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Original Article

Urban commuting interventions for greenhouse gas emissions reduction

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Abstract

Transportation is a major contributor to climate change. Commuting plays a key role in the greenhouse gas (GHG) emissions of the transport sector, which are expected to increase owing to increasing passenger car use. Reducing these emissions requires efforts to shift travel behaviour, with low-emission commuting interventions providing a viable path forward. However, limited research and quantified evidence exist on the impact of such interventions. This study evaluated 21 low-GHG emission commuting interventions implemented in six organisations in Lahti, Finland. Using primary data from pre- and post-intervention surveys, along with life-cycle emission factors reported in the literature, this study quantified a 12.5% reduction in commuting-related GHG emissions among respondents who completed both surveys (210/547 respondents). Communication and awareness, transportation infrastructure improvements, and transport service enhancements were the most effective interventions, whereas incentive-based and health and well-being coach approaches showed limited impacts. However, the results might have been impacted by confounding factors, and the GHG emission reduction was mainly due to the reduction in passenger car use. The findings of this study reveal the intervention

types that most strongly drive emission reductions and highlight the need for future research to understand why certain interventions underperform, the factors that limit shift to low-emission modes, and how intervention combinations can be optimised. This study provides novel insights that support organisations, city planners, and policymakers in prioritising interventions that meaningfully shift travel behaviour and advance sustainable urban mobility strategies.

Keywords: Travel behaviour, transportation emissions, mobility strategies, behavioural change, low-carbon mobility, climate mitigation

INTRODUCTION

The increasing concentration of greenhouse gas (GHG) emissions is a major driver of anthropogenic climate change[1], causing higher global temperatures, natural disasters, social challenges, and risks to the energy, agriculture, and forestry sectors, among others[2]. Global surface temperatures increased by 1.1 °C from the 1900 levels in the 2020s, while emissions continue to increase[3]. A 2 °C increase would markedly heighten the risk of severe impacts, including extreme weather events, rising sea levels, and ecosystem disruptions[4]. The European Commission's roadmap stipulates that the European Union (EU) must reduce GHG emissions to 90% of the 1990 levels by 2040 to achieve a net-zero economy by 2050. However, with the current measures, emissions are projected to decline by only 60% by 2040 and 64% by 2050[5]. Hence, additional reduction efforts and stricter climate policies are essential to meet the 2040 targets.

Transportation is vital for modern life and economic development but remains a major contributor to climate change. The sector emits approximately 8.7 billion metric tonnes of CO_2 equivalent annually, accounting for approximately 15% of the total GHG emissions and 23-26% of the global energy-related CO_2 emissions[6,7]. It is the second largest source of GHG emissions after the energy sector[8]. Road transport is the primary source of transport-related GHGs[9] and is responsible for nearly 75% of emissions[6]. Within this, passenger vehicles, including cars and buses, account for 45%[10], highlighting commuting as a key emissions driver[11]. Unlike other sectors, transport emissions continue to grow, increasing at an average annual rate of 1.8% over the past decade, largely owing to road traffic[6,7].

The literature outlines four key actions for low-emission and sustainable mobility: reducing travel demand, encouraging modal shifts, shortening trip lengths, and improving transport efficiency[12]. These can be achieved through remote work, active and public transport, well-located housing, and the adoption of clean technologies[12]. However, achieving low-emission transport also requires behavioural change to shift societal norms towards more environmentally conscious and inclusive mobility[13]. Technological solutions alone are insufficient to meet the 1.5 °C target and that public support and behavioural changes are essential[14]. Their findings underscore the need for further research on the role of behaviour in reducing consumption-based emissions.

Evidence synthesised across literature reviews shows that transport-related interventions can reduce car use, but effects are often small, inconsistent, and context dependent[15-18]. Specifically, 74% of 31 reviewed studies observed reductions in car use after transport-related interventions, stemming from hard interventions (e.g. parking restrictions, congestion charging, and pedestrian infrastructure development), soft interventions (e.g. personalised travel planning campaigns), and combined approaches; however, only seven of the studies demonstrated a statistically significant reduction in car use[15]. Similarly, an umbrella review reported positive but variable effectiveness across 18 included reviews, concluding that interventions such as active school travel, teen mobility programmes, organisational travel plans, and walking for transport can contribute to reduced car dependence when implemented in combination[18]. The review further emphasised that addressing the continued growth in private vehicle use requires integrated strategies that combine supportive 'carrot' measures with restrictive 'stick' policies.

Complementing these findings, a meta-analysis of 41 well-controlled studies identified a statistically significant 7% reduction in car modal share from soft interventions, driven primarily by measures targeting social and moral norms; broader contextual factors such as city size, incentives, and gender did not significantly affect outcomes[16]. Soft measures can motivate voluntary shifts from car use, though substantial gaps remain in evidence, particularly regarding long-term effects and synergies with hard infrastructure[17]. By contrast, a large-scale field experiment involving 68,915 employees revealed that behavioural interventions previously effective in other contexts, such as personalised travel plans, free bus trials, peer-testimonial letters, and loss-framed messages, had negligible impacts on reducing single-occupancy vehicle commuting, suggesting that soft interventions alone may be insufficient to overcome deeply rooted travel habits[19].

Additional evidence from air pollution-related behaviour studies shows that travellers often make only short-term adjustments, such as changing routes or travel times, rather than shifting to sustainable travelling modes[20]. Similarly, a review of nearly 800 interventions, found that only a small fraction of interventions, namely congestion charging, parking and traffic control, and limited traffic zone, were most effective at reducing car use[21]. They further noted that the evidence base for effective car-use reduction has shown little improvement over the past decade due to persistent methodological gaps, including a lack of real-world evaluations, absence of standardised metrics, and limited reporting of GHG outcomes[21]. Taking together, these reviews suggest that a wide range of interventions can reduce car dependence. However, there is still limited strong evidence on their magnitude, significance, durability, and mechanisms of change, highlighting the need for further rigorous real-world evaluations of multi-intervention strategies.

A review of cycling interventions found that individual measures, such as dedicated bike lanes, bicycle parking facilities, and promotional programmes, can increase cycling[22]. However, the largest and most sustained gains occurred when cities implemented comprehensive packages combining infrastructure, education, supportive land-use planning, and restrictions on car use. Behaviour-focused cycling interventions, such as personalised travel planning and mobile apps, showed modest but positive effects[23].

Broader policy literature emphasises that no single policy is sufficient and that integrated packages combining demand reduction, modal shift, and efficiency measures are necessary to meet climate goals[24,25]. Furthermore, understanding the interactions between behavioural, infrastructural, and regulatory tools is critical, though evidence on their synergies remains limited[26]. Scientometric reviews have identified growing research on car use, cycling, and public transport while emphasising major gaps in trip-avoidance strategies, such as remote or hybrid work[27]. Reviews of travel reduction and eco-driving have similarly stressed the need for institutional measures that target behavioural drivers alongside technology[28].

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Behavioural science from adjacent domains reinforces these insights. Reviews of transport-related behavioural interventions have identified GHG reductions from incentives while noting gaps in experimental designs and long-term follow-ups[29]. Furthermore, attitudes and travel behaviours are not linearly linked; rather, habits, social norms, perceived control, and personal identity play a pivotal role in shaping mobility choices and should be explicitly accounted for in policy design[30].

Despite this progress, community- and workplace-scale empirical studies remain limited. High-involvement organisational programmes can reduce car use[31], but most evaluations lack longitudinal data and direct measurements of emission reductions. A systematic review found no peer-reviewed experimental evaluations of community-wide GHG interventions[32]. Collectively, these gaps highlight the need for rigorous real-world studies that assess bundled interventions, measure actual emissions, examine organisational and policy interactions, and incorporate equity and cost considerations[18,22,24].

While a substantial body of research has examined low-emission transport strategies, much of the evidence relies on scenario-based analyses or evaluates individual interventions in isolation, limiting applicability to real-world multi-intervention settings. For instance, one study modelled future scenarios comparing business-as-usual conditions with individual interventions such as metro expansion and bus priority corridors and found shifts towards public and non-motorised transport but without assessing combined effects[33]. Similarly, shared-mobility CO_2 reductions have been simulated without integrating complementary strategies[34], and incentive and deterrent measures have been examined without quantifying emissions outcomes[35]. Collectively, these studies illustrate that the current evidence base remains largely fragmented, with limited empirical evaluation of how multiple interventions interact under real commuting conditions.

Responding to these gaps, this research provides a real-world, community-scale evaluation of multiple commuting interventions, including communication and awareness campaigns, nudging-based messaging, workplace transport infrastructure improvements, and transport service enhancements and their combined effects on travel behaviours and GHG emissions. It empirically evaluated 21 low-emission commuting interventions,

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grouped into five categories, across six case organisations in a mid-sized European city, using matched before-after commuting data and life-cycle emission factors (EFs). Unlike many prior studies that focused on single interventions or relied on modelling, this research examined the effectiveness of various intervention types and combinations under actual implementation conditions. This research investigated three core questions:

•What are the changes in modal shares after the set of interventions implemented in six organisations in the city of Lahti, Finland?

•How did GHG emissions change after the implementation of commuting-related interventions?

•How did behavioural impact scores (BISs) differ across intervention categories?

By answering these questions, this research makes the following contributions:
1.Empirical novelty: The study provides evidence on the real-world impacts of combined commuting interventions on travel behaviours and commuting-related GHG emissions. It quantifies observed changes in modal use, commuting distance, and GHG emissions by using primary survey data collected before and after the intervention period.

2.Methodological contribution: The study introduces the BIS approach to quantify the behavioural influence of each intervention category by integrating reach, uptake, and perceived effect. This provides insight into how strongly each category contributes to conditions that support modal shift.

3.Policy relevance: The findings inform policies aimed at reducing commuting-related GHG emissions by highlighting the importance of organisational-level, multi-strategy intervention packages. The results suggest that employers and local authorities should combine nudging-based communication and awareness measures with structural interventions, such as workplace location decisions, transport service improvements, and cycling or walking infrastructure. Such integrated approaches are needed to reduce private car commuting distances and to achieve meaningful emissions reductions.

Together, these contributions help build a clearer understanding of sustainable transport transitions by focusing on integrated, evidence-based approaches rather than isolated interventions.

METHODOLOGY

Study area

The analysis of this study focused on the city of Lahti, Finland, the capital of the Päijät-Häme region and the country's eighth largest city, with a population of 120,000[36]. Finland's long, cold winters and seasonal variability significantly influence mobility choices, especially a strong reliance on private passenger cars—an important consideration for designing emission reduction strategies[37].

Lahti has 665 km of streets and 543 km of bicycle paths, including 166 km reserved for non-motorised traffic. A bike-sharing programme with 500 bikes at 62 stations was launched in 2023[38]. Alongside other micromobility options such as e-scooters, these features support a shift towards more sustainable and low-emission urban transport. Despite this infrastructure, private car dependence remains high. According to Päijät-Häme's 2021 passenger mobility study, 70% of households in Lahti own cars. Passenger cars accounted for 66% of trips (51% as drivers and 15% as passengers), whereas walking, cycling, and bus use remained low at 23%, 6%, and 3%, respectively, highlighting significant potential for modal shift[37].

Methodological steps

This study employed an empirical evaluation framework based on primary data from pre- and post-intervention employee commuting surveys, which captured self-reported commuting modes, distances, and frequencies. These survey data were combined with transport mode–specific life-cycle EFs from the literature to estimate changes in commuting-related GHG emissions on a per person-kilometre basis. The primary objective of this approach was to evaluate the climate impacts of the interventions by comparing commuting GHG emissions before and after implementation.

The approach consisted of three steps: (1) collecting pre- and post-intervention data on commuting habits in selected case organisations, (2) calculating commuting-related GHG emissions, and (3) evaluating intervention impacts using reach, uptake and perceived effect scores [Figure 1].

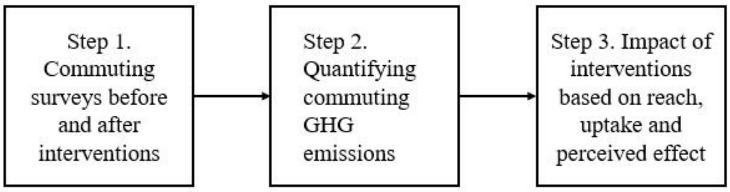

Figure 1. Outline of the research.

Commuting surveys before and after the interventions

Two surveys were conducted in six case organisations in Lahti, Finland, one before and one after the interventions, to capture information related to commuting behaviour. The participating organisations represented diverse sectors and were located at multiple sites across the city. The surveys collected self-reported data on employees' commuting modes, distances, and frequencies and the perceived intervention impact on commuting behaviour, forming the basis for calculating commuting-related GHG emissions and intervention impacts. Survey participation was voluntary and anonymous, and questionnaires were distributed via email and organisational intranet platforms using a Webropol link.

Round-trip distances were assumed to be twice the reported one-way trip distances collected in the surveys. To account for seasonal variation, the survey collected data for both summer (April–September) and winter (October-March) commuting, assuming that both seasons are of equal duration in Finland. The average annual commuting distance was calculated by averaging the summer and winter values. For each transport mode, the total average daily distance was calculated by aggregating the average daily distances reported by all respondents.

The baseline survey (Survey 1 [S1]), conducted between November 2023 and February 2024, collected data on employees' current commuting habits (n = 547), representing approximately 33% of the total employee population across the six case organisations (n = 1,638). A second survey (S2) was conducted between November and December 2024 to assess changes in commuting modes and distances after the implementation of the interventions. As S2 was conducted at the onset of winter, the respondents were asked to estimate their upcoming seasonal commuting behaviours. S2 received responses from 308 respondents, of which 210 had also participated in S1, corresponding to 13% of the total employee population and 38% of the baseline sample.

Statistical analyses were performed to assess whether the differences observed between S1 and S2 reflected meaningful changes in commuting distance, modal share, and commuting frequency rather than random variation. As the surveys were fully anonymous, individual responses could not be linked across surveys, and paired analyses were not possible. Thus, S1 and S2 were analysed as independent cross-sectional samples for behavioural outcomes, with all valid respondents in S2 (n = 308) included to represent post-intervention commuting behaviours. Restricting the behavioural analysis to only respondents who completed both surveys would have reduced the number of responses analysed and made it more difficult to detect real changes. By contrast, emissions analysis was restricted to respondents who participated in both survey rounds, as described in Section 2.2.2.

Quantifying commuting GHG emissions

Commuting-related GHG emissions were analysed for respondents who self-reported participation in both survey rounds (n = 210). These respondents were identified through a question in S2 about whether they had responded to S1. However, individual responses could not be linked across surveys. Thus, limiting the analysis to this subgroup provided a stable aggregate population basis for comparing emissions intensity (gCO_2e pkm^{-1}) before and after the intervention period. Including all respondents from S2 would mix real behavioural changes with changes in respondent composition.

This study applied a life-cycle assessment (LCA) approach to estimate GHG emissions from commuting across six organisations, using data from participants who completed both baseline and follow-up surveys. Transport mode-specific EFs from established LCA literature were applied when they were relevant to the mode and data were available; where EFs were lacking, assumptions were made. These EFs were based on comprehensive LCAs that included vehicle production and well-to-wheels fuel emissions but excluded end-of-life processes and infrastructure-related emissions (e.g. road and pathway construction and maintenance; Figure 2).

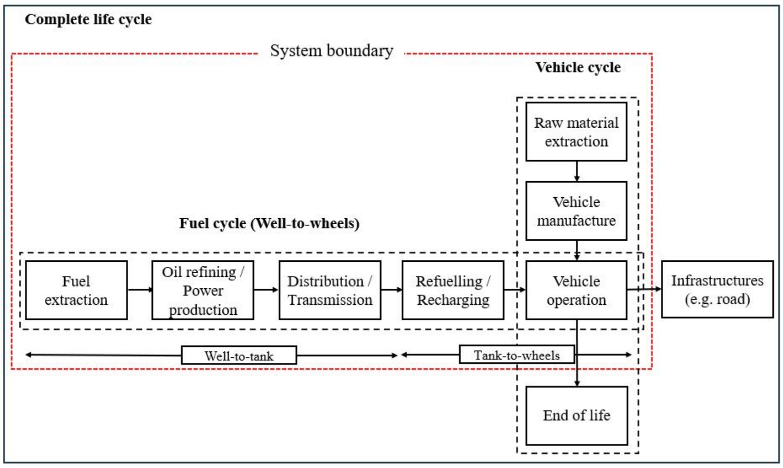

Figure 2. The system boundary applied in the study.

Excluding end-of-life (EoL) processes and infrastructure introduces some uncertainty to the emission estimates; however, their contributions are typically small for car-dominated commuting with internal combustion engine (ICE) vehicles[39,40]. Moreover, road infrastructure emissions per passenger-kilometre are low under high traffic volumes[39]. These assumptions are less robust for rail-based commuting, where infrastructure can dominate the share of life-cycle emissions[41,42]. Similarly, for battery electric vehicles (BEVs), EoL matters more because the recycling effect of BEVs is more substantial than that of ICE vehicles[43,44]. Nevertheless, studies have shown that BEVs have lower total life-cycle emissions than ICE cars and that rail often has lower per-passenger life-cycle emissions than road travel, although both depend on occupancy and local electricity mix[45,46]. As a result, this limits the influence of these exclusions on the overall results.

EFs for various transport modes were collected to quantify commuting GHG emissions. They were sourced from four literature references [Figure 3] and are expressed in grams of CO_2 equivalent per passenger-kilometre (gCO_2e pkm^{-1}). EF values for private cars (petrol and diesel, hybrid, and electric), carpooling, motorcycles, shared cars, company cars, urban buses, railways, and bicycles were adopted from the Lahti region dataset[14], which assumed a 50:50 split between electric and diesel buses and treated the company car as a battery electric vehicle (BEV). Carpooling vehicles were assumed to run on petrol or diesel, with twice the occupancy of private cars; accordingly, carpooling emissions were estimated at half those of solo car trips, with no significant detours or fuel efficiency changes assumed[47].

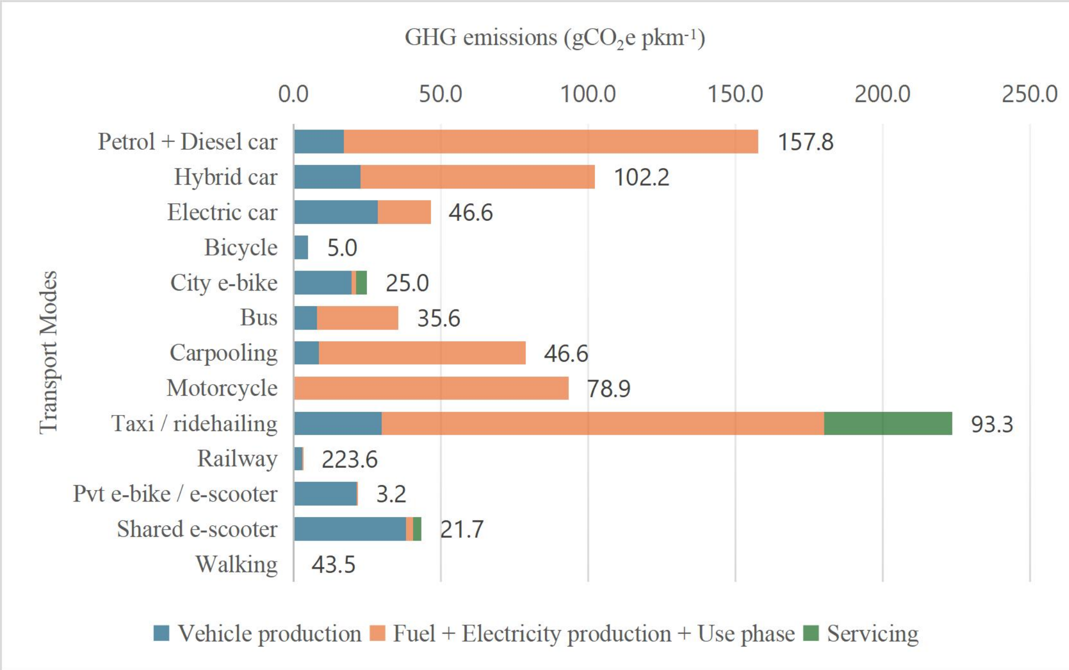

Figure 3. Emission factors of various transportation modes, including vehicle production, fuel and electricity production, and use phases. Some modes additionally include servicing (i.e. collection, redistribution, and maintenance of vehicles). Pvt: private[14,48,49,50].

The EFs for taxis and private e-bikes were adopted from the study conducted in Stockholm, another Nordic city[48]. The EF for private e-scooters was obtained from the study carried out in Germany[49]. Although that study did not disaggregate life-cycle phases, it was assumed that the 'Fuel + Electricity production + Use phase' accounts for a similar share of total emissions (0.7%), as reported for private e-bikes. The EF for private e-bikes/e-scooters was subsequently calculated as the average of the two modes. For shared e-scooters, the EF was derived from the LCA of TIER Mobility's VI model conducted in Germany[50], which is particularly relevant given that TIER is the primary provider of shared e-scooters in Lahti. The EF for the city e-bike was obtained from official data provided by the administrators of Lahti's city e-bike system.

The climate impacts of the commuting habits of the survey respondents from the case organisations before and after the interventions were quantified by calculating GHG emissions from commuting. The GHG emissions for each transport mode were calculated by multiplying the average daily commuting distance by the corresponding EF (Equation

1), following the method outlined in the GHG Protocol Corporate Standard[51]. Emissions were analysed descriptively at the aggregate level and expressed relative to the distance travelled, as follows:

$$E = d \times EF \qquad (1)$$

where

E = GHG emissions, expressed as kilograms of CO_2-equivalents per day [kg CO_2e person^{-1} d^{-1}]

d = Average daily commuting distance travelled by an individual or population [km d^{-1}]

EF = Emission factor of a specific transport mode, representing GHG emissions per passenger-distance travelled [kg CO_2e pkm^{-1}].

The average daily commuting distance was calculated by multiplying the respondent's round-trip commuting distance (i.e. the distance travelled to work and back home) by the number of commuting days per week and dividing by five, assuming a conventional 5-day work week. This approach ensures comparability across respondents with different commuting frequencies.

Statistical testing of emissions was not conducted because emissions are derived quantities, and individual respondents could not be linked across two surveys, preventing the assessment of emission changes for the same individuals. Thus, mode-specific distance data indicate aggregate changes in kilometres travelled by each mode (e.g. reduced car kilometres) but do not indicate whether individuals switched between models. This approach allows emissions estimates to reflect changes in overall commuting behaviour (distance and mode use) while avoiding misleading inferences that could arise from inconsistent respondent samples or unlinked individual observations.

Emissions intensity per person-kilometre

Changes in commuting-related GHG emissions after the interventions were first assessed in terms of emissions intensity, defined as the average GHG emissions per person-kilometre (gCO_2e pkm^{-1}) travelled. Emission intensity reflects how carbon intensive an average kilometre of commuting is and allows meaningful comparison between two

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surveys because it normalises emissions by total commuting distance, thereby reducing the influence of differences in travel distance and sample size. Emission intensity before and after the intervention period was calculated using Equation (2).

$$\text{Emissions change per person kilometre} = \left(\sum_i \left(\frac{D_{BI,i} \times EF_i}{\sum_i D_{BI,\,i}}\right)\right) - \left(\sum_i \left(\frac{D_{AI,i} \times EF_i}{\sum_i D_{AI,\,i}}\right)\right) \quad (2)$$

where

i = each commuting transport mode
$D_{\mathrm{BI,i}}$ = commuting distance per person [km] for transport mode i before the intervention
$D_{\mathrm{AI,i}}$ = commuting distance per person [km] for transport mode i after the intervention
EF_i = emission factor [gCO_2e pkm^{-1}] for transport mode i
$\sum_i D_{BI,\,i}$ = total commuting distance across all modes before the interventions
$\sum_i D_{AI,\,i}$ = total commuting distance across all modes after the interventions

Decomposition of absolute emissions into modal and distance effects

To distinguish the contributions of modal change and distance reduction to the observed change in commuting-related GHG emissions, absolute emissions were further analysed using a simple decomposition approach. This decomposition was performed using absolute emissions (gCO_2e person^{-1} day^{-1}) because emissions intensity (gCO_2e pkm^{-1}) depends on the mix of transport modes rather than the total travel distance. Changes in total commuting distance affect total emissions but do not change emissions intensity unless the modal composition changes. Thus, emission intensity cannot be decomposed into separate distance and modal components. The contributions of modal change and distance reduction were calculated using Equations (3) and (4), respectively, as follows:

$$\Delta E_{\mathrm{mode}} = E^{*} - E_1 \quad (3)$$

$$\Delta E_{\mathrm{distance}} = E_2 - E^{*} \quad (4)$$

Here, E_1 denotes baseline absolute GHG emissions in Survey 1, calculated using observed mode-specific person-kilometres and fixed EFs, and E_2 denotes observed absolute emissions in Survey 2. A counterfactual emissions level (E^{*}) was calculated by holding the total commuting distance constant at the Survey 1 level while applying the modal distance shares observed in Survey 2. Accordingly, ΔE_{mode} represents the change in emissions attributable to modal composition changes alone, while $\Delta E_{\mathrm{distance}}$ captures the additional change in emissions associated with reduced total commuting distance. By construction, the total observed emissions change satisfies ΔE=E_2-E_1=ΔE_{mode}+$\Delta E_{\mathrm{distance}}$.

Impact of interventions on GHG emissions based on reach, uptake and perceived effects

In step 3, the impacts of the implemented interventions on GHG emissions were quantified. The target was to help recognise the most effective interventions in changing travel behaviour and reducing GHG emissions.

Twenty-one low-emission commuting interventions were implemented and grouped into five categories [Table 1], each with the specific aim of promoting low-emission commuting. These interventions were implemented in six case organisations between spring and autumn 2024 according to the organisations' specific needs and practical feasibility of the interventions. The interventions implemented in each of the case organisations were different, but some of the interventions were implemented in several organisations. Selecting and implementing the interventions are outside the scope of this study.

Table 1. Implemented interventions in the case organisations.

Intervention number	Intervention
	1. Financial incentives
1	A discount on the public bus ticket
2	A discount for a city e-bike season ticket
	2. Health and well-being coaching
3	Wellness coaching
	3. Infrastructure improvements
4	Bike rack with frame lock
5	Public transport timetable display (main lobby and event arena)
6	Motion sensor light at the bike storage area
7	Separate entrance for cyclists at the gate
	4. Transport service improvements

8	New city e-bike station
9	Revised bus routes 12 and 12K since August
10	Expansion of shared e-scooters' operational area
	5. Communication and awareness
11	City e-bike season ticket raffle
12	Exercise supporting workplace well-being lecture
13	Health and safety week (occupational health care and road safety)
14	Autumn commuting events (well-being and traffic safety)
15	Bike to workday (helmet raffle, cyclists' breakfast, and bike maintenance)
16	Winter cycling event
17	Walking race challenge
18	Cycling race challenge
19	Bike maintenance opportunity at the workplace
20	Intranet page on sustainable commuting
21	Communication on sustainable commuting (videos and lectures)

Financial incentives were aimed at encouraging low-emission travel by lowering the cost of public bus tickets and shared city e-bike access. Health and well-being coaching was intended to motivate behavioural change by linking active commuting with personal health and wellness benefits. Infrastructure improvements were focused on making low-emission travel more convenient and attractive through upgrades, such as bike facilities, sensor lighting, and secure storage. Transport service improvements were aimed at enhancing the accessibility and reach of low-emission options such as buses, city e-bikes, and shared e-scooters. Lastly, communication and awareness interventions were designed to inform, engage, and inspire employees through events, campaigns, and educational content to choose low-emission commuting options.

Intervention analysis

To assess the behavioural influence of the five implemented intervention categories, a BIS was developed based on three stages: (1) reach (awareness of the intervention), (2) uptake (participation), and (3) perceived effect on commuting behaviour. This approach allowed for the systematic evaluation of the behavioural influence of each intervention category. To calculate reach, uptake, and perceived effect, responses to two key questions from the second survey were used:

- 'Which of the following commuting-related measures have you noticed and/or utilised?' was used to derive both *reach* and *uptake* based on the following response options:
  - *I have not noticed.*
  - *I have noticed but not wanted to utilise.*
  - *I have noticed but not been able to utilise.*
  - *I have noticed and utilised.*

- 'How much have the following measures affected your commuting habits?' was used to calculate the *perceived effect* using four ordered categories:
  - *Not at all*
  - *Not much*
  - *Quite a lot*
  - *Very much*

Reach$_k$: Exposure to intervention category *k*

Reach quantifies the proportion of respondents who reported noticing at least one intervention within intervention category *k*, regardless of utilisation. It included only respondents who had the opportunity to perceive the intervention. To calculate reach for category *k*, the number of respondents who noticed each intervention was first determined for all interventions within the category across organisations. Then, for each organisation where category *k* was implemented, the maximum value across interventions was selected to avoid double counting, and these values were summed across organisations, as defined in Equation (5).

$$Reach_k = \frac{\sum_{o \in O_k} \left[\max_{i \in I_{ok}} (T_{io} - N_{io}) \right]}{\sum_{o \in O_k} T_o} \quad (5)$$

where

- k = intervention category
- o = organisation
- i = individual intervention within intervention category k

- O_k= set of organisations implementing ≥1 intervention in category k
- I_{ok}= set of interventions in category k implemented by organisation o
- T_{io}= total respondents in organisation o exposed to intervention i
- N_{io}= respondents in organisation o selecting ‘I have not noticed’
- T_o= total respondents in organisation o
- the *max* operator prevents double counting by selecting the highest number of respondents who noticed any intervention within category k for each organisation, ensuring that each respondent is counted only once per category.

Uptake$_k$: Behavioural use of category k interventions

Uptake measures the proportion of respondents who actively used at least one intervention within intervention category k. Respondents who selected ‘I have noticed and utilised’ for any intervention in the category were counted once per organisation, even if they utilised multiple interventions, because the category represents a single behavioural mechanism. This deduplication avoids double counting and ensures comparability across categories. Uptake for category k is calculated as shown in Equation (6).

$$Uptake_k = \frac{\sum_{o \in O_k} \left[\max_{i \in I_{ok}} U_{io} \right]}{\sum_{o \in O_k} \left[\max_{i \in I_{ok}} (T_{io} - N_{io}) \right]} \tag{6}$$

where

- U_{io}= respondents who selected ‘I have noticed and utilised’ for intervention i in the organisation
- the *max* operator ensures that the respondents are not double-counted, so each person is counted only once per category k.

Effect$_k$: Perceived influence (weighted influence score)

The effect captures the self-reported extent to which the interventions influenced commuting behaviour. For category k, a weighted average was calculated from all responses. The category-level perceived influence is calculated shown in Equation (7).

$$Effect_k=\frac{\sum_{i\in I_k}\sum_{j=0}^{3}(R_{ji}\cdot G_j)}{3\times R_k^{\mathrm{reach}}} \qquad (7)$$

where

- j = response level index (0, 1, 2, 3)
- R_{ji}= number of respondents associated with intervention i who selected response level j within intervention category k
- G_j= effect category score (0–3)
  - 0 = Not at all
  - 1 = Not much
  - 2 = Quite a lot
  - 3 = Very much
- $R_k^{\mathrm{reach}}=\sum_{o\in O_k}\max_{i\in I_{ok}}(T_{io}\text{-}N_{io})$ = total number of respondents who noticed at least one intervention within category k
- the denominator $3\times R_k^{reach}$ is the maximum possible score if all respondents selected "very much," thereby normalising the perceived influence score to a 0–1 scale.

Perceived effect was calculated by first aggregating responses across all organisations for each intervention i and then summing across interventions within each category.

Behavioural Impact Score (BIS_k)

BIS combines exposure, uptake, and effect into a single behaviourally meaningful measure, as shown in Equation (8).

$$BIS_k=Reach_k\times Uptake_k\times Effect_k \qquad (8)$$

The multiplicative structure ensures that an intervention category achieves a high score only when it performs well across all three behavioural stages. It reflects the combined probability that a respondent was exposed to the intervention category, used at least one of its interventions, and perceived it as behaviourally influential within category k. The BIS ranges from 0 (no influence) to 1 (maximum behavioural penetration). It was calculated for all five intervention categories.

Relative Impact (RI_k)

BIS values were normalised across five intervention categories to calculate relative impact (RI_k), expressing each category's share of total behavioural intervention influence, as shown in Figure (9).

$$RI_k = \frac{BIS_k}{\sum_{k'=1}^{K} BIS_{k'}} \times 100 \quad (9)$$

where

k' = summation index over all intervention categories

K = total number of intervention categories.

This approach avoids assigning specific emission reductions to individual interventions. Instead, it provides a behaviourally informed assessment of category-level influence, which is appropriate given the anonymous, cross-sectional nature of the data.

RESULTS

This section is structured as follows: Section 3.1 presents changes in commuting behaviour, including commuting distance, modal shares, and commuting frequency. Section 3.2 then examines the implications of these behavioural changes for commuting-related GHG emissions, reporting both emissions intensity and absolute emissions together with a decomposition of modal share and commuting distance effects. Finally, Section 3.3 analyses the influence of the intervention categories on the observed behavioural changes (BIS and RI).

Results of the survey

Commuting distances per person before and after the interventions

The commuting distance data for summer, winter, and the full year were tested for normality using the Shapiro–Wilk test, which revealed strong non-normality in all the cases. Thus, differences in one-way commuting distance between S1 and S2 were analysed using the non-parametric Wilcoxon rank-sum test. Results are reported as medians and interquartile ranges (IQRs), as the commuting distances were skewed and included a small number of very long trips, which could strongly influence means and make average values less representative of the typical commuting behaviour. Table 2 summarises the one-way commuting distances per person for S1 and S2 under summer, winter, and full-year conditions.

Table 2. Seasonal and full-year commuting distances per person (one-way kilometre).

Period	Survey	Median (km)	IQR (km)	*P* value
Summer	S1	8.0	4.5-21.0	0.0048
	S2	6.0	3.0-17.0	
Winter	S1	8.0	4.0-18.0	0.0810
	S2	6.0	3.0-17.0	
Full year	S1	8.0	4.25-20.0	0.0145
	S2	6.0	3.0-17.0	

In summer, the median one-way commuting distance decreased from 8 km in S1 (IQR, 4.5-21 km) to 6 km in S2 (IQR, 3-17 km). This reduction was statistically significant (Wilcoxon $W = 94{,}000$, $P = 0.0048$), indicating a clear decrease in typical travel distances during the summer season after the intervention period. In winter, the median distance also decreased from 8 km (IQR, 4-18 km) to 6 km (IQR, 3-17 km), but this difference did not reach statistical significance at the 5% level ($W = 90{,}282$, $P = 0.081$). Although commuting distances varied widely in both seasons, winter distances were more similar between S1 and S2 (with almost equal interquartile ranges), which made the change more difficult to detect statistically.

When summer and winter distances were averaged to create a full-year commuting distance estimate per person, the median full-year distance decreased from 8 km (IQR, 4.25-20 km) in S1 to 6 km (IQR, 3-17 km) in S2, corresponding to a 25% reduction. This decrease was statistically significant ($W = 92{,}707$, $P = 0.0145$).

Taken together, these results [Table 2] indicate that commuting distances per person decreased over the study period, particularly in summer and on an annual basis. Although the winter trend follows the same direction, the evidence is weaker. This seasonal difference may reflect more constrained commuting patterns during winter, which is reasonable in a Nordic context, where travel choices are less flexible.

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The implications of the distance changes for commuting-related GHG emissions are examined in Section 3.2, while the potential influence of organisational relocation is assessed through a sensitivity analysis in Section 3.3.

Changes in modal shares

For each season, the respondents were classified as users of a mode if they travelled kilometres (>0 km) for that mode. As the respondents may use multiple modes across different days or combine modes within trips, the modal categories are not mutually exclusive, and the percentages do not sum to 100%. Thus, percentages represent the proportion of respondents who reported using a given mode at least once during the season and do not represent shares of trips or kilometres travelled. The results are presented in Tables 3 and 4 for summer and winter, respectively.

In summer [Table 3], private cars remained the most commonly used commuting mode in both surveys, but its share decreased notably after the interventions. The proportion of respondents who used private cars as their main commuting mode decreased from 54.1% (296/547) in S1 to 43.8% (135/308) in S2. This decrease of approximately 10.3 percentage points was statistically significant (two-sample proportion test, P = 0.0049, 95% confidence interval for the difference: 3.1-17.5 percentage points), indicating a reduction in car dependence during the summer season.

Table 3. Share of respondents using each commuting mode at least once during summer in S1 and S2.

Mode	S1 users, *n*	S1 %	S2 users, *n*	S2%	*P* value	Interpretation
Car	296	54.1	135	43.8	0.0049	Significant decrease
Shared car	14	2.6	4	1.3	0.3248	NS
Public transport (PT)	103	18.8	50	16.2	0.3910	NS
Cycling	137	25.0	89	28.9	0.2522	NS
Micromobility	48	8.8	19	6.2	0.2191	NS

Walking	99	18.1	40	13.0	0.0646	Borderline, NS

NS = Not significant; n_S1 = 547, n_S2 = 308.

The shares of the other modes changed less: Shared car remained a marginal mode in both surveys and showed no significant change, public transport decreased slightly from 18.8% to 16.2% (P = 0.39), cycling increased from 25.0% to 28.9% (P = 0.25), micromobility declined from 8.8% to 6.2% (P = 0.22), and walking decreased from 18.1% to 13.0% (P = 0.065). None of these changes reached statistical significance, although the decline in walking was borderline.

In winter, modal shares appeared more stable [Table 4]. The share of respondents who used a private car decreased from 57.8% in S1 to 51.6% in S2, but this change did not reach conventional significance (P = 0.096). Public transport use remained almost unchanged at 22.9% in S1 compared with the 22.7% in S2 (P = 1.00), as did walking (20.5% in both surveys; P = 1.00). Cycling increased from 6.4% to 10.4% (P = 0.051), which suggests a small but borderline increase in winter cycling. Micromobility remained a niche mode with very low and statistically unchanged shares across the two surveys.

Table 4. Share of respondents using each commuting mode at least once during winter in S1 and S2.

Mode	S1 users, *n*	S1 %	S2 users, *n*	S2%	*P* value	Interpretation
Car	316	57.8	159	51.6	0.0960	Trend decrease, NS
Shared car	18	3.3	3	1.0	0.0614	Borderline, NS
Public transport (PT)	125	22.9	70	22.7	1.0000	NS
Cycling	35	6.4	32	10.4	0.0509	Borderline increase
Micromobility	14	2.6	7	2.3	0.9762	NS
Walking	112	20.5	63	20.5	1.0000	NS

NS = Not significant; *n*_S1 = 547, *n*_S2 = 308.

Overall, these results [Tables 3 and 4] show that while the share of respondents who used a private car decreased significantly in summer and tended to decrease in winter, the shares of public transport, cycling, walking, and micromobility did not increase significantly. This implies that only a minority of reduced car commuting was replaced by sustainable modes. The robustness of the observed reduction in summer car use to organisational relocation is assessed in a sensitivity analysis in Section 3.3.

As many respondents used multiple modes (e.g. combining walking with public transport) and commuted different distances, changes in the number of people who used a certain mode do not necessarily translate into changes in the total distance travelled by that mode. Thus, the implications of these behavioural changes for commuting-related GHG emissions are examined separately using per person-kilometre metrics in Section 3.2 [Figure 4].

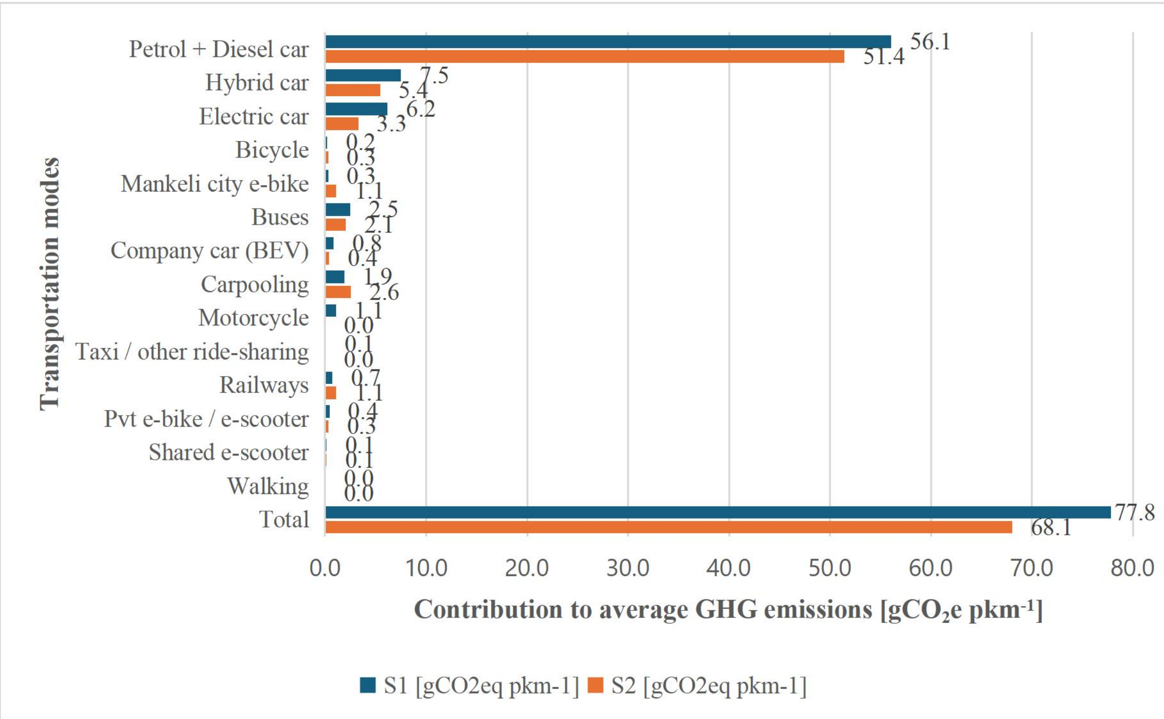

Figure 4. Average commuting-related GHG emissions intensity before (S1) and after (S2) the intervention period among the participating respondents in both surveys (n = 210).

Commuting frequency (workdays per week)

As reductions in commuting distance and car use could, in principle, be driven by increased remote work rather than mode shift or distance shortening, commuting frequency was examined separately. Table 5 summarises commuting frequency in terms of the number of days per week the respondents travelled to their workplaces (0–5) and the proportions of very low–frequency and frequent commuters. The distributions of commuting days were non-normal (Shapiro–Wilk $P < 0.001$). Thus, the differences between S1 and S2 were analysed using Wilcoxon rank-sum and two-sample proportion tests (prop.test) to assess whether the share of respondents in the key frequency categories differed between the two surveys.

Table 5. Commuting frequency (workdays per week) in S1 and S2.

Metric	S1 (*n* = 547)	S2 (*n* = 308)	Test	*P* value
Median commuting days week^{-1} (IQR)	3 (2-5)	3 (2-5)	Wilcoxon rank-sum (*W*)	0.2816
Very low-frequency commuters (≤ 1 day wk^{-1})	109 (19.9%)	63 (20.5%)	prop.test	0.9236
Frequent commuters (≥ 4 days wk^{-1})	271 (49.5%)	133 (43.2%)	prop.test	0.0859

The median commuting frequency remained unchanged at 3 days per week in both S1 and S2 (IQR, 2-5 days in both surveys), and the Wilcoxon test revealed no statistically significant difference between the two distributions ($W = 87{,}862$, $P = 0.282$). To examine changes at the extremes of the distribution, two prevalent measures were analysed. Very low–frequency commuting, defined as commuting ≤ 1 day per week, accounted for 19.9% (109/547) of the respondents in S1 and 20.5% (63/308) in S2, a difference that was not statistically significant ($P = 0.924$). Frequent onsite commuting, defined as commuting ≥ 4 days per week, decreased from 49.5% (271/547) in S1 to 43.2% (133/308) in S2, but this change also did not reach significance ($P = 0.086$).

These findings indicate that the frequency of commuting did not change significantly between the two surveys, either in terms of central tendency or in the prevalence of high- and low-frequency commuters. This suggests that the observed reductions in commuting distance and private car use are not primarily driven by changes in the number of commuting days (e.g. increased remote work) but rather by changes in how people travel and how far they travel when commuting.

Changes in GHG emissions from commuting

Figure 4 presents mode-specific contributions to average commuting emissions intensity, which were derived from fixed life-cycle EFs and reported travel distances. Over the intervention period, the average daily commuting distance decreased from 24.5 pkm day^{-1} to 18.4 pkm day^{-1}, corresponding to a 24.7% reduction. Correspondingly, the average emissions intensity decreased from 77.8 gCO_2e pkm^{-1} before the interventions to 68.1 gCO_2e pkm^{-1} after the interventions, representing a 12.5% reduction.

When expressed as absolute emissions, the average commuting-related GHG emissions decreased from 1,905.1 gCO_2e person^{-1} day^{-1} in S1 to 1,253.7 gCO_2e person^{-1} day^{-1} in S2, representing a total reduction of 651.4 gCO_2e person^{-1} day^{-1} over the intervention period. This observed reduction reflects the combined effects of changes in modal composition and total commuting distance.

Under the counterfactual scenario, when the total commuting distance in S1 was kept constant while applying the modal distance shares observed in S2, the emissions decreased by 239.7 gCO_2e person^{-1} day^{-1}, corresponding to approximately 37% of the total absolute emissions reduction attributable to modal changes alone. The remaining reduction of 411.7 gCO_2e person^{-1} day^{-1} (approximately 63% of the total reduction) is attributable to the reduced commuting distance, including structural changes such as organisational relocation.

Together, these components fully explain the observed total emissions reduction. These results indicate that while distance reduction was the dominant driver of GHG emissions reduction, changes in mode choice also reduced emissions even when total commuting distance was held constant. From the perspective of this research, GHG emissions reduction via modal shifts is more interesting because it was the aim of the interventions.

Sensitivity analysis: Role of organisational relocation

To assess the influence of organisational relocation on the observed changes in commuting behaviour and emissions, a sensitivity analysis was performed, excluding the organisation that underwent relocation. This analysis was applied consistently across commuting distance, modal shares, and emissions outcomes.

Effects on commuting distance

When the relocated organisation was excluded, the median annual commuting distance still decreased from 7.5 km to 6.0 km (approximately 20%), but the change was no longer statistically significant ($P = 0.265$). This indicates that reductions in typical commuting distances were not limited to relocation alone.

However, the average daily commuting distance (pkm day^{-1}) remained effectively unchanged, increasing slightly from 15.8 pkm day^{-1} to 15.9 pkm day^{-1}. In simple terms, although many respondents shortened their commute, the longer trips made by a smaller number of respondents offset these reductions, so the total distance travelled per person did not decrease. This indicates that the substantial distance reduction observed in the full sample is largely attributable to organisational relocation.

Effects on modal shares

The sensitivity analysis that excluded the relocated organisation showed that the reduction in summer private car use persisted, declining from 47.5% to 39.8% (by approximately 8 percentage points), although the change was no longer statistically significant ($P = 0.07$). In winter, car use also declined slightly, but the change did not reach statistical significance. Changes in the share of respondents who used shared cars, public transport, cycling, micromobility, and walking remained small and statistically non-significant in both seasons, consistent in direction with the main analysis. These results suggest that organisational relocation amplified the observed changes in summer car use but was not their sole driver.

Effects on GHG emissions and decomposition

Despite the absence of distance reduction, commuting-related GHG emissions intensity still declined from 72.5 gCO_2e pkm^{-1} to 67.8 gCO_2e pkm^{-1}, corresponding to a reduction of approximately 6.5%. When expressed as absolute emissions, average commuting-related GHG emissions also decreased by approximately 6%. The decomposition of absolute emissions shows that when relocation was excluded, emissions reductions were driven entirely by modal change, while changes in commuting distance contributed a small increase in emissions. This confirms that behavioural changes in mode choice can reduce emissions, even in the absence of reduced commuting distance, although the magnitude of emissions reduction is smaller than that in the full sample.

Intervention category influence (BIS and RI)

To understand which intervention strategies were most influential in shaping commuting behaviour, BIS was calculated for each of the five intervention categories by combining their category-level reach (exposure), uptake (behavioural use), and effect (perceived influence). Table 6 reports category-level reach, uptake, and effect values, along with BIS and the resulting RI values obtained by normalising BIS across categories.

The results show that communication and awareness interventions had the highest BIS and largest RI, accounting for 42% of the total behavioural influence. This category included intranet communications, videos, lectures, commuting events, mobility campaigns, and other informational or motivational activities and was characterised by high reach (83.7% of respondents in implementing organisations), substantial uptake (32.7% of those reached used at least one communication tool), and the highest perceived effect score (56.2%). Financial incentives (discounts for public transport tickets and city e-bike passes) formed the second most influential category with an RI of 28%. Although uptake was lower than that for awareness activities, those exposed to and who used financial incentives reported a relatively strong influence on their commuting decisions (effect score, 42.9%).

Infrastructure improvements, such as enhanced bicycle parking, lighting, and access for cyclists, resulted in an RI of 14%, based on moderately high reach (76.3%) and uptake (33.1%) but relatively modest perceived influence (20.0%). Transport service improvements, including timetable displays, route changes, and new bike stations, generated an RI of 13% from high reach (84.1%) but lower uptake (16.2%) and intermediate perceived effect (34.2%). Health and well-being coaching had limited reach, uptake, and perceived effect, resulting in an RI of 3%.

Table 6. Theme-level behavioural influence metrics (reach, uptake, effect, BIS, and RI).

Category	Reach	Uptake	Effect	BIS	RI
1. Financial incentives	82.4%	28.6%	42.9%	0.10	27.9%
2. Health & wellbeing coaching	22.9%	22.9%	19.4%	0.01	2.8%
3. Infrastructure improvements	76.3%	33.1%	20.0%	0.05	14.0%
4. Transport service improvements	84.1%	16.2%	34.2%	0.05	12.9%
5.Communication and awareness	83.7%	32.7%	56.2%	0.15	42.5%
Total				0.36	100%

All percentages are on a 0-100% scale. BIS is computed with reach, uptake, effect in 0-1 form.

Together, these results [Table 6] indicate that both ‘soft’ measures (communication, awareness, and financial incentives) and ‘hard’ measures (infrastructure and service improvements) played important roles in shaping commuting behaviour. Altogether, these categories account for 97% of the total BIS and thus capture almost all behaviourally weighted intervention influence. The strong influences of communication and awareness are consistent with the significant summer reduction in car share and commuting distance, while infrastructure and service categories provided enabling conditions that likely supported cycling, walking, and public transport use even if their modal shares did not increase significantly at the employee level.

DISCUSSION

This study examined the impacts of a set of low-emission commuting interventions implemented across six organisations in Lahti, Finland, with a focus on three key questions: (i) how modal shares changed after the interventions, (ii) how commuting-related GHG emissions evolved as a result of these behavioural changes, and (iii) how the BISs differed across intervention categories. The results reveal measurable changes in commuting behaviour and a clear reduction in commuting-related GHG emissions, while also highlighting differences in effectiveness between the intervention types.

By linking the observed changes in modal shares and commuting distance to the GHG emissions outcomes and intervention impact scores, the study provides empirical, real-world evidence on how combinations of workplace-level interventions could boost the utilisation of low-emission commuting. This study contributes to the literature on active, low-emission, and sustainable transportation by documenting before-after commute emission intensities impacted by integrated intervention packages combining behavioural measures, workplace infrastructure improvements, and transport service enhancements. These findings are particularly relevant for urban climate policy and municipal and institutional emission reduction achievements, where scalable behavioural and organisational strategies are increasingly needed to complement technological decarbonisation and address commuting-related GHG emissions.

How did modal shares change after the interventions?

Across the two cross-sectional survey rounds, the participants reported modest but consistent changes in commuting behaviour. The most notable change was a reduction in private car use, particularly in summer, while winter car use showed a weaker and less consistent decline. Despite this reduction, the prevalence of alternative modes, including public transport, cycling, walking, micromobility, and shared car use, did not increase substantially at the employee level.

These results suggest that the observed behavioural change was primarily driven by a decrease in reliance on private car use. Seasonal differences indicate that behavioural shifts were more pronounced under favourable conditions (summer), whereas winter travel patterns remained comparatively stable, possibly reflecting environmental and infrastructural constraints.

A reduction in commuting distance was also observed; however, as distance was not directly targeted by the interventions and may reflect structural factors, such as organisational relocation and sample composition, it is interpreted here as a contextual change rather than a primary behavioural outcome.

Commuting frequency remained stable across the survey waves, indicating that the observed changes were not driven by increased remote work. Taken together, these findings suggest that the primary behavioural response during the intervention period was reduced private car use, with limited substitution for alternative modes.

How did commuting-related GHG emissions evolve as a result of these behavioural changes?

The observed 12.5% reduction in commuting-related GHG emissions intensity reflects the combined effects of changes in commuting behaviour over the intervention period. Although emissions could not be statistically compared because of the anonymous cross-sectional survey design, the direction and magnitude of the observed emissions reduction are consistent with the statistically significant reductions in car use and commuting distance.

The decomposition of absolute emissions shows that the emissions reduction was driven primarily by reduced commuting distance, which accounted for approximately two-thirds of the total absolute emissions reduction, while the changes in modal composition contributed the remaining one-third. This indicates that distance reduction, amplified by structural factors such as organisational relocation, played a dominant role in lowering commuting-related emissions, while modal shifts provided a secondary but meaningful contribution.

Because commuting frequency did not change significantly, the observed emissions reductions cannot be attributed to increased remote work alone. Rather, the findings support a multi-mechanism explanation in which (i) shorter commuting distances; (ii) reduced car-based travel, especially in summer; and (iii) the combined influence of different intervention categories jointly contributed to emissions reductions. Together, these results highlight that while modal change is important for reducing emissions intensity, substantial emissions reductions in organisational contexts are strongly dependent on factors that reduce total commuting distance, either directly or indirectly.

The sensitivity analysis, which excluded the relocated organisation, provides additional insight into the mechanisms underlying emissions reductions. When relocation was excluded, the average daily commuting distance per person no longer decreased and instead increased slightly, indicating that the substantial distance reduction observed in the full sample was largely driven by relocation rather than by behavioural interventions alone.

Emissions intensity and absolute emissions still declined in the absence of a distance reduction. The decomposition of absolute emissions when relocation was excluded shows that modal change becomes the sole driver of emissions reduction, while distance change slightly counteracts it. This demonstrates that behavioural changes in mode choice, such as reduced car use and increased use of lower-emission modes, are sufficient to reduce emissions intensity, even when commuting distances remain unchanged.

Taken together, these results indicate that large emissions reductions in organisational settings are strongly amplified by structural factors that reduce commuting distance, such as relocation, whereas modal change represents a robust but smaller behavioural pathway to emissions reduction. This distinction is critical for interpreting the effectiveness of workplace commuting interventions and setting realistic expectations regarding their emissions impacts. In the absence of relocation, behavioural changes in mode choice emerged as the main mechanism underlying emissions reductions, even without substantial changes in total commuting distance.

How did the BISs differ across the intervention categories?

The BIS provided a structured way to evaluate which intervention themes were most influential in shaping commuting behaviour. BIS integrates reach, uptake, and perceived effect, providing a behaviourally grounded way to assess how strongly each intervention theme influenced commuting decisions

The communication and awareness theme had the highest BIS and RI (42%). These interventions, which range from employer communications to mobility events and campaigns, were widely noticed and perceived as meaningfully influencing commuting choices. Their strong behavioural visibility possibly contributed to the observed reduction in car use and increased awareness of alternative modes.

Financial incentives (28% RI) formed the second most influential theme. However, this influence did not translate into statistically significant increases in public transport or city e-bike use, which were the specific submodes incentivised. As the modal-share analysis aggregates bus and rail into a single public transport category and city e-bikes with pedal bicycles, submode-level changes cannot be isolated statistically. Moreover, financial incentives may increase motivation, readiness, and positive attitudes among users without overcoming structural barriers, such as route suitability, service frequency, seasonal conditions, and limited operational coverage[52,53]. Consequently, financial incentives may have reinforced behaviour among the existing or occasional users rather than generating a measurable modal shift at the employee level. This interpretation aligns with the transport-behaviour literature demonstrating that incentives are most effective when viable modal alternatives already available[54,55].

Infrastructure improvements (14%) and transport service enhancements (13%) provided enabling conditions that may explain the small but positive trends in cycling (especially in winter). These themes were characterised by high reach but more modest uptake, which suggests that while infrastructural and service actions are important enablers, they are most effective when combined with motivational or informational interventions. This may also be partly explained by their focus on facilitating only a limited number of low-carbon travel modes. In addition, these measures were predominantly supportive rather than restrictive in nature (e.g. reducing parking availability), which may have limited their overall behavioural impacts. The health and well-being category, which consisted solely of coaching service, showed minimal influence (3%), possibly owing to lower reach and perceived behavioural impact.

Taken together, the BIS results indicate that interventions influenced behaviour primarily through motivational pathways (communication and incentives) and secondarily through environmental restructuring (infrastructure and services). These behavioural mechanisms help explain the observed reductions in commuting distance and car dependence. In this context, the BIS approach proved useful for comparing behavioural influences across intervention categories in a multi-intervention context where causal attribution is not feasible.

Comparison with previous studies on communication-based interventions

Previous research on communication-based commuting interventions has shown mixed, context-dependent effectiveness, with most studies measuring behavioural intentions or self-reported outcomes rather than direct GHG emissions. While personalised or wellframed messages that account for individual values and social norms can influence travel choices in the short term[56-59], systematic reviews and large-scale field experiments have found limited and inconsistent effects on car use and modal shift[19,60,61].

A key limitation across the literature is the scarcity of direct emissions measurement; only a small number of studies have quantified vehicle use-related GHG reductions, with wide variation in reported outcomes[29]. Methodological constraints, including non-randomised designs, short observation periods[61], and discrepancies between self-reported and actual behaviour[62], further obscure true intervention effects. Evidence also suggests that effectiveness varies considerably by institutional and cultural contexts[61].

The present study aligns with the literature in finding that communication measures contribute to emissions reductions but are insufficient for large-scale modal substitution alone.

The present study aligns with the broader literature in finding that communication measures can encourage modal shift towards sustainable transport but are insufficient for large-scale substitution when applied alone[61,63]. The results support multi-strategy intervention packages in which communication complements structural measures, such as infrastructure and transport service improvements. Importantly, this study extends previous work by quantifying observed GHG changes under real organisational conditions, thereby bridging the gap between behavioural research and climate-relevant outcomes.

Confounding factors and limitations

Several limitations must be considered when interpreting the findings of this study. First, the study was conducted solely in Lahti, Finland, which may limit the generalisability of the results to other regions with different infrastructure conditions, cultural norms, or climatic contexts. Thus, the observed behavioural responses and intervention effects may not translate directly to other contexts.

Second, the emissions analysis was restricted to respondents who self-reported participation in both survey rounds (38% of the baseline sample). While this restriction was necessary to ensure a stable aggregate population basis for emissions comparison, it may have introduced selection bias, as respondents who participated in both surveys may differ systematically from those who participated only once. For instance, if more car-dependent employees were less likely to answer the second survey, emissions might appear to decrease even if some commuting behaviours did not actually change. As a result, emissions outcomes are interpreted as descriptive aggregate trends rather than population-wide causal effects.

Third, the 6-month study period was relatively short for capturing sustained behavioural change. Although statistically significant reductions in commuting distance and summer car use were observed during the intervention period, the study could not determine whether these changes persisted over time. The lack of long-term follow-up limits the ability to assess the persistence of intervention effects.

The short intervention duration also restricts the ability to account for seasonal variation[64] and the gradual nature of habit formation[65]. Future research should extend over at least 12 months to capture seasonal dynamics and support behavioural consolidation. Ideally, longitudinal studies spanning 18-24 months would provide more robust evidence on the long-term impacts and sustainability of behavioural changes[65,66].

Seasonality presented another confounding factor, as evidenced by the stronger behavioural changes observed in summer than in winter. Finnish winter conditions can suppress active modes and reinforce car dependence, potentially limiting the observable impact of interventions targeting cycling, walking, or micromobility. In addition, the second survey required respondents to retrospectively estimate winter commuting behaviour, which might have introduced recall bias.

Organisational factors further complicate interpretation. One participating organisation underwent office relocation near a train station during the study period, which possibly contributed to shorter commuting distances for a subset of respondents. As shown by the sensitivity analysis, relocation influenced the magnitude but not the direction of observed changes, indicating that behavioural outcomes cannot be attributed solely to the interventions. In addition, commuting frequency did not change significantly between the two surveys, which suggests that neither increased remote work nor organisational relocation materially affected the number of weekly commuting days.

Finally, interventions were implemented heterogeneously across organisations and within diverse organisational contexts, resulting in variations in reach, uptake, and perceived effect. This heterogeneity limits direct comparability across organisations and makes it difficult to isolate the effects of individual intervention themes. Moreover, because the surveys were anonymous and cross-sectional, individual-level causal inference was not possible. In addition, the study did not include a control group of organisations without interventions, which limits the ability to isolate intervention effects from other concurrent changes. Commuting distances and modal choices were self-reported, which may further introduce measurement and recall errors.

Implications

The results of the study highlight the importance of integrating motivation-focused interventions (communication and incentives) with infrastructure and transport service improvements. While workplace-level modal shifts were modest, statistically significant reductions in car use and commuting distances demonstrate that combined intervention strategies can meaningfully influence commuting behaviours. The findings show that reducing car-based travel distance and reliance, with modal substitution, can deliver measurable climate benefits.

From a methodological perspective, the BIS approach provides a practical framework for assessing the relative influences of intervention categories in real-world organisational settings where individual-level tracking is not possible. By integrating reach, uptake, and perceived effect, BIS provides a transparent way to interpret behavioural influence alongside observed changes in commuting behaviour and emissions. While it does not measure direct causal impacts of emissions or modal shift, it complements outcome-based analyses by revealing underlying behavioural processes.

For policymakers and organisational practice, the results highlight that measurable emissions reductions can be achieved through changes in commuting behaviour, particularly reductions in car use. While large-scale modal shifts to low-emission modes remain important for achieving deeper emission reductions, the findings of this study show that shifts away from private car use alone can contribute meaningfully to emission reductions. Structural factors such as the strategic location of workplaces, particularly in central areas or near public transport hubs, can further support emissions reductions by influencing both travel distances and access to low-emission modes, even though such factors were not the primary focus of the interventions studied. In this study, changes in commuting distance were largely associated with organisational relocation rather than with the implemented interventions, highlighting the importance of spatial planning as a complementary approach to behavioural measures. These insights are particularly relevant in mid-sized and seasonally constrained urban contexts.

Future research would benefit from longer observation periods; standardised intervention designs across organisations, including appropriate control groups; and longitudinal or digitally tracked commuting data to better isolate causal mechanisms and assess the long-term sustainability of behavioural change. Extending study durations beyond 1 year would also allow seasonal dynamics and habit-formation processes to be examined more robustly.

CONCLUSION

This study provides empirical evidence that integrated low-emission commuting interventions can influence travel behaviours and reduce transport-related GHG emissions in organisational settings. Implemented across six organisations in Lahti, Finland, the interventions were associated with a 12.5% decrease in emissions intensity and a 34.2% reduction in absolute commuting-related GHG emissions. The counterfactual analysis results indicated that approximately 37% of the total emissions reduction was attributable to changes in modal choice alone, demonstrating that shifts away from car use contributed meaningfully to emission reductions, even when total commuting distance was held constant. The remaining reduction was attributable to decreased commuting distance, including structural factors such as organisational relocation. These findings suggest that while distance reduction was the dominant driver of emissions reductions, modal shifts generated measurable benefits and contributed substantially to the observed outcomes. Communication and awareness strategies appeared to be particularly influential in supporting behavioural change, followed by infrastructure and transport service improvements.

At the same time, the findings highlight important limitations. Behavioural changes were shaped not only by the interventions but also by contextual factors, such as organisational relocation, seasonality, and broader structural conditions. Only a minority of reduced car travel was replaced by low-emission modes, and financial incentives alone produced limited observable increases in public transport or city e- bike use. These results suggest that motivational tools alone are insufficient when structural barriers remain in place, reinforcing the importance of integrated, user-centred approaches.

Despite measurable progress, private car use remained relatively high, underscoring the need for sustained and coordinated efforts to reduce car dependence. Overall, the study demonstrates that incremental reductions in car-based travel distance, rather than large-scale modal shifts, can deliver meaningful climate benefits, particularly in mid-sized and seasonally constrained urban contexts. By combining behavioural interventions with supportive infrastructure and services, organisations and cities can advance low-emission commuting in a practical and scalable manner.

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Authors' contributions

Made substantial contributions to the conception and design of the study, methodology development, validation, formal analysis, investigation, data curation, visualization, manuscript drafting, and manuscript revision: Basnet M;

Made substantial contributions to the conception and design of the study, methodology development, validation, formal analysis, investigation, resource provision, manuscript revision, supervision, project administration, and funding acquisition: Marttila M, Uusitalo V.

Availability of data and materials

Individual-level survey data are not publicly available due to privacy and confidentiality considerations. However, the aggregated datasets and calculation files used for greenhouse gas emissions estimation, intervention analysis, and statistical analyses are available from the corresponding author upon reasonable request.

AI and AI-assisted tools statement

During the preparation of this manuscript, the AI tool Microsoft Copilot was used only for language editing, literature search assistance, and the generation of certain visual materials (e.g., car illustrations used in the graphical abstract). The tool did not contribute to the study design, data collection, analysis, interpretation, or the scientific conclusions of the study. The authors critically reviewed, verified, and edited all AI-generated outputs as necessary. All authors take full responsibility for the content of this manuscript.

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Conflict of interest

All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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