Sustainable Cities and Society 149 (2026) 107771

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Using agent-based modelling for investigating the impact of travel behaviour interventions on mode shift: A travel behaviour simulation in Dublin

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ARTICLE INFO

Keywords:
Sustainable mobility
Agent-based model
Travel behaviour change
Outcome measures
Behavioural stages
Transport policy
Intervention effectiveness

ABSTRACT

The present study examines the impact of various strategic interventions on behavioural changes from private car use to sustainable travel modes in Dublin City, using an agent-based modelling (ABM) approach with a particular focus on soft policy (i.e., cycling promotion campaigns and travel feedback programs) and hard policy (i.e., motor tax and fuel price increments) measures. Utilising the Irish National Household Travel Survey (NHTS), we analysed changes in travel mode share, behavioural stage progression, and CO_2 emissions under different policy scenarios. The findings suggest that soft interventions, such as cycling promotion campaigns and travel feedback programs, have consistent impacts on reducing car use, progressing behavioural stages (a shift from lower stages like precontemplation to higher stages like action), and lowering CO_2 emissions, with effects amplified when combined with motor tax and fuel price measures. The findings further highlight that using multiple outcome measures provides a more comprehensive evaluation of the impact, making it valuable for policymakers and decision-makers in assessing different transport policy interventions.

1. Introduction

In Ireland, approximately three-quarters of people choose to drive every day, and these travel habits are not aligned with the country's greenhouse gas reduction goals, which aim to reduce emissions from the transport sector by 50% by 2030 (OECD, 2022). Achieving these targets requires not only substantial reductions in private car use, but also robust evidence on which policy interventions are most effective in initiating and sustaining behavioural change. Transport policies have the potential to facilitate and accelerate this mobility transition by shaping the transport system and promoting sustainable alternatives to private car use.

These policy measures can be broadly categorised into two distinct groups (Semenescu et al., 2020): "hard" interventions that intervene at physical infrastructures (e.g., congestion pricing, motor tax increment, and infrastructure improvements such as new cycle lanes) and "soft" interventions that intervene at psychological elements of individual's behaviour (e.g., travel feedback programs, mobility challenges, informational campaigns, and trials such as e-bike trials) (Zarabi et al., 2024). Hard measures seek to reshape social contexts and structures. In contrast, soft measures aim to influence individuals' perceptions, beliefs, attitudes, values, and norms (Semenescu et al., 2020) and influence behaviour through nudges that change how choices are presented to people (Kormos et al., 2021). While interventions which are soft in nature can be politically more feasible and more likely to be accepted by citizens than coercive measures (Eriksson et al., 2008), their impact on travel behaviour change has been found to be limited (e.g., Arnott et al., 2014). Despite these limitations, soft interventions hold the potential to encourage modal shifts when combined with hard measures (Clarke, 2012; Ding et al., 2018).

Although field experiments offer insights into the combined impact of transport policies (Piras et al., 2022), they face several challenges, including high costs, time constraints, logistical and ethical concerns, and difficulty in isolating policy effects (Murphy et al., 2020; Tørnblad et al., 2014). These limitations have prompted interest in alternative methods, such as agent-based modelling (ABM), for evaluating policy

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https://doi.org/10.1016/j.scs.2026.107771
Received 1 February 2026; Received in revised form 4 July 2026; Accepted 1 August 2026
Available online 2 August 2026

and behavioural interventions. ABMs have become a widely used alternative to field experiments, enabling researchers to test policies in simulated environments that account for complex individual behaviours and social dynamics, particularly in the transport sector (Mehdizadeh et al., 2022). Many ABM studies in transport have primarily focused on infrastructure-related and price-based interventions, such as expanding public transport networks, adjusting fuel taxes or parking charges, and improving active travel infrastructure (Aziz et al., 2018; Carroll et al., 2021; Lemoine et al., 2016). These studies generally conclude that disincentives for car use and physical infrastructure improvements are among the most effective tools for shifting travel mode choices. However, soft interventions, such as information campaigns and awareness-raising strategies, have received comparatively less attention in the ABM literature. Although a few noteworthy studies have laid the foundation for their integration.

Natalini and Bravo (2014) developed the Mobility-USA (MUSA) framework to analyse the impact of ex-ante policy on commuting behaviours in the USA. Maggi and Vallino (2021) adopted the same framework to study the policy impact on commuting behaviour in Varese, Italy. However, their approach centred on relatively broad policy instruments (price-based and preference-based policies) and behavioural dynamics are under-theorised. The model incorporated only three transport modes: car, bus, and bicycle. Moreover, the model did not account for individual travel patterns based on real travel survey data, nor did it incorporate agents' socio-demographic characteristics in the simulation setup. Another limitation is that behavioural change was measured solely by changes in aggregated mode share, without considering how individuals may gradually shift through behavioural stages, as suggested by theories of change. These theories suggest that behavioural change is a process articulated in several phases that lead to the final change (Meloni et al., 2013). These constraints limit the model's ability to accurately reflect real-world diversity in travel choices and the nuanced process of behavioural transitions.

To address these limitations, the present study adapted and extended the ABM used by Maggi and Vallino (2021) to the context of Dublin City, Ireland, incorporating both soft (i.e., cycling promotion campaign, travel feedback program) and hard interventions (i.e., motor tax and fuel price increment) while broadening the set of transport modes to include walking, cycling, public transport, and private cars. The model utilised real-world travel diary data obtained from the 2016 Irish National Household Travel Survey (NTHS) and simulated behaviour at the individual level, integrating socio-demographic information and the behavioural stages of change approach to provide a more comprehensive picture of mobility transition.

This study makes the following contributions. Firstly, it improves previous models by expanding transport modes considered, testing different types of soft and hard interventions, and incorporating behavioural stages as an outcome measure. Secondly, it enhances the behavioural dynamics by deriving weights for satisfaction elements from empirically calibrated distributions and introducing a memory parameter to reflect habitual behaviour in mode choice behaviour. Thirdly, the study explores the combined effects of soft and hard interventions, giving insight into which combinations are most effective in different behavioural scenarios.

The remainder of the paper is organised as follows: Section 2 contains a brief literature review on agent-based modelling frameworks. Then Section 3 briefly summarises the ABM framework used in the present study. Section 4 then presents the ABM model outputs, followed by the discussion and conclusion in Sections 5 and 6, respectively.

2. Literature review

The transport sector contributes significantly to global greenhouse gas emissions. As a result, decarbonisation has become a central focus for national governments and local authorities (Jamali et al., 2025; Shen et al., 2026). Urban mobility is a significant factor in emission reduction, where dependence on private motorised vehicles remains a dominant challenge (Huang et al., 2026). Therefore, shifting car trips onto public transport and active modes has become a central focus for authorities (Winkler et al., 2023), and governments worldwide employ a range of travel behaviour intervention strategies (Skarin et al., 2019). It has been empirically shown that such mode shifts can lead to meaningful emission reductions. For example, Abhijina et al. (2025) found that the introduction of new metro lines led to substantial shifts away from private vehicles, with a reduction in transport-related emissions. Further, Ulpiani et al. (2025) identified transport accessibility interventions as one of the most commonly pursued measures among the European cities committed to climate neutrality. Although they noted that strategies often remain generic rather than targeted at specific populations. Therefore, there is a growing body of research that focuses on understanding how these policy interventions can effectively influence behaviour change.

In this regard, agent-based modelling (ABM) has emerged as a powerful alternative to traditional modelling approaches, which have been criticised for their aggregate nature and limited ability to capture individual-level travel behaviour and interactions (Bastarianto et al., 2023; Zhang et al., 2024). ABMs can simulate various scenarios, allowing hypothesis testing without the constraints of the real world (Bruch & Atwell, 2015). These advantages make ABM useful and an increasingly popular tool to inform policy decisions in many other fields of practical importance such as public health (Hammond, 2015), climate mitigation (Castro et al., 2020), and energy (Hansen et al., 2019). Furthermore, ABMs have become a widely used alternative to field experiments, particularly in the transport sector (Mehdizadeh et al., 2022).

In recent years, the application of ABM in the transport sector has grown considerably. Poliziani et al. (2026) developed a regional-scale ABM to assess the environmental health impact of four policy intervention scenarios, including walk and bike incentives and free transit across the San Francisco Bay Area, demonstrating the capacity of ABM to evaluate multifaceted policy impacts at scale. Huang et al. (2026) combined machine learning with ABM to examine travel behaviour for urban park visits in Chengdu, embedding survey-based behavioural parameters. Saha and Fatmi (2026) extended an existing activity-based model to simulate bicycle users' travel behaviour and tested ownership-based policy scenarios in a Canadian region, showing ABM's capabilities to assess the impact of mode-specific infrastructure investments. Beyond these applications, several studies have demonstrated ABM's capacity within a sustainable urban contexts. Luquezi et al. (2025) used agent-based exposure modelling to assess the noise impacts across mobility patterns and social groups. Lu et al. (2019) employed spatial ABM to optimise free-floating bike-sharing system design in Hong Kong. Collectively, this growing body of literature reflects increasing recognition of ABM as a versatile simulation tool for sustainable urban mobility research.

One useful application of ABM is the assessment of ex-ante transport policy impacts (Bastarianto et al., 2023). ABMs enable researchers to forecast potential effects of transport policies prior to their implementation in the real-world. For example, Valentini et al. (2026) examined how green policy measures influence last-mile delivery operations. Furthermore, Ahanchian et al. (2019) examined a range of measures including incentive schemes, disincentives for car use and expansion of public transport infrastructure. Dingil et al. (2025) analysed the impact of a cycleway infrastructure expansion and bus priority scenario. Lemoine et al. (2016) examined how the expansion of bus rapid transit (BRT) affected walking for transportation. Lu et al. (2018) studied environmental and social impacts of bike infrastructure extensions and bike sharing incentives through ABM. More recently, Saha and Fatmi (2026) demonstrated using ABM that policies combining reduced car ownership and increased bicycle ownership produced the greatest reduction in car use and emissions. Huang et al. (2026) similarly showed that multiple policies combining environmental quality improvements and facility enhancements achieved the most balanced mode shifts and highest emission reductions. Many of these ABM studies have primarily focused on assessing the impact of 'hard' interventions in contrast to 'soft' interventions.

Few studies have managed to incorporate soft interventions into their ABM frameworks. Natalini and Bravo (2014) developed an ABM framework to ex-ante assess the impact of policies on commuting behaviours in the context of American households. They assessed the impact of both price-based ('hard' interventions such as carbon tax that aimed at motorised transport by increasing their costs) and preference-based ('soft' interventions such as marketing campaigns or information provision) policy interventions. This ABM framework was further extended by Maggi and Vallino (2021) to the Italian urban context. Both these studies relied on the shift in mode share and changes in total emissions to assess the impact of the interventions. Both studies confined their policy evaluation to relatively broad policy categories. Moreover, their frameworks did not integrate socio-demographics into the simulation design. Salazar-Serna et al. (2024)'s ABM framework was grounded in survey data, and they examined the impact of fare-free public transport policy in Colombia. Their model was still limited to three transport modes, and evaluation was limited to a single policy measure. Collectively, these shortcomings limit the ability of the existing frameworks to analyse real-world individual-level travel behaviour, nuanced dynamics of behaviour change, and different types of soft and hard interventions in an ABM framework. This present study addresses these gaps.

3. Methodology

3.1. Overview of the model

This study uses NetLogo (Wilensky, 1999) to design a modelling framework in which the daily transport mode choices among private car, private bicycle, walking, and public transport of 5000 agents (representing commuters) are modelled. The model consists of two main phases: setup and decision-making. In the set-up phase, agents' socio-demographic and travel-related information, agents' social network, characteristics of the travel modes, and policies are established. In the decision-making phase, agents make a travel mode choice decision based on the information available to them. A summary of the model is provided in Fig. 1, and the following sub-sections give more details about the two phases.

In the mode characteristic initialisation, the unit costs (i.e., cost of using a mode per day per person) and emission rates (gCO_2 emission per passenger km) are estimated for the Irish context to increase the realism of the simulation model. A synthetic population representing Dublin city (Fig. 2) is developed in the agent initialisation step. The travel mode preferences estimated using a multinomial logit model are used as inputs. These preferences play a significant role in agents' decision-making process. They are also influenced by soft policy measures. Car type (emission band and fuel type) is also assigned at this stage, which allows introducing policy measures such as motor tax and fuel price increments. The relative costs (i.e., the cost of using a mode relative to the car) are estimated in this step to reflect the influence of cost in the agents' decision-making process. Agents' social networks (neighbourhoods) are established to reflect the role of social influence in the agents' decision-making process.

3.2. Decision-making phase of the model

In the decision-making phase, agents first choose the trip type based on their trip distance, and then use a deliberative process for their mode choice. For short-distance trips (distance of 5 km or less), all travel modes are available, while for medium-distance trips (distance of between 5 km and 8 km), walking is not an option. The distance thresholds for short and medium-distance trips are based on previous studies (Beckx et al., 2013; Fan & Harper, 2022). For longer trips (with a distance higher than 8 km), only the car and public transport are available to choose from.

The agents use the deliberative process developed by Janssen and Jager (2002) to select a travel mode based on a combination of total satisfaction and uncertainty. Total satisfaction (TS_t) is the weighted sum of past satisfaction (S_{t-1} – satisfaction related to past travel mode) and current satisfaction (S_t – related to current travel mode).

$$TS_t = S_{t-1} \times \alpha + S_t\,(1-\alpha) \tag{1}$$

As described in Eq. (1), alpha (α) is a weighting parameter that determines the weight given to past satisfaction. It is estimated during the calibration process for the model (see Section 3.7). The satisfaction (S_k –

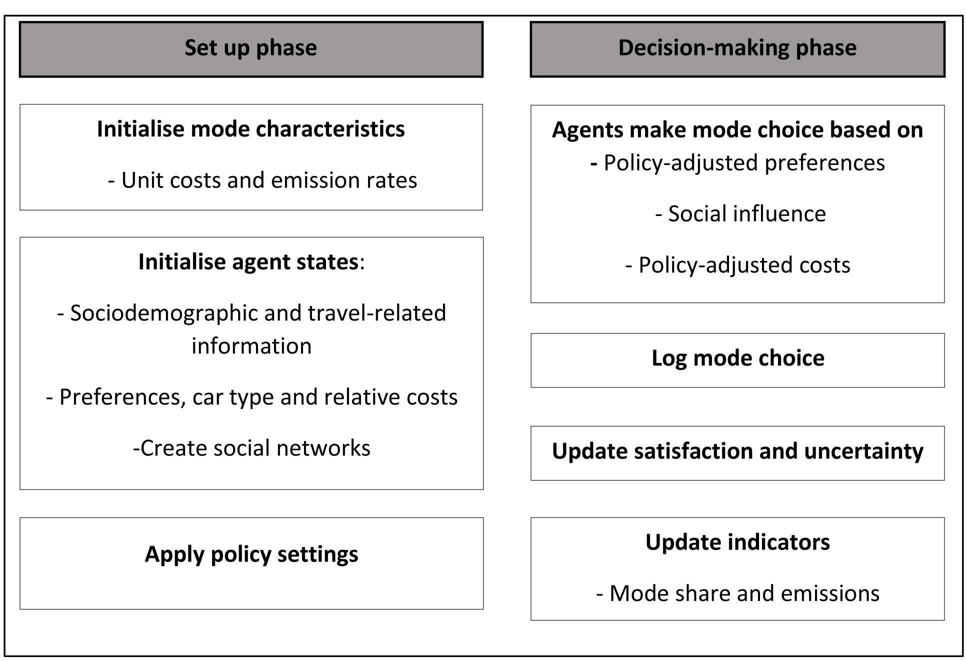

Fig. 1. The model summary.

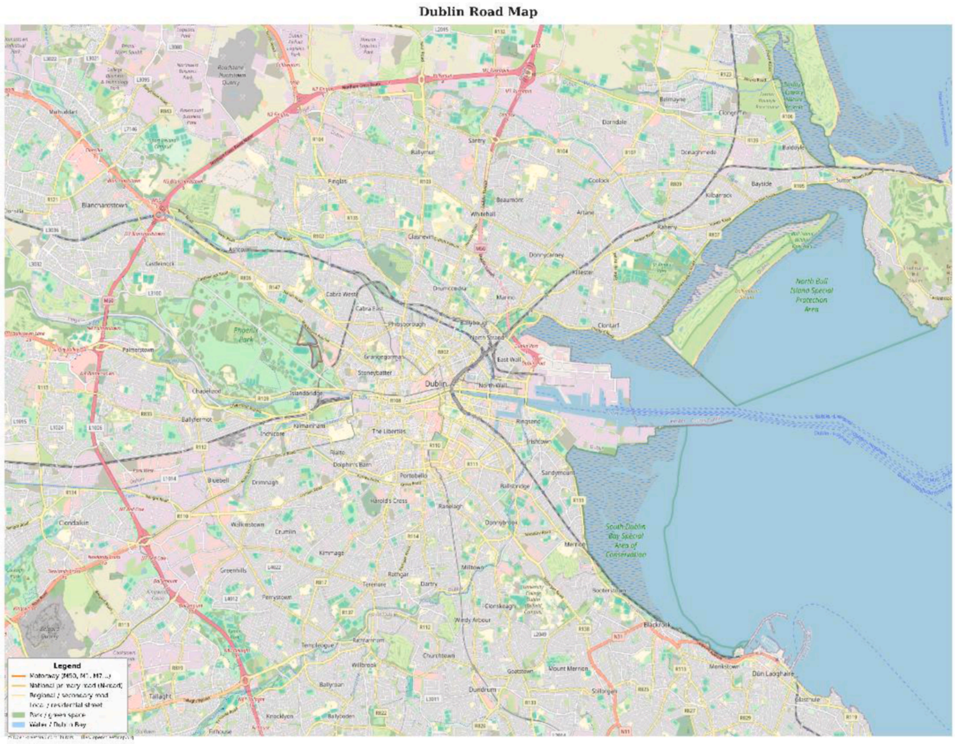

Fig. 2. A map of Dublin city (source: OpenStreetMap).

associated with travel mode) is the weighted sum of personal (PS_k) and social satisfaction (SS_k) divided by the relative price (RP_k).

$$S_k = \frac{PS_{\ k} \ \times \beta \ + SS_{\ k} \ \times \ (1 - \beta)}{RP_{\ k}} \tag{2}$$

As described in Eq. (2), beta (β) is a weighting parameter and is assigned to agents during the agent initialisation step (see section 3.4). Personal satisfaction (PS_k) is estimated based on the preference value corresponding to the mode choice. Social satisfaction (SS_k) is calculated based on the proportion of agents in the neighbourhood choosing the same travel mode as the agent.

$$U_k = \sqrt{|TS_{tk} - TS_{k(t-1)}|} \tag{3}$$

Uncertainty (U_k) reflects the variation in total satisfaction between consecutive time steps. It is estimated as the square root of the absolute difference in the agent's total satisfaction between two consecutive time steps (Maggi & Vallino, 2021) as described in Eq. (3). These values are evaluated against context-specific thresholds for satisfaction (TS_{min}) and uncertainty (U_{max}) (between 0 and 1), guiding agents through one of four decision strategies as illustrated in Table 1. At each time step, the agent first determines its level of satisfaction, followed by its level of uncertainty. Based on their positions relative to the threshold values, the agent selects one of four possible deliberation processes to choose the travel mode.

Table 1
Summary of the deliberative process (from Natalini and Bravo (2014)).

Conditions for the process	Process details
$TS \geq TS_{min}$ and $U > U_{max}$	Imitation: The agent imitates the most adopted choice among the members of its neighbourhood.
$TS < TS_{min}$ and $U \leq U_{max}$	Rationale: The agent calculates the satisfaction for all travel modes and chooses one that offers the highest satisfaction.
$TS \geq TS_{min}$ and $U \leq U_{max}$	Repetition: The agent repeats the decision of the previous time step.
$TS \langle TS_{min}$ and $U \rangle U_{max}$	Social comparison: The agent identifies the most common travel mode in the neighbourhood, then compares the expected satisfaction of that travel mode with the previous choice and selects the one leading to the highest satisfaction. In the event of a tie, the agent randomly chooses one.

The model assumes agents make a round trip to their work or study destination in each time step, and that one time step represents 1 day in real life. When all agents make mode choices, 1 time step is complete. At each time step, model logs the travel mode choices made by each agent. The simulation continues until the specified time-steps (100 time steps) are completed.

3.3. Set up phase of the model – initialising mode characteristics

The model defines transport-mode characteristics (unit costs and daily emission rates) during the setup phase. The daily emission rates are taken from the Irish Passenger Transport Emissions and Mobility (IPTEM) model (O'Riordan et al., 2022) as shown in Table 2. Based on these values, the model estimates total emissions for each policy scenario, taking into account agents' travel distance.

For unit costs, the daily fixed cost of owning a car is first estimated using the annual cost of owning a family vehicle in Ireland (AA, 2017) for each emission band. The fixed cost of owning a car is then adjusted to a base car cost, taking into account the motor tax proportion as

Table 2
CO_2 emission intensity by mode type (gCO_2/pkm) from the Irish Passenger Transport Emissions and Mobility (IPTEM) model (O'Riordan et al., 2022).

Travel mode	2016
Private car – Driver	122.5
Private car – Passenger	122.5
Walk	0.0
Bus	77.8
Cycle	0.0
Rail/Dart/Luas	55.7
Taxi/hackney	122.5

described in Eq. (4).

$$\text{fixed cost of owning} = \text{Base cost}\left(1 + \frac{\text{Motor tax}}{100}\right) \quad (4)$$

Table 3 summarises the cost elements for each emission band of cars. The operating costs (variable costs) are used to calculate the unit cost of a car for each agent, based on the emission band and travel distance, using Eq. (5).

$$\text{Unit cost} = \text{fixed cost of owning} + \text{Variable cost of owning} \times \text{Travel distance} \quad (5)$$

We draw on data from Gössling et al. (2019) for cycling and walking, and Dublin bus fare caps for public transport (National Transport Authority, 2016), as summarised in Table 4. For Cycling and walking, the relative cost proportions (relative to the car) proportions are approximated based on operating costs in Europe (Gössling et al., 2019). The unit costs are then back-calculated using the relative costs and are fixed in the model. While absolute cost and emission values are subject to uncertainty, the model is primarily concerned with relative differences between travel modes and across policy scenarios. This comparative framing ensures that results are robust to reasonable variation in absolute parameter values, while still capturing the directional impacts of policy interventions.

3.4. Set up phase of the model – initialising the agents

3.4.1. Travel mode preference estimation

We first developed a synthetic population of 5000 agents using the Iterative Proportional Fitting method (Prédhumeau & Manley, 2023). Marginal distributions for age and gender are drawn from the Central Statistics Office (CSO).

Synthetic agents are assigned socio-demographic and travel-related attributes by randomly sampling from survey respondents with matching demographic profiles. This information is fed into the model with the estimated preferences for travel modes and car emission bands. We developed a multinomial logit (MNL) model with car as the reference mode (for more details, see Appendix A). The predicted probabilities from the MNL model serve as proxies for travel mode preferences. Each agent is assigned a preference (ranging from 0 to 1) for each of the travel modes. These preferences are used for the ABM under the assumption that they effectively represent agents' actual travel mode choices.

3.4.2. Car type assignment

To assign car types, we relied on data from the CSO, assuming that the car type distribution by fuel type and emission band is similar to that for new private cars licensed for the first time in 2016. Fuel types and emission bands (Categories A to G) are assigned based on the conditional probabilities, as described in Table 5.

Table 3
The cost structure of a car per year (adapted from AA, 2017) for 2016.

Cost element	CO_2 Emission Bands						
	Band A	Band B	Band C	Band D	Band E	Band F	Average
Cost of owning Euro € (per day)	19.51	21.42	24.42	27.20	35.21	45.14	28.82
Motor tax (%)	2	4	4	6	6	7	5
Base cost € (per day)	19.13	20.60	23.48	25.66	33.22	42.19	27.45
Cost of operating Euro € (per km)	0.16	0.20	0.21	0.25	0.27	0.29	0.23

3.4.3. Relative cost estimation

To set the relative costs for each travel mode, we divided the unit cost of the travel mode by the unit cost of the car. The unit cost of the car for each agent is estimated based on its emission band in combination with fuel type and travel distance. For non-car owning agents, average values were assigned. For alternative modes, the unit costs derived (see Section 3.3) are fixed and remain constant across all agents.

3.4.4. Weighting parameter assignment

The beta weighting parameter (β) determines the weight assigned to personal satisfaction and social satisfaction elements in the satisfaction calculation (see Eq. (2)). Assuming this weighting parameter is normally distributed among the agents, values were drawn from a normal distribution, parameterised with a mean (β_m) and a standard deviation (β_{sd}). The 'β_m' and 'β_{sd}' parameters were identified during the model calibration stage (see Section 3.7).

3.4.5. Initialising the agents – establishing a social network

During the setup phase of the model, agents' preferences are used to form their 'neighbourhoods', known as social circles, by linking with other agents who share similar preferences. These social links are held constant across scenarios to isolate the causal effects of policy interventions on decision-making. The agents are clustered into neighbourhoods if their preference-based distance falls below a certain threshold, and social links are established between agents within the same cluster. The threshold value is fixed at 0.5 due to its minimal impact on travel mode share. Furthermore, it created a more reasonable social network for each agent by averaging their neighbours to about 3 agents.

3.5. Set up phase of the model – apply policy setting

We apply motor tax and fuel cost increments as hard policies which change the unit costs of car. By adjusting the motor tax and operating cost elements in Eqs. (4) and 5, different levels of policy measures are introduced. Fuel cost increments are restricted to fuel-operated cars. Here, we assumed that the fuel cost increment is similar across fuel types. For the basic (no policy scenario), no cost increments are applied. By modifying the relative cost structure, these policies influence agents' satisfaction evaluations and subsequent decision-making processes.

For soft policies, we adjusted the preferences of agents to reflect travel feedback programs and cycling promotional campaigns. Promotional campaign for cycling is introduced using a, policy parameter that affects preferences, similar to that of Maggi and Vallino (2021). Specifically, we assume that the intervention can increase commuters' preference for cycling and, at the same time, reduce their preference for private car use (Lanzendorf & Busch-Geertsema, 2014; Ogilvie et al., 2004). The policy parameter ranges from 0 to 1 to represent different intensities of the campaign. For example, a high-intensity intervention may involve personalised information and tailored support, whereas a low-intensity intervention may rely on generalised awareness campaigns (Shafran et al., 2021). For the basic (no policy scenario), the policy intensity is set to zero.

Regarding feedback programs, we assume that they can reduce the preference for private car use and, at the same time, enhance the preference for sustainable modes (walking, cycling, and public transport) (Fujii & Taniguchi, 2005). The feedback program is applied based on each agent's travel history over 14 ticks (representing 14 days). At the end of each 14-tick interval, if an agent's car trip proportion is higher than 50%, the agent's preference for the car is reduced by a certain amount; conversely, the agent's preference for the most frequently used sustainable mode increases by a certain amount. The details of policy interventions are summarised in Table 6. By directly modifying the preferences, these policies influence decision-making processes.

Soft policies are applied only after social networks have been established, ensuring that social circles remains constant across

Table 4
Absolute and relative cost of transportation modes.

Mode	Unit value per traveller per day	Relative cost	Notes	Source
Cycling	-	0.19	Approximated based on operating costs in Europe	(Gössling et al., 2019)
Walking	-	0.14	Approximated based on operating costs in Europe	(Gössling et al., 2019)
Public transport	€7	-	Dublin bus daily cap	(National Transport Authority, 2016)

Table 5
Proportion of new private cars licensed for the first time by type of fuel and CO_2 emission band, 2016 (Central Statistics Office, 2017).

Type of fuel	CO_2 bands (%)						
	A	B	C	D	E	F	G
Petrol	64.63	32.65	1.75	0.53	0.20	0.17	0.07
Diesel	83.03	12.67	2.79	0.58	0.60	0.32	0.02
Electric*	91.72	7.93	0.32	0.03	0.00	0.00	0.00

* Including hybrid and plug-in electric.

Table 6
Applied policy interventions and their descriptions.

Policy intervention	Level description	Real-world example
Promotional campaign	*Low intensity*: car preference reduced and cycle preference increased by 20%	General awareness campaign highlighting cycling benefits, usage, examples and opportunities.
	High intensity: car preference reduced, and cycle preference increased by 80%	Provision of detailed, personalised information and consultancy about cycling.
Feedback program	*Low intensity*: car preference reduced, and preference for the most used sustainable mode increased by 20%	Basic feedback on travel habits, emissions, step count and money savings to raise awareness.
	High intensity: car preference reduced, and preference for the most used sustainable mode increased by 80%	Personalised travel plans and tailored support, in addition to basic feedback, to support sustainable practice.
Motor tax increment	*Low intensity*: Increase motor tax by 20%	A 20% increase in the current motor tax, based on the emission band.
	High intensity: increase motor tax by 80%	An 80% increase for the current motor tax based on the emission band.
Fuel price increment	*Low intensity*: Increase fuel cost by 20%	A 20% increase in the fuel price for all cars except electric cars.
	High intensity: Increase fuel cost by 80%	An 80% increase in the fuel price for all cars except electric cars

scenarios with varying policy intensities, allowing any observed behavioural change to be attributed to the policy's impact.

3.6. Model outcome measures

The model uses several outcome measures. First, shifts in travel mode share and total CO_2 emissions are evaluated. Second, we incorporate behavioural stages of change based on the Transtheoretical Model (TTM) as an outcome measure. The behavioural stages approach gauges the potential of an intervention to facilitate an individual's progression from a low stage, like pre-decisional inhibition (people believe it would be good to change but feel it is impossible), to a higher stage, like pre-actional (people intend to change behaviour soon but do not know how to). Despite not leading to a change in behaviour, stage progression signals increased motivation (Friman et al., 2019). Using the pre-defined classification method described by Lowe et al. (2024), we assign agents to five behavioural stages. To support this, the model records each agent's travel mode choice at every time step, along with simulation time and agent identifiers. At the end of the simulation, we aggregate this data to identify stage membership and track transitions between stages. Third, we utilise socio-demographic attributes to explore which types of agents are more responsive to policy interventions. The model is not intended to provide point forecasts of future mode shares or emissions. Rather, it is designed as an exploratory policy evaluation tool to compare the relative effectiveness of different intervention types under controlled behavioural assumptions.

3.7. Model calibration

We calibrated the model[1] to represent the current mode share for Dublin City. We tested all combinations of five variables which play significant roles in agents' decision making process: satisfaction (TS_{min}), uncertainty (U_{max}), beta-mean (β_m) (from 0.1 to 0.9 in increments of 0.1), beta-standard deviation (β_{sd}) (from 0 to 0.2 in increments of 0.05), and alpha (α) (from 0.6 to 0.9 in increments of 0.1). The range for alpha (α) is restricted to the upper end of the range to reflect habitual behaviour of agents by giving more weight to the past satisfaction. We varied all values and ran 10 simulations for each combination (162,000 runs in total), which took 103 h and 40 min. We calculated the mean squared error (MSE) between the simulated outcomes and the NHTS figures for each parameter combination to identify the combination that produced a mode share most similar to the NHTS figures. The combination that resulted in the lowest MSE was $TS_{min} = 0.5$, $U_{max} = 0.4$, $\beta_m = 0.9$, $\beta_{sd} = 0.2$, and $\alpha = 0.6$, yielding a MSE of 0.0523. This configuration produced the following commuting mode distribution: 46.82% travelled by car (46.58%, NHTS), 15.77% by public transport (15.80%, NHTS), 7.18% by cycling (7.54% NHTS) and 30.23% by walking (30.08%, NHTS).

4. Results

Using the calibrated parameter values, we first implemented the model under no policy scenario. The model was then run under different policy scenarios. As the model allows adjustment of policy intensity (see section 3.5), we first evaluated the intervention at a low intensity (20%) and then at a high intensity (80%). The model was executed 10 times at each intensity level to examine how outputs varied across.

4.1. Impact of individual interventions

We first assessed the interventions separately. As Table 7 illustrates, greater behavioural progression, reduced car use, and reduced CO_2 emissions were observed at soft interventions with high-intensity levels. Among the two soft interventions, the promotional campaign had the greater impact, with 26% of agents progressing to a higher behavioural stage, while regression remained relatively low at 5%. Stability was also low as more agents transitioned between stages of behavioural change. The intervention also produced a higher reduction in car mode share, reaching a 5% decrease at the high intensity. Correspondingly, total CO_2 emissions decreased by 0.12 tonnes, indicating meaningful environmental benefits. However, greater emission reductions were observed

[1] The NetLogo model code used in this study is openly available at: https://www.comses.net/codebases/3418b951-0215-4ca5-ad7c-1da10cb82737/releases/1.1.0/

Table 7
Impact of soft policy interventions on behavioural stages progression, travel mode share, and CO_2 emissions.

	Policy intensity	Progression	Regression	Stability	Reduction in car use mode share	Reduction in total CO_2 emission (t)
Basic scenario	No policy	0%	0%	100%	0%	0.00
Promotional campaign	Low	10%	8%	82%	1%	0.02
	High	26%	5%	69%	5%	0.12
Feedback program	Low	10%	8%	82%	2%	0.06
	High	12%	7%	81%	4%	0.10
Both soft interventions	Low	13%	7%	80%	3%	0.08
	High	26%	5%	69%	5%	0.15

Progression: The proportion of agents who progressed to higher stages (at least one stage), Regression: The proportion of agents who regressed to lower stages (at least one stage), Stability: The proportion of agents who remained at the same stage.

when both soft interventions were implemented together at high intensity level. Notably, behavioural progression rates were substantially higher than observed reductions in car mode share, indicating that soft interventions primarily operate by shifting individuals' motivational states rather than producing immediate behavioural change. This distinction would not be visible if evaluation relied on mode share outcomes alone.

We then tested the hard policy scenarios (see Table 8). Overall, the progression rates were lower than those for the soft interventions. However, a similar progression was shown when both interventions were implemented together. Nevertheless, the impacts on car use reduction and CO_2 emissions were modest. Only a 1% decrease in car use and only 0.03 tonnes of emissions saved were observed, even under high-intensity levels of hard interventions. This suggests a limited but positive impact of financial disincentives on travel behaviour. Although hard pricing interventions yield modest reductions in car use, their contribution to behavioural progression suggests a latent effect that may amplify the impact of complementary soft measures.

4.2. Impact of combined interventions (soft and hard interventions together)

This analysis aimed to assess the combined impact of the two policy types when applied together at varying intensity levels. The combined implementation produced more substantial changes, as shown in Table 9. Behavioural progression rates were markedly higher, with 28% of agents moving to higher stages in several combined policy scenarios. Regression remained relatively low at 5%, and stability was low as expected due to increased behavioural transitions in these policy scenarios. The greatest change was observed when all four interventions were implemented together. Reduction in car use reached 7%, and reduction in total CO_2 emissions was also high at 0.21 tonnes. Reported emission reductions reflect changes within the simulated agent population over the modelled time horizon and should be interpreted comparatively across scenarios rather than as citywide totals.

When both soft interventions were implemented in combination with the fuel price increment policy, car use reduced by up to 6% and the reduction in total CO_2 emissions was 0.20 tonnes. When the promotional campaign was implemented alongside both hard interventions, car use reduced by 5% and emissions by a 0.14-tonne. When both soft interventions were implemented alongside the motor tax policy, car use decreased by 6% and emissions reduced by 0.16 tonnes. When a promotional campaign was implemented with the motor tax policy or the fuel price policy, car use decreased by 5% and emission reduction was by 0.13 and 0.12, respectively. Behavioural progression rates were also high in some policy scenarios, reaching up to 27% as illustrated in Table 9. These findings demonstrate a clear synergistic effect, whereby the combined implementation of soft and hard policies produces outcomes that exceed the additive impacts of individual interventions.

4.3. Impact of interventions by trip type

This analysis aimed to assess the most impactful intervention across different trip types by trip distance. We considered only high-intensity levels for this purpose. As illustrated in Fig. 3, when each intervention is considered separately, promotional campaigns appeared most effective for short- and medium-distance trips, followed by feedback programs. However, for long-distance trips, feedback programs appeared highly influential. The effectiveness of the fuel price increase remained similar for all trip types, while the motor tax policy was most effective for medium-distance trips.

We also assessed the effectiveness of combined policy strategies for different types of trips (Fig. 4). For short-distance trips, the most effective combination was soft interventions combined with the motor tax policy; for long-distance trips, it was soft interventions combined with a fuel price policy. For medium-distance trips, the combination of promotional campaigns and the motor tax appeared highly effective in reducing car use. The greater effectiveness of soft interventions for short-distance trips likely reflects lower perceived feasibility barriers, whereas cost-based measures exert stronger influence on longer trips where monetary costs are more salient. This highlights the importance of aligning policy instruments with the dominant constraints associated with different trip lengths.

4.4. Sociodemographic profiles

To assess socio-demographic profiles of agents whose travel behaviour was influenced by different interventions, we conducted Welch's two-sample *t*-tests for continuous variables and Pearson's Chi-squared test for categorical variables. Age and gender were not significant

Table 8
Impact of hard interventions in terms of behavioural stages, travel mode share and CO_2 emissions.

	Policy intensity	Progression	Regression	Stability	Reduction in car use mode share	Reduction in total CO_2 emission (t)
Basic scenario	No policy	0%	0%	100%	0%	0.00
Motor tax increment	Low	9%	8%	83%	0%	0.01
	High	10%	8%	82%	1%	0.02
Fuel cost increment	Low	9%	8%	83%	0%	0.00
	High	10%	8%	82%	1%	0.03
Both hard interventions	Low	13%	7%	80%	0%	0.00
	High	26%	5%	69%	1%	0.03

Progression: The proportion of agents who progressed to higher stages (at least one stage), Regression: The proportion of agents who regressed to lower stages (at least one stage), Stability: The proportion of agents who remained at the same stage.

Table 9
Impact of both types of policy interventions in terms of behavioural stages, travel mode share and CO_2 emissions.

	Policy intensity	Progression	Regression	Stability	Reduction in car use mode share	Reduction in total CO_2 emission (t)
Basic scenario	No policy	0%	0%	100%	0%	0.00
Feedback + Fuel	Low	10%	7%	82%	2%	0.06
	High	12%	7%	81%	5%	0.15
Feedback + Motor tax	Low	11%	8%	81%	2%	0.05
	High	12%	7%	81%	5%	0.11
Promotional + Fuel	Low	11%	8%	82%	1%	0.03
	High	27%	6%	69%	5%	0.12
Promotional + Motor tax	Low	11%	8%	82%	1%	0.02
	High	27%	5%	68%	5%	0.13
Feedback + Fuel + Motor tax	Low	11%	8%	82%	3%	0.03
	High	13%	7%	80%	5%	0.03
Promotional + Fuel + Motor tax	Low	10%	8%	82%	1%	0.03
	High	28%	5%	68%	5%	0.14
Feedback + Promotional + Fuel	Low	13%	7%	80%	3%	0.08
	High	28%	6%	68%	6%	0.20
Feedback + Promotional + Motor tax	Low	16%	6%	77%	5%	0.12
	High	27%	5%	68%	6%	0.16
All interventions	Low	14%	7%	80%	3%	0.08
	High	28%	5%	68%	7%	0.21

Progression: The proportion of agents who progressed to higher stages (at least one stage), Regression: The proportion of agents who regressed to lower stages (at least one stage), Stability: The proportion of agents who remained at the same stage.
Note: Percentages may not sum to 100% due to rounding.

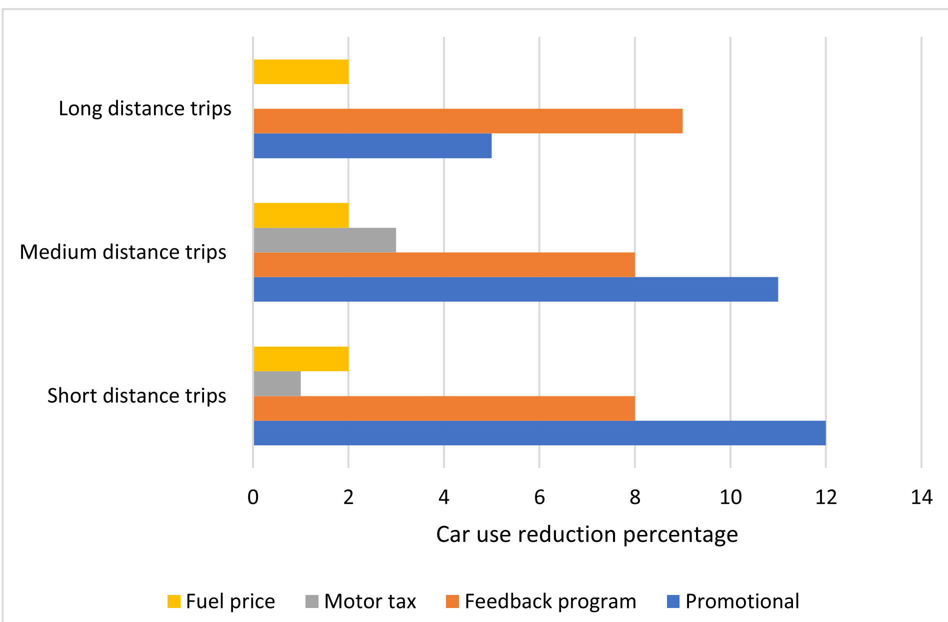

Fig. 3. Relative impact (relative to no policy scenario) of individual interventions on car use reduction across different trip types.

factors for agents who changed their behaviour, while having a bicycle was. Having a driving licence was associated with the adoption of only soft interventions. Agents with household income (more than € 75,000) were more inclined to adopt promotional campaigns, while agents who refused to disclose their household income were more inclined towards feedback programs. Household car ownership (mean: 1.27) was a significant factor for promotional campaign adoption, while household size (mean: 3.16) was substantial for feedback programs. These results suggest that individuals with a high car ownership rate, high income, and high household size, who hold a driving license, were the demographic group most responsive to the soft interventions tested. In contrast, individuals who own a bicycle are more responsive to both hard and soft interventions. The findings do not imply that policy interventions should be restricted to specific demographic groups, but rather indicate where behavioural responsiveness may be greatest, informing the design and sequencing of interventions.

5. Discussion

The primary focus of the present paper was to investigate the relative impact of various interventions (e.g., a cycling promotion campaign, a feedback program, a motor tax increment, and a fuel price increment) on behavioural changes in Dublin City using an agent-based modelling approach. We implemented an ABM framework that integrates socio-demographic attributes, calibrates travel preferences based on real-world survey data, and tracks behavioural stages. The incorporation of real-world survey data enabled a more realistic simulation of individual travel behaviours under different policy scenarios, and the use of behavioural stages as an outcome variable captures the incremental nature of behaviour change more explicitly than earlier models that primarily focused on aggregate mode share outcomes. The results of this study offer valuable insights into how different types of policy interventions (both independently and in combination) can influence

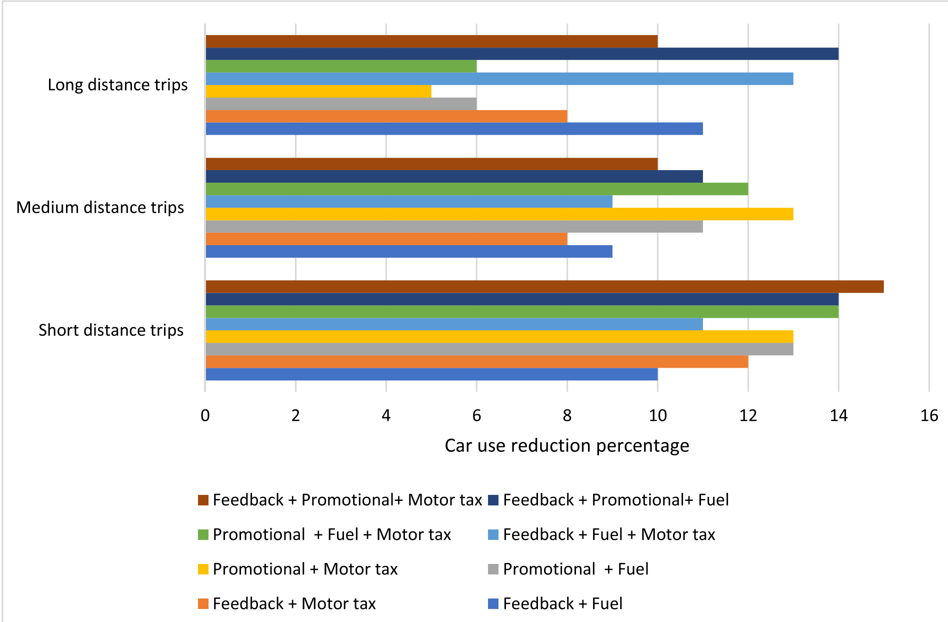

Fig. 4. Relative impact (relative to no policy scenario) of combined interventions on car use reduction across different trip types.

travel behaviour and support a shift towards more sustainable mobility patterns.

A central implication of the results is that policy evaluations based solely on observed mode shift risk underestimating the effectiveness of soft interventions. Behavioural stage progression provides critical insight into latent change processes that precede observable behavioural outcomes. The findings suggest that soft interventions, such as cycling promotion campaigns and feedback programs, can achieve substantial behavioural shifts towards sustainable modes at high intensity levels, consistent with previous research highlighting the effectiveness of informational and motivational strategies in influencing travel behaviour (Piras et al., 2021; Sivasubramaniyam et al., 2021). The findings further showed that promotional campaigns are more effective than feedback programs in progressing agents through behavioural stages and reducing car mode share under high-intensity conditions. These results are in line with prior studies, which have shown that soft measures, although often gradual in effect, can successfully influence travel behaviours when agents are exposed to consistent and targeted information campaigns (Maggi & Vallino, 2021; Mundorf et al., 2018; Natalini & Bravo, 2014). In contrast, hard interventions such as the motor tax and fuel price interventions produced more modest changes, even under a substantial increase in tax and fuel price, highlighting that financial disincentives alone may not be sufficient to drive large-scale behavioural change (Allen et al., 2004), unless they are sufficiently large.

Notably, the combined implementation of different soft and hard interventions demonstrated an apparent synergistic effect, resulting in higher rates of behavioural progression and a substantial reduction in car use, suggesting that integrated policy strategies can be more effective than isolated measures. These results, in line with previous studies (e.g., Maggi & Vallino, 2021; Mosca et al., 2024; Natalini & Bravo, 2014; Riggs, 2017), offer valuable insights into how different types of policy interventions, both independently and in combination, can influence individual travel behaviour and support a shift towards more sustainable mobility patterns. Specific combinations, such as all four interventions together, both soft interventions with the fuel price increment, and a promotional campaign alongside both hard interventions, showed comparatively higher effectiveness in terms of behavioural shifts, indicating that different combinations of policy interventions produce different outcomes. Therefore, attention should be paid to the composition of policy bundles to achieve the maximum impact.

Further, the findings showed that effects vary across different trip types by distance. For short-distance trips, the most effective combination was soft interventions with the motor tax policy, while for long-distance trips, it was soft interventions combined with the fuel price policy. For medium-distance trips, the combination of promotional campaigns and motor tax interventions appeared highly effective. Therefore, when implementing policy bundles, the combination of policy interventions should consider the targeted trip type by distance. Socio-demographic profiles suggest that individuals with a high car ownership rate, high income, and high household size, who hold a driving licence, are the demographic group most responsive to the soft interventions tested, making them a target audience for achieving substantial behavioural shifts when implementing these interventions. Furthermore, the analysis of socio-demographic profiles suggests that cycle owners are more inclined to adopt all these policy interventions. This information should be taken into account when implementing these types of soft and hard interventions to achieve the maximum outcome. Based on all these findings, several policy implications are suggested.

- ***Prioritise combined policy interventions over single interventions.*** The synergic effect of combined soft and hard interventions resulted in higher rates of behavioural stage progression and reductions in car use than single measures alone. Therefore, policy practitioners should consider developing policy bundles that include both types of interventions.
- ***Tailor interventions to trip types by distance.*** Policy effectiveness varied across trip types. Therefore, policy reactionaries should consider trip distance profiles (short, medium, and long) of the target population for more effective intervention designs.
- ***Target specific groups of demographics for a stronger influence of soft interventions.*** Socio-demographic profiles indicated that individuals with higher car ownership, income, household size, and a driving licence were more responsive to soft interventions. Therefore, aiming promotional campaigns and feedback programs toward this demographic is likely to result in significant behaviour changes.
- ***Use multiple outcome measures for policy evaluation frameworks.*** Evaluations solely based on mode share masked the impact that interventions have on individual behaviour change. Tracking changes

in behavioural stages alongside mode share and emissions provides a more comprehensive picture of policy impacts.

A key strength of the present study lies in the integration of real-world demographic data and travel behaviour patterns into the agent-based model, which improves the realism and contextual relevance of the simulations (Maggi & Vallino, 2021). Furthermore, by incorporating behavioural stage tracking, the model offers a clear understanding of how agents progress through different stages of change, beyond simple shifts in travel mode share (Lowe et al., 2024). The inclusion of socio-demographic attributes also enables a richer analysis of how individual characteristics influence responsiveness to policy interventions. In addition, the explicit incorporation of a motor tax policy and fuel price based on real-world cost estimates enhances the model's ability to realistically simulate the financial incentives and disincentives faced by commuters, providing a more realistic assessment of policy impacts.

The successful adaptation of the model to the Dublin context, building on previous applications in the United States (Natalini & Bravo, 2014) and Italy (Maggi & Vallino, 2021), further supports the robustness of the ABM framework in simulating travel behaviour change across diverse urban environments.

Although the study is conducted in the context of Dublin city, the ABM framework is transferable to other urban contexts. The key model parameters (satisfaction threshold (TS_{min}), uncertainty threshold (U_{max}), beta-mean (β_m), beta-standard deviation (β_{sd}), and alpha (α)) would require a systematic recalibration for the local context when applying to a different city. The parameters relevant to policy interventions, such as fuel and motor tax increment and preference adjustments, can be used adapted to reflect specific policy intensities for the target city. Fuel prices and motor tax proportions for the basic scenario need to be adjusted to reflect the local conditions. In addition, agent-level individual data, which is the main input for the ABM needs to be constructed for the local conditions.

Despite the strengths of the present study, several limitations should be acknowledged. The model assumes static social networks, which may not fully capture the evolving nature of peer influence over longer periods. Therefore, future extensions could improve the ABM framework by incorporating a dynamic social network. Additionally, the representation of transport mode availability is simplified and does not account for spatial variability in infrastructure or service quality within the city. Future studies could enhance the model by incorporating spatially explicit data (such as OpenStreetMap-based or GIS based network) on transport networks, accessibility, and service frequency, allowing for a more detailed assessment of how local infrastructure differences influence individual travel behaviour and responsiveness to policy interventions. Further modelling simplifications should be acknowledged. Regarding hard policy measures, the model does not account for the possibility that different types of monetary cost may affect perceived utility differently across modes. Regarding soft policy measures, the precise magnitude of the preference adjustments cannot derived from the empirical sources and therefore it does have a degree of approximation. These simplifications called for further ABM framework improvements. Further, validation of behavioural mechanisms related to interventions remains limited and therefore future studies could strengthen model validation by conducting questionnaire surveys to validate the behavioural mechanisms. Although the study shows how low- and high-intensity policy interventions influence travel behaviour, additional intensity levels could further strengthen the sensitivity analysis. Furthermore, validation of stage transitions through longitudinal panel data would provide a strong empirical basis for the model's dynamic output and remains a challenge for future research. Although the MNL model was used to derive agent's mode preferences, future work could explore machine learning approaches which may offer improved predictive performances for initial preference. In addition, several limitations inherent to the ABM method should also be acknowledged. The complex dynamics among model variables can sometimes create a 'black box' effect, making it difficult to fully trace and interpret the causal pathways leading from inputs to outputs (Maggi & Vallino, 2021). As highlighted by Crooks et al. (2008), while ABMs aim to represent the real world in a rich and detailed manner, there is a risk that increasing model complexity introduces a high degree of arbitrariness, particularly when operationalising the model for practical use. While this tension remains a fundamental challenge in ABM development, future work must carefully balance model complexity with interpretability to ensure transparency and practical relevance.

6. Conclusion

Overall, the findings of this study demonstrate that both soft and hard interventions have the potential to influence travel behaviour, although their effectiveness differs. Findings suggest that soft interventions with high intensity, such as personalised campaigns and travel feedback programs, have high potential to reduce car use, progress individuals through behavioural stages, and decrease CO_2 emissions. In contrast, the hard interventions, such as motor tax and fuel price policies, produced more modest impacts, even under extreme conditions, when implemented alone. However, when applied together, the combined interventions had a significantly greater overall effect. Different combinations lead to higher rates of behavioural change and substantially lower emissions, indicating the importance of a combination of soft and hard interventions. The analysis of socio-demographic profiles further revealed that individuals with a high car ownership rate, high income, and high household size, who hold a driving license, were more likely to respond to soft policy measures. At the same time, bicycle owners are more inclined to adopt both soft and hard interventions. The findings regarding policy effectiveness might be applicable to other cities with similar urban structures and travel behaviour patterns. The adaptability of the main ABM framework across different contexts (the US, Italy, and Ireland) suggests its transferability with sufficient travel behaviour data to calibrate the model. These results underscore the importance of integrated intervention strategies and demonstrate the potential of agent-based models as a tool for evaluating sustainable mobility policies in urban contexts. By demonstrating how policy conclusions vary depending on the outcome measures employed, this study highlights the need for behaviourally informed evaluation frameworks when designing and assessing sustainable transport policies.

CRediT authorship contribution statement

Warnakulasooriya Umesh Ashen Lowe: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Páraic Carroll:** Writing – review & editing, Visualization, Resources, Conceptualization. **Leonhard Lades:** Writing – review & editing, Visualization, Resources, Conceptualization. **Beatriz Martinez-Pastor:** Writing – review & editing, Visualization, Resources.

Declaration of competing interest

The authors declare that they have no competing interests.

Acknowledgements

The research conducted in this publication was funded by Research Ireland (SFI) and co-funding partners under grant number 21/SPP/3756 through the NexSys Strategic Partnership Programme.

Appendix A

	Cycle		Public transport		Walking		Other	
	CO	SE	CO	SE	CO	SE	CO	SE
Intercept	−15.147***	0.333	−16.385***	0.214	−1.927	2.684	−15.933***	3.201
Travel distance	−0.216***	0.033	−0.092***	0.010	−1.263***	0.045	0.000	0.018
Travel time	0.027*	0.011	0.069***	0.005	0.161***	0.006	0.017	0.019
HH companions	−1.708***	0.238	−1.122***	0.108	−0.752***	0.075	−1.381*	0.703
Children companions	1.154**	0.378	−0.862*	0.412	0.921***	0.211	−1.041	1.856
Non-HH companions	−0.238	0.353	−0.333·	0.179	−0.038	0.103	−3.389	2.613
Age	0.002	0.004	−0.002	0.002	−0.003	0.002	0.002	0.008
Gender male (female)	0.300·	0.156	0.158	0.100	0.121	0.098	0.693·	0.377
Occ. working (student)	0.628*	0.307	−0.398*	0.183	0.290	0.199	−0.935	0.929
Occ. retired (student)	−0.744	0.500	−0.587**	0.224	−0.011	0.226	−3.689·	2.094
Occ. unemployed (student)	−0.508	0.476	−0.653**	0.229	0.579**	0.215	−3.848*	1.811
Occ. other (student)	−6.973***	0.000	−0.453	0.680	−2.531***	0.760	−9.429·	5.575
Driving licence Yes (no)	−2.063***	0.237	−2.487***	0.141	−1.881***	0.144	1.616	1.381
Use carshare scheme Yes (no)	0.915**	0.350	1.096***	0.195	−0.032	0.216	−5.192	3.723
Use PT ticket Yes (no)	−1.714***	0.486	5.183***	0.216	3.709	2.554	3.927	3.624
Own a bike (No)	4.482***	0.286	0.422***	0.121	0.528***	0.119	−0.132	0.449
Use bikeshare scheme (no)	1.119***	0.232	0.098	0.227	0.438*	0.212	−4.267	4.040
HH size	0.351***	0.073	0.049	0.054	0.085	0.053	0.195	0.185
HH car ownership	−0.480***	0.110	−0.715***	0.069	−0.665***	0.068	0.536*	0.228
HH type alone (family)	1.120**	0.395	0.091	0.193	−0.205	0.195	−0.563	0.945
HH type couple (family)	2.821***	0.253	1.806***	0.178	1.746***	0.194	−6.770***	0.111
HH type other (family)	0.936**	0.290	−0.404*	0.174	0.150	0.158	−3.226	2.209
Have quick access to a bus stop	2.113***	0.336	14.739***	0.214	0.869	0.710	−2.675	4.369
Have quick access to a pharmacy	0.462	0.970	−0.649*	0.388	−0.449	0.411	−1.185	4.887
Have quick access to a Doctor	−0.912**	0.295	0.857***	0.222	0.223	0.226	5.018*	2.567
Have quick access to a pub	10.805***	0.333	−0.075	0.510	1.466*	0.586	0.736	3.109
Have quick access Post office	0.763·	0.390	−1.013***	0.238	−0.570*	0.279	−2.470	1.888
Have quick access a shop	2.950***	0.341	−0.339	0.509	−0.040	0.513	3.443	3.685
Non-home-based trip (home-based trip)	−0.398·	0.159	0.118	0.101	0.280*	0.099	0.278	0.376
Income 25k-50k (<25k)	−1.411***	0.259	−0.489***	0.146	−0.748***	0.147	2.946·	1.791
Income 50k – 75k (<25k)	−0.395	0.280	−0.157	0.179	−0.424*	0.174	−1.736	2.733
Income > 75k (<25k)	−0.301	0.419	−1.707·	0.447	−0.890**	0.326	−2.620**	0.916
Income refused to answer (<25k)	−2.593***	0.435	−0.435**	0.165	−1.517***	0.164	3.009·	1.798
Trips per day	−0.343***	0.09	−0.006	0.049	0.067	0.042	0.656***	0.121

Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Residual Deviance: 6729.901, AIC: 7001.901, pseudo $R^2 = 0.4492$.
CO: Coefficient, SE: Standard Error, HH: Household, PT: Public Transport.

Data availability

The authors do not have permission to share data.

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