

Understanding the effectiveness of active travel policy portfolios with agent-based modelling

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ABSTRACT

Transport decarbonisation is a major challenge that requires the implementation of effective policies by local and national governments. This paper simulates mobility policies intended to effect a modal shift from private car to active modes (i.e., cycling and walking), using an agent-based transport simulation framework (MATSim). A set of urban mobility policies aiming to change the built environment and mobility behaviour is defined, simulated and assessed in the Tyne and Wear region of England. Results obtained show that economic rewards (e.g. £0.15 subsidy per kilometre walked or cycled) and penalties (daily £2.50 charge when using cars) are effective in shifting individuals from private car (7%-points and 14%-points change respectively) to active modes (10%-points and 4%-points). Furthermore, effectiveness is greater when several policies are combined, achieving a 13%-points car reduction and 22%-points increase in active modes when the economic rewards are implemented in conjunction with a cycle path improvement scheme; and a 18%-points reduction in car use and a 12%-point increase in active modes when the economic penalties are combined with cycle paths. Further analyses are conducted to quantify the impacts of policies based on the distance travelled by mode of transport, the geospatial distribution of cycling routes and economic benefits.

1. Introduction

Since 2016, the transport sector has been the largest contributor of greenhouse gas (GHG) emissions in the UK (DfT, 2022a). Consequently, there is a need for effective urban mobility policies to achieve the Paris Agreement goals (United Nations, 2016) in line with the UK's defined carbon budgets (DfT, 2021a), and the 2030 Agenda for Sustainable Development Goals (United Nations, 2015). Before their implementation, however, transport policies need to be tested to understand their impact and effectiveness. Transport models are used for this task as they provide an abstraction of the system, allowing experimentation with policy alternatives and conversations with stakeholders to explore the impacts of changes made to different aspects of the transport system in the model (e.g. origin and destination flows, network capacities) (Ghaffarzadegan et al., 2010; Ford et al., 2018). From the range of available transport model types, Agent-Based Models (AgBMs) stand out. They allow planners to consider a large variety of transport modes (e.g., cars, public transport, active modes), travellers with different

mobility patterns and socio-demographic attributes, and their interactions in space and time. The strength of AgBMs is the emergent behaviour of the simulated system of individuals, with a greater focus on behaviourally realistic representation of daily human mobility and disaggregation of results than other transport modelling approaches.

This paper focuses on the simulation and analysis of transport policies aiming at incentivising walking and cycling in preference to private motor vehicles, applying 'stick' (or push) and 'carrot' (or pull) policies, using an AgBM. To explore this topic, the following research questions are posed:

- How can AgBMs be defined to simulate stick (or push) and carrots (or pull) policies to incentivise walking and cycling in preference to private motor vehicles?
- How can results of simulations of different policy scenarios be analysed to quantify their impact by combining behavioural modelling with spatial analysis and economic evaluation?

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- What packages of policies are more effective in shifting people from cars to more sustainable modes?

The methodology presented in Alvarez Castro et al. (2024), which provides a detailed explanation of how to build (tools, datasets and parameters), calibrate and validate a MATSim model (Horni et al., 2016) for any region in the UK, is followed to build the AgBM transport simulation model in this study. The model provides a simulation environment for the Tyne and Wear region of England, which is then used as baseline to assess a set of mobility policies in terms of their effectiveness in reducing motorised travel in favour of active modes.

The remainder of this paper is structured as follows: Section 2 presents an analysis of the literature to summarise UK transport decarbonisation policies, global mobility policies for reduction of car dependency, and a review of transport modelling approaches currently used to estimate the effectiveness of urban mobility policies. Section 3 explains the methodologies followed to build the MATSim model for the Tyne and Wear region, its calibration, validation and the definition of the analysed scenarios. Section 4 presents the results obtained for each of the scenarios simulated. Section 5 discusses the results obtained and future work and, lastly, Section 6 draws a conclusion.

2. Literature review

The literature review in this paper covers three main components: the strategies identified by the UK to tackle GHG transport emissions (Section 2.1), the different urban mobility policies considered to shift travel from motor vehicles towards more sustainable modes (Section 2.2), and finally the different transport models used to estimate the impact of urban mobility policies (Section 2.3).

2.1. The UK transport strategies to reduce GHG emissions

In 2019, the UK set in law the goal to reach ‘net zero’ GHG (i.e. total territorial emissions produced must be taken up by carbon sinks) by 2050 (UK Parliament, 2019), becoming the first major economy to set legally binding carbon budgets and to legislate to end its contribution to climate change (DfT, 2020a). Since then, a major policy focus has been decarbonising the road transport fleet and modal shift to public and active transport. The first is mainly focused on replacing fossil-fuelled vehicles with zero-tailpipe-emission electric vehicles (EVs), while the second aims to enable people to use sustainable modes (e.g., public and active travel modes).

The use of EVs is seen as a promising solution to reduce GHG emissions in the transport sector (Desreaveux et al., 2023; Agusdinata and Liu, 2023). A rapid take-up by larger shares of the population is unlikely in the short and medium term, however, mainly due to the current vehicle costs (Pratico et al., 2020) and the required energy source (Desreaveux et al., 2023; Vrabie, 2022), whilst numerous with EV adoption as a decarbonisation strategy remain, including the significant ecological impact during the battery production (Peters et al., 2017; Marmioli et al., 2018); the potential lack of critical materials (Habib et al., 2020); an underdeveloped supporting vehicle charging infrastructure (Pamidimukkala et al., 2024; Wang and Witlox, 2025); side effects of their lower noise levels in urban areas for other road users (Pardo-Ferreira et al., 2020) and the negative impacts of maintaining the so-called ‘vicious cycle of car dependency’ and the transport injustice and inequality for those without access to private vehicles (Sovacool et al., 2019; Mattioli et al., 2020).

The use of public modes is often framed as a key component of building sustainable cities (Friman et al., 2020). They can provide energy-efficient transport in an urban setting competing against private vehicles (Schiller et al., 2017), minimise GHG emissions and other pollutants, reduce consumption of land, travel time and cost, improve social access, increase economic efficiency and contribute to economic activity (Miller et al., 2016). Nevertheless, obstacles such as poor

accessibility (OSCI, 2021), a bad perception by users (Shah et al., 2021), the lack of information about the services (Lyons and Harman, 2002) and a poor financial situation (DfT, 2023a) limit their use by the public. In England, less than 10% of trips were undertaken by public transport in 2024 (DfT, 2025).

Active travel (i.e., walking and cycling) is considered the most sustainable form of personal transport (Brand et al., 2021) and one of the most promising ways to reduce transport emissions, particularly for short trips (Neves and Brand, 2019; Quarmby et al., 2019). Apart from the absence of GHG emission production (except from breathing), these modes can provide better health conditions, both physical (Public Health England, 2017) and mental (Singleton, 2019), and support urban restructuring with more green spaces, and noise reduction (Sustrans, 2020). Unfortunately, there are barriers that affect the uptake of active travel, the most critical being safety and security of users (DfT, 2023b), weather conditions (Shoman et al., 2023), the lack of policy implementations (Shah et al., 2021) and a low change willingness of citizens (Ipsos, 2022). Despite these barriers, countries such as Denmark, the Netherlands and Germany have demonstrated the ability to achieve high levels of walking and cycling over previous decades, achieving a much higher percentage of active travel than similar countries, by providing separate and safe cycling facilities, bicycle parking facilities, a full integration with public transport, a comprehensive traffic education and training of the population, alongside the implementation of policies that limit the use of private cars (Pucher and Buehler, 2008). Fig. 1 summarises the impact of each strategy besides their potential disadvantages.

2.2. Urban mobility policies to reduce GHG transport emissions

Kuss and Nicholas (2022) identified seven effective interventions to reduce the use of cars in urban areas and support climate goals based on almost 800 peer-reviewed studies and case studies published since 2010. These categories are:

- Charging and pricing (Börjesson and Kristoffersson, 2015; Beria, 2016; Metz, 2018),
- Time-dependent access limitations (DeRobertis and Tira, 2016),
- Parking and traffic control (European Commission, 2024),
- Mobility services for commuters (European Commission, 2019),
- Integrated car-sharing plans (Fred Dotter, 2015; Glotz-Richter, 2016),
- Travel planning (Cairns et al., 2010; Bamberg and Rees, 2017), and
- Gamification approaches (e.g., providing rewards) to promote sustainable mobility (ITL, 2018).

Within the review, it was observed that the most frequently studied categories were charging and pricing, and travel planning, with the most effective measures being those including congestion charging, parking and traffic control, and limited traffic zone measures. An example is the Ultra-Low Emission Zone (ULEZ) in London, deployed in 2019. This measure operates throughout the day and requires car users to pay a £12.50 daily charge to drive within the zone (TfL, 2024). Ding et al. (2022) analysed the impact of ULEZ in the use of public bicycle sharing and identified a significant increase in demand, up to 27.9%, mainly for short (less than 15 min) and intermediate (between 15 and 30 min) trips, between May and October 2019.

Low Traffic Neighbourhoods (LTNs) are another measure used to remove through motor vehicle traffic from residential streets (except for residents) using ‘modal filter’ measures such as planters or lockable bollards (Goodman et al., 2021; Larkin et al., 2025) to disincentivise the use of those vehicles and enable the use of more sustainable modes. Although this policy is facing great controversy in several regions in the UK (Dudley et al., 2022), LTNs have been widely trialled in some cities (Laverty et al., 2021).

The implementation of fully segregated and safe cycle paths is a

	Road transport decarbonisation	Public transport	Active travel
Air pollution reduction			
Noise reduction			
Congestion reduction			
Health improvement			
Urban redevelopment			
Transport injustice and inequality			

Potential disadvantages	Underdeveloped charging infrastructure	Privatised Sector	Weather conditions
	Energy source requirements	Uneven Accessibility	Safety and Security
	Ecological impact	Human attitudes and perceptions	Policy Implementation
	Transport injustice		Low citizen willingness
	Electric vehicle cost		
	Lack of critical materials		

Fig. 1. Characteristics and potential disadvantages of each of the decarbonisation strategies considered in the UK.

popular measure to incentivise cycling. In this context, the development of a fully segregated cycle network in Seville (Spain) was analysed by [Marqués et al. \(2015\)](#). The results showed that a connected, continuous, bi-directional and comfortable network doubled the number of cyclists in four years. However, and despite the effectiveness of the measure, seasonality considerations need to be addressed, as different values were obtained depending on the weather conditions (i.e., warm months showed low values, while other times of year showed strong peaks).

Finally, alongside economic penalties limiting car use and road modifications for active modes, economic incentives for people using active modes have been considered. [Máca et al. \(2020\)](#) developed an experiment to increase regular commuter cycling in cities by providing financial and non-financial (i.e., gamification) motivational features. Results suggest that these features can motivate individuals and are more effective when financial rewards are given and particularly when used in combination with other measures. Additionally, some countries reward individuals if they commute by bicycle. Examples are found in the Netherlands, which provides a mileage allowance of up to 0.19 euros per kilometre when commuting to work ([Government of The Netherlands, 2023](#)), and Belgium, rewarding 0.27 euros per kilometres up to a daily cap of 40 km ([The Brussels Times, 2023](#)).

However, some urban mobility policies, particularly those penalising the use of private cars (e.g. congestion charging, parking and traffic control, limited traffic zone measures, LTNs), could produce negative environmental impacts. This is the case with GHG emissions increases in peripheral areas of those urban areas where mobility policies are implemented, as more car drivers could travel through these areas when

adapting their travel behaviours to the new norm ([Chan and Morrow, 2019](#); [Li, 2023](#); [Player et al., 2023](#)), leading to environmental injustice in the vicinities ([Barnes et al., 2019](#)).

2.3. Transport modelling

The implementation of urban mobility policies such as those highlighted above initially requires a good understanding of both the region and population that can benefit from them. Traditionally, the process of analysis and assessment of policies consists of the development of transport models, which work as abstract and simplified representations of reality, either already existing or planned, to study and explain observed phenomena or to analyse future situations ([Bandini et al., 2009](#)). Several transport models have been developed over preceding decades, such as four-step models (Section 2.3.1), activity-based models (Section 2.3.2) and agent-based models (Section 2.3.3).

2.3.1. Four-step models

Four-step models (FSMs) are the most well-known models of transport and are the primary tool for forecasting, understanding and assessing future demand and performance of a transportation system ([McNally, 2008](#)). The model output describes the demand for transport as a set of aggregated flows of traffic on the routes of the network and spatially resolved by zones ([Scherr et al., 2020](#); [Ziemke, 2023](#)), which are used to analyse policies such as road expansions or the introduction of tolls ([Kagho et al., 2020](#)). Despite their worldwide application, these models entail some simplifications, as stability in time is assumed

(McNally and Rindt, 2008) (or modelled in a limited manner (Ziemke, 2023)), the underlying motivation to conduct travel is not considered (McNally and Rindt, 2008), and various spatio-temporal constraints are ignored (Franco et al., 2020; Ziemke, 2023). Pinjari and Bhat (2011) state that previously highlighted issues, especially the temporal, spatial and modal linkages between trips, could lead to illogical trip chain estimations.

2.3.2. Activity-based models

Fundamental changes in urban environments and human behaviour (McNally and Rindt, 2008; Franco et al., 2020; Nguyen et al., 2021), alongside the inclusion of new transport modes such as active modes and micro-mobility (e.g., e-scooters) (Kagho et al., 2020; Franco et al., 2020), have made travel behaviour gradually more difficult to estimate (Franco et al., 2020; Holmberg et al., 2016; DfT, 2019), requiring new models to analyse transport mobility. Activity-based models (AcBMs) are one of these new models that analyse travel as daily or multi-day patterns of behaviour, related to and derived from differences in lifestyles and activity participation among the population (McNally and Rindt, 2008). Shifting from FSM to AcBMs, therefore, modelling moves from computations on zonal aggregates to a representation of decision-making of individuals (Horni, 2005), as well as allowing the better analyses of policy impacts in certain subgroups of the population (Kitamura, 1988), based on similar socio-demographic characteristics. AcBMs are supported by four main pillars: higher spatial and temporal resolution, improved foundations of human behaviours, model systems integrity, and greater sensitivity to the interdependencies between trip generation, destination choice, transport mode choice and route choice (Rasouli and Timmermans, 2014).

2.3.3. Agent-based models

Agent-Based Models (AgBMs) are spatio-temporal computational simulations of agents (independent and autonomous individuals) interacting with the environment and with other agents to achieve their goals. In transport, agents interact during their daily activities, providing a microscopic representation of the agents' travel decisions, their behaviour and interactions in the transport system (Kagho et al., 2020). These models are unique in their ability to combine heterogeneous and dynamically changing processes of complex systems from autonomous agents, intending to investigate the emergent and collective effects on the system (Huang et al., 2022; Moyo Oliveros and Nagel, 2016).

Several AgBM tools have been developed and used for a wide variety of transport modelling purposes. Nguyen et al. (2021) developed a very detailed list of more than 35 AgBM tools, highlighting MATSim (Horni et al., 2016), POLARIS (Auld et al., 2016), the integration of SUMO (Krajewicz, 2010) and JADE (Bellifemine et al., 2005), AgentPolis (Jakob et al., 2012), ITSUMO (Bazzan et al., 2010) and SimMobility (Adnan et al., 2016). Tzouras et al. (2023) conducted a qualitative assessment about the use of different transport AgBM tools based on the following ten criteria:

- Is open-source and allows the development or integration of multiple extensions?
- Has been used to simulate shared mobility?
- Has been used to perform large scale transport networks?
- Can describe spatiotemporal variation of demand?
- Can simulate bicycle traffic in cycle lanes?
- Can simulate pedestrians on sidewalks?
- Can simulate mixed traffic?
- Considers socio-demographic characteristics?
- Can integrate new choice models?
- Can simulate multimodal trips?

Within the compared tools, MATSim and SimMobility were the ones that achieved the best results (nine out of ten criteria in both cases).

MATSim lacks a proper simulation of pedestrians on sidewalks, although it is possible to consider them as part of the simulation using a dedicated network. SimMobility lacks the simulation of bicycle traffic in cycle lanes, which implies that bicycles always share the roads with other vehicles and are not treated differently to cars.

Bastariento et al. (2023) reviewed the use of dedicated transport AgBMs in urban transportation from 2006 to 2022 and identified an exponential increase in the number of publications since 2015, evolving the topics from congestion pricing to emerging transport modes (e.g., ride sharing, demand responsive transport and electric vehicles). Maggi and Vallino (2021) analyse the potential impact of price-based and preference-based policies on commuter's mode choice in urban areas. Park et al. (2018) analyse active modes in New York City (USA) to support investment decisions and evaluate the impact of infrastructure changes for walking and cycling. Jafari (2022) analyses cycling in the region of Greater Melbourne (Australia) to test different built-environmental interventions affecting different societal groups, such as the implementation of cycle lanes and the impact of traffic signals on cycling, considering different subgroups of the population. Finally, Hite and Joubert (2023) developed a model to estimate a potential cycling demand in Cape Town (South Africa).

Based on the mobility policies to be simulated and analysed and the fulfillment of the above criteria, MATSim was chosen as the AgBM tool to simulate the status-quo urban mobility of the study area, and then the different urban mobility policies aiming to achieve more sustainable and decarbonised transport.

3. Methodology

This section explains the methodology used to simulate urban mobility policies in the Tyne and Wear region in the North-East of England (ca. 2.6 million inhabitants), applying AgBM techniques (Fig. 2, right). MATSim (Section 3.1) (grey box in Fig. 2) requires the development of two main components: a synthetic travel demand (Demand, purple box) (Section 3.2), and a representation of the transport network (Supply, green box) (Section 3.3). A detailed description of the setup (required inputs, tools and parameters) of the model for the Tyne and Wear region as well as the model's calibration and validation (orange box) (Section 3.4) is given by Alvarez Castro et al. (2024). Based on this baseline scenario, several urban mobility policy scenarios are defined and simulated (red box) (Section 3.5), which is the focus of the present paper.

3.1. MATSim

MATSim (Horni et al., 2016) consists of a co-evolutionary framework (Fig. 3) that allows the agents to compete in space and time for transport resources to achieve their goals in an efficient manner (Stage 2). After each iteration, the satisfaction (i.e., a utility, typically referred to as 'score' in MATSim) of each agent is computed, using the Charypar-Nagel scoring function (Charypar and Nagel, 2005; Nagel et al., 2016), where the score (utility) of performing activities and travelling between activities are considered (Stage 3).

After scores have been computed, a certain share of the agents is allowed to modify their plans (Stage 4) (e.g., change transport mode, choose an alternative route or leave an activity earlier or later (Horni et al., 2016)). Once this replanning stage is finished, the loop of simulation, scoring and replanning stages is iterated as many times as the modeller defines. Through each iteration, agents learn from their interactions in space and time and adapt their behaviours to achieve their goals, i.e. to maximise their score. The last stage (Stage 5) is reached once the iterative loop is finished and outputs are generated. Different datasets containing the interactions of the agents in space and time are generated.

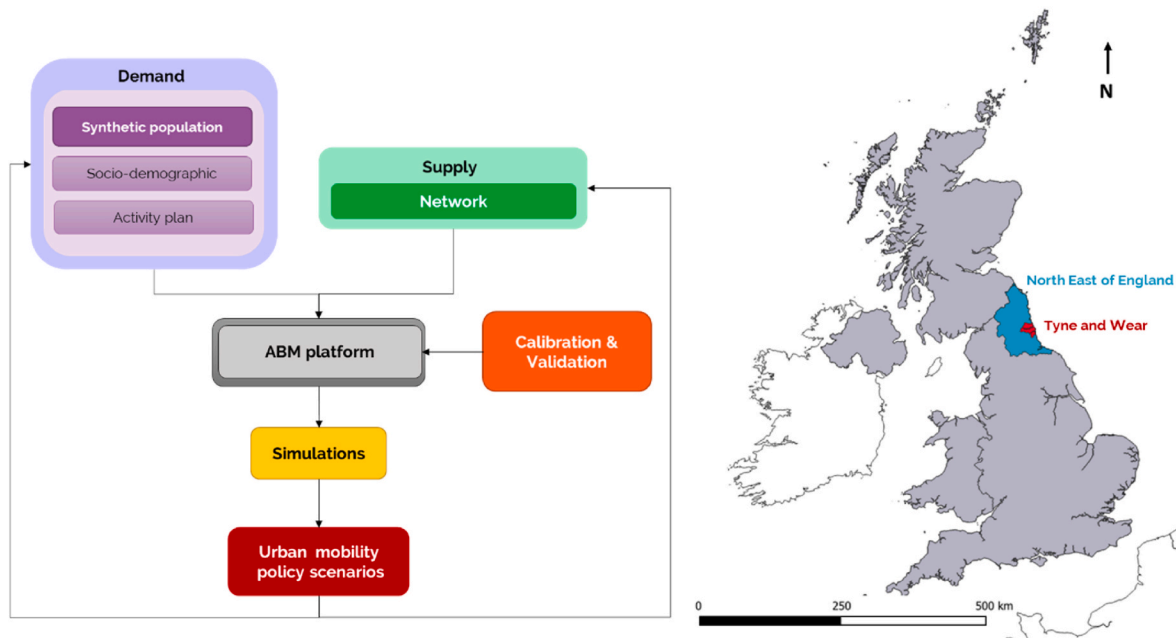


Fig. 2. Followed workflow diagram to simulate urban mobility in favour of active modes (left) and map showing the study area (Tyne and Wear) (right).

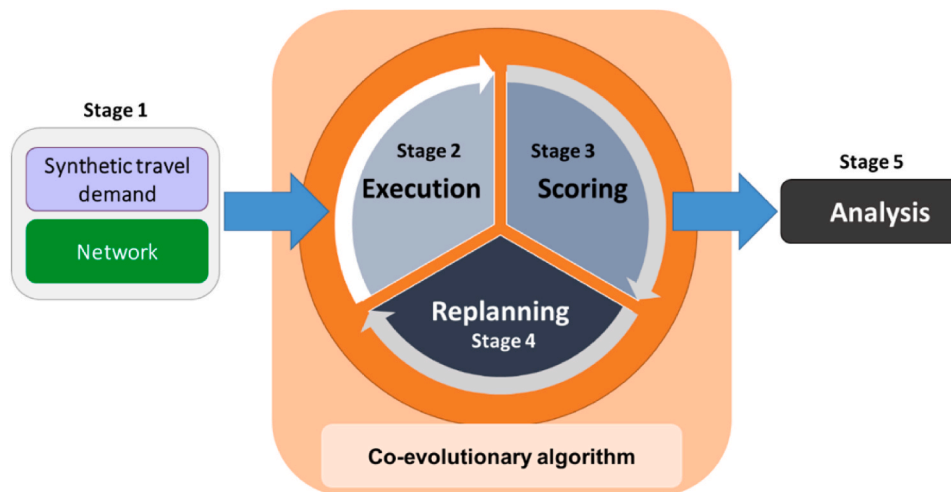


Fig. 3. MATSim co-evolutionary framework.

3.2. Synthetic travel demand

Synthetic travel demand is needed to run transport simulations with MATSim (Stage 1 in Fig. 3), and this is created based on two main datasets: a synthetic population and activity plans.

Synthetic populations are a simplified and realistic microscopic representation of individuals (Fabrice Yaméogo et al., 2020; Moeckel et al., 2003). The methodology used to develop the synthetic population in this study is a combination of two tools: SPENSER (Lomax et al., 2022) and synthetic_population_dev (Alvarez Castro, 2022). The outcome is a detailed synthetic population where each member is characterised by 12 socio-demographic attributes (individual ID, household ID, age, sex, marital status, children dependency, economic activity, occupation, annual gross income, driving license, car access, bicycle access).

Activity plans define the activities performed by each individual during a regular working day, containing information about the purpose of trips, start and end times, activity locations and transport modes, among other attributes. Activity plans were obtained from the National

Travel Survey (NTS) travel diaries (DfT, 2022b), the primary source of data on personal travel patterns in England, and containing information on how, why, when and where people travel as well as factors affecting travel, in addition to their socio-demographic attributes, at Local Authority level (DfT, 2023c). A household-to-dwelling assignment tool (Pregolato et al., 2017) and the ActivityPlans_ABm (Alvarez Castro, 2023) tool were used to assign the household and the activity locations (e.g., workplace, education, shopping, medical), respectively, based on common socio-demographic attributes. This approach assumes that people with similar characteristics behave similarly.

3.3. Transport network

The second main component required to run transport AgBMs (Stage 1 in Fig. 3) is the network. This is a digital geospatial representation of the transport network used by the agents to move between activities, containing information about the type of network (e.g. road, rail), allowed transport modes and capacities, among other attributes. This information is obtained from open-source OpenStreetMap data

(Geofabrik, 2023), which is then combined with public transport data (e.g., schedules, stops, routes) to allow the agents to use the different public transport modes in the study area. This information is obtained in General Transit Feed Specification (GTFS) format from Rail Delivery Group (2023) and Traveline (2023) for rail and the rest of the public transport modes, respectively. GTFS datasets are joined with the transport network using PUMA (Arup, 2022a).

For cycling, two fundamental characteristics need to be considered in addition to the default set of attributes: the road gradient and the 'quietness'. The first is added to the network applying GeNet (Arup, 2022b). The second component classifies each road segment for cycling on a scale from 0.00 to 1.00, depending on their characteristics (e.g., road type, cycle infrastructure, path width and quality, existence of barriers or obstructions), based on Cyclestreets (2022) data. These two components are used within the updated MATSim bicycle extension developed by Ziemke et al. (2019), which allows the cyclists to consider these two characteristics in their scoring of their travel, substituting the attributes in the original setup of the MATSim bicycle extension. This is useful as the quietness attribute is richer and more accurate than the OSM-based comfort attribute.

3.4. Calibration and validation

The model simulates a 20% sample of the synthetic travel demand until no further changes in agents' scores and transport mode choice are observed, which is the case after 1500 iterations. Eight different transport modes (car, car passenger, walk, bicycle, bus, rail, subway and ferry) are considered, where the use of cars is restricted to the agents with access to a car in the household based on the attributes of the synthetic population (Boolean 'car access' attribute). Public transport modes are simulated as deterministic modes (i.e., they are governed by their schedules, stop locations and service times, with no interactions with other transport modes), using the SwissRailRaptor and SBBPT modules. Cycling is simulated applying MATSim's bicycle extension (Ziemke et al., 2019), while walking agents are 'teleported', i.e. relocated from origin to destination with a time delay based on an assumed walk speed, which also assumes that walking is possible in all locations. The model was validated against UK official transport statistics (DfT, 2020b) (e.g., transport mode shares and average trip distances by transport mode) and hourly vehicle counts in specific road links in the study area, using data from the Traffic and Accident Data Unit (TADU) (Gateshead Council, 2023). For a detailed description and discussion about model calibration and validation, see Alvarez Castro et al. (2024).

3.5. Policy scenarios

To simulate the implementation of different urban mobility policies that promote the use of active travel modes and reduce the use of private motor vehicles, a number of policy scenarios were developed. Policy scenarios include:

- Fully segregated and safe cycle paths (Scenario 1),
- Low Traffic Neighbourhoods (LTNs) (Scenario 2),
- Active travel economic reward (Scenario 3),
- Daily economic penalty for car use (Scenario 4), and
- Multiple combinations of the previous four scenarios (Scenarios 5.X).

3.5.1. Scenario 1: fully segregated and safe cycle paths

The implementation of fully segregated and safe cycle paths are the most frequently cited responses by individuals in England when asked about things that would encourage them to cycle more, even if their implementation reduces the road space for cars (DfT, 2021b). To test the effectiveness of this policy, a new network was generated, where all roads include a fully segregated and, therefore, safe cycle path with the 'quietness' value set to the maximum (1.00). Additionally, the flow

capacity in those roads was reduced proportionally to the number of lanes, assuming that road space for vehicles is reduced by the space now dedicated to the new fully segregated cycle paths.

3.5.2. Scenario 2: Low Traffic Neighbourhoods

Low traffic neighbourhoods (LTNs), as described in Section 2.2, are schemes that remove motorised through traffic from residential streets (except for residents) (Goodman et al., 2021; Larkin et al., 2025) to discourage the use of cars and enable the use of more sustainable modes. This scenario was implemented by dis-allowing cars on residential roads (e.g., roads of the categories tertiary, residential, service, living street links in the MATSim network), and updating their 'quietness' to the maximum value, assuming they become fully safe for cycling.

3.5.3. Scenario 3: active travel economic reward

Reward-based instruments have the potential to encourage individuals to shift towards multimodal mobility options, thus contributing to a more sustainable and resilient transport environment (Tsirimpa et al., 2019). Based on examples of this type of policy from European countries (Section 2.2), a similar scenario was developed for the study area. In this policy, the use of cycling and walking are rewarded with £0.15 per kilometre, as a measure to incentivise both modes for any type of trip.

3.5.4. Scenario 4: daily economic penalty for car use

Contrary to the previous scenario, there is the possibility to penalise the use of private motor vehicles, as described in Section 2.2. A policy was implemented where any agent using a car within the study area is charged with a daily penalty of £2.50, independent of the distance or number of trips made. Note that this policy differs from the previous policy not only by the sign of the payment, but also by the type of payment (here: lumpsum payment, Scenario 3: distance-dependent).

3.5.5. Scenarios 5.X: multiple combination of previous scenarios

Lastly, several combinations of the aforementioned policies ('policy packages') were implemented to identify if certain combinations can generate a greater impact than when the policies are introduced individually. Firstly, the fully segregated and safe cycle paths (Scenario 1) were combined with LTNs (Scenario 2) to test how a complete restructuring of road space could reduce the use of motorised vehicles and increase active modes (Scenario 5.1). Secondly, Scenario 3 was additionally incorporated with Scenario 5.1, adding an economic reward to boost the use of active modes (Scenario 5.2). Thirdly, Scenarios 1 (Fully segregated and safe cycle paths implementation), 2 (LTNs) and 4 (daily penalty for car use) were combined to test the effect of the road space restructuring with a daily economic penalty for the use of private vehicles (Scenario 5.3). Lastly, all scenarios were combined (Scenario 5.4).

4. Results

In total eight scenarios (four policies described in Section 3.5 plus four combinations of policies) are simulated and their effectiveness estimated by comparing transport mode shares, distances travelled by mode, geospatial distribution of cycling routes taken by users, active modes trips, and economic benefits against the baseline scenario.

4.1. Transport mode shares

Fig. 4 summarises transport mode shifts achieved by each simulated scenario compared with the baseline scenario (row in yellow). Percentage point reductions are shown in red, increases in green.

The policy goal of reducing cars on the roads is achieved in all scenarios, although with different levels of impact. The highest effect is observed in those scenarios including an economic penalty (i.e., Scenarios 4, 5.3 and 5.4). The two 'policy packages' without economic penalties (i.e., 5.1 and 5.2) reached lower percentage point reductions

	Car	Public transport	Walk	Bicycle
Baseline scenario	52.2%	20.5%	25.5%	1.8%
Scenario 1 Fully segregated and safe cycle paths	-2.1%	1.1%	-0.3%	1.3%
Scenario 2 Low Traffic Neighbourhoods (LTNs)	-3.2%	3.0%	1.0%	-0.7%
Scenario 3 Active travel economic reward	-6.9%	-2.7%	3.3%	6.3%
Scenario 4 Daily economic penalty for car use	-14.2%	9.9%	2.1%	2.2%
Scenario 5.1 (1+2) Fully segregated and safe cycle paths + LTNs	-4.1%	-1.2%	1.4%	3.9%
Scenario 5.2 (1+2+3) Fully segregated and safe cycle paths + LTNs + active travel reward	-13.2%	-8.5%	4.7%	17.0%
Scenario 5.3 (1+2+4) Fully segregated and safe cycle paths + LTNs + pay-when-you drive	-18.0%	6.2%	3.7%	8.1%
Scenario 5.4 (1+2+3+4) Full combination of scenarios 1 to 4	-27.5%	-5.1%	6.5%	26.1%

Fig. 4. Summary of the percentage point differences achieved in each simulated scenario when compared with the baseline scenario, by transport modes.

than Scenario 4, which only applies the economic penalty individually. These results indicate a stronger impact of the toll by itself than when car space reduction and road restrictions are applied. Another notable finding is the lack of additional car reductions when several policies are combined in the same scenario, as the percentage point reductions are similar to those obtained when the results of the individual policies are summed (e.g., Scenario 5.3 achieve a 18%-point reduction in the use of cars, while the sum of scenarios 1, 2 and 4 is 19.5%-points).

In terms of the active modes, the highest percentage points increases are observed with economic policies. The highest mode shifts to active mobility are obtained with economic rewards (i.e., Scenarios 3, 5.2 and 5.4). The combination of policies to increase the use of active modes achieved surplus benefits exceeding the sum of the effects of the individual policies that are included in this scenario. This effect was almost five (Scenario 5.1), three (Scenario 5.4) and two times (Scenarios 5.2 and 5.3) higher in the combined scenarios than the simple sum of the effects of the individual policies. This is an important finding, suggesting that the effects of the policies reinforce on another when they are

combined into a 'policy package'. Within the active modes, the use of the bicycle saw the most benefit, although walking reached higher percentage point increases in one scenario (Scenario 2) where cycling was penalised (i.e., because of not being able to overtake cars in congested areas (see more details in Section 5)). In the remaining scenarios, the shifted trips mainly move towards cycling, especially for policy combinations. There are two fundamental reasons for the differences between the modes: firstly, most policies are focused on cycling; secondly, cycling is faster than walking, making cycling a better substitute for trips done by driving originally.

The effects on the use of public transport are diverse. Alongside shifting trips towards cycling, the individual policies (i.e., Scenarios 1, 2 and 4), also effect an increase in the use of public transport as they make driving less attractive, making people look for alternatives. An exception is Scenario 3, where economic rewards are only applied to active modes users and therefore make public transport users shift to active modes. In terms of the policy combinations, the use of public transport is reduced in all cases except in the one that penalises car users economically

without economic rewards to active modes (i.e., Scenario 5.3).

These results show a ‘conflict’ between the active and public modes, as both ‘compete’ for shifting car users, while at the same time there can be mode shift effects between public transport and the active modes. The shift of public transport users towards active modes could be an issue in reality: if fewer people use public modes, less revenue is generated, fewer investments could be approved, with the potential to increase prices and diminish services. Such an outcome would particularly affect those people who are unable to use active modes (i.e. people with mobility issues) or do not have the possibility of using any other mode (e.g., vulnerable people without access to a car).

4.2. Distances travelled by transport mode

When analysing the percentage values for all distances, more than 70% of all kilometres are made by cars (around or above 3,000,000 daily kilometres) in all single-policy scenarios (1-4), followed by public transport (up to 25%) (from 500,000 to 1,000,000 km) and by active modes far in distance (up to 4 and 6% for walking and cycling, respectively). However, these trends are altered when several policies are combined in the same scenario (5.1 – 5.4). Scenarios that include economic policies show reductions in car trips ranging from 10% (Scenario 5.2) to 24% (Scenario 5.4). Furthermore, in both scenarios, the percentage of kilometres travelled by bicycle exceeds that of public transport modes, doubling the percentage of kilometres in the best scenario (Scenario 5.4).

Fig. 5 shows the percentage of kilometres travelled by each transport mode, considering all distances and a set of distance ranges (i.e., up to 2 km, 2-5 km, 5-10 km, 10-50 km, and more than 50 km). Red backgrounds mean percentage points reductions when compared to the baseline (yellow background), while green increases.

By analysing the differences in mode share according to distance travelled, it is possible to analyse how the different policies modified the agents' behaviours, and therefore, identify their effectiveness depending on the distances travelled. The main insights are as follows:

- Car usage is reduced in all ranges of distance, but most strongly in short and medium distances (between 2 and 10 km).

- All simulated policies are effective for walking distances up to 2 km (except when implementing fully segregated cycle paths (Scenario 1)), while their impact in other distances is minimal.
- For public transport, the effects are diverse. Increase is observed when economic penalties to car users are included (Scenarios 4 and 5.3) particularly in distances between 2 and 50 km. Moderate increases are also observed in the implementation of LTNs (Scenario 2). Reductions in use are obtained, however, when economic rewards to active modes are provided (Scenarios 3, 5.2 and 5.4), mainly in distances up to 10 km.
- The use of the bicycle particularly increases in distances from 2 to 10 km (i.e., Scenarios 3 and 4). When combining policies, positive benefits are also observed in distances up to 50 km, particularly in those including economic measures (i.e., Scenarios 5.2, 5.3 and 5.4).
- For distances greater than 50 km, the simulated policies do not produce any change towards active modes, but a very small shift to public modes (3.1% in the best case (Scenario 5.4)). This is not surprising, given active modes are hardly feasible for very long daily journeys and the simulated policies are not aimed at increasing public transport use.
- The combination of policies without any economic component (Scenario 5.1) that increases the use of active modes shows the strongest effect for distances of up to 10 km, which could indicate the maximum range of distances that this type of measure can reach. Economic policies can be seen as a boost to increase the number of active travellers in further distances, mainly for cyclists.

In line with these results, daily GHG car emission reductions can be estimated (Fig. 6), based on the total number of kilometres travelled by motor vehicles and the following criteria:

- All vehicles are considered new and emit the average value of CO₂ emissions per kilometre provided by the [European Environment Agency \(2024\)](#) for the year 2019 (i.e., 122.3 g/km).
- All vehicles emit the same average amount of CO₂ independently of the vehicle type (e.g., car, van, truck).
- All vehicles emit the same amount of CO₂ in time: no variances depending on the vehicle speed are considered.

	Differences in percentage-points of trips by mode and range of distance											
	All distances				Up to 2km				From 2 to 5 km			
	Car	Public transport	Walk	Bicycle	Car	Public transport	Walk	Bicycle	Car	Public transport	Walk	Bicycle
Baseline	81.7	14.5	3.0	0.8	22.8	13.5	63.0	0.7	51.8	37.0	5.6	5.6
Scenario 1	-1.7	1.1	-0.1	0.7	-0.5	0.7	-0.6	0.4	-3.8	0.7	-0.6	3.6
Scenario 2	-1.2	1.5	0.0	-0.3	-6.3	2.9	3.8	-0.4	-2.9	5.0	0.0	-2.1
Scenario 3	-5.2	-1.4	1.0	5.6	-4.4	-1.1	5.0	0.5	-7.1	-5.6	1.3	11.4
Scenario 4	-11.9	10.0	0.4	1.4	-8.8	3.7	4.8	0.2	-19.6	13.4	1.0	5.2
Scenario 5.1	-1.4	-0.6	0.0	2.0	-5.9	-0.1	5.0	0.9	-5.5	-4.5	-1.2	11.1
Scenario 5.2	-10.0	-6.0	1.0	15.0	-9.7	-2.6	9.4	2.8	-13.0	-17.1	-0.3	30.4
Scenario 5.3	-13.6	8.2	0.5	4.9	-12.8	1.9	9.2	1.7	-23.9	4.1	-0.1	19.9
Scenario 5.4	-24.5	-2.1	1.5	25.1	-15.7	-1.2	12.5	4.4	-31.0	-12.1	0.5	42.7

	Differences in percentage-points of trips by mode and range of distance, per scenario											
	From 5 to 10 km				From 10 to 50 km				> 50 km			
	Car	Public transport	Walk	Bicycle	Car	Public transport	Walk	Bicycle	Car	Public transport	Walk	Bicycle
Baseline	72.1	26.4	1.0	0.4	89.5	10.1	0.3	0.1	97.1	2.7	0.2	0.1
Scenario 1	-3.1	1.9	-0.1	1.3	-1.5	1.5	0.0	0.0	-0.2	0.2	0.0	0.0
Scenario 2	-3.2	3.4	-0.2	-0.1	-0.5	0.5	0.0	0.0	-0.1	0.1	0.0	0.0
Scenario 3	-10.3	-4.9	0.4	14.8	-1.1	-1.8	0.1	2.8	-1.6	1.5	0.0	0.0
Scenario 4	-22.8	18.0	0.2	4.6	-11.5	11.4	0.1	0.1	-1.1	1.1	0.0	0.0
Scenario 5.1	-2.5	-1.0	-0.4	3.9	-0.3	0.3	-0.1	0.0	-0.1	0.1	0.0	0.0
Scenario 5.2	-19.7	-16.3	-0.3	36.4	-5.1	-4.3	0.0	9.4	-1.5	1.5	0.0	0.0
Scenario 5.3	-26.5	13.2	-0.2	13.6	-12.2	12.0	0.0	0.3	-1.3	1.3	0.0	0.0
Scenario 5.4	-44.0	-12.1	-0.3	56.3	-21.3	0.3	0.0	21.0	-3.1	3.1	0.0	0.0

Fig. 5. Distances travelled by transport mode, per scenario simulated.

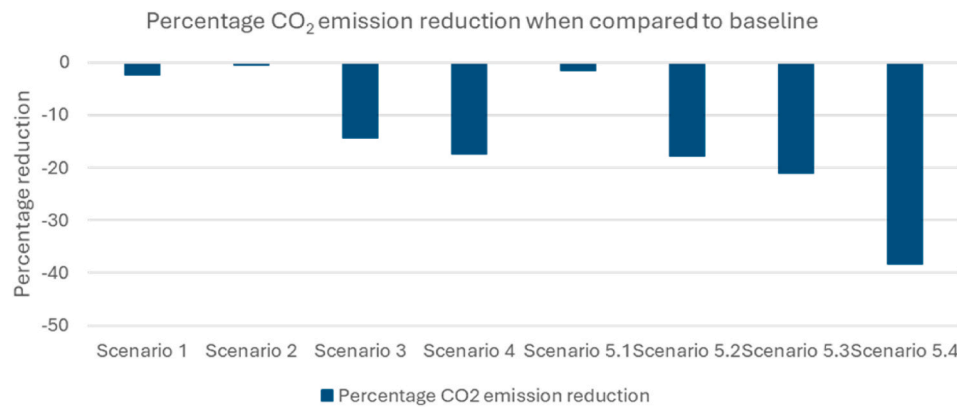


Fig. 6. Percentage of CO2 emission reduction per scenario simulated.

From the individual scenarios (1-4), economic policies deliver the greatest reductions in CO₂ emissions, with economic penalties to car users leading to a 17.3% reduction (71.9 tonnes) in Scenario 4 and rewards to active modes users delivering a 14.2% reduction (59.2 tonnes) in Scenario 3. When policies are combined, those scenarios with economic policies are also the ones achieving the best results: 38.3% reduction (159.4 tonnes) in Scenario 5.4; 21.0% reduction (87.5 tonnes) in Scenario 5.3; and 17.8% reduction (73.9 tonnes) in Scenario 5.2.

Very limited effects are observed, however, when only policies adapting the built environment are considered (e.g., Scenarios 1, 2 and 5.1), with reductions below 10 tonnes (2.5%) in the best case (Scenario 1). A comparison of emissions between Scenarios 5.1 and 1 shows that, while a greater reduction in car use was observed in Scenario 5.1 (4.1%) than in Scenario 1 (2.1%) (see Fig. 4), the latter achieved a greater reduction in emissions (2.3% reduction in Scenario 1, while 1.6% in Scenario 5.1). Although fewer car trips were made in Scenario 5.1 than in Scenario 1 (4% fewer, mostly under 10 km), more emissions were generated due to longer journeys (1.5% more trips over 10 km). This shows that reducing car journeys is not always directly proportional to reducing emissions; total distances travelled play a key role in emissions.

4.3. Geospatial distribution of followed cycling routes

Next, the geospatial effects of the policies are analysed based on counts of bicycles *en route* on each road segment and a comparison against the baseline scenario to identify areas with increase and decrease of bicycle ridership. This can be helpful to decision-makers to prioritise cycling infrastructure investment as it may reveal the latent demand for cycling by showing areas where people would use bicycles if safe infrastructure existed. Fig. 7 shows, for Scenarios 1-4, the change in bicycle counts on each link in the network. The maps on the left show the number of bicycles counted per road. The brighter the green, the greater number of cyclists counted. The maps on the right show the differences in number of bicycles per road per scenario compared against the baseline scenario. Green lines represent an increase in the number of cyclists, while red represent a reduction, the width of the line being proportional to the increase or reduction of cyclists passing through them. For visualisation purposes, only roads with differences above or below 100 bicycles compared with the baseline are shown on the maps on the right.

The same specific cycling routes were identified in the majority of the scenarios (e.g., the W-E corridor in the north of Newcastle, the N-S corridor in North Tyneside, the routes in Gateshead connecting with the Team Valley trading estate and the N-S corridor in Sunderland), except in Scenario 2 where a reduction of cyclists was observed as a result of the inability of cyclists to overtake cars (see more details in Section 5). These spatial patterns could be useful in cycle network planning, enabling future cycling infrastructure investments to be prioritised on these links,

as it could be argued that they are an indication of latent demand, where people might shift to cycling if enabled.

4.4. Contribution of simulated policies to existing policy goals

Active Travel England (ATE), an executive agency of the UK Department for Transport with responsibility for walking, wheeling and cycling, has defined a goal to achieve 50% of trips below 5 km to be walked or cycled in urban areas by 2030. Their 2019 baseline shows that 41% of short trips are walked or cycled in urban areas (ATE, 2023), while results obtained in the baseline modelling scenario in this study reached 43%.

This analysis identifies if the analysed scenarios can achieve the goal established by ATE. Fig. 8 shows the percentage of short trips (e.g., below 5 km) that are made either walking or cycling, per scenario. The orange bar shows the ATE baseline, the grey bar represents the results from the modelled baseline, while the blue bars depict the mode shares achieved per scenario. The horizontal dashed red line marks the threshold defined by ATE for the year 2030.

The ATE goal is reached by only one single-policy scenario (Scenario 3), which offers economic rewards to agents who cycle and walk. In contrast, all policy packages (Scenarios 5.1 to 5.4) achieve the goal, with those that include economic policies, particularly rewards (Scenarios 5.2 and 5.4), being more successful. Like in previous sections, combining policies achieves better results from an active travel perspective, boosting their outcomes.

4.5. Economic benefits

Some scenarios apply economic rewards and/or penalties to influence the behaviours of the agents, which also affects the economic resources of governments. Scenario 3 requires governments to pay everyone using active modes, while Scenario 4 generates income by payments from private car users. Additionally, health effects can also generate an economic impact. Table 1 quantifies the annual economic impact of each scenario only considering the previous three factors (accounting for 260 working days in a year). Economic reward and penalty values were derived from the simulated results (i.e., number of kilometres walked or cycled multiplied by the reward (£0.15), and number of unique agents using private cars multiplied by the toll (£2.5), respectively). Economic health benefits were derived from the HEAT tool (WHO, 2024), using the average kilometres walked and cycled per agent.

Results show that individual policies applying economic rewards to active mode users (Scenarios 3) require a substantial economic investment (£15.5 million). This outcome makes this type of policy difficult to implement in the real world, due to the limited budgets, although exceptions can be found in the Netherlands and Belgium, as described in

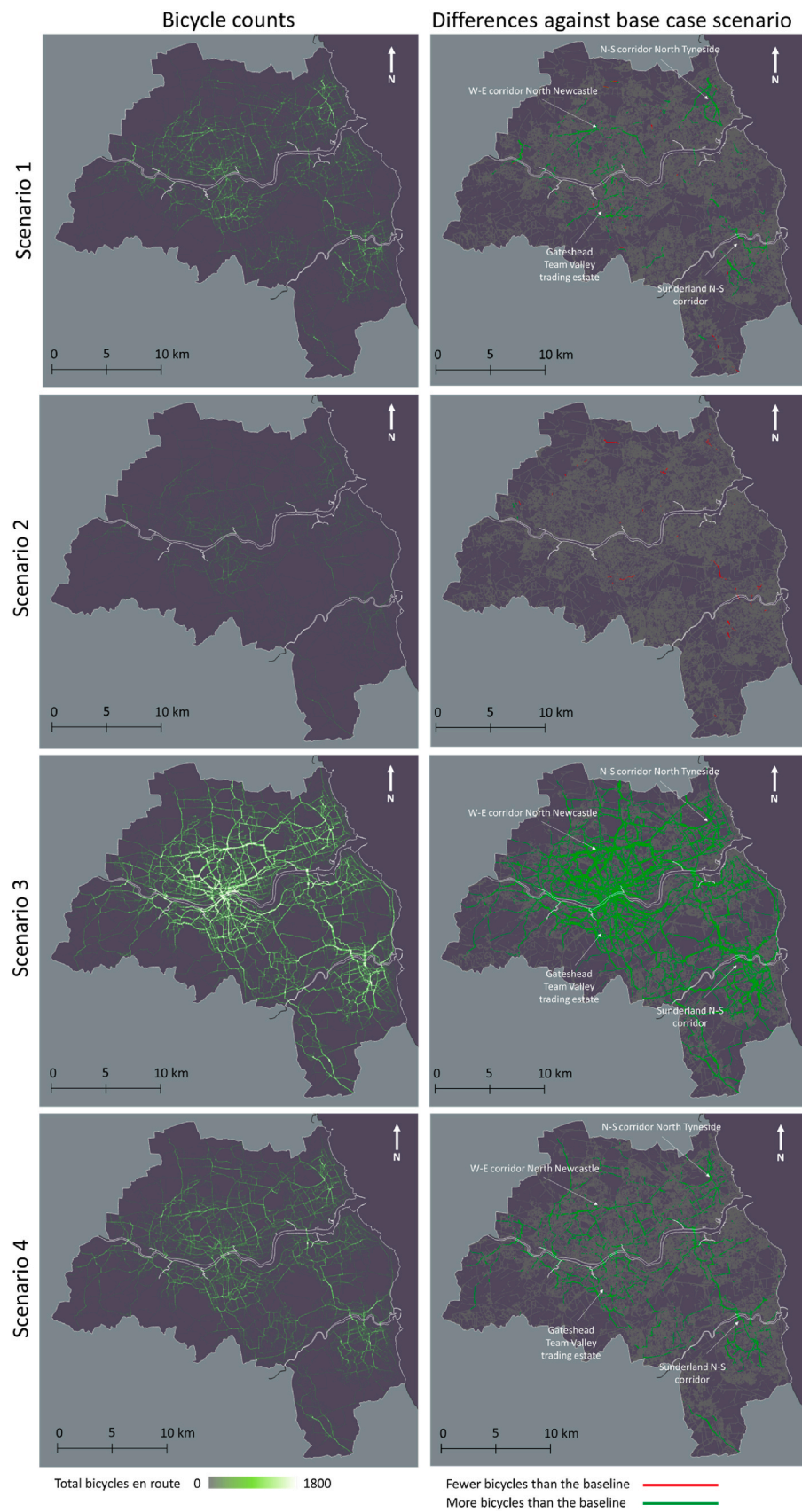


Fig. 7. Bicycle counts in Scenarios 1-4 (left) and differences when compared with the baseline (right).

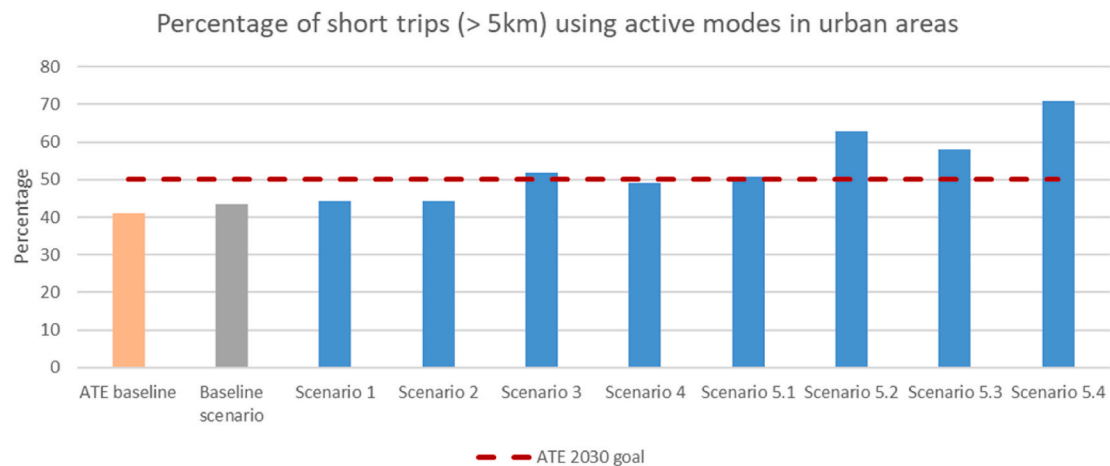


Fig. 8. Percentage of short trips made in urban areas in each scenario simulated (blue bars), with the 50% ATE goal (red dotted line). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1

Economic benefits or debts obtained per scenario when considering the economic rewards, penalties and health impacts in a year.

	Annual economic reward required (£ millions)	Annual economic penalty collected (£ millions)	Annual economic health impact (£ millions)	Total Annual economic impact (£ millions)
Scenario 1			0.2	0.2
Scenario 2			0.04	0.04
Scenario 3	15.5		5.2	−10.3
Scenario 4		49.8	1.9	51.7
Scenario 5.1			1.3	1.3
Scenario 5.2	28.9		10.6	−18.3
Scenario 5.3		45.0	4.4	49.4
Scenario 5.4	43.5	31.4	17.3	5.2

Section 2.2. Policies that impose penalties on car users (Scenario 4) could raise significant revenue (£49.8 million) that could be reinvested in policies that support a sustainable transport future (e.g., fully segregated cycle paths, public transport services improvements), strengthening commitment to a decarbonised and more resilient transport sector.

Different results are obtained from policy packages. While tolls for car users collect higher economic benefits (£49.8 million in Scenario 4) than the amount required when providing economic rewards to active users (£15.5 million in Scenario 3) when applied individually, the

Table 2

Summary of the main results achieved for active modes.

Policies including economic components (penalties or rewards) achieve the highest percentage increases of active modes users
Policy packages in favour of active modes provide extra benefits, which results are multiplied by five in the best case (Scenario 5.1), when compared to the sum of the effects of the individual policies.
Cycling is mainly increased in distances from 2 to 10 km, while additional walking occurs up to 2 km
Policy packages adapting only the built-environment show the strongest effect for distances of up to 10 km.
The same specific cycling routes were identified in the majority of the scenarios, which could be prioritised as future cycling infrastructures as a symptom of potential latent demand willing to shift to cycling.
Economic reward policies and all policy packages enable achieving ATE goal of 50% of trips below 5 km to be walked or cycled in urban areas.
Individual policies applying economic rewards to active mode users (Scenario 3) require a substantial economic investment, while policies that impose penalties on car users (Scenario 4) could raise significant revenue. However, when combined, revenues could be higher than penalties collected.

opposite occurs when both policies are combined (£43.5 and £31.4 million, respectively in Scenario 5.4). This is a consequence of having fewer cars on the roads (i.e., fewer benefits collected) and more people using active modes (i.e., more investment required to pay them per kilometre walked/cycled). This is an important concern, as potential clashes and side effects between different policies combined need to be considered. When adding the potential economic benefits derived from the health benefits (£17.3 million), a positive balance (£5.2 million) is achieved in this type of scenario.

Table 2 summarises the main results achieved for active modes:

5. Discussion and outlook

Simulated scenarios combine behavioural modelling with spatial analysis and economic evaluation to quantify the impact of individual policies and policy packages in shifting car users to active modes. This approach provides a coherent and integrated analysis of policy implementation considering travel behaviours, spatial, temporal and economic components. This is enabled using an agent-based transport modelling framework (Alvarez Castro et al., 2024), which generates results at the individual level thanks to the interactions between agents and the environment in space and time. Different behavioural changes emerge as a consequence of the mobility policies that the agents must face, adapting their mobility patterns accordingly. This level of detail enhances the level and number of analyses that can be performed in contrast to traditional transport models, where aggregated results are mainly obtained.

In all simulated policy scenarios (individual and combined) there was a reduction in car use, while effects on the use of public modes are diverse – showing an increase in public transport use in some scenarios (Scenarios 1, 2, 4 and 5.3) and a decrease in others (3, 5.1 and 5.4). The combination of policies amplifies the number of individuals using active modes, while the car use reduction appears to be similar than when

results from individual policies are added together, with the use of public modes the most affected by the combination of policies. Within the combined scenarios, those rewarding active travel modes economically (Scenarios 5.2 and 5.4) reach the greatest shifts to active modes, while those penalising the use of cars economically (Scenarios 5.3 and 5.4) achieve the highest reductions in the use of this mode, although the shift to active modes is lower unless an economic reward is applied (Scenario 5.4).

Furthermore, the analysis of the distances travelled by mode showed the impact of the policies and how they alter agents' mobility patterns. The simulated individual mobility policies can effect a shift from cars to other modes mainly for trips of up to 10 km, whereas shifts for trips of up to 50 km are only achieved in relevant magnitudes by policy packages. The share of walking is increased for trips of up to 2 km distances, while the share of cycling can be increased for trips of up to 10 km based on single policies, whereas increases in trips of up to 50 km can be achieved with policy packages.

Additionally, the simulated scenarios allowed the identification of specific cycling routes within the study area that could be prioritised for future cycling network extensions, specifically based on the routes that are favoured in multiple of the different scenarios.

Lastly, an economic analysis of the simulated policies reveals the potential positive or negative economic impacts to government budgets, considering the annual economic reward required, collected and the health impact achieved. The potential different economic outcomes that governments could obtain when economic policy rewards (Scenario 3) and penalties (Scenario 4) are applied separately or combined within a policy package (Scenario 5.4) were assessed. The combination shows non-linear outcomes from the individual results, indicating that individual policies could compete between each other when combined to impact (for economic penalties) or attract (for economic rewards) more individuals. While the amount of money collected with economic penalties (£49.8 million in Scenario 4) is greater than the amount of money required to pay economic rewards (£15.5 million in Scenario 3) when applied individually, the opposite result is obtained when both policies are combined (£31.4 and £43.5 million, respectively in Scenario 5.4). Therefore, contradictory results can emerge from the combinations, which must be considered by policymakers before implementing them, particularly in times where budgets are limited and scarce. Additionally, it is important to consider the evolution of the policy package over time, as more individuals could move from cars to active modes, which would induce lower economic penalty collection and greater economic reward requirements, potentially making the balance negative even if economic health impacts are still considered. At that point, policymakers could argue that lower or non-economic rewards would be provided, as new mobility behaviours could have been established and a great proportion of the population would continue using active modes instead of moving back to private cars.

Policy results validation was not possible, as simulated policies have not been implemented in the study area. However, simulated results can be compared against outcomes from research analysed in Section 2.2. Kuss and Nicholas (2022) highlighted that the most effecting measures analysed to reduce the use of cars in urban areas were economic measures (e.g., congestion charging, parking and traffic control), which aligns with the results obtained in scenarios including economic penalties (Scenarios 4, 5.3 and 5.4). Similarly, Marqués et al. (2015) identified that connected, continuous, bi-directional and comfortable cycling network enables doubling the number of users in Seville (Spain). This outcome is similar to results achieved in Scenario 1 (i.e. connected, continuous and bi-directional routes, assuming comfort), where 70% increase in cyclists was obtained. Lastly, Máca et al. (2020) analysed financial rewards for cycling, highlighting that these types of measures can motivate individuals, although without providing any values for comparison. Results from Scenarios 3, 5.2 and 5.4 shows that economic rewards have a huge impact, multiplying the percentage of cyclists by 3, 9 and 14 respectively.

Nevertheless, the applied baseline for the Tyne and Wear region developed by Alvarez Castro et al. (2024) may be affected by some limitations. It would be recommended to include new attributes for the agents, where health status is considered and avoid the assumption that all synthetic individuals have good mobility conditions. Attitudes towards the use of different transport modes were not considered, either different environmental concerns or different attitudes towards alternative travel modes. Currently, these differences are only considered in a limited way based on the diversity of agents' activity plans.

Another set of assumptions made are related to the mobility of different transport modes. Firstly, public transport modes were simulated as deterministic modes (i.e., they are not part of the traffic flow, avoiding any potential congestion), being ruled only by their timetables. Secondly, walked trips were teleported, not being part of the simulation. Thirdly, cyclists were not allowed to overtake cars that line up in intersections (with MATSim's link dynamics set to 'PassingQ', as default), which had a side-effect in Scenario 2, where cyclists were stuck in congestion without the possibility to overtake cars. This effect could be avoided, by applying MATSim's link dynamics specification 'seepage' that allows cyclists to 'seep' through the car queue at intersections. Consequently, these assumptions could have an impact in the results achieved, particularly in the surplus benefits achieved in policy packages increasing the number of active mode users. A further analysis limiting these assumptions is encouraged to test their potential impact in the final results.

Uncertainty analysis in AgBMs is an important topic and ensembles of model runs would ideally be simulated to understand the potential range of outputs for a given scenario. If multiple simulations per scenario were conducted, it would be possible to compute confidence intervals or variability ranges for the scenario results and perform sensitivity analysis on key parameters (e.g., reward levels, penalties) to better understand the range of potential outputs. The required computation time meant that this was not done in this study but should be considered for future work.

The implementation of tailored urban mobility policies for specific groups in the population or areas could help identifying targets within the society. The previous simulated policies could be focused on specific social groups, based on: 1) common socio-demographic attributes and attitudes (e.g., young adults passionate about tackling the climate crisis); 2) family dependencies (e.g., parents accompanying their children to school); and 3) geospatial locations (e.g., cycle and walking paths improvements in specific zones).

Lastly, the potential new policies explored in this paper, alongside many others involving built environment or financial aspects, can be replicated in other UK regions by following the same framework. The modelling methodology adopted in this study is transferable to other UK regions, with Alvarez Castro et al. (2024) providing a detailed description of how to replicate these results in other study areas.

6. Conclusion

This paper presents the results of different physical and economic policy scenarios to reduce the use of private motor vehicles in favour of active modes, based on an AgBM for the Tyne and Wear region of the UK. The tested scenarios include (1) fully segregated and safe cycle paths along with a proportional reduction of the road space for cars, (2) the restriction of cars in residential roads, (3) economic rewards for walking and cycling (£0.15 per kilometre), (4) daily economic penalty (£2.50) for using private cars (i.e. a generic toll study area), and several combinations of these scenarios to identify possible 'surplus benefits', i.e. effects of mutual reinforcement among the policies that make their benefit higher than the sum of their individual contributions in terms of the desired mode shift to active mobility.

The study demonstrates the use and value of AgBMs to simulate the impact of these types of policies, sustained on the level of detail and granularity provided. Behavioural changes emerge from the simulation

when agents face the effects of the different urban mobility policies simulated, considering their different travel patterns, as well as their interactions in space and time in the environment.

As a key result, the study demonstrates the importance of considering combinations of policy measures ('policy packages') to reach mode shift targets, but also reveals further insights such as their impact depending on the distance travelled, potential cycle infrastructure investment prioritisation by identifying latent demand, the scope of the objective set by ATE to reach 50% of short trips by active modes, and the economic benefits that could be achieved when the economic rewards and penalties to influence the behaviours of the agents, besides the health impacts in economic terms. The results show the need for policy measures that incorporate both 'carrots' (pull) and 'sticks' (push) to effectively change transport user behaviour and deliver on environmental, social, and economic objectives.

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CRediT authorship contribution statement

David Alvarez Castro: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft. **Alistair Ford:** Conceptualization, Formal analysis, Methodology, Supervision, Validation, Visualization, Writing – review & editing. **Roberto Palacin:** Conceptualization, Formal analysis, Supervision, Writing – review & editing. **Philip James:** Conceptualization, Formal analysis, Supervision, Writing – review & editing. **Dominik Ziemke:** Conceptualization, Formal analysis, Software, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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Data availability

The authors do not have permission to share data.

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