# Potential of e-bikes to replace passenger car trips and reduce greenhouse gas emissions



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# Potential of e-bikes to replace passenger car trips and reduce greenhouse gas emissions

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ABSTRACT

In Sweden, the transport sector accounts for 32% of greenhouse gas emissions, with passenger cars contributing to 62% of these. In this context, electric bikes, commonly known as e-bikes, have emerged as a promising solution for reducing carbon emissions in the transport sector. This paper explores the potential of e-bikes in substituting passenger car trips and reducing transportation-related emissions. To achieve this objective, we use a synthetic population in the Västra Götaland (VG) region, Sweden, with daily activity schedules and simulate an average weekday of travelling with e-bikes instead of their private cars. For assessing the potential for e-bike substitution, the current literature often relies on trip-level analysis, which does not adequately consider people's daily travel-activity plans, resulting in an unrealistic estimation of replaceable trips and their carbon emissions reduction. Combining an e-bike speed model by agents' characteristics and an open-source routing engine, our simulation identifies potential car trips that can be replaced with e-bikes, considering all activities and the travel between them for an average weekday. The simulation results suggest that e-bikes could replace 57.6% of car trips. Building on this, we explore the potential reduction in greenhouse gas emissions from car trips taken by residents in the study area. If the top 70% of feasible car users, ranked by shortest to longest daily travel distances, switch to e-bikes, emissions could be reduced by 10.1% compared to 2018 levels. If all feasible car users adopt e-bikes, a reduction of up to 22.8% in emissions could be achieved, representing the upper limit presented by our study. The findings also reveal that males under 40 years old provide the highest e-bike substitution rates in their daily activity schedules, and in areas with a high population density, replaceable car trips are more common than in rural areas. This research provides valuable insights into e-bike substitution and its impact on emission reduction. It contributes to the existing literature through its modelling approach that realistically considers individuals' socio-demographic characteristics and daily activity schedules when assessing the substitution potential.

## 1. Introduction

The world faces a significant challenge in reducing greenhouse gas (GHG) emissions to mitigate the negative effects of climate change. The IPCC (Intergovernmental Panel on Climate Change) report states, with high confidence, that meeting climate mitigation goals would require transformative changes in the transportation sector (Jaramillo et al., 2022). In Sweden, transportation is responsible for 32% of GHG emissions, and passenger cars within the sector have the most significant share, with 62% of the emissions (SMHI, 2023).

In response to this challenge, many countries and organisations have taken decisive actions to reshape the existing transport system and accelerate the transformation to a sustainable transportation sector. The current strategies predominantly focus on increasing the use of zero- or low-emission vehicles, e.g., purchase subsidies or tax benefits, as seen in France (Anon, 2023a), Canada (Anon, 2023b), Germany (Anon, 2023c), etc. However, there is growing recognition within the academic community that while technological substitution solutions like electrifying car fleets certainly play a role, they may not constitute the sole or quickest strategy for achieving a sustainable transformation of the transportation system (Creutzig et al., 2018). Various international and national scenarios highlight that behaviour changes are critical in achieving climate goals (International Transport Forum, 2021; Brand et al., 2020). Mårtensson et al. (Berg Mårtensson et al., 2023) underscore the importance of a significant reduction in car use to meet Swedish climate targets, which aim for a 70% reduction in domestic transportation emissions by 2030. Therefore, comprehensive approaches are needed, including significant policies investing and incentivising 'active travel' modes, e.g., walking and cycling.

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Electric bikes, commonly known as e-bikes, have emerged as a promising solution to reduce GHG emissions from transportation (Bourne et al., 2018). The prevalent type of e-bike in Europe requires pedalling and offers assistance up to 25 km/h. Unlike motorised vehicles, e-bikes are highly energy-efficient due to their lightweight and small electric motor (Weiss et al., 2015; Fishman and Cherry, 2016). In most cases, e-bikes consume less than 2 kWh per 100 kilometres, roughly one-tenth of a small electric car's energy for the same distance (Ji et al., 2012). Furthermore, e-bike emissions are much lower than conventional cars, although emission values may vary depending on the power plant where the electricity is produced (Fishman and Cherry, 2016). A comprehensive understanding of the limits of e-bike usage in the transportation system, including their spatial and socioeconomic distribution, is necessary for effective policy-making and transport planning. This understanding could assist decision-making processes regarding infrastructure investments and strategies promoting e-bike use.

People's travel behaviours and preferences can shift towards more sustainable transportation choices, such as e-bikes, despite individual preferences being complex and influenced by various factors, e.g., personal habits, weather conditions, social norms, etc. Collaborative efforts involving government policies and active citizen engagement are crucial for increasing cycling's share within the transportation system (Dill and McNeil, 2013; Ruan et al., 2014). Combining strategies that increase the attractiveness of sustainable options (e.g., improved infrastructure) with measures that disincentivize unsustainable choices (e.g., congestion pricing) alongside public awareness campaigns can yield significant benefits. For example, actively promoting cycling, London has seen a notable increase in daily bike trips, rising by 6.3% from 1.19 million in 2022 to 1.26 million in 2023, representing a 20% rise since 2019 (Transport for London (TfL), 2023). Choice models are frequently applied to predict the likelihood and direction of shifts in the transportation system and generally provide a satisfactory understanding of individuals' behaviours (Hallberg et al., 2021; Fosgerau et al., 2023). However, predicting a substantial shift in the system based on past transportation surveys could pose challenges (Haboucha et al., 2017; García-Melero et al., 2021).

On the other hand, identifying the upper limits can provide policymakers and urban planners a benchmark for maximum achievable outcomes, potentially inspiring broader systemic changes. By complementing existing studies that model individual preferences through choice models, the present study explores the upper limits of e-bikes serving as a baseline scenario to further integrate other important factors.

Several studies have explored the potential of e-bikes as a sustainable mode of transportation, revealing their significant role in mitigating emissions. To assess e-bike potential within the transportation system, these studies approach e-bike substitution from different perspectives, e.g., estimating individuals' physical abilities (Philips et al., 2022) to make e-bike trips or generating scenarios based on external conditions like inclement weather (Bucher et al., 2019). However, these studies use trip-level analysis, which often overlooks the positioning of e-bikes within individuals' daily trip chains and their interactions with activities. Trip-level analyses might overestimate replaceable trips by e-bikes when evaluating comprehensive daily activity plans.

Our study contributes to the existing literature by proposing a novel modelling approach to assess the upper potential of e-bikes in reducing carbon emissions. Traditional trip-level analyses often fail to capture the complex interactions between activities in daily plans and the corresponding trips, thereby missing crucial nuances for evaluating e-bike feasibility and practicality. Instead of employing trip-level analysis, we carefully consider the replacement of car trips with e-bikes within the context of individual daily activity-travel plans. Specifically, this study investigates the potential of e-bikes to reduce emissions from passenger cars using a synthetic population with daily activity schedules in the Västra Götaland (VG) region. To identify e-bike trips that can replace cars in activity-travel schedules, we simulate an average weekday, considering each person's activity and trip characteristics. Additionally, this study provides detailed insights into population groups providing the highest substitution rates of e-bikes in their daily activity schedules and presents the spatial distribution of substitution and emission reduction.

The remainder of this paper is structured as follows: Section 2 reviews the related literature. Section 3 describes the data sources and explains our methodology for simulating e-bike trips. Section 4 presents the results regarding e-bike substitution in individuals' daily activity-travel plans and the spatial distribution of reduced GHG emissions from passenger cars. In Section 5, we discuss the limitations of our analysis by considering the broader context of e-bike substitution and provide suggestions for future work. Section 6 concludes the paper by summarising our key findings.

## 2. Related work

With the increasing popularity of e-bikes, a growing body of research explores the impacts of e-bike usage as a transportation mode on mobility, environment, health, and safety (Fishman and Cherry, 2016). E-bikes in this study operate on a similar principle to conventional bicycles (referred to here as "bicycles"), requiring pedalling for movement. However, several barriers, such as lack of knowledge, misperceptions, limited access, high purchase costs, and limited infrastructure, may impede the widespread adoption of e-bikes (Lee and Sener, 2023). Despite these challenges, the unique features of e-bikes, e.g., motorised assistance, may present a solution to address people's mobility needs. While many individuals express interest in bicycles as a transportation mode, they may opt for other modes due to existing or perceived barriers (Dill and McNeil, 2013). E-bikes can help overcome certain challenges preventing people from cycling, e.g., time constraints and physical abilities. They significantly extend the usability of bicycles by facilitating faster travel with less physical exertion, allowing for the coverage of longer distances (Bucher et al., 2019). Researchers indicate the willingness of e-bike users to travel longer distances (over 25 km) (Wei et al., 2013), particularly during epidemic situations (Kazemzadeh and Koglin, 2021), suggesting that e-bikes can significantly enhance the practicality of bicycles as a transport mode.

Empirical studies from different countries show e-bike adoption generally leads to reductions in car use to varying degrees, even though there is some substitution between conventional bikes and e-bikes. For example, a survey conducted among e-bike owners in Sweden illustrates a noticeable shift from cars to e-bikes after purchasing an e-bike. In rural areas, 42% to 60% of the respondents shift from car mode, the main transport mode previously used to make trips, whereas in urban areas, it soars between 71% and 86% of the respondents (Hiselius and Svensson, 2017). Brand et al. (Neves and Brand, 2019) find that active travel could replace 41% of short car trips and significantly reduce carbon emissions from personal travel, considering survey participants' travel patterns and constraints. A survey in Norway indicates that individuals who cycle the least are most interested in purchasing an e-bike (Fyhri et al., 2017). The study's results suggest that e-bikes have minor effects on regular cycling but contribute more to shifting people away from motorised transport. Studies show the varied patterns of e-bike substitution depending on the dominant travel modes in the transportation system. A study on existing e-bike users in Rome shows that e-bikes primarily substituted 49% of car trips and 33% of trips by other or multiple modes. In Antwerp, e-bikes replaced 38% of the car trips and 34% of the bike trips (Castro et al., 2019). However, the mode shift to e-bikes measured at trip level is only one facet. In the Netherlands, where cars and bicycles represent the two largest shares of the mode distribution by trip numbers, the adoption of e-bikes, despite replacing some cycling trips, resulted in a 9.6% reduction in the share of car kilometres travelled, a considerable portion of the total (Sun et al., 2020). While these studies offer valuable insights about e-bike substitution, a common shortcoming is that they mostly have a limited sample size. Moreover, they make inferences by asking questions to current e-bike owners or people in certain e-bike programs, which may lead to limited representation of the general population.

A body of research creates scenarios to assess the *potential* utilisation of e-bikes within the transportation sector and the consequent reduction in GHG emissions. Bucher et al. (2019) evaluate the potential e-bike adoption in commuting trips in Switzerland by analysing factors like temperature, precipitation, and travel distance, and the study presents the spatial distribution of GHG emission reductions by e-bike adoption. McQueen et al. (2020) presents a travel mode replacement model for a given e-bike mode share using a survey of e-bike users. The model calculates a reduction in transportation emissions by scaling down the distance travelled by other modes in proportion to the person miles travelled replaced by e-bikes. Philips et al. (2022) model the adoption of electric bicycles as a mode of travel, accounting for the physical abilities of individuals. By estimating individuals' maximum e-bike travel distance, the study identifies trips that can be feasibly switched from cars to e-bikes. Accordingly, it calculates emission reduction resulting from avoiding the car.

Although previous studies present the potential of e-bikes to reduce emissions using different approaches, these studies have trip-level analyses while ignoring the complexity of individuals' daily schedules and the interconnectedness of planned activities. These studies often fail to adequately consider the positioning of e-bikes in the daily trip chain and their interactions with activity patterns. This limitation overlooks crucial factors like time constraints, activity compatibility, and individual differences, potentially overestimating the number of replaceable trips and GHG emissions reduction.

To address this gap, our study utilises Hägerstrand's time-geography concept (Hägerstrand, 1970), which explains how individuals implement their activity agenda while considering three main constraints. **Capability constraints** encompass individual limitations due to their physical or mental abilities and available resources. For example, an individual's ability to use an e-bike may be influenced by factors such as age and physical fitness. **Coupling constraints** reflect the spatial and temporal links between activities and resources. One instance is that a workplace located beyond the cycling range could restrict the feasibility of using an e-bike for all subsequent trips throughout the day. **Authority constraints** include social norms, regulations, and infrastructure limitations influencing travel choices. For instance, maximum e-bike speed limit regulation or designated biking lanes can incentivise or discourage e-bike use.

In this study, we use 284,000 agents with socioeconomic attributes and detailed activity-travel plans from the synthetic population. By adopting Hägerstrand's time-geography concept, we evaluate the potential of e-bike substitution within the context of individuals' daily activity-travel plans. Our assessment considers e-bike trip features, activity-related constraints, trip-related constraints, and personal characteristics and reflects the place of e-bikes in individuals' daily activity-travel plans. However, individual preferences, social norms, etc., are beyond the scope of this study.

## 3. Methodology

This section explains the key modelling concepts employed to calculate the trip replacement and CO2 reduction potential of e-bikes (Fig. 1). In the study, we use a synthetic population with daily activity schedules. The data were generated by a large-scale transportation modelling framework, the Synthetic Sweden Mobility Model (SySMo) (Tozluoğlu et al., 2022; Tozluoğlu et al., 2023) and simulated using MATSim (Liao et al., 2023) (please see details in Appendix A).

The SySMo model generates over 10 million agents with their activity schedules. In this study, we use only agents with car trips in their daily schedule and residing in the Västra Götaland (VG) region, which includes Gothenburg, Sweden's second-largest city. The data used in the study contains 284,000 agents, representing 35% of all car users and 18% of the total population living in the region. We ensure that this share is representative of the population by sampling proportionally according to Demographic Statistical Areas (DeSO) (Anon, 2020).

To identify replaceable car trips within individuals' daily activity-travel plans, our model utilises Hagerstrand's time-geography concept. This concept analyses how individuals construct their daily schedules within the confines of time and space. It takes into account three main constraints related to users' capability, coupling and authorities. We incorporate these constraints at several points in our methodology. The capability constraint involves calculating individuals' cycling speed, considering factors like age and gender. The cycling speed impacts the feasibility of e-bike trips in terms of space and time. We incorporate coupling constraints by recalculating individuals' daily activity schedules to ensure that e-bike trips fit within their planned activities. Additionally, we address authority constraints by considering the available biking infrastructure and cycling regulations. A thorough exploration of these constraints' limits, our model not only identifies where e-bikes could feasibly replace car trips but also explores the maximum extent to which this could occur.

### 3.1. Simulating e-bike trips

The study's methodology starts by assigning an e-bike to all car trips in the agents' daily travel plans and simulating e-bike trips on the road network. The e-bike simulation provides e-bike trips' distance and duration by personal, activity, and infrastructure characteristics. We then re-calculate agents' daily activity-travel plans using the calculated trip duration shifted to an e-bike. To perform the e-bike simulation, we first deduce e-bike movement trajectories and then calculate trip duration using a speed model that we developed.

*E-bike movement trajectories*

We use a routing engine, OpenTripPlanner (OTP) (OTP, 2023), to produce e-bike movement trajectories and, accordingly, trip distances. OTP, which is utilised in various research projects (Pereira, 2019; Tenkanen and Toivonen, 2020; Liao et al., 2020; Feng et al., 2021), works similarly to most popular trip-planning applications like Google Maps or Apple Maps and provides potential travel routes based on given parameters, i.e., origin, destination, and chosen travel mode. For the e-bike simulation, we first feed OpenStreetMap (OSM) data (OSP, 2023) and the elevation data (Copernicus Programme, 2022) into OTP for creating a routable road network. Then the OTP, serving as a routing engine, uses the created network to extract e-bike movement trajectories with the origin and destination locations of the car trips that are assumed to be replaced with e-bikes. OTP identifies e-bike routes on the given network while considering bike-friendly infrastructures (e.g., separated bikeways, low-traffic streets, etc.) indicated by the OSM road network.

*E-bike speed model*

To assess the potential of car trips replaced by e-bikes, we need the e-bike trips' duration. While OTP provides this information and the moving trajectories, it does not encompass personal and trip-specific characteristics. To address this limitation, we design an e-bike speed model to calculate the trip's duration and integrate the e-bike cycling speed model into the simulation. Specifically, we combine this e-bike cycling speed model with the output from the OTP: the e-bike trip distances and the elevation profiles of their movement trajectories. Our speed model incorporates demographic characteristics (age and gender), activity type (work or other), and infrastructure characteristics (road gradient). These factors are based on data from two empirical studies (Flügel et al., 2019; Schleinitz et al., 2017) which observed cycling behaviour across a variety of infrastructural settings, including carriageways, dedicated bicycle paths, pavements, and varied traffic

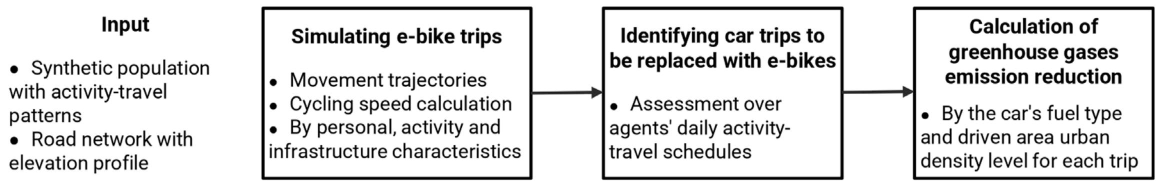


**Fig. 1.** Methodology overview of the study showing carbon reduction capability of e-bikes through substituting to car trips in the Västra Götaland region.

**Table 1**
The average Speed distribution parameters by age group Schleinitz et al. (2017).

| Age group | Mean (km/h) | Standard deviation (km/h) | Minimum (km/h) | Maximum (km/h) |
|---|---|---|---|---|
| ≤ 40 | 20.5 | 5.2 | 12.9 | 31.0 |
| 41–64 | 17.5 | 4.0 | 12.2 | 25.3 |
| ≥ 65 | 14.5 | 1.9 | 12.2 | 18.6 |

Twisk et al. (2021) report average speeds of 20.1 km/h in urban areas and 22.2 km/h in rural settings, based on data from 14 riders in the Netherlands. Similarly, the study (Dozza et al., 2016) from Sweden reports an average speed of 16.9 km/h (SD = 2.9 km/h) observed among 14 cyclists. Furthermore, research (Huertas-Leyva et al., 2018) in Italy involving a small sample of six cyclists records an average speed of 20.4 km/h (SD = 7.8 km/h).

conditions like traffic lights. Nevertheless, it is worth noting that certain factors, e.g., crossings, traffic lights, and road curvature, are represented as average speed, not modelled at the link level in the current model. Incorporating these factors into the speed model can represent an area for potential improvement.

The speed model starts with calculating the average cycling speed for each individual to use as a baseline for all e-bike trips of that individual. We first derive a speed value by age group to set the individual average speed. Introducing variability, the speed value is drawn from a normal distribution based on the individual's age, informed by the research by Schleinitz et al. (2017). Besides age, we also add the gender multiplier as another parameter, considering potential differences in cycling behaviour between genders (Flügel et al., 2019). We multiply the sampled speed value from age-based normal distribution by the gender parameter and get the average cycling speed for each individual. To make the average speed realistic, the deduced speed values are truncated using minimum and maximum bounds (Schleinitz et al., 2017).

We then calculate the e-bike speed for each road segment (link) in each cycling trip for an individual's activity-travel plan. We use the individually assigned average cycling speed while considering two trip-specific factors: trip purpose and road gradient. The trip purpose is recognised as one of the determinants of cycling behaviour (Flügel et al., 2019). Our model considers the trips for two purposes: work and non-work. The model also comprehensively accounts for the effects of the road gradient on cycling speed. The road gradient is divided into 18 categories, including both positive and negative gradients. Using the trip-specific parameters, we calculate the speed for each e-bike trip at the road segment level.

Let $S'_{ij}$ represent the e-bike speed value for individual $i$ in age group $j$, drawn from a normal distribution with mean $\mu_j$ and standard deviation $\sigma_j$ specific to the age group $j$. The sampled speed value is scaled by a gender parameter $X_i$ and truncated by the lower $S_{min_j}$ or upper bounds $S_{min_j}$. The average cycling speed $A_{ij}$ for each individual can be calculated as in Eq. (1). To calculate the speed of a particular road segment $t$ for each cycling trip in an individual's activity schedule $S_{it}$, the average cycling speed $A_{ij}$ is scaled with the activity purpose $P_i$ and the road gradient $G_t$ parameters (in Eq. (2)). The values $\mu_j$, $\sigma_j$, $S_{min_j}$ and $S_{min_j}$ are obtained from the study (Schleinitz et al., 2017) (Table 1), and $X_i$, $P_i$ and $G_t$ values from the study (Flügel et al., 2019) (Table 2).

$$S'_{ij} \sim N(\mu_j, \sigma_j)$$
$$A_{ij} = S_{min_j} \leq S'_{ij} \cdot e^{X_i} \leq S_{max_j} \tag{1}$$

**Table 2**
Parameters for the e-bike speed model (Flügel et al., 2019).

| Parameter | Subcategories | Coefficient |
|---|---|---|
| Gender ($X_i$) | Male | 0.0491 |
| | Female | 0.0 |
| Activity purpose ($P_i$) | Work trips | 0.1071 |
| | Non-work trips | 0.0 |
| Gradient ($G_t$) | < −9% | 0.0518 |
| | −9 to −7% | 0.0617 |
| | −7 to −6% | 0.1228 |
| | −6 to −5% | 0.1861 |
| | −5 to −4% | 0.1488 |
| | −4 to −3% | 0.1196 |
| | −3 to −2% | 0.0779 |
| | −2 to −1% | 0.0312 |
| | −1 to 0% | 0.0196 |
| | 0 to 1% | 0.0 |
| | 1 to 2% | −0.0376 |
| | 2 to 3% | −0.1299 |
| | 3 to 4% | −0.1951 |
| | 4 to 5% | −0.2669 |
| | 5 to 6% | −0.3034 |
| | 6 to 7% | −0.3854 |
| | 7 to 9% | −0.3949 |
| | > 9% | −0.4267 |

$$S_{it} = A_{ij} \cdot e^{(P_i + G_t)} \tag{2}$$

### 3.2. Mode replacement

Not all the agents' updated activity-travel schedules using e-bikes instead of cars are feasible in reality. We propose an algorithm to evaluate these replaced schedules to identify the car trips that e-bikes can potentially replace (Algorithm 1 and Fig. 2). The algorithm incorporates constraints on individual trips, activities, tours, and daily activity-travel plans. Each agent has daily activity-travel plans, including activities and trips to access the activities. A trip series that begins and ends at home locations constitutes a tour. People are more likely to leave their cars and switch to alternative travel modes, e.g. e-bikes, when they are at home rather than at other activity locations.

The algorithm's initial step involves evaluating all trips against two criteria: a maximum cycling distance and a maximum allowable delay in reaching the destination activity. E-bikes can enable relatively longer distance trips compared to conventional bicycles. In a review of 18

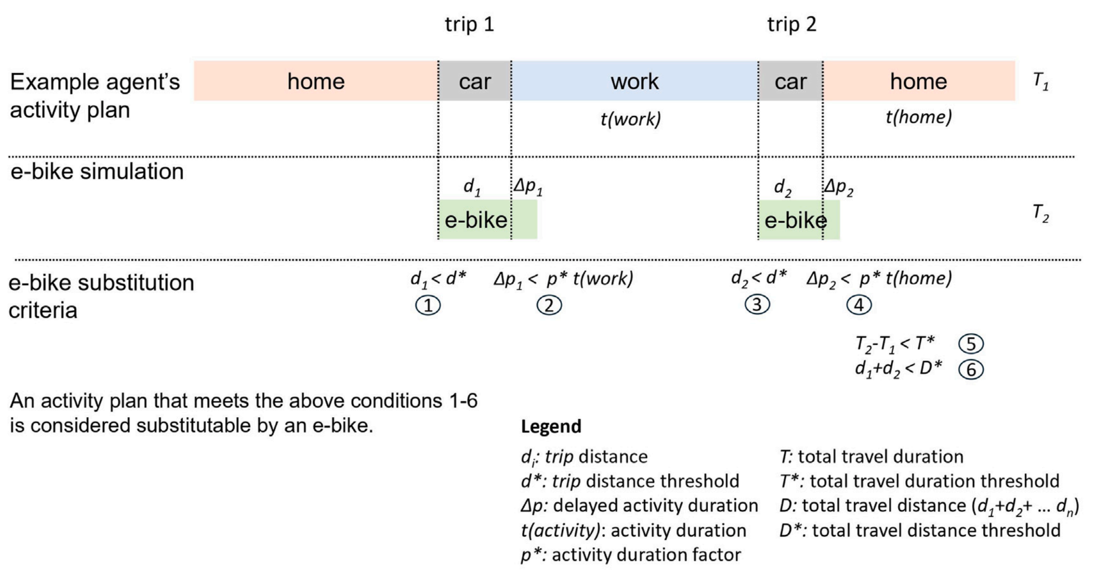


**Fig. 2.** Overview of the e-bike substitution methodology.

**Algorithm 1:** E-bike substitution algorithm.

**Initialise:**
trip distance $d$ with a threshold $d^*$
trip duration change $\Delta p$ with a threshold factor $p^*$
daily total travel duration change $\Delta T$ with a threshold $T^*$
daily total travel distance $D$ with a threshold $D^*$
**for** each individual with daily activity-travel plan in the population **do**
  **for** each tour in the daily activity-travel plan **do**
    **for** each car trip in the tour **do**
      **if** $(d < d^*)$ & $(\Delta p < (p^* \cdot$ the next activity duration$))$ **then**
        the car trip can be replaced
      **end if**
    **end for**
    Initialise variable *allCarTripsintheTourchangeable* as **true**
    **for** each car trip in the tour **do**
      **if** car trip is not changeable **then**
        Set *allCarTripsintheTourchangeable* to **false**
        **pass**
      **end if**
    **end for**
  **end for**
  **if** $(\Delta T > T^*)$ & $(D > D^*)$ **then**
    the car trips are not changeable
  **end if**
**end for**

European studies (including grey literature), Cairns et al. (2017) show that the average trip distances of e-bike trips spanned up to 30 km. Furthermore, studies from Belgium (Lopez et al., 2017) and China (Wei et al., 2013) reveal a bimodal distribution of e-bike trip distances, with an initial peak of less than 5 km and a significant second peak of around 22 km, extending up to 40 km. Similarly, Dane et al. (2020) show that maximum e-bike trip distances exceed 30 km using mobile phone GPS data in the Netherlands. To capture the broad range of e-bike trips in our analysis and explore the upper limits of e-bike usability, we set the maximum distance for e-bikes at 30 km. This threshold enables us to cover a comprehensive range of possible e-bike trips.

The algorithm also evaluates e-bike substitution regarding potential delays to arrival activities caused by the substitution.[1] Econometric utility functions are widely used to model activity-travel plans (Bowman and Ben-Akiva, 2001; Arentze et al., 2011). This approach considers the utility of performing an activity and the disutilities, e.g., being early or late to the activity. To evaluate the potential delays, we adopt a similar method to the Charypar–Nagel Utility Function (W. Axhausen et al., 2023). In this function, the default value of the disutility of being late for an activity is three times the magnitude of the utility of performing that activity. For instance, the disutility of one hour being late equals losing the utility of three hours of performing an activity. Accordingly, we assign the maximum allowable delay in travel time as being less than 30% of the duration of the arrival activity. If the delay surpasses this threshold, there is no utility in performing the activity. Thus, we assume that the activity and associated trip are not feasible, and the e-bike cannot replace the car.

Next, the algorithm evaluates tours, i.e., trip series that begin and end at home locations. For a car trip within a tour to be replaceable by an e-bike, all trips within the tour must satisfy the above-mentioned criteria. For instance, let us consider a tour that originates from home and includes trips to work, shopping, and the return trip home. To replace the trip between home and work with an e-bike, the other leg of the tour containing a shopping trip must also be replaceable with an e-bike.

In the last step, the algorithm assesses the cumulative impact of these substitutions on total daily travel duration and travel distance by e-bike by comparing them against thresholds. To examine daily total changes in daily travel time following substitutions, we established a threshold of 1.5 h. This threshold is derived from Schäfer and Victor's travel time budget (Schafer and Victor, 2000), which represents the average daily travel time for individuals. To assess the cumulative impact of distance, the algorithm compares the total daily trip distances of the agents against a threshold, representing the average range of the e-bike battery. We assume that individuals start their day with a fully

[1] An ideal modelling approach would adjust trip departure times backwards and forwards, accounting for leaving earlier from a previous activity or arriving late for a subsequent one. This modelling practice, however, requires information about individuals' activity priorities. Due to data limitations, we represent travel time changes as delays. Future research could explore more detailed modelling of departure times.

**Table 3**
The average GHG emissions factors for passenger cars by fuel types. TTW: tank to wheels, i.e. direct GHG emissions at the exhaust pipe.

| Passenger car fuel type | TTW (kg $CO_2$ eq./km) | | |
|---|---|---|---|
| | Urban | Rural | Mix |
| Gasoline | 0.17 | 0.16 | 0.16 |
| Diesel | 0.14 | 0.14 | 0.14 |
| Electric | 0.0 | 0.0 | 0.0 |
| PHEV gasoline | 0.08 | 0.1 | 0.1 |
| PHEV diesel | 0.06 | 0.08 | 0.07 |
| Ethanol | 0.2 | 0.18 | 0.19 |
| Gas | 0.03 | 0.03 | 0.03 |

charged battery on their e-bikes and do not recharge them during their daily plans. We set the daily cycling range threshold at 80 km using the widely recognised e-bike manufacturers, Bosch and Specialised's range calculation assistants (Bosch, 2023; Specialized, 2023). The e-bike range shows variability by various factors, e.g., battery size, driver weight, speed, and terrain. We selected a 400 Wh battery, an 80 kg rider, an average 18 km/h speed, and hilly terrain as parameters for our calculations.

### 3.3. Estimation of reduced emissions

After identifying potential e-bike trips, we calculate GHG emissions from passenger cars for both the baseline scenario for 2018 and the scenario where e-bikes replace passenger car trips. Our study focuses solely on the evaluation of tank-to-wheel (TTW) emissions, thus not taking into consideration upstream emissions. TTH emissions are normally those attributed to the transport sector and on which specific goals are set. We consider the car fleet from 2018, while the changes in the fleet composition are beyond the scope of this study.

To determine reduced emissions, we first deduce the fuel type of the cars driven in the simulation. The included fuel types are gasoline, diesel, electric, hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV), ethanol, and natural gas. Using a probabilistic approach, we assign fuel types using the municipalities' car fleet fuel type distributions (Trafikanalys, 2023) and the cars' total kilometres driven daily. Given that diesel cars typically have higher average mileage compared to other fuel types (Anon, 2021), the employed approach increases the probability of assigning diesel to cars with longer travel distances than the median travel distance in the municipality. This method adjusts the probability of assigning diesel to cars in proportion to the difference between each car's travel distance and the median travel distance in the municipality, while still maintaining the overall fuel type distribution.

Subsequently, we calculate the average TTW emissions for each trip using the assigned car types of agents, road characteristics, and average emission factors. The Swedish Transport Agency publishes emission factors for vehicle and fuel types (Trafikverket, 2023) using the Handbook Emission Factors for Road Transport (HBEFA) model (Notter et al., 2019). The average emission factors consider various parameters, including the age and size class distribution of the vehicle fleet in Sweden, and provide GHG emissions in CO2 equivalent (Table 3). However, it is worth noting that the data does not include the emission factor for HEV. Therefore, we assume the HEV's emission factor is the same as that of the gasoline fuel type.

In the study, we use average emission factors for passenger cars, categorised by fuel type and urban density level for 2021, which is the closest available date to the base year. The data has three categories of urban density levels: urban, rural, and mixed. We categorise the road network used in the simulation by utilising DeSO zones (Anon, 2020), which cover the entirety of Sweden and consist of 5,984 zones. We then calculate average GHG emissions at a link level for each car trip for the base and e-bike substitution scenarios.

Finally, we calculate the reduction in passenger car emissions and present the spatial distribution of carbon emissions reduction for residents in the VG region.

## 4. Results

This study reveals e-bike substitution in individuals' daily activity-travel plans and the spatial distribution of reduced GHG emissions from passenger cars. We first examine the e-bike substitution results across different population groups. And then, we present the potential emissions reductions, comparing the baseline scenario with the scenario where e-bikes replace cars. We also provide the sensitivity analysis results, demonstrating how changes in the model's constraints influence the e-bikes' potential for GHG reduction from private car driving.

### 4.1. E-bike car trip substitution

The study reveals the potential of e-bikes to replace passenger car trips using the algorithm incorporating constraints at the individual trip, tour, and daily plan levels. Initially, we evaluate all trips by the maximum trip distance and allowable delay to the next activity constraints. At the trip level, our findings suggest that e-bikes could potentially replace 72.4% of all car trips. We then evaluate tours by ensuring that all trips within a tour meet the constraints established at the trip level. At the tour level, car trips where e-bikes can potentially replace up to 60.6% of all car trips. The final step involves considering e-bike substitution by evaluating daily plans based on total daily travel duration change and travel distance. Our ultimate finding is that the potential e-bike substitution is 57.6% of all car trips, with a distance distribution of the cycling trips illustrated in Appendix B. This finding shows that to understand the potential substitution capability of e-bikes, the full-day schedule needs to be taken into consideration, and not only individual trips such as commuting.

We also assess the population groups providing the highest e-bike substitution rates to give a more comprehensive perspective on e-bike substitution dynamics. Fig. 3 presents e-bike substitution by age and gender in the population. According to the developed speed model, these two personal attributes are among the variables that affect individuals' cycling speed. We see the highest e-bike substitution rate at 66% among males under 40 years old. The e-bike substitution potential tends to decrease with age, with a large change for females compared to males. Pearson correlation analysis reveals a small yet statistically significant negative correlation between age and e-bike substitution, with a correlation coefficient of −0.2 and a $p$-value of less than 0.01. Furthermore, t-test results highlight distinct substitution patterns between the youngest and oldest age groups. These findings suggest varying patterns of e-bike substitution across different demographics.

### 4.2. Upper limit of emissions reduction

After identifying the potential e-bike trips, we calculate GHG emissions reduction from passenger cars using the baseline scenario and the scenario where e-bikes replace passenger car trips. The baseline scenario is established for 2018 to align with the synthetic population data. In the baseline scenario, our results suggest that VG region residents' total GHG emissions from passenger cars on an average weekday is 2,501 tons of CO2 eq. and 2,175 tons of CO2 eq. within the VG region. The calculated emission for the baseline scenario is comparable with the official statistics (see Appendix C). However, despite e-bikes replacing more than 50% of car trips, we find that the benefit of e-bikes in reducing GHG emissions from car trips within the VG region is limited by 25.6%. This outcome can be explained by the fact that e-bikes are mostly substituted in short or medium-distance trips. Summing it up, while over 50% of the trips can be replaced, these represent only 22.4% of the total car kilometres. When we extend our analysis to encompass all car trips taken by VG residents, i.e., even those ending and starting outside of the region, the emissions reduction from car trips drops to 22.8%. This decrease is primarily due to the fact that trips outside of VG are often long-distance trips.

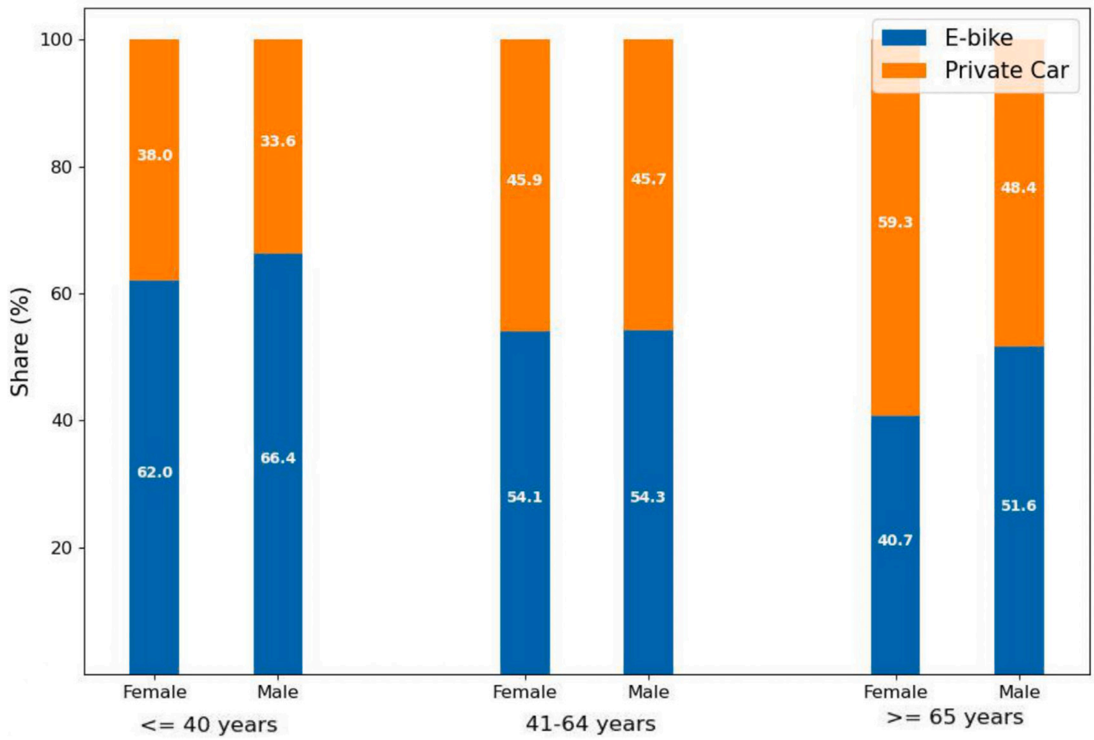


**Fig. 3.** Trip mode share by age and gender after e-bike substitution.

Furthermore, we analyse the spatial distribution of GHG emission reduction from e-bike replacement. Fig. 4 illustrates the percentage emission reduction by DeSO zones on the VG region map. E-bike emission reduction potential is higher for people residing in urban areas than in rural areas. We also analyse e-bike emission reduction potential at the municipality level (see Appendix D). The municipalities with a high population density, e.g., Gothenburg Partille and Mölndal provide the highest emission reduction from car trips.

### 4.3. Range of the emissions reduction

We explore the range of potential emission reductions based on varying e-bike adoption levels among car users identified as feasible for adopting e-bikes by Algorithm 1. The analysis ranks the car users according to their daily trip distances in ascending order, assuming that the shorter the distance, the higher the likelihood of switching to e-bikes. Fig. 5 illustrates the emission reduction potential by the share of substituted e-bike users. If the top 50% of feasible car users, ranked from shortest to longest daily travel distances, adopt e-bikes, we estimate a reduction of 5.1% in emissions. When the share extends to the top 70% and 90%, the emission reduction increases to 10.1% and 17.6%, respectively. If all feasible car users adopt e-bikes, according to our algorithm, we could achieve an emissions reduction of up to 22.8%, reaching the upper limit presented by our study.

### 4.4. Sensitivity analysis

We conducted a sensitivity analysis to illustrate how the simulation outcomes vary by the constraints employed in our e-bike substitution algorithm (see Algorithm 1). These constraints include maximum cycling trip distance, maximum allowable delay, total daily travel duration change, and total daily travel distance by e-bike. We tested our algorithm by systematically varying each constraint plus or minus 30% and 15%. The sensitivity analysis results are presented in Fig. 6 (detailed in Appendix E).

We present the sensitivity analysis results by travel mode replacement and emission reduction. For the mode replacement outcomes, our simulation exhibits the highest sensitivity to the maximum allowable delay constraint to the next activity. When this threshold is changed by plus or minus 30%, the mode replacement from a car to an e-bike results are 59.7% and 54.2%, respectively. For the emission reduction results, the simulation displays the highest sensitivity to changes in the maximum trip distance constraint. When this threshold is varied by plus or minus 30%, the emission reduction shares from car trips within the VG region range between 27.1% and 22.0%, respectively. Although there are about five percentage point changes by the constraints in the mode replacement and emissions reduction results, our simulation results generally demonstrate low variability to these constraint changes.

## 5. Discussion

In this study, we analyse the upper limits of e-bike substitution and calculate the corresponding reduction in GHG emissions using a synthetic population with daily activity-travel plans. Building on Hägerstrand's time-geography concept, we delve into the constraints shaping individuals' daily plans and evaluate the potential of e-bike substitution. This assessment considers three main constraints: capability, considering individuals' abilities by age and gender; coupling, considering individuals' daily activity schedules with e-bikes; and authority, considering the available biking infrastructure to perform their daily activities.

Many studies highlight the impact of daily plans on travel mode choices and their importance in providing a more realistic examination of travel mode preferences (Schneider et al., 2021). Our results from the trip level assessments suggest that e-bikes potentially replace 72.4% of all passenger car trips. However, when examining e-bike substitution within the context of daily plans, we find that the e-bike replacement rate in car trips drops to 57.6%. This outcome shows the importance of considering individuals' full-day schedules to comprehend the substitution potential of e-bikes.

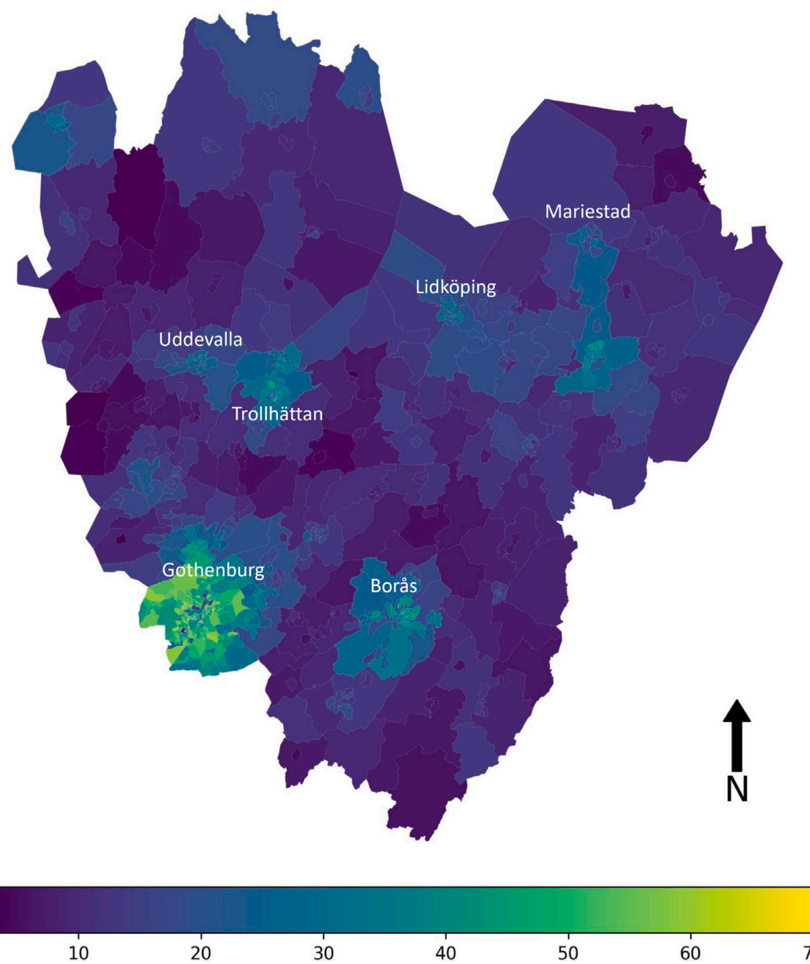


**Fig. 4.** Spatial distribution of passenger cars emission reductions aggregated by the driver's residential DeSO zone (in %).

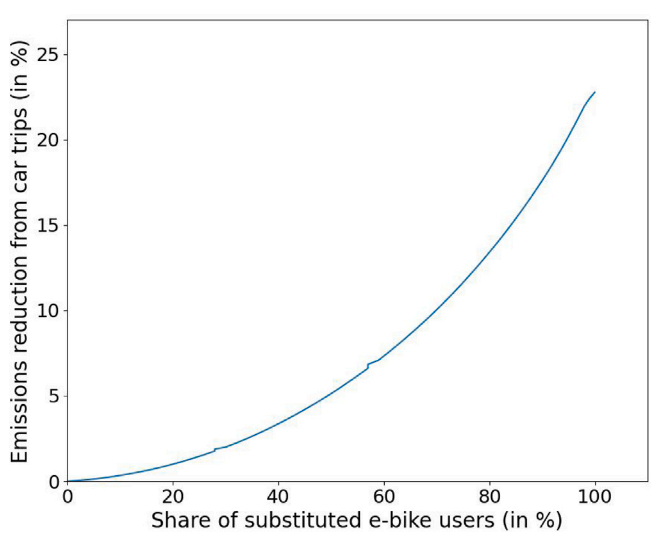


**Fig. 5.** Emission reductions from passenger car users who have substituted car travelling with e-bikes. The *y*-axis is in ascending order of users' daily travel distance.

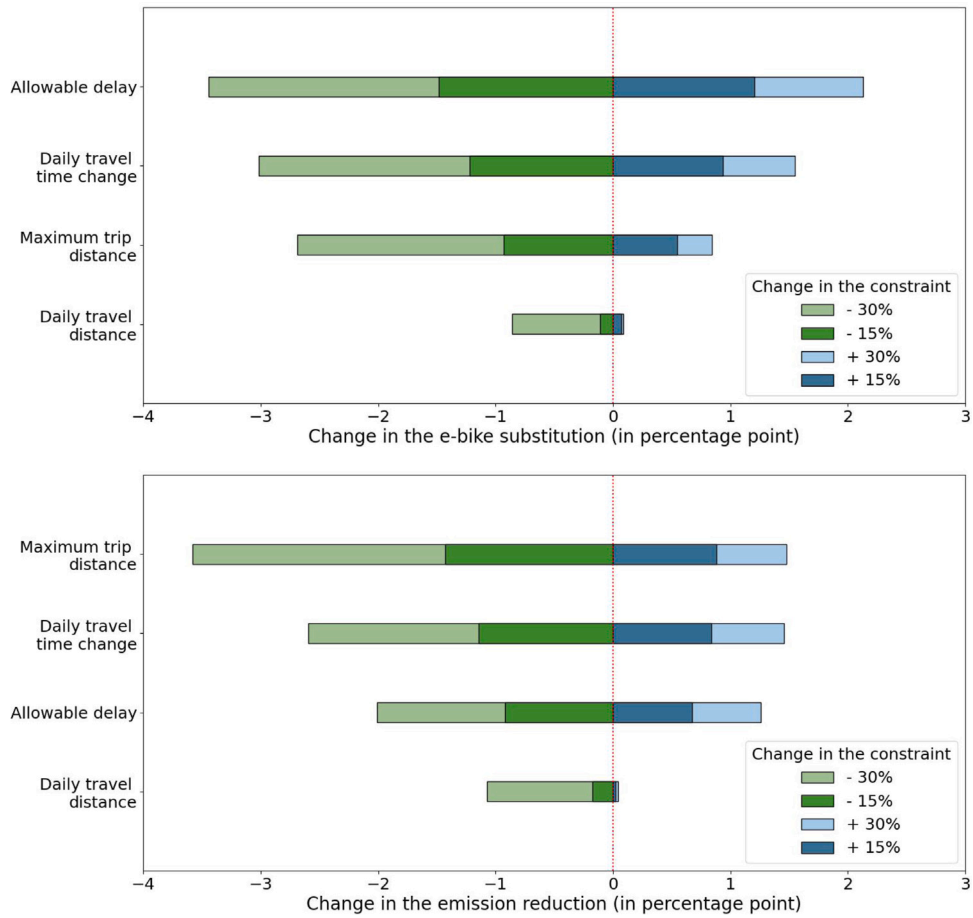


**Fig. 6.** Sensitivity of e-bike potential in replacing private cars in response to varying constraints in Algorithm 1. The upper panel shows the change in the e-bike substitution in car trips, and the lower panel shows the change in the emission reduction from passenger cars compared with the selected parameters of these thresholds.

Our research reveals that e-bikes reduce emissions from passenger cars within the VG region by 25.6% compared to the 2018 baseline scenario, despite e-bikes replacing more than 50% of car trips. The limited emission reduction is due to utilising e-bikes mostly in short and medium-distance trips. The analysis of the total car kilometres after the substitution shows that e-bikes replace 22.4% of the total car kilometres of VG residents. This reduction is almost equivalent to the magnitude that Mårtensson et al. (Berg Mårtensson et al., 2023) describe as necessary to achieve Swedish transport goals, which aim for at least a 70% reduction in transportation-related emissions by 2030 compared to 2010 levels. Their study highlights that achieving the Swedish transport target through the substitution of electric cars and biofuels alone is not possible without reducing person car kilometres.

Several studies explore the potential of e-bikes to reduce transportation-related emissions from various perspectives. For example, Bucher et al. (2019) examine the potential impacts of e-bike adoption scenarios in commuting trips in Switzerland, considering variables, e.g., temperature and precipitation. Their research reveals that reductions of up to 17.5% in fossil fuel-based emissions are possible. Additionally, McQueen et al. (2020) estimate that a 15% e-bike person miles travelled (PMT) mode share penetration could deliver a 12% reduction in carbon dioxide (CO2) emissions from passenger transportation, using a mode replacement model based on survey data. These studies have slightly lower emissions reduction estimates than our study's results because they focus on a specific trip purpose, e.g., commuting, or consider, to some extent, an individual's willingness to take a cycling trip.

Furthermore, some studies use a life cycle assessment (LCA) approach, which captures vehicles' entire life cycle, including manufacturing, usage, and disposal, to assess e-bike potential. According to the life cycle emission estimates by Weiss et al. (2015), e-bikes emit 25 g CO2 eq., while cars emit 240 g CO2 eq. per person kilometre in Europe. Considering the vehicle life cycle, Philips et al. (2022) demonstrate that the mean saving for individuals replacing car kilometres with an e-bike is 0.58 tons of CO2 per year. The study also argues that the emission-saving potential of switching to e-bikes is higher in rural compared to urban areas in England. In contrast, our study reveals higher potential in urban areas in Sweden. This discrepancy highlights the significance of considering the geographical context in e-bike substitution and the value of studies like ours in obtaining a more comprehensive understanding of the benefits of e-bikes in various geographical contexts.

Additionally, the sensitivity analysis demonstrates that our simulation results have relatively low variability to changes in constraints employed in our e-bike substitution algorithm. When constraints are either increased or decreased by 30%, the mode replacement rates from car to e-bike and the corresponding reduction in car emissions fluctuate within a narrow range of 5%. The sensitivity analysis also shows that the changes are not symmetrical. Decreasing the constraint values has a larger effect on the simulation results regarding e-bike substitution and emission reduction when compared to increasing the constraints. Moreover, our research reveals that possible delays to the next activity are an essential factor affecting the results of e-bike substitution. These outputs may provide valuable insights for transportation modellers in model construction and guide policymakers in crafting e-bike policies.

While our study unravels the potential of e-bikes in replacing car trips and mitigating carbon emissions within the transportation sector, it is also important to acknowledge the limitations of our analysis and consider the broader context of sustainable transportation strategies. Firstly, our study focuses on the potential upper limits of e-bike adoption and does not consider individuals' transportation preferences influenced by internal factors, e.g., personal habits, health concerns and psychological barriers or external factors, e.g., weather conditions, social norms and air quality (Schoenau and Mueller, 2017; Passafaro et al., 2014). Despite being on the hyperthetical side of modal shift, these exclusions enable us to explore the benchmark for maximum achievable outcomes. Additionally, our analysis does not consider whether trips involve transporting heavy goods or needing to accompany another person, e.g., driving young children to school. Incorporating these factors into the analysis would most likely show lower e-bike integration than our findings and could provide a more detailed understanding of e-bike usage by preferences.

Secondly, we base our calculations on this year, given that the synthetic population belongs to 2018. When we compare the base year of 2018 in official statistics and the year 2021, the most recent published date, there has been an approximately 10% decrease in emissions in passenger vehicles in Sweden (Anon, 2020). This implies that comparing to more recent years the emission reduction potential will be lower simply because TTW emissions from cars will be lower.

In this study, we examine e-bike substitution within average weekday schedules while keeping other factors unchanged, e.g., activity locations. We assume that individuals largely maintain their current activity patterns and locations when switching from car mode to e-bike. However, it is important to acknowledge that adopting e-bikes may lead individuals to reconsider their daily routines, potentially resulting in changes to their activity locations. Moreover, the analysis results could vary when examining different days of the week separately. In our future research, we could explore e-bikes' potential by considering shifts in activity locations and patterns stemming from e-bike adoption and extend the analysis to different days of the week for a more comprehensive understanding of e-bike's potential in reducing carbon emissions.

There is also a possibility of a rebound effect associated with reducing car use resulting from the transition to cycling. This effect could occur as reduced traffic congestion might incentivise people to use passenger cars (Malmaeus et al., 2023). The rebound effect may result in a lower emission reduction than the calculated. However, in response, policymakers could consider measures to counteract the rebound effect and maintain the benefits of e-bike usage. One effective strategy might be to promote e-bike usage by expanding dedicated e-bike infrastructure while discouraging car use by limiting road space or implementing pricing mechanisms for passenger cars.

To realise the potential of e-bikes, a range of measures are required, including reducing car usage and promoting sustainable transportation modes (Verplanken and Roy, 2016; Rye and Hrelja, 2020; Michie et al., 2011; Brand et al., 2013). However, robust empirical evidence regarding the effectiveness of interventions in promoting cycling for travel, especially in countries with a low bike mode share, remains limited (Stewart et al., 2015). A study conducted in Gothenburg shows that the transition to cycling as a primary mode of transportation is an ongoing, dynamic process influenced by positive and negative experiences (Strömberg and Wallgren, 2022). Dedicated cycling infrastructure encourages individuals to integrate biking into daily routines (Stewart et al., 2015). Equipment availability, e.g., clothing and bells, is an essential factor in mitigating the associated challenges alongside cycling infrastructure (Strömberg and Wallgren, 2022).

Although e-bikes have the potential to increase the share of active travel modes in the transportation system and reduce greenhouse gas emissions, achieving climate goals requires a more comprehensive approach. E-bikes are insufficient to replace long-distance passenger car trips and provide a substantial reduction in the total distance travelled by cars. Therefore, examining the potential emission reductions that active mobility can bring through integration with electrified public transport, considering daily plans and geographical context, could be a future research direction.

## 6. Conclusion

The study provides insights into the potential of e-bikes in replacing car trips and thus reducing carbon emissions within the transportation sector, with a specific focus on Sweden's Västra Götaland (VG) region. Using a methodology that considers individuals' socio-demographic characteristics and daily activity schedules, we have achieved a better understanding of the potential for e-bike adoption, which is valuable for effective policy formulation and transport planning.

We have identified that e-bikes can replace a substantial portion of passenger car trips, leading to a 25% reduction compared to 2018 in GHG emissions from car trips within the VG region. Furthermore, our analysis shows the spatial distribution of GHG emission reduction. In areas with higher population density, there is a greater potential for replaceable car trips and emissions reduction from e-bike adoption. For instance, in Gothenburg municipality, the emissions reduction potential is almost 45% of car emissions. This spatial understanding could be valuable for Sweden's second-largest city, which aims to achieve a 90% reduction in transportation emissions by 2030 compared to 2010. Additionally, these findings are relevant to policymakers and urban planners targeting to promote e-bike usage and develop appropriate infrastructure. The study's findings may not directly apply to other geographical regions due to their derivation from the sociodemographic variables, mobility patterns, and road network specific to the Västra Götaland Region. Nonetheless, the methodology of this study can be adapted to any region with synthetic populations and travel surveys, and the other datasets can be collected from open-access platforms. Furthermore, the e-bike simulation leverages open-source software tools, including MATSim and OTP, enhancing its applicability and reproducibility.

As the transportation sector plays a significant role in GHG emissions, promoting e-bikes as a sustainable mode of transportation can be considered a viable strategy for mitigating climate change. The study underscores the need for comprehensive approaches, including behaviour change and active travel modes, e.g., cycling, alongside technological solutions. As countries and regions seek to significantly reduce their emissions, integrating e-bikes into transportation systems offers a promising avenue for achieving sustainable and environmentally friendly mobility. Future research may include the exploration of potential synergies between e-bikes and public transport to enhance emission reduction further.

## Ethics statements

The authors declare that this work does not involve the use of human subjects, social media data, or experimentation with animals.

## CRediT authorship contribution statement

**Çağlar Tozluoğlu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Data curation, Conceptualization. **Yuan Liao:** Writing – review & editing, Validation, Software, Methodology, Data curation, Conceptualization. **Frances Sprei:** Writing – review & editing, Project administration, Methodology, Conceptualization.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Frances Sprei reports financial support was provided by Swedish Research Council Formas. 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.

## Data availability

Data will be made available on request.

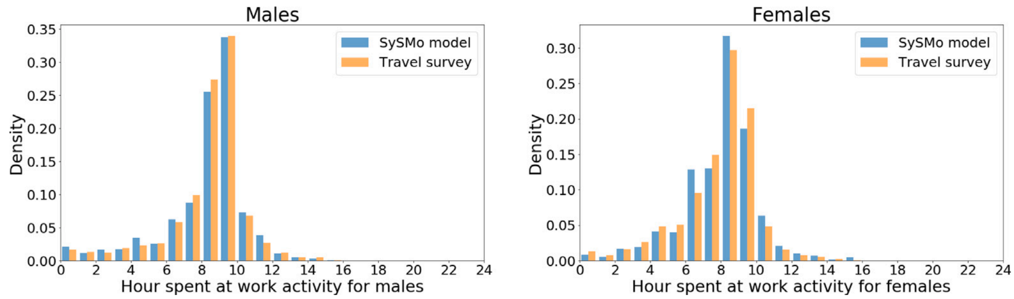


**Fig. 7.** Comparison of work activity duration by gender. The left panel shows the number of hours spent on work activity for males (JS distance = 0.05) and the right panel females (JS distance = 0.08).

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

During the preparation of this work, the authors used ChatGPT in order to improve language and readability, with caution. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

### Acknowledgments

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### Appendix A. Synthetic Sweden Mobility (SySMo) model

The Synthetic Sweden Mobility (SySMo) model (Tozluoğlu et al., 2023) is a large-scale agent-based transportation model which simulates the Swedish population's transport behaviours on an average weekday. SySMo generates a synthetic replica of over 10 million individuals with certain socio-demographic and household attributes. These attributes form the basis for constructing the travel demand in the population. The model assigns a daily activity-travel pattern to each agent in the population.

SySMo's methodology contains three main components: population synthesis, activity generation, and location and mode assignment. The model synthesises the synthetic population using statistical data from Statistics Sweden (SCB), creating agents and households. In the synthetic population, each agent has a list of socio-demographic attributes, e.g., age, gender, civil status, residential zone, personal income, car ownership, employment, etc. Each agent is also associated with a household, including key socioeconomic attributes, e.g., household size and number of children $\leq$ 6 years old in the household, etc. Accordingly, the SySMo model generates activity-travel patterns using the Swedish National Travel Survey (Anon, 2021). The agents' activity schedules show the activity type (i.e., home, work, school, and other), start and end times, duration, sequence, activity locations, and the travel mode between activities (i.e., walk, bike, car, car passenger and public transport). While only agents over the age of 18 can be car drivers, people of all ages can take other transport modes. However, the synthetic population assumes all trips are taken alone and does not model trips involving additional persons who require rides, e.g., children being dropped off and picked up from school and other escorting trips.

The SySMo model's performance is evaluated against official statistics from Statistics Sweden and Trafikanalys. The synthesised population is compared at the DeSO zone level, revealing that over 92% of zones show a gender assignment error within a range of –0.5% to 0.5%. Similarly, age discrepancies remain within -1% to 1% for more than 78% of zones. These results confirm the synthetic population's attribute distributions closely match the statistical data.

The synthetic population's activity duration distributions are compared to the travel survey, using Jensen–Shannon (JS) distance to quantify distribution similarities. JS distance takes values from 0 to 1, which demonstrates different distributions. Fig. 7 shows the JS distances for work activity durations are 0.05 for males and 0.08 for females. Similar analyses on school, home, and other activities illustrate JS distances between 0.05 and 0.13. Furthermore, Fig. 8 displays the comparison of travel distances between home and work by car and car passenger modes in the SySMo and Sampers's west regional models. The overall travel distance distributions align closely with those of the Sampers model, indicating a reasonable approximation of the activity-travel patterns to the validation data.

For more details on the SySMo model methodology and model performance assessments, please refer to the model documentation (Tozluoğlu et al., 2022).

We use MATSim to deduce realistic daily activity schedules of agents. MATSim is an open-source framework for simulating large-scale transportation systems that focus on individual agents' behaviour (W. Axhausen et al., 2016). Using an agent-based modelling approach, MATSim enables the representation of agents within a dynamic transportation network. Within the MATSim simulation, each agent tries to optimise their activity schedules by adjusting various potential decision factors, e.g., altering routes or changing departure time. MATSim iteratively executes simulations, with each activity plan evaluated through its scoring system. This scoring system takes timely attendance to the event as a positive factor while penalising traffic-related delays. To run simulations, we feed MATsim with the SySMo model's results and the road network data (OSP, 2023), and, consequently, extract the travel trajectories of individual agents from the MATSim simulation.

### Appendix B. Cycling trip distance distribution

The e-bike substitution algorithm incorporates constraints at various levels, e.g., constraints on individual trips, activities, tours, and daily activity-travel plans and identifies feasible car trips that can be replaced by an e-bike within the daily activity plan. In Fig. 9, we present the distribution of cycling trip distances based on our simulation results. Only 3.2% of cycling trips exceed 22 km, and 1.1% exceed 26 km.

### Appendix C. Baseline scenario: GHG emissions from passenger cars

In the baseline scenario, our calculations show that VG region residents' total GHG emissions from passenger cars on an average weekday is 2,501 tons of CO2 eq. and 2,175 tons of CO2 eq. is emitted within the VG region. To find the total emissions for all residents, we scaled the calculated emissions number within the region (2,175 tons CO2 eq.) by 35% and yielded 6,214 tons of CO2 eq.

We validate the calculated GHG emission for the baseline scenario using data representing 35% of all car users in VG. For comparison, we rely on the national emissions database (Anon, 2020), which compiles Sweden's GHG and air pollutant emissions by sector, subsector, and

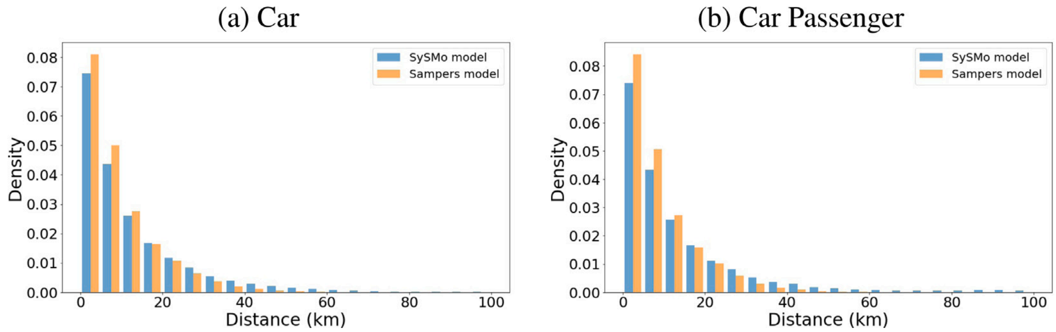


**Fig. 8.** Daily travel distance distribution between home and work by travel modes in Vastra Gotland.

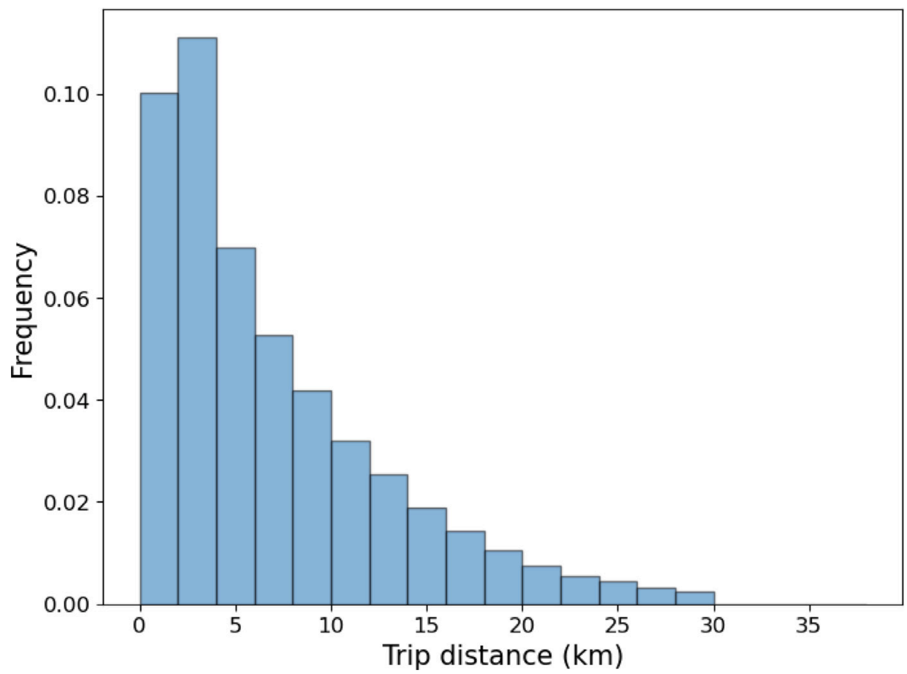


**Fig. 9.** Cycling trip distance distribution (2 km bins).

county based on Sweden's official emissions statistics. We use the data on the total GHG emissions from passenger cars within the VG region per year for 2018.

Subsequently, we compare our results with the data showing annual total emissions from passenger cars within the VG region. The total emission is 1,878,328 tons of CO2 eq., per year in the obtained data. We can calculate the daily average emissions of 5,146 tons of CO2 eq., per day. Given that the obtained figure also accounts for weekends and holidays, the difference between our calculated and the obtained figure is considered acceptable.

## Appendix D. Emission reduction by municipalities

We show e-bike emission reduction potential by municipalities in descending order of population density in Fig. 10. Municipalities with high population density have the highest emission reduction from car trips. Residents of Gothenburg and the surrounding municipalities of Partille and Mölndal have the potential to reduce car emissions by approximately 40% through the adoption of e-bikes.

## Appendix E. The sensitivity analysis results

In this section, we provide a detailed presentation of our sensitivity analysis results. Table 4 presents mode replacement results for each constraint in the e-bike substitution algorithm (refer to Algorithm 1). The impact of each constraint is analysed at different operational levels: the individual trip level, where constraints such as maximum trip distance and allowable delay influence single trips or activities; the tour level, where all trips within a tour collectively meet the constraints imposed at the individual trip level; and the daily plan level, where the cumulative effect of constraints on an individual's entire daily activity-travel schedule is considered, including total daily travel time change and total daily travel distance. The interplay of the constraints makes the algorithm robust and mitigates large variations in e-bike substitution against the changes in the constraints. Tables 5, 6, 7, 8 summarises the sensitivity analysis results of each constraint.

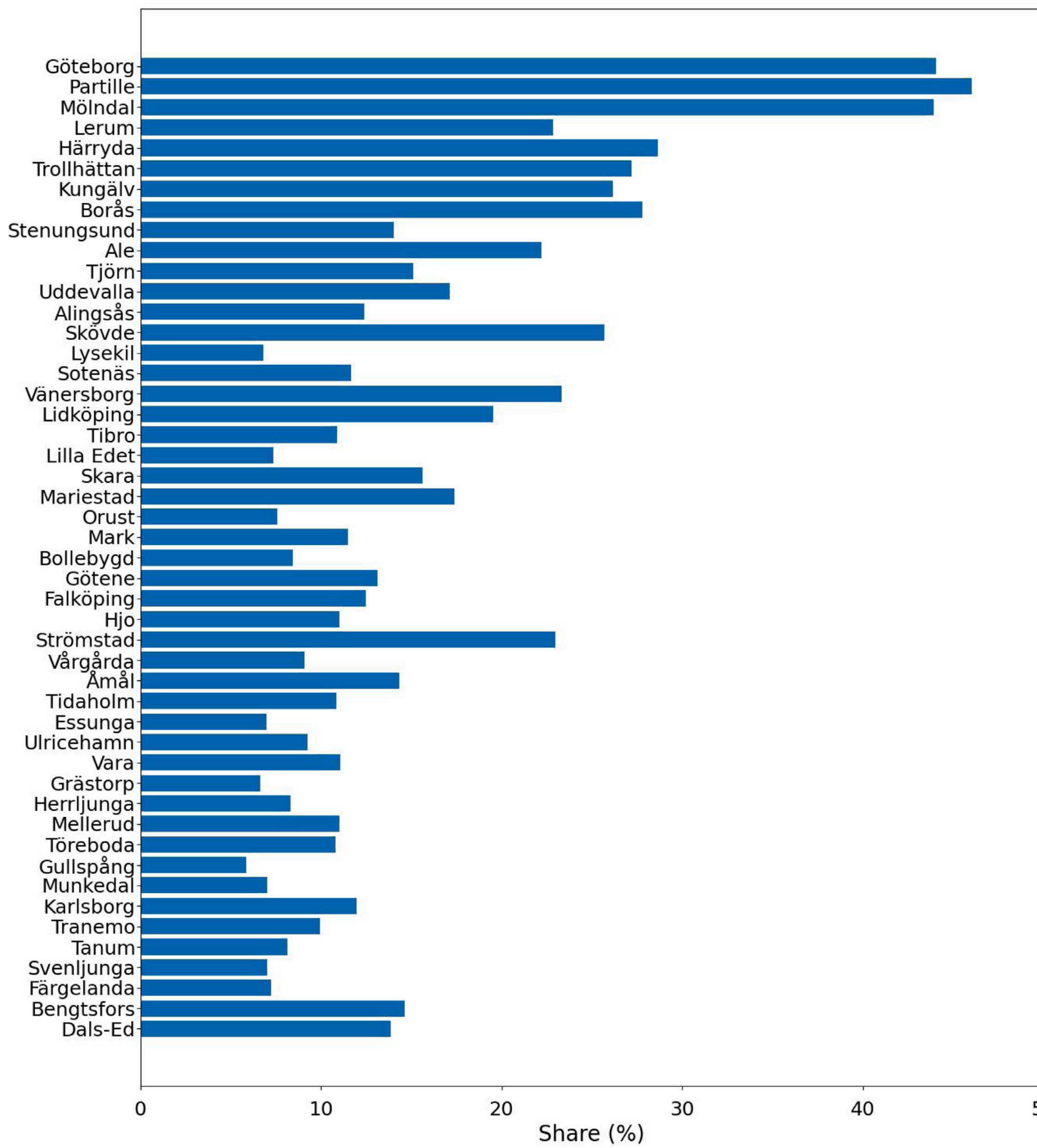


**Fig. 10.** Emission reductions from passenger cars by municipalities. The *y*-axis is in descending order of municipality population density.

**Table 4**
The sensitivity analysis results for mode replacement by trip, tour and daily plan levels in Algorithm 1.

| Constraint | Change | Trip Level Results (in %) | Tour Level Results (in %) | Daily Plan Level Results (in %) |
|---|---|---|---|---|
| Maximum Trip Distance | −30% | 66.6 | 56.2 | 54.9 |
| | −15% | 69.9 | 58.8 | 56.7 |
| | **0%** | **72.4** | **60.6** | **57.6** |
| | 15% | 74.3 | 61.9 | 58.1 |
| | 30% | 75.7 | 62.9 | 58.4 |
| Allowable Delay | −30% | 69.7 | 56.3 | 54.2 |
| | −15% | 71.2 | 58.7 | 56.1 |
| | **0%** | **72.4** | **60.6** | **57.6** |
| | 15% | 73.3 | 62.2 | 58.8 |
| | 30% | 74.1 | 63.6 | 59.7 |
| Daily Travel Time Change | −30% | | | 54.6 |
| | −15% | | | 56.4 |
| | **0%** | | | **57.6** |
| | 15% | | | 58.5 |
| | 30% | | | 59.1 |
| Daily Travel Distance | −30% | | | 56.7 |
| | −15% | | | 57.5 |
| | **0%** | | | **57.6** |
| | 15% | | | 57.7 |
| | 30% | | | 57.7 |

**Table 5**
The sensitivity analysis results for the maximum trip distance constraint.

| Change (in %) | Threshold (in km) | Mode replacement (in %) | Emission Reduction (in %) | Emission Reduction within VG region (in %) |
|---|---|---|---|---|
| −30 | 21 | 54.9 | 19.5 | 22.0 |
| −15 | 25.5 | 56.7 | 21.5 | 24.2 |
| **0** | **30** | **57.6** | **22.8** | **25.6** |
| 15 | 34.5 | 58.2 | 23.6 | 26.5 |
| 30 | 39 | 58.5 | 24.2 | 27.1 |

**Table 6**
The sensitivity analysis results for the maximum allowable delay to the next activity constraint.

| Change (in %) | Threshold | Mode replacement (in %) | Emission Reduction (in %) | Emission Reduction within VG region (in %) |
|---|---|---|---|---|
| −30 | 0.21 | 54.2 | 21.0 | 23.6 |
| −15 | 0.255 | 56.1 | 22.0 | 24.7 |
| **0** | **0.3** | **57.6** | **22.8** | **25.6** |
| 15 | 0.345 | 58.8 | 23.4 | 26.3 |
| 30 | 0.39 | 59.7 | 23.9 | 26.9 |

**Table 7**
The sensitivity analysis results for the total daily travel time change constraint.

| Change (in %) | Threshold (in sec) | Mode replacement (in %) | Emission Reduction (in %) | Emission Reduction within VG region (in %) |
|---|---|---|---|---|
| −30 | 3780 | 54.6 | 20.4 | 23.0 |
| −15 | 4590 | 56.4 | 21.7 | 24.5 |
| **0** | **5400** | **57.6** | **22.8** | **25.6** |
| 15 | 6210 | 58.5 | 23.6 | 26.4 |
| 30 | 7020 | 59.2 | 24.1 | 27.1 |

**Table 8**
The sensitivity analysis results for the total daily travel distance constraint.

| Change (in %) | Threshold (in km) | Mode replacement (in %) | Emission Reduction (in %) | Emission Reduction within VG region (in %) |
|---|---|---|---|---|
| −30 | 56 | 56.7 | 21.8 | 24.5 |
| −15 | 68 | 57.5 | 22.6 | 25.4 |
| **0** | **80** | **57.6** | **22.8** | **25.6** |
| 15 | 92 | 57.7 | 22.8 | 25.6 |
| 30 | 104 | 57.7 | 22.8 | 25.6 |

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