near the corridor. Pritchard and Frøyen (2019) examined workplace relocations from suburban to inner-city locations in Norway, which reduced commute distances and increased accessibility, and found substantial increases in cycling and walking among employees. Félix et al. (2020) evaluated the combined expansion of a cycling network and introduction of an e-bike sharing system in Lisbon, which increased access to cycling and reduced travel friction, and was associated with substantial increases in cycling volumes.

Across positive studies, increases in cycling behaviour are often associated with specific interventions or exposure conditions and are observed over defined time periods, including changes in mode choice and reductions in car use (e.g. Söderberg et al., 2021; Ton and Duives, 2021; Pritchard and Frøyen, 2019). At the same time, many studies report only small changes (e.g. Goodman et al., 2013; Pedroso et al., 2016; Nielsen and Haustein, 2019).

4.4. Studies coded as negative

Negative effects are rare and typically reflect substitution toward competing modes or improved efficiency reducing time spent cycling. For example, Dill et al. (2014) evaluated bicycle boulevards in Portland, USA, and found no overall increase in cycling, with some evidence of small but statistically significant reductions in cycling time and trips. Sun et al. (2020) evaluated the introduction of a new urban metro system on cycling and walking in Nanchang, China, and found large and statistically significant declines in cycling time following the transport system change, reflecting substitution toward metro use and broader reductions in active travel.

5. Behavioural mechanisms and outcome patterns

To examine the relationship between behavioural mechanisms and cycling outcomes, studies were analysed according to both their primary behavioural mechanism and all mechanisms present within each intervention. This section proceeds in three steps. First, it compares outcome direction by behavioural mechanism. Second, it examines coded signal strength among studies with positive outcomes. Third, it relates these mechanism patterns to intervention type and cost.

5.1. Outcome direction by behavioural mechanism

Across both analyses, a consistent pattern emerges, with differences between mechanisms that are central to interventions (Table 4; Fig. 1A) and those that are more broadly present. When considering all mechanisms (Table 5; Fig. 1B), access-related mechanisms (ACC) show the highest proportion of positive outcomes relative to no change. This represents interventions that directly provide access to bicycles or e-bikes, including trials, subsidies, and bike-share programmes, which are associated with increases in cycling and reductions in car use (e.g. Fyhri and Fearnley, 2015; Söderberg et al., 2021; Ton and Duives, 2021; Bjørnarå et al., 2019; Hosford et al., 2019).

Habit-related mechanisms (HAB) show a relatively high proportion of positive outcomes when all mechanisms are considered, but this pattern is not observed when HAB is the primary mechanism. Evidence from behaviour change programmes suggests that habit-based interventions can produce increases in cycling behaviour when implemented on their own, but these effects are typically small (e.g. Ruiz et al., 2018). Larger increases are observed where habit formation occurs alongside other mechanisms, such as incentives, social programmes, or improved access (e.g. Minnich, 2023; Ciccone et al., 2021; Mendoza et al., 2017; McDonald et al., 2013). When examining primary mechanisms (Table 4; Fig. 1A), safety (SAF), motivation (MOT), and access (ACC) show similar proportions of positive outcomes, indicating that these mechanisms can be associated with positive change.

In contrast, mechanisms related to information (INF) and capability (CAP) show limited and inconsistent associations with cycling behaviour. While some interventions that build skills or confidence report increases in cycling (e.g. Schneider et al., 2018; Carlson et al., 2020; Kearns et al., 2019), these effects are typically small, context-specific, or, statistically, lower-confidence. Evidence for information-based mechanisms is more limited, with few cases where information is the primary driver of change (e.g. Olsson et al., 2021), and most positive change being associated with broader interventions (e.g. Biondi et al., 2022; McDonald et al., 2013).

Safety-related (SAF) mechanisms are widely represented and are associated with positive outcomes in some cases, particularly in infrastructure interventions that improve cycling conditions in specific locations (e.g. Li et al., 2018; Boarnet et al., 2005; McDonald et al., 2014). However, these effects are often localised and are not consistently associated with population-level change. Mechanisms related to motivation (MOT) and convenience (CON) show mixed effects. Positive outcomes are observed in some cases, particularly in interventions that provide financial incentives or rewards (e.g. Máca et al., 2020; Ciccone et al., 2021; Sundfør and Fyhri, 2022), but effects vary depending on design and duration. For example, financial incentives can substantially increase cycling behaviour, while gamification-based interventions show more variable effects (e.g. Minnich, 2023).

5.2. Signal strength by behavioural mechanism

Patterns of signal strength further refine these findings (Table 6; Fig. 2). The strength categories should be interpreted as coded signal categories rather than directly comparable effect sizes, since the substantive meaning of a percentage change varies across outcome types, denominators, and exposure populations. Within this coding framework, positive outcomes involving access-related (ACC) mechanisms were most often coded as small to moderate with one strong signal observed in a multi-component intervention. Motivation-related (MOT) mechanisms show a similar distribution, particularly when combined with other mechanisms. In contrast, safety (SAF) and convenience (CON) are most commonly associated with small or trace effects, while habit (HAB), social influence (SOC), and capability (CAP) show stronger coded signals primarily when combined with other mechanisms. Information-based mechanisms remain associated primarily with trace-level effects.

One notable example is a school-based bicycle train intervention in Seattle (Mendoza et al., 2017), which reported a strong effect in a randomized controlled trial; however, this intervention combined bicycle and equipment provision, structured group riding, training, and repeated participation, indicating that the observed effect reflects multiple reinforcing mechanisms rather than a single mechanism acting independently.

5.3. Intervention type, cost and mechanism alignment

These patterns also align with differences in intervention type (Fig. 3) and cost (Fig. 4). Resource and incentive interventions (RES), generally medium cost, are most consistently associated with measurable changes in cycling behaviour, particularly where they increase access (ACC) and, in some cases, reinforce behaviour through incentives (MOT), as observed in e-bike provision, subsidy, and incentive studies (e.g. Söderberg et al., 2021; Fyhri and Fearnley, 2015; Sundfør and Fyhri, 2022; Máca et al., 2020; Ciccone et al., 2021).

Structural interventions (STR), generally high cost, are more frequently associated with changes in local conditions, including improvements in safety (SAF) and convenience, but often produce localised or spatially concentrated effects, reflecting redistribution of cycling within the network (e.g. Skov Petersen et al., 2017; Rissel et al., 2015; Heesch et al., 2016). Behavioural interventions (BEH), generally low cost, are commonly associated with changes in intermediate outcomes such as knowledge, confidence, or motivation, but are not consistently associated with sustained behavioural change (e.g. Ducheyne et al., 2014; Stark et al., 2018; Bungum et al., 2014).

Taken together, intervention type and cost broadly align with the mechanisms through which change occurs. A general conclusion is that resource-intensive interventions are more likely to alter access and travel conditions, while lower-cost interventions are more likely to influence perceptions and capabilities without producing substantial behavioural change on their own.

Overall, these findings indicate a hierarchy of behavioural

Table 4
Outcome direction by primary behavioural mechanism.

Mechanism	Definition	Positive	No Change	Mixed	Negative	Total
ACC	Access / opportunity enabling	9	11	2	1	23
SAF	Safety / risk reduction	19	22	1	1	43
MOT	Motivation & incentives	8	9	2	0	19
SOC	Social influence & norms	5	8	0	0	13
CAP	Capability & self-efficacy	3	8	0	0	11
INF	Information & awareness	1	4	2	0	7
HAB	Habit formation / prompting	1	4	0	0	5
CON	Convenience / friction reduction	1	2	0	0	3
Total		**47**	**68**	**7**	**2**	**124**

One mechanism per study; n = 124.

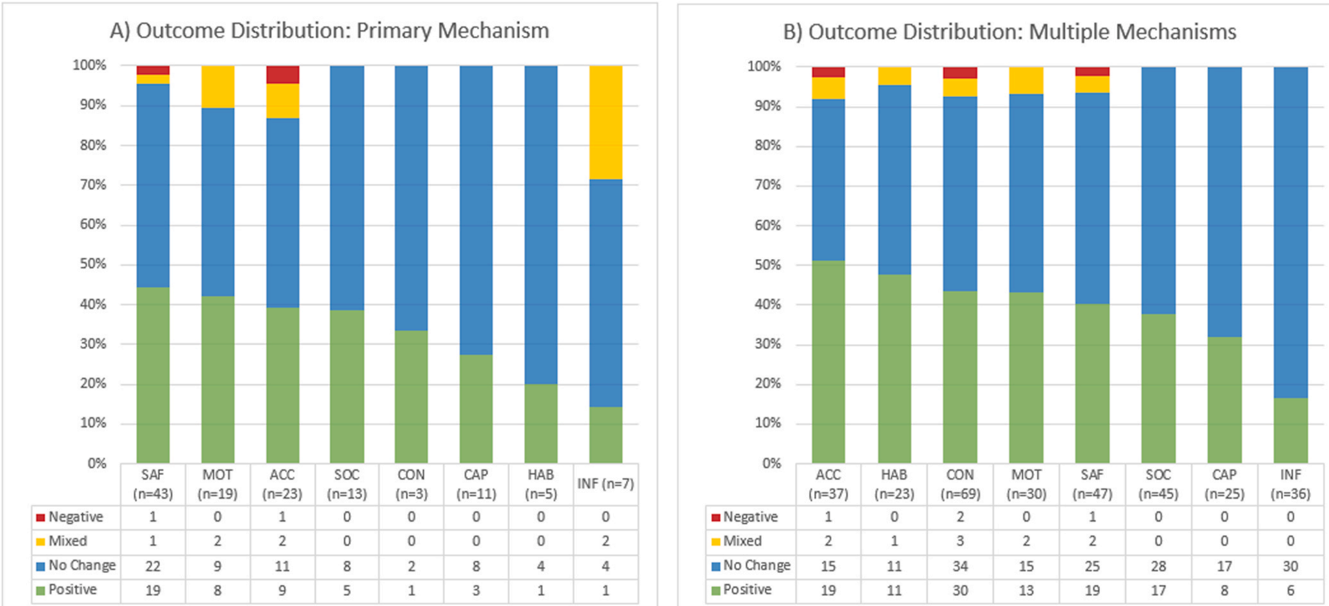


Fig. 1. Outcome distribution by behavioural mechanism (A) Primary mechanism only: each study is assigned a single primary behavioural mechanism. (N = 124) (B) Multiple mechanisms: all behavioural mechanisms present within each intervention are included (N = 312). Bars show the percentage distribution of outcome direction for each mechanism. Results indicate that while safety (SAF), motivation (MOT), and access (ACC) show similar proportions of positive outcomes when considered as primary mechanisms, access-related mechanisms are most consistently associated with positive outcomes across multi-component interventions. In contrast, information (INF) and capability (CAP) are predominantly associated with no change in both analyses.

Table 5
Outcome direction by all behavioural mechanisms present.

Mechanism	Definition	Positive	No Change	Mixed	Negative	n of mechanism
CON	Convenience / friction reduction	30	34	3	2	69
SAF	Safety / risk reduction	19	25	2	1	47
SOC	Social influence & norms	17	28	0	0	45
ACC	Access / opportunity enabling	19	15	2	1	37
INF	Information & awareness	6	30	0	0	36
MOT	Motivation & incentives	13	15	2	0	30
CAP	Capability & self-efficacy	8	17	0	0	25
HAB	Habit formation / prompting	11	11	1	0	23
Total		123	175	10	4	**312**

N refers to the number of coded intervention–outcome observations in which the mechanism was present. Mechanisms were not mutually exclusive, so totals across rows exceed the number of studies/interventions.

Table 6
Signal strength by all behavioural mechanisms.

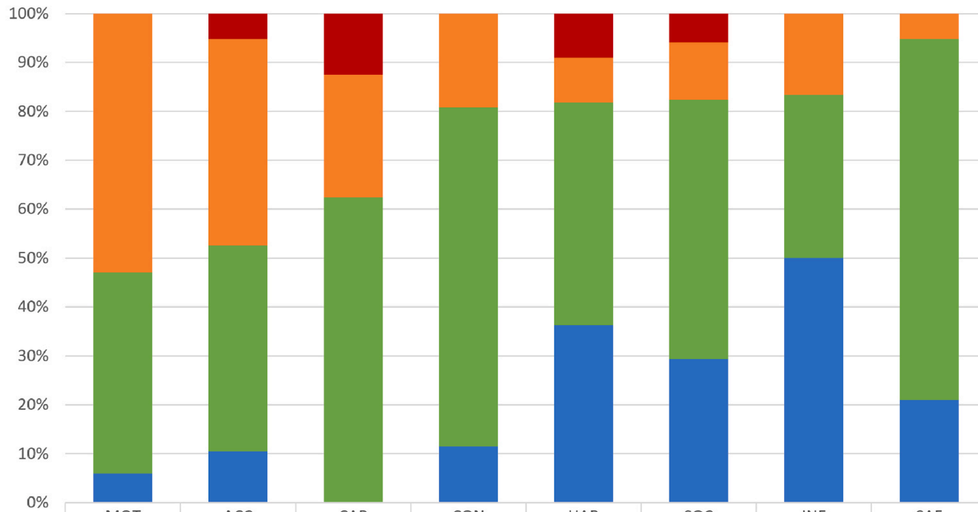
Mechanism	Definition	Trace	Small	Moderate	Strong	Share coded moderate / strong %
MOT	Motivation & incentives	1	7	9	0	52.9
ACC	Access / opportunity enabling	2	8	8	1	47.4
CAP	Capability & self-efficacy	0	5	2	1	37.5
CON	Convenience / friction reduction	3	18	5	0	19.2
HAB	Habit formation / prompting	4	5	1	1	18.2
SOC	Social influence & norms	5	9	2	1	17.6
INF	Information & awareness	3	2	1	0	16.7
SAF	Safety / risk reduction	4	14	1	0	5.3

Positive studies only; multiple mechanisms per study allowed; counts exceed total studies.

mechanisms. Access and opportunity (ACC) are most consistently associated with positive outcomes across multi-component interventions, while safety (SAF) and motivation (MOT) can also produce behavioural change when they are the primary mechanism. Habit formation (HAB) appears to contribute to behavioural change but is associated with only small effects when targeted on its own, and plays a more important role in reinforcing behaviour alongside other mechanisms. In contrast, changes in information, capability, and social influence alone are not consistently associated with sustained behavioural change. In conclusion, behaviour change is most consistently associated with interventions that enable access to cycling, with other mechanisms contributing in more context-dependent ways.

6. Discussion

The findings point to a consistent pattern in how cycling behaviour



	MOT	ACC	CAP	CON	HAB	SOC	INF	SAF
Strong	0	1	1	0	1	1	0	0
Moderate	9	8	2	5	1	2	1	1
Small	7	8	5	18	5	9	2	14
Trace	1	2	0	3	4	5	3	4

Fig. 2. Distribution of coded signal strength by behavioural mechanism (positive studies only) Bars show the percentage distribution of coded signal strength (trace, small, moderate, strong) among studies reporting positive outcomes (n of positive studies=47, n of mechanisms=123). These categories are not directly comparable effect sizes. Because multiple mechanisms may be present within a single study, totals exceed the number of studies. Mechanisms are ordered by the proportion of moderate and strong coded signals based on multi-mechanism counts (i.e. the share coded moderate/strong percent in Table 6). Access-related mechanisms (ACC) and motivation-related mechanisms (MOT) are most frequently associated with moderate coded signals, and in some cases strong signals when combined with other mechanisms, while safety (SAF) and convenience (CON) are predominantly associated with small or trace coded signals. Habit (HAB), social influence (SOC), and capability (CAP) show stronger coded signals primarily in combination with other mechanisms, while information-based mechanisms (INF) are largely associated with trace-level coded signals.

Fig. 3. Types of interventions by coded signal direction and strength Distribution of studies by primary intervention type (behavioural [BEH], resource and incentive [RES], and structural [STR]) across signal direction (positive, mixed, no change, negative) and signal strength (1–4). Each point represents an individual study. Positive signals are most frequently observed among RES interventions at moderate strength, while STR interventions are more widely distributed across positive and no-change outcomes, often with smaller or mixed effects. BEH interventions are concentrated in the no-change and small positive signal categories, indicating more frequent effects on intermediate outcomes without consistent evidence of sustained behavioural change.

responds to different types of interventions and behavioural mechanisms, but these patterns should be interpreted in light of

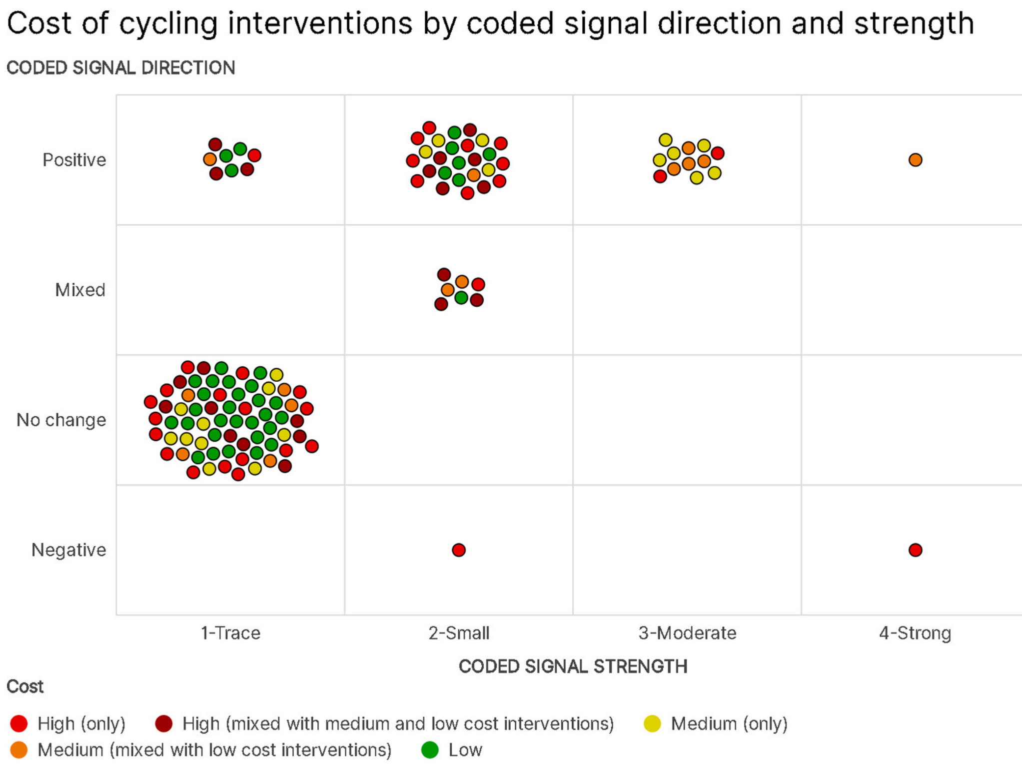


Fig. 4. Cost of cycling interventions by coded signal direction and strength Distribution of studies by intervention cost (low, medium, high, and mixed-cost classifications) across signal direction (positive, mixed, no change, negative) and signal strength (1–4). Each point represents an individual study. Medium-cost interventions are most frequently associated with positive signals of moderate strength, while low-cost interventions are concentrated in the no-change and small-effect categories. High-cost interventions are more widely distributed, including both positive and null findings, reflecting variability in outcomes and potential spatial redistribution effects.

variation in the distribution of evidence across mechanisms and intervention types. Some mechanisms, particularly those related to safety and structural interventions, are more frequently studied than others, reflecting both policy priorities and the relative ease of evaluating infrastructure-based changes (Pearson et al., 2025).

In contrast, mechanisms such as convenience, habit formation, and information are less often examined as primary drivers of behaviour change. As a result, observed differences reflect both variation in effectiveness and differences in the volume and type of available evidence. However, access-related mechanisms (access to bicycles, equipment, or facilities) are most frequently associated with positive outcomes across both primary and multi-mechanism analyses despite not being the most frequently studied category - suggesting that their observed effectiveness is unlikely to be explained solely by differences in evidence density.

These findings are broadly consistent with recent reviews, while extending them through a more explicit focus on behavioural mechanisms. Roaf et al. (2024) emphasise the importance of multicomponent interventions, e-bikes, and cycle-sharing schemes, while Pearson et al. (2025) find the strongest effects for physical environmental restructuring, with additional evidence for e-bike provision and tailored behavioural programmes. Fitch-Polse and Agarwal (2025) similarly highlight the role of access, perceptions, land use, network connectivity, and policy context. The present study supports these conclusions, but suggests that differences across intervention types can partly be understood in terms of whether interventions alter opportunity and access, or instead seek to influence information, skills, or motivation within existing constraints.

Taken together, the results indicate that interventions are most consistently associated with behavioural change when they directly alter the conditions required to cycle, rather than when they seek to influence behaviour alone. Interventions that enable access, such as providing bicycles or reducing cost barriers, change the set of feasible travel options, while interventions focused on information, skills, or motivation tend to operate within existing constraints.

COM-B provides a useful basis for interpreting these patterns because it helps distinguish between interventions that alter the feasibility of cycling and those that mainly alter readiness to cycle. In this evidence base, interventions targeting capability or motivation often improved knowledge, confidence, attitudes, or intention, but did not consistently change behaviour where the opportunity to cycle remained constrained. By contrast, access-oriented interventions appear to change the conditions under which cycling becomes a feasible option, by providing bicycles or e-bikes, reducing cost barriers, or making cycling more practically available. The implication is not that capability or motivation are unimportant, but that they appear more likely to translate into sustained cycling when opportunity conditions are also altered.

This distinction helps explain why structural and behavioural interventions often produce changes in intermediate outcomes without corresponding changes in behaviour (Larsen et al., 2024; Roaf et al., 2024). Improvements in safety, convenience, knowledge, or confidence may reduce barriers or increase willingness to cycle (e.g., Vera-Villarroel et al., 2016; von Stülpnagel and Binnig, 2022), but do not necessarily result in uptake where access, distance, or competing travel options remain unchanged. In this context, redistribution effects observed in infrastructure interventions can be explained by route choice changes.

The findings also suggest that behavioural mechanisms operate differently depending on whether they act as primary drivers or reinforcing conditions. Access-related mechanisms are most consistently associated with measurable change, while mechanisms such as motivation, habit formation, and social influence appear to play a supporting role (Aldred and Jungnickel, 2014), strengthening or sustaining behaviour. This is consistent with the pattern observed in multi-component interventions, where larger effects are more likely to occur when multiple mechanisms operate together (Roaf et al., 2024).

Differences in effect size further reflect this structure. Many interventions produce only small or context-specific changes, while larger effects are less common and tend to occur where access is combined with reinforcing mechanisms or where structural conditions substantially alter travel patterns. This helps explain the concentration of moderate effects among resource and incentive interventions, as well as the more variable outcomes observed in structural interventions.

Cost patterns broadly align with these findings, although they should be interpreted cautiously given difference in intervention scale and exposure definition. Lower-cost behavioural interventions are more frequently associated with changes in perceptions, knowledge, or motivation without sustained behavioural change, while medium-cost interventions that improve access are more consistently associated with measurable effects among exposed participants. Higher-cost structural interventions show more variable outcomes, reflecting both their potential to alter travel conditions and the likelihood that observed changes may be spatially concentrated, diluted across broader evaluation populations or offset by redistribution.

The findings support the argument that sustained increases in cycling are likely to require continuous and combined interventions that reshape both opportunity structures and social norms over time. This is reflected in real-world cases such as Copenhagen, where long-term, sustained investment in cycling infrastructure, averaging approximately DKK 160 million (€21 million) annually between 2016 and 2025, with a substantial increase to around DKK 600 million (€80 million) in 2026, has contributed to high cycling levels (Wonderful Copenhagen, 2025). Notably, these investments have been accompanied by campaigns focused on identity (Gössling, 2013). Such cases illustrate how repeated and complementary interventions can gradually shift both structural conditions, socio-cultural expectations and social identities.

At the same time, the findings highlight important limitations in the evidence base. Variation in study design, outcome measurement, and follow-up duration limits comparability across studies. A further limitation concerns variation in intervention scale and exposure definition. Studies of infrastructure interventions often evaluate outcomes across broad areas or populations, such as neighbourhoods, corridors, or cities, while studies of incentives, e-bike provision, or access-based programmes often evaluate participants who directly received the intervention. As a result, the same percentage change may have different substantive meanings across intervention types. Some observed differences between structural, behavioural, and resource-based interventions may therefore reflect not only differences in intervention effectiveness, but also systematic differences in study design, exposure population, outcome measurement, and evaluation scale. Many studies also present short-term outcomes, making it difficult to assess persistence of behavioural change over time. In addition, relatively few studies explicitly examine equity or distributional effects, limiting understanding of how interventions affect different population groups. The classification framework applied in this study improves consistency in interpretation but does not eliminate the limitations set by the available studies.

A COM-B-informed approach also highlights a reporting limitation in the cycling intervention literature. Many studies describe the intervention delivered, but not the behavioural pathway through which it was expected to change cycling. This makes mechanism coding partly interpretive, especially for multicomponent interventions. Future studies would therefore benefit from specifying the intended behavioural mechanism more clearly, alongside the intervention components and cycling outcomes.

These findings have implications for both research and practice. For research, they suggest the value of moving beyond intervention typologies toward approaches that explicitly consider behavioural mechanisms and their interaction. For practice, they highlight the importance of aligning intervention design with the mechanisms most likely to produce change, particularly where interventions aim to increase cycling at the population level rather than redistribute existing demand.

7. Conclusion

This study provides a structured synthesis of evidence on cycling interventions, combining a rule-based outcome classification framework with a behavioural mechanism approach to enable comparison across heterogeneous study designs. By shifting focus from intervention types to the mechanisms through which interventions operate, the analysis offers a more consistent basis for understanding how and under what conditions cycling behaviour changes.

Across the evidence base, changes in cycling behaviour are most consistently associated with interventions that enable access to cycling, particularly where these are supported by additional mechanisms such as incentives, social reinforcement, or repeated engagement. In contrast, interventions that primarily target information, skills, or motivation are less consistently associated with sustained behavioural change when implemented in isolation, despite their role in shaping intermediate outcomes.

These findings suggest that increasing cycling at the population level depends less on influencing individual attitudes or intentions alone, and more on altering the conditions that make cycling a viable and accessible option. At the same time, the interaction between mechanisms highlights the importance of multi-component approaches, where enabling conditions are reinforced through complementary behavioural strategies.

The analysis also underscores the importance of consistency in outcome measurement and interpretation. The rule-based signal classification framework applied in this study provides one approach to addressing variability in study design and reporting, supporting more transparent comparison across interventions. However, differences in context, implementation, and study design remain important constraints on generalisability.

Overall, the findings highlight the need to align intervention design with the mechanisms most likely to produce behavioural change, while recognising the role of context and the limitations of the current evidence base. Future research would benefit from longer-term evaluation, greater attention to distributional effects, and more explicit integration of behavioural mechanisms into study design and analysis.

CRediT authorship contribution statement

Stefan Gössling: Writing – original draft, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Shawna McKinley:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT−5.3 in order to assist with developing and applying classification frameworks, and supporting the organisation and coding of study characteristics. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Shawna McKinley reports financial support was provided by the European Union's, Horizon Europe Framework Programme (HORIZON) under GA No 101094639 – THE URBAN BURDEN OF DISEASE ESTIMATION FOR POLICY MAKING (UBDPolicy). Stefan Gössling reports financial support was provided by the European Union's, Horizon Europe Framework Programme (HORIZON) under GA No 101094639 – THE URBAN BURDEN OF DISEASE ESTIMATION FOR POLICY MAKING

(UBDPolicy). If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This project has received funding from the European Union's, Horizon Europe Framework Programme (HORIZON) under GA No 101094639 – THE URBAN BURDEN OF DISEASE ESTIMATION FOR POLICY MAKING (UBDPolicy).

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jcmr.2026.100123.

Data availability

Data is provided in Appendix A.

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