Transportation
https://doi.org/10.1007/s11116-026-10784-0

Evaluating soft travel behaviour interventions using behavioural stages of change within an agent-based modelling framework

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Received: 17 November 2025 / Accepted: 15 May 2026

Abstract
The effectiveness of interventions that aim to change travel behaviour is usually measured by the sudden shift from pre- to post-intervention. However, this binary perspective overlooks the gradual evolution of an individual's travel behaviour over time. Our study challenges this paradigm and suggests the behavioural stages approach as a more precise tool for evaluating the efficacy of 'soft' travel behaviour interventions—those designed to influence perceptions, attitudes, and social norms or induce travel behaviour change through changes in the choice architecture. Many individual soft interventions could lead people to progress from a low stage like "pre-contemplation" to a higher stage like "preparation"—without resulting in behavioural change. Therefore, a more nuanced outcome measure is needed to assess individual soft interventions. An agent-based modelling framework is applied in this study to demonstrate the utility of the behaviour stage approach compared to traditional outcome measures. The findings show that the behavioural stages approach can detect the effects of interventions that more conventional measures like modal shift, travel frequency, travel distance, and attitudinal changes cannot detect. Moreover, the approach outlines the proportion of individuals who have progressed through stages, remained in the same stage, and regressed through stages post-intervention. The behavioural stage approach is thus a valuable tool for assessing the impact of soft interventions, and policymakers and decision-makers could devote more attention to this approach when evaluating travel behaviour interventions.

Keywords Agent-based model · Soft travel behaviour interventions · Travel behaviour change · Stage model

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Published online: 26 May 2026

Abbreviations

TTM Trans-theoretical model
ABM Agent-based modelling

Introduction

Current mobility patterns continue to challenge the attainment of environmental targets set for the transport sector in many countries worldwide (Ribeiro et al. 2024). A range of travel behaviour interventions known as Travel Demand Management (TDM) measures have been developed and deployed to address this issue. Among these TDM measures are "soft" interventions, such as travel feedback programs (Fujii et al. 2009), mobility challenges (Minnich 2023), informational campaigns (Jiao et al. 2024), and e-bike trials (Andersson et al. 2021). These soft interventions aim to influence individuals' perceptions, beliefs, attitudes, values, and norms (Semenescu et al. 2020) and change behaviour through nudges that modify how choices are presented to people (Kormos et al. 2021; Thaler and Sunstein 2021). Soft interventions have gained attention in recent years to encourage pro-environmental behaviours (Department of the Environment Ireland 2023), partly because they can be politically more feasible and are more likely to be accepted by citizens than coercive measures (Eriksson et al. 2008). However, their impact on behaviour change has been found to be limited (e.g. Gravert and Olsson Collentine 2021; Kristal and Whillans 2020). A meta-analysis spanning over three decades of soft interventions revealed only a modest impact of a 7% reduction in car usage (Semenescu et al. 2020).

One potential reason for the limited reported impact of soft interventions in the transport sector is how their impact is assessed as a sudden behavioural shift from pre- to post-intervention. The effect of most soft travel behaviour interventions is measured as changes in modal choice, trip frequency, travel distances, and changes in emissions (Piras et al. 2022). While these traditional approaches can provide valuable information, they may not fully highlight the comprehensive behavioural transformation process, ranging from contemplation to realised action. According to theories of change, which study the dynamic evolution of individual behaviour across time, behaviour change is a process articulated in several phases that lead to the final change (Meloni et al. 2013). Understanding the progression of behaviour change through stages is crucial as it indicates a readiness for behaviour change that could translate into more significant behavioural shifts over time. Traditional outcome measures are not sensitive enough to measure people's advancement to higher stages due to the intervention.

The behavioural stages approach is based on models like the Transtheoretical Model (TTM) (Prochaska and Velicer 1997) and the Stage Model of Self-Regulated Behavioural Change (SSBC) (Bamberg 2013). Although it should be noted that there is an ongoing debate around labelling and the number of stages in stage models, all of them adhere to the same logic and stage structure, moving from a weaker to a greater motivation to change (Olsson et al. 2021). Figure 1 illustrates the stages of TTM. The behavioural stages approach has been rarely used in transportation research to assess the effectiveness of travel behaviour interventions, as suggested in a systematic review (Friman et al. 2017). Friman et al. (2017) further explain that the lack of empirical studies, mismatches between processes and stages, variability in study qualities, and lack of knowledge regarding the potential of TTM

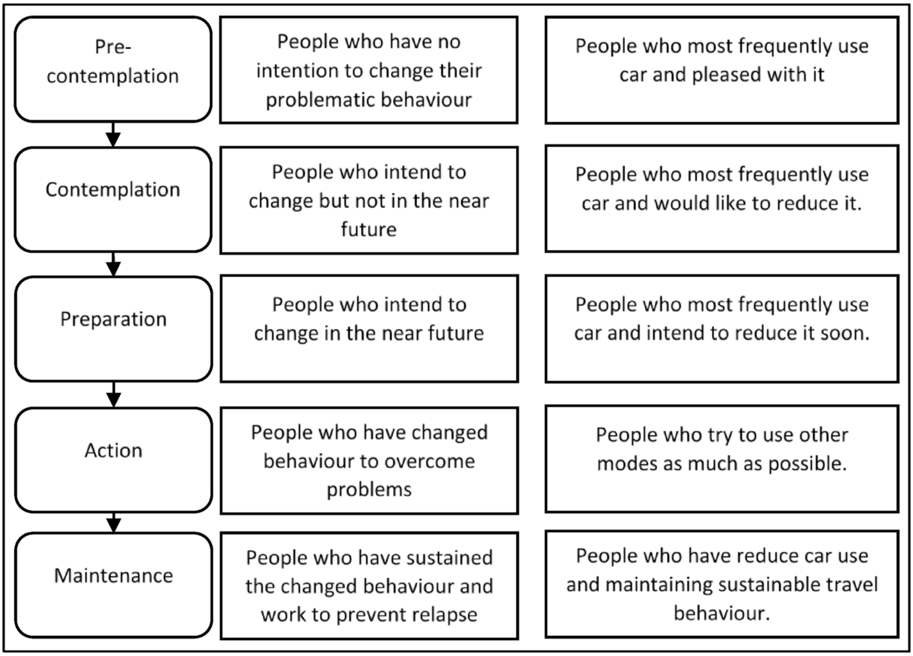

Fig. 1 Transtheoretical model stages (Adopted from Thigpen et al. 2019 and Olsson et al. 2018)

could be the underlying reasons for it. However, some studies used the behavioural stages approach (Olsson et al. 2018, 2021; Friman et al. 2019; Ahmed et al. 2020; Mundorf et al. (2018). These studies relied on self-reported surveys to place people at different stages pre and post-intervention.

While it is feasible to rely on self-reported surveys when conducting field experiments, surveys are less viable for other methodologies, such as agent-based modelling (ABM) (Abdulkareem et al. 2019), which cannot rely on pre- and post-intervention self-reports to integrate stages. Despite being a popular policy informative tool in the transportation sector (Gaudou Jaime Simão and Sichman 2015; Le Pira et al. 2017), only a few academic studies have been able to incorporate soft travel behaviour interventions into the ABM framework (Natalini and Bravo 2014; Maggi and Vallino 2021). These studies also rely on traditional approaches for intervention evaluation and have not utilised the behaviour stages approach as an outcome measurement tool.

Therefore, integrating the behaviour stages approach into the ABM framework to offer a more comprehensive approach to evaluating the ex-ante impact of soft interventions is a gap that needs to be addressed. To this date, behaviour stage models have been applied primarily in field experiments and survey-based studies, but have not been incorporated int ABM frameworks as an outcome measure for policy evaluation. Traditional approaches often fail to capture individual-level behaviour changes that may result from such intervention. The fulfilment of this gap will allow scholars and policy planners to evaluate the impact of transport policies at an individual level within the ABM framework. Incorporating TTM stages into the ABM framework is suggested via the approach proposed by Lowe et al. (2024), who demonstrated that it is possible to use objective travel data to place people in different stages of TTM, making it a viable option for agent-based models. The approach will advance the current ABM frameworks by integrating a more comprehensive outcome measure for policy impact assessment in the transport sector. This paper uses an agent-based modelling framework to show that the behavioural stages approach can be used as an alternative and more sensitive method for assessing the effectiveness of soft travel behaviour interventions. For this purpose, we adopt the publicly available agent-based model and data set by Maggi and Vallino (2021) and extend the ABM framework to incorporate TTM stages using the approach proposed by Lowe et al. (2024).

The remainder of the paper is organised as follows: Sect. 2 reviews the literature, beginning with the studies that utilised the behavioural stage approach to assess soft travel behaviour interventions. It then focuses on the evaluation of soft travel behaviour interventions within an agent-based modelling framework. Section 3 presents the methodology and explains the modification made to the existing agent-based modelling framework to incorporate behaviour stages. Section 4 presents the results, followed by the discussion and conclusion section.

Literature review

Traditional approaches to assessing soft travel interventions

Traditional outcome measures, such as changes in mode shares and matter emissions, can provide valuable information regarding the impact of soft interventions. The shift in mode choice and share is widely used to indicate the effectiveness of various soft interventions (Busch-Geertsema et al. 2021; Friman et al. 2019; Meloni et al. 2017; Merlin et al. 2022; Moser et al. 2019; Olsson et al. 2021; Piras et al. 2018; Ralph and Brown 2019; Sottile et al. 2021; Teixeira et al. 2019). It tracks changes in the proportions of people utilising different modes of transport. Additionally, multiple outcome measures—spanning mode share, travel frequency, and travel distance—are often combined for a more comprehensive analysis.

Travel frequency and travel time are also commonly adopted in studies focusing on mobility-related challenges and reward interventions, such as those aimed at increasing cycling (Arroyo et al. 2018; Biondi et al. 2022; Huang et al. 2021, 2022; Minnich 2023; Ruiz et al. 2018; Teixeira et al. 2019; Weber et al. 2018). Travel frequency measures changes in the number and pattern of trips made, which are trackable through surveys or tracking technology. However, increasing travel frequency, while indicating more usage, does not necessarily signify a shift in choice of travel mode. It could, instead, suggest that the users of a particular travel mode began to utilise it more regularly rather than adopting a different mode.

The attitude shift approach attempts to capture the changes in attitudes towards various travel modes and intervention programs. These types of evaluations are frequently used to assess information campaigns, wherein participants are informed about the advantages of sustainable travel (Abdul Sukor et al. 2018; Mundorf et al. 2018; Piras et al. 2021; Sivasubramaniyam et al. 2021). While it is important to know the positive shift in attitude, a change in attitude can be temporary or not strong enough to overcome powerful habits.

Even though all these measures summarised above provide valuable information regarding the positive influence of an intervention, they view mode adoption decisions as an instantaneous transition from pre-intervention to post-intervention usage, except for the attitude shift approach. This perspective can oversimplify the complex process of behavioural change, failing to capture the gradual progression in individuals' travel behaviours over time.

Behavioural stage approaches to assessing soft travel interventions

The literature on behaviour stages in travel behaviour change has employed differing range of stage names and models. Therefore, the review in this section used general terminology such as lower and higher stages, stage progressions and regression. The five stages of trans-theoretical model which forms the basis for the present study is discussed in detail in the methodology section.

An example of a behavioural change measure in stages is one's shift 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, it signals increased motivation (Friman et al. 2019).

A few recent studies have explored the behaviour stage approach as an alternative tool for evaluating the impact of soft interventions in the transport sector, predominantly using the six-stage model proposed by Olsson et al. (2018). For example, Friman et al. (2019) used behaviour stages and shifts in mode share to evaluate the impact of a trial intervention offering a 30-day free public transport ticket. They conducted online pre- and post-intervention surveys to collect information and used cross-tabulation to report the frequencies of participants at different stages before and after the intervention. Similarly, Ahmed et al. (2020) measured the impact of a travel feedback program using changes in the Vehicle kilometre travelled (VKT) by car and the behavioural stage approach. While they also relied on a questionnaire-based survey approach to capture post-intervention changes, they reported the outcome of behaviour stages in terms of proportions of participants at different stages before and after the intervention rather than their frequencies.

In addition to using travel frequency changes, Olsson et al. (2021) also used behaviour stages and reported the impact of a mobility-related challenge intervention using a cross-tabulation similar to Friman et al. (2019). While all these studies reported the behaviour stages of participants in terms of frequencies or proportions, Mundorf et al. (2018), who relied on the transtheoretical model, only reported the proportion of participants who progressed from pre-contemplation and contemplation to a higher stage as measured through online surveys before and after the intervention.

These papers show that the behaviour stage approach has received some attention in the transport literature as an outcome measure for soft interventions. In these studies, researchers conducted a survey before and after the intervention to place individuals in different behavioural stages. While conducting field experiments coupled with surveys is an important approach to inform efficient transport policies (Dolan and Galizzi 2014), there are several barriers to running field experiments. Amongst these barriers are cost, time, physical ability, lack of appropriate control groups, inability to analyse policy elements in isolation, and misconceptions about ethics and logistics (Murphy et al. 2020; Tornblad et al. 2014; Dolan and Galizzi 2014). These barriers have led scholars and policymakers to explore alternative methodologies to evaluate the effectiveness of policies and behavioural interventions.

Ex-ante assessment of transport policies using agent-based models

Agent-based modelling (ABM) is one of the methodologies that can evaluate policies without requiring field experiments. ABM has at least two distinct advantages. First, it offers unprecedented control over agents' behaviour and interactions, allowing for testing hypotheses in a controlled environment (Jackson et al. 2017). Second, it can simulate various scenarios, allowing hypothesis testing without the constraints of the real world (Bruch and Atwell 2015). These advantages make ABM useful, especially in investigating group behaviour or evolutionary processes (Jackson et al. 2017). As a result, ABM has become a popular tool to inform policy decisions in many fields of practical importance, such as public health (Hammond 2015), agriculture (Kremmydas et al. 2018), consumer behaviour (McCulloch et al. 2022), climate mitigation (Castro et al. 2020), and energy (Hansen et al. 2020). Moreover, ABM has become an invaluable tool for capturing the dynamics of complex and adaptive systems (Faboya et al. 2020). It allows for modelling how agents interact with one another and their environment. These agents can learn from their experiences and influence one another, leading to emergent system-level behaviours. In the simulated environment, agents interact with each other and the environment to make autonomous travel decisions. The agents pro-act or react, given the previous experiences and communications, and evolve based on their interactions and time-based feedback (Shukla et al. 2013).

While agent-based modelling has been applied in a wide range of scientific fields, its use in the transport sector has been particularly extensive (Mehdizadeh et al. 2022). From modelling individual travel behaviour to simulating large-scale transportation systems, ABM offers a powerful approach to assessing various transportation dynamics. One of its most valuable applications in this area is the assessment of ex-ante policy impacts, where models help predict the potential outcomes of transport policies before they are implemented. For example, Valentini et al. (2026) examined the impact of green policies in last-mile delivery. FurtherAhanchian et al. (2019) and Carroll et al. (2020) investigated the impact of expanding public transport infrastructure and service improvements, provision of incentives for sustainable modes (decreasing public transport ticket prices, free parking for public transport users, and free charging e-bike users) and the provision of disincentives for car use (increase fuel price, tax, tolls and parking charges) on travel mode shift. They found that disincentivising car users has the highest impact, followed by infrastructure improvements. Similar findings have been reported by Aziz et al. (2018), who investigated the impact of infrastructure improvements such as improving active mode infrastructures, namely widening sidewalks and providing more extended bike lanes.Lemoine et al. (2016) focused on the impact of the growth of Bus Rapid Transit (BRT) (increased lanes and increased density) on walking for transportation, and they found that it increases the number of minutes that individuals walk for transportation.Shirzadi Babakan et al. (2015) showed that improvements to the existing infrastructure and the development of new infrastructure, such as a new highway, subway and bus rapid transit (BRT) line, can make considerable changes in the commuting travel mode choices. Many of these studies have primarily focused on assessing the impact of 'hard' interventions in contrast to 'soft' interventions, which have received comparatively less attention within ABM frameworks.

Despite the lack of attention given to 'soft' interventions in ABM frameworks, few notable studies have provided the groundwork for their inclusion. Natalini and Bravo (2014) developed the Mobility-USA (MUSA) framework to analyse the impact of ex-ante policy on commuting behaviours in the USA. They focused on two types of policy scenarios: price-based and preference-based. The price-based policy scenario represented 'hard' interventions such as a carbon tax meant to affect the use of motorised transports by increasing their price. The preference-based policy scenario reflected the 'soft' interventions such as marketing campaigns or providing information about commuting alternatives to the agents. They found that preference-based policies lead to the highest share of non-motorised transports and CO_2 emissions reduction for both short and long commutes. Furthermore, they found that a combination of these two types of policies can be remarkably effective on short commutes but not on long ones. Maggi and Vallino (2021) adopted the same framework to study the policy impact on commuting behaviour in an urban city in Italy. They focused on short commutes and found that price-based policies are less effective than preference-based policies, and the best outcome can be achieved by using a combination of both types. Both these studies relied on the shift in mode share to assess the impact of soft interventions within the ABM framework. In addition, they have utilised changes in the total amount of particular matter emissions as another assessment tool. While both these metrics provide valuable insights, they only revealed the overall impact and the positive impact following the intervention.

Despite these advances, the existing ABM frameworks have mostly relied on aggregate outcome measures such as mode share shifts and total emissions to assess the impact of soft interventions. The stage-based behavioural models, which have demonstrated sensitivity to incremental behaviour change in field experiments (Mundorf et al. 2018; Friman et al. 2019; Olsson et al. 2021), have not been integrated into ABM frameworks as an outcome measure. This reflects that existing ABMs fall short in detecting the nuanced individual-level changes that soft interventions are designed to produce.

Research gap

It is apparent that only a few studies have incorporated soft travel behaviour interventions into the ABM framework, and they have not utilised the behaviour stages approach as an outcome measurement tool. As discussed in Sect. 2.2, the behavioural stages approach offers valuable insights into an intervention's impact over traditional measures. By incorporating behavioural stages into ABM, we can assess the impact of intervention at individual levels, allowing policymakers and scholars to examine both positive and unintended negative impacts. The present study addresses the question: can behavioural stage models be integrated into ABM framework to provide a more comprehensive measure of ex-ante impact of soft travel behaviour interventions? By doing so, the study makes a novel contribution by being, to the best of authors' knowledge the first to incorporate TTM based behavioural stages as an outcome measure within an ABM framework for transport policy evaluations. We rely on the same ABM framework and dataset Maggi and Vallino (2021) used to bridge this gap.

Methodology

To integrate the behavioural stages approach into an ABM framework for an ex-ante transport policy assessment, we utilise the modelling framework and dataset by Maggi and Vallino (2021). Appendix A summarises this framework. The model was developed and implemented using NetLogo software (Wilensky 1999). As illustrated in Fig. 2, the model has two phases. In the setup phase, 5000 agents representing commuters in Varese Italy are initialised with mode preference for private car, non-motorised modes, and public transport. Agents then form social networks based on preference similarity, creating a social circle

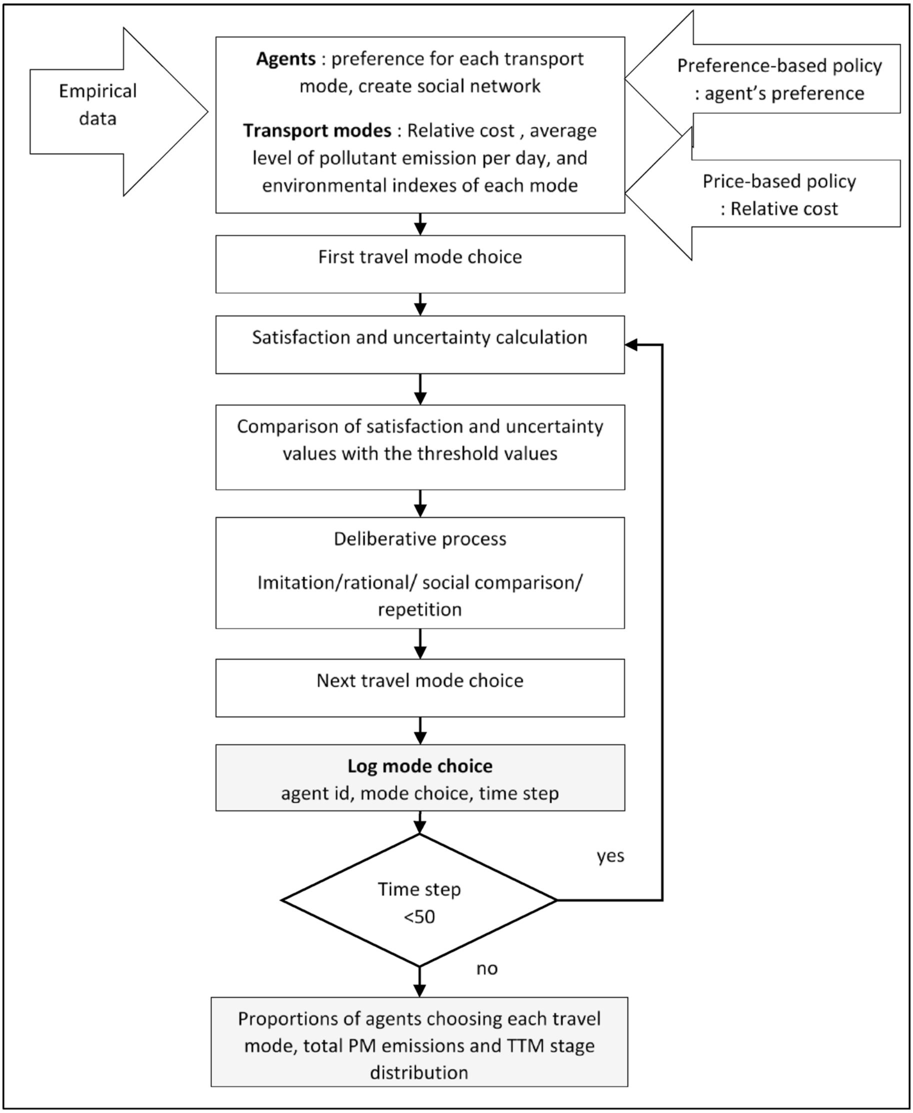

Fig. 2 Modified model diagram (Adopted from Maggi and Vallino (2021))

structure. Each transport mode is also assigned empirically derived attributes including relative cost, pollutant emissions, and environmental index.

In the decision-making phase, agents iteratively select a travel mode over 50 time-steps (representing 50 days) based on a deliberative process governed by their total satisfaction and uncertainty levels. Depending on how these values compare against predefined thresholds, each agent follows one of four processes: repetition, rational deliberation, imitation or social comparison. Soft interventions are simulated through a preference-based policy parameter (P_q) that simultaneously reduces agents' preference for private car use while increasing preference for other modes. The policy impact is then assessed by comparing mode shares and emission between intervention and baseline scenarios. Below, we explain two key modifications made to the original framework. The first one is related to the specification of the soft intervention. The present study used the preference policy parameter to reflect soft intervention that promote cycling, thereby allowing the simulation of targeted soft intervention. The second one is to introduce behavioural stages where travel mode shares of each agents is estimated over the simulation and used to assign TTM stages following a classification approach to be use it as an outcome measure.

Incorporation of specific soft travel behaviour interventions

In the decision-making process in the agent-based model, agents select the travel mode based on total satisfaction, defined as the weighted sum of personal needs and social satisfaction divided by the relative price. Personal satisfaction is estimated based on the preference value corresponding to the mode choice in the past time-step/ iteration. Social satisfaction is estimated based on the proportion of agents in the neighbourhood choosing the same travel mode as the agent. The relative price is the cost of using each travel mode compared to using the car. The total satisfaction parameter is influenced when different policies are introduced.

The first modification of the framework byMaggi and Vallino (2021) is the representation of a soft intervention designed to promote cycling within the ABM framework. The framework byMaggi and Vallino (2021) uses a single parameter P_q to capture the effect of all preference-based policies (such as school education programs, general information campaigns, social learning promotion, diffusion of more information about transport alternatives and Travel Feedback Programs (TFPs). If a policy is successful in shifting preferences from car use towards bicycles and buses, P_q is deducted from agents' initial preference for cars and added to their preference towards bicycles and buses. For the present study, we focus on a soft intervention to encourage cycling among commuters. Therefore, we assume that the intervention can increase commuters' preference for bicycles and, at the same time, reduce the preference for private car use. Consequently, to represent this policy, the P_q parameter is added to the initial preference for bicycles for all agents and reduced from the initial preference for cars for all agents. Furthermore, as the parameter (P_q) is adjustable between 0 and 1. It reflects varying levels of intervention intensity. For example, a high-intensity (P_q = 0.5–1.0) intervention may involve personalised information and tailored support such as a personalised travel plan intervention (Giubergia et al. 2023), whereas a low-intensity (P_q = 0.1–0.5) intervention may rely on generalised awareness campaigns at the population level (Shafran et al. 2021).

In addition, we introduced the policy parameter(P_q), once the social network has been established, rather than at the outset. If the parameter is introduced at the outset, once the policy is applied, the social circle of an agent is changed. Therefore, to effectively isolate the impact of the soft intervention on individual behaviour, the parameter is introduced after the social circle of an agent is created. As a result, agents' social networks remain unchanged despite the policy being implemented. In other words, agents maintain the same social network in the policy and the basic scenarios.

Incorporation of behaviour stages

The second modification is the incorporation of behaviour stages. In addition to changes in the travel mode share measure, the present study advanced the model to measure the behavioural stages of agents in each scenario as an outcome measure. For this purpose, we rely on a methodology proposed by Lowe et al. (2024), illustrated in Fig. 2. The "pre-defined" approach explained by Lowe et al. (2024) takes each agent's share of trips taken by car and bicycle to assign them into five stages of the TTM. First, the agents are classified into three main groups (green multi-modal users, quasi multi-modal users, and quasi uni-modal users) based on the share of car trips. Agents who make less than 10% of their trips by car are classified as green multi-modal users (MM_{green}). Quasi multi-modal users (QMM_{car}) make between 10% and 90% of their trips by car. Quasi-uni-modal users (QUM_{car}) drive 90% or more of their trips. Quasi multi-modal users and green multi-modal users are further subdivided into groups based on their shares of cycle trips. These subgroups include multi-modal users with 0% cycling share, multi-modal users with cycling share of 0–20%, and multi-modal users with a cycling share of 20% or more. Therefore, the pre-defined approach identifies seven groups of multi-modal users based on the share of bicycle and car trips. Then, these seven groups are assigned to the five stages of the TTM, as illustrated in Fig. 3. Full details of the classification thresholds are provided in Lowe et al. (2024).

In order to use this approach, we modified the model by Maggi and Vallino (2021) to track the mode choice of each agent in each time step and estimate the travel mode share of each agent over the simulation. We implemented a logging mechanism that records the travel mode selected by the agent at each time step, along with the corresponding simulation time step and the agent's unique identifier. Then, at the end of the simulation, based on car mode and bicycle share, we identified seven groups of agents. After that, these seven groups are assigned to five stages of TTM in each simulation scenario. Thereafter, we developed cross-tabulations to track the agents' movements between TTM stages following the soft intervention to assess its impact.

We use cross-tabulation tables to present the results and assess the effectiveness of soft travel behaviour interventions based on the TTM stages. Table 1 illustrates a typical cross-tabulation used by previous studies (Ahmed et al. 2020; Olsson et al. 2021), illustrating the type of insights that can be derived from the behavioural stage approach. For example, the approach identifies the proportion of individuals who progressed to higher stages. Each cell contains the individuals belonging to each stage before and after the intervention. The diagonal cells contain the number of individuals who remained in each stage despite the intervention. The upper triangle marked with dark grey in Table 1 shows the individuals who progressed to a higher stage following the intervention. The lower triangle marked with white contains the number of individuals in each stage who regressed to a lower stage following the intervention. For the present study, we also develop a cross-tabulation to report the impact of a soft intervention using the behaviour stage approach.

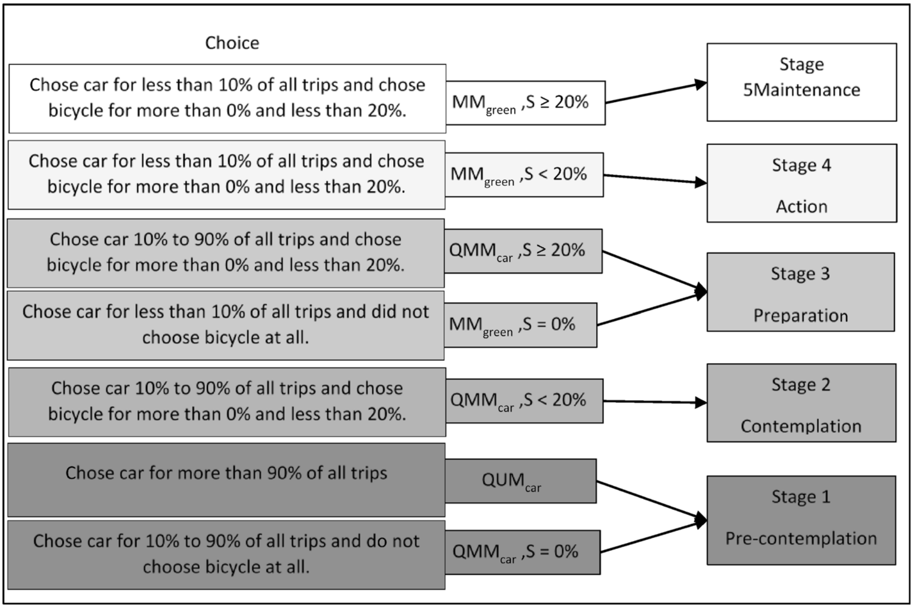

Fig. 3 Pre-defined approach to assigning agents to TTM stages (adopted from Lowe et al. (2024). *Note*: QUMcar = Quasi uni-modal user; QMMcar = Quasi multi-modal user; MMgreen = Green multi-modal user; and S = share of trips made by cycling

Table 1 A typical cross-tabulation of behaviour stages before and after an intervention illustrating the impact of a soft travel behaviour intervention

		Pre-intervention				
		Maintenance	Action	Preparation	Contemplation	Pre-contemplation
Post-intervention	Maintenance					
	Action					
	Preparation					
	Contemplation					
	Pre-contemplation					

Light grey cells: individuals who stayed in the same stage
Dark grey cells: individuals progressed to a higher stage
White cells : individuals progressed to a higher stage

Results

We implemented the modified ABM model with a basic (no policy) scenario to identify the TTM stages of each agent before implementing the soft intervention using the calibration results (minimum satisfaction level (N_{min}) = 0.7, and the maximum acceptance level (U_{max}) = 0.4) presented by Maggi and Vallino (2021). To ensure the validity of the model developed using NetLogo (Wilensky 1999), we compared the output of the basic scenario (no policy) with the results of Maggi and Vallino (2021) in terms of travel mode distribution (44%- car use, 37%- bicycle use, and 19%- public transport use) and total PM emissions (343 PM g/trip) where we obtained matching results (as shown in Appendix B). As the behavioural stages outcome measure derived from existing mode choices, replication of original mode share and emission outputs provides sufficient evidence that model foundation operates as intended, and the validity of the stage classification approach is supported by its reliance on empirically grounded approach proposed by Lowe et al. (2024).

The model was executed with the policy scenario to assess the impact of the soft intervention in terms of both shifts in mode share and shifts in individual TTM stages. As the model allows for adjustment of the policy intensity, we first executed the policy scenario with an intensity of 0.1. Table 2 shows the cross-tabulation of frequencies of agents at different TTM stages before and after the intervention, as predicted by the model.

With the soft policy implementation, the proportion of agents progressing to higher stages (310–6%) outweighs those regressing (215–4%). Regarding mode share, car share is predicted to reduce by only 2% (44–42%). These results indicate that soft interventions can progress some individuals to higher stages of behaviour change even with the intervention's low intensity. Furthermore, it also showed the negative impact of the intervention, indicating the ability of the behaviour stage approach to reveal all underlying impacts of a soft intervention compared to traditional outcome measures such as shifts in mode share (Fig. 4).

We increased the intensity of the policy step by step (by increasing P_q by 0.1) and implemented the model multiple times to investigate the output changes of the model. A summary of this analysis is given in Table 3. Although the intensity kept increasing, we observed a clear difference between the proportion of agent progress and the reduction in car use mode share. According to Fig. 3, from intensity level 0.2 to 0.5, the changes in these two parameters are steep. However, changes became steady after that. This indicates that the impact of the soft intervention is most substantial when the intensity level is between 0 and 0.5. The proportion of agents who regressed to lower stages decreased from 4% to 2% when the intensity hit 0.4 and became steady afterwards. The agents that remained in the same stages dropped rapidly from 90% to 39% during this intensity increment, and the drop level became lower after the intensity reached 0.5. At the maximum level of intensity 1, where agents' preferences are increased by 1, the model reached the maximum possible outcome, which is not far from the outcome reached at the intensity level of 0.5. Since agents' preferences are capped at 1 and 0, all agents would have a maximum preference (value of 1) for bicycles and a minimum preference (value of 0) for cars. It is important to notice that when

Table 2 The cross-tabulation of frequencies of agents at different TTM stages before and after the intervention (policy intensity 0.1)

		Before intervention				
		Maintenance	Action	Preparation	Contemplation	Pre-contemplation
After intervention	Maintenance	1615	3	73	0	164
	Action	0	0	4	0	0
	Preparation	64	0	867	0	66
	Contemplation	0	0	0	0	0
	Pre-contemplation	93	0	58	0	1993

Each cell contains a number of agents. There are 5000 agents representing the city (Varese) in Italy

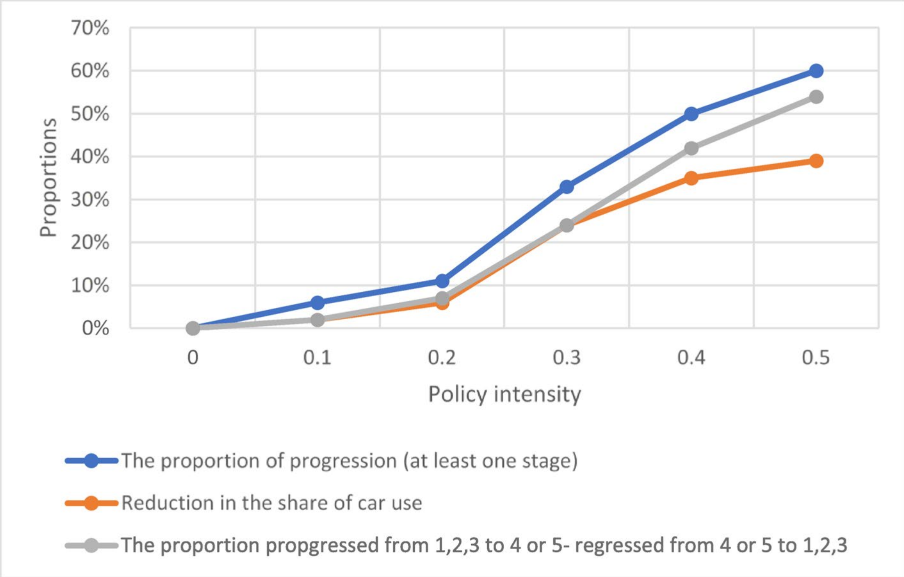

Fig. 4 Modified agent-based model under information policy scenario

Table 3 Impact of soft policy intervention in terms of behavioural stages and travel mode share

Level of policy intensity	The proportion of agents progressed to higher stages (at least one stage) (%)	The proportion of agents progressed to higher stages (to 4 or 5 from 1,2 or 3)- agents regressed to lower stages (from 4 or 5 to 1, 2 or 3) (%)	The proportion of agents regressed to lower stages (%)	The proportion of agents stayed in the same stage (%)	Reduction in the share of car use (%)
0.0	0	0	0	100	0
0.1	6	2	4	90	2
0.2	11	7	3	86	6
0.3	33	24	3	64	24
0.4	50	42	2	48	35
0.5	60	54	2	39	39

policy intensity approaches 1, it becomes inevitable that all agents abandon car use as their car preference drops to zero. Since this pattern is already evident from intensity level 0.5, we present results only up to this threshold.

In addition to the proportion of agents progressing to higher stages (at least one stage), we drew a line representing the difference between agents who progressed to stages 4 or 5 from 1, 2 to 3 and agents who regressed to stages 1, 2 or 3 from 4 to 5 stages. Up to an intensity level of 0.3, this line closely aligns with the line representing a reduction in car use, suggesting that most agents progressing were initially primary car users. Beyond this point, the line follows the overall progression trend more closely, indicating that, at higher intensity levels, agents who previously relied on public transport are also shifting towards cycling.

These findings suggest that moderate-intensity soft interventions are sufficient to trigger considerable behavioural stage progression (moving agents out of habitual car dependent stages) for the majority of agents. If the stage progression is sustained, it is more likely to result in long term behaviour change which is significant from long-term policy perspective.

Discussion and conclusion

Discussion

The primary focus of this study was to investigate how the stage-based approach can be employed to evaluate the impact of soft interventions and where it stands compared to other outcome measures. Traditionally, outcomes such as vehicle kilometres travelled, mean car use per week, mode share, and attitude change have been the primary indicators of intervention impact, often quantified using effect sizes like Cohen's d. However, the modest effect sizes reported in the reviewed studies may undervalue the influence of soft interventions. By incorporating the behaviour change stages approach within an agent-based modelling framework, we demonstrated that a more nuanced picture of soft intervention effectiveness can be observed.

The literature review revealed promising results from the studies that utilised the behavioural stage approach. Although the share of car use has not decreased considerably, a substantial proportion of individuals have progressed towards more sustainable travel behaviours. This progression is crucial as it indicates a readiness for change that could translate into more significant behavioural shifts over time. Empirical evidence supports that stage progression, even in the absence of immediate modal shift, can be associated with sustainable mode adoption in the long run (Olsson et al. 2021). The difference between the proportion of individuals who progressed and car mode share reduction underscores the potential drawback of employing only the traditional outcome measures for evaluating soft interventions and provides reasonable explanations for the limited impact of soft interventions reported in the literature. Moreover, person-centred effect sizes can reveal patterns in the data that the traditional effect sizes can miss (Grice et al. 2020).

Our agent-based model output highlights the importance of the behaviour stage approach for soft intervention evaluation. Using this approach, we can observe both the positive and negative impacts of soft interventions, painting a more nuanced picture of the effectiveness of soft interventions. Even with a low-intensity level, the soft intervention could progress agents towards more readiness to change state. Mundorf et al. (2018) reported similar findings regarding a brief video intervention. They found that following the intervention, individuals (34%) in pre-contemplation and contemplation stages progressed to higher stages. Conversely, some individuals regressed to lower stages, indicating the unintended impacts of the intervention. Although the negative influence decreased as the intensity of the policy increased, it did not reach zero. This suggests that even though we only see positive impacts, such as a reduction in car use following the implementation of a soft intervention, there could be unintended negative consequences as well. Only a few studies have shown that regression to lower stages can occur following a soft intervention (Friman et al. 2019;

Ahmed et al. 2020). From an ex-ante policy evaluation perspective, the framework offer planner a practical tool to test and compare intervention scenarios to identify both expected benefits and unintended consequences of soft interventions under different intensity levels.

For future travel behaviour change interventions, policymakers can adopt the behaviour stages approach as a more sensitive performance metric, enabling them to identify success and any unintended consequences of the intervention. In particular, the stage-based output of the model can inform targeted behaviour change strategies by identifying which segments of the population are more responsive to a given intervention intensity, enabling effective intervention designs. Further, the scholars should consider including the behaviour stage approach as an alternative outcome measure in their study designs to evaluate travel behaviour interventions to reduce car use. Future research endeavours should explore the causal mechanisms underpinning the relationship between soft interventions and behaviour stage progression. Cross-validation studies, aligning stage progression with actual travel behaviour changes, can boost the evidence supporting the adoption of the behavioural stage approach as a robust outcome measure.

Limitations

While the agent-based model provides valuable insights, it inherently involves assumptions and simplifications such as preference formulation and deliberative decision-making process that may not fully capture the complexity of real-world travel behaviour. Additionally, preference dynamics are simulated based on empirical data from a single Italian city which may limit the generalisability of the findings to other urban contexts. As the TTM stage classification were originally derived from a US dataset, cross-validation of the classification approach to the study context would strengthen the transferability of the findings. Further, the model assumes that soft intervention is introduced after social network formation, which isolates the policy effect from social influence dynamics but it may not fully reflect real-world scenarios. Future studies could explore whether stage progression is amplified though social network that changes overtime. Additionally, the soft policy parameter is applied uniformly to all agents which does not reflect real-world influence of soft interventions. Future research could explore heterogenous policy effects by taking individual differences into account. Furthermore, the behavioural stage transitions modelled here are driven by simulated preference changes rather than empirically validated psychological mechanisms, and future research should seek to calibrate these transitions against real-world data to strengthen predictive validity of the framework.

Conclusion

This paper shows the significance of behavioural stages as an evaluation tool for soft travel behaviour interventions by comparing it with traditional outcome measures and demonstrating its capabilities within an agent-based modelling framework. The literature review showed that while conventional outcome measures indicated a modest reduction in car use, the behavioural stage approach revealed that many participants progressed to higher stages of change. The agent-based model further demonstrated that the behavioural stage approach offers a more nuanced understanding of the intervention's effectiveness, particularly in highlighting both the positive behavioural shift and unintended negative impacts. These findings suggest that policymakers should adopt the behavioural stage approach as a more sensitive performance metric for assessing the success of future travel behaviour interventions, which are increasingly needed due to inherent pressures to stimulate lasting sustainable behaviour change and reduce private car dependency. In addition, scholars should incorporate the approach in their study designs to evaluate the ex-ante impact of travel behaviour interventions.

Appendix A: Evaluating soft travel behaviour interventions using behavioural stages of change within an agent-based modelling framework

A1. The TransportVarese agent-based modelling framework by Maggi and Vallino (2021)

The TransportVarese model illustrated in Figure 5 was developed by Maggi and Vallino (2021) using NetLogo software to study the policy impact in an urban city (Varese) in Italy. In this framework, 5000 agents represent commuters of Varese City in northern Italy, and the model reproduces their daily transport mode choices and the corresponding particulate matter (PM) emissions. The agents have preferences (ranging from 0 to 1) for three possible transport modes (private car, private bicycle and public transport) under the assumption that it includes information on the subjective perception of comfort, on the average speed of the transport mode, on the easiness of use, and the congestion of the habitual route. Throughout the process, these preferences are influenced by different policies, leading to a change in their travel mode choice.

The model has two phases: set-up and decision-making. In the set-up phase, agents' preferences are set based on the data collected by the Italian National Statistical Office:, They applied a beta distribution method to create a virtual preference distribution for the 5000 agents based on the observed modal choices from the census data. Then, based on their preferences, agents establish links with other agents with similar preferences. This process builds the neighbourhoods of agents, creating the social network structure known as social circle, which contains important features of large social networks such as high clustering (one's friends are also friends of each other) and low density (one with many friends are less) (Hamill and Gilbert 2009; Maggi and Vallino, 2021). After that, the model sets the features of transportation modes that influence the agents' decision-making process. These features include relative cost of using each travel mode compared to using car (car- 1, bicycle—0.13 and public transport- 0.26), average level of pollutant emission per day (car-0. 125 PM g/day, bicycle—0 PM g/day, and public transport—0.07 PM g/day), and an environmental index (car-0, bicycle—1, and public transport—0.44) taking the most polluting means (car) as a benchmark. The values of these variables and indexes are derived from empirical data linked to Italian scenarios. Refer to Maggi and Vallino (2021) for more preference and index estimation information.

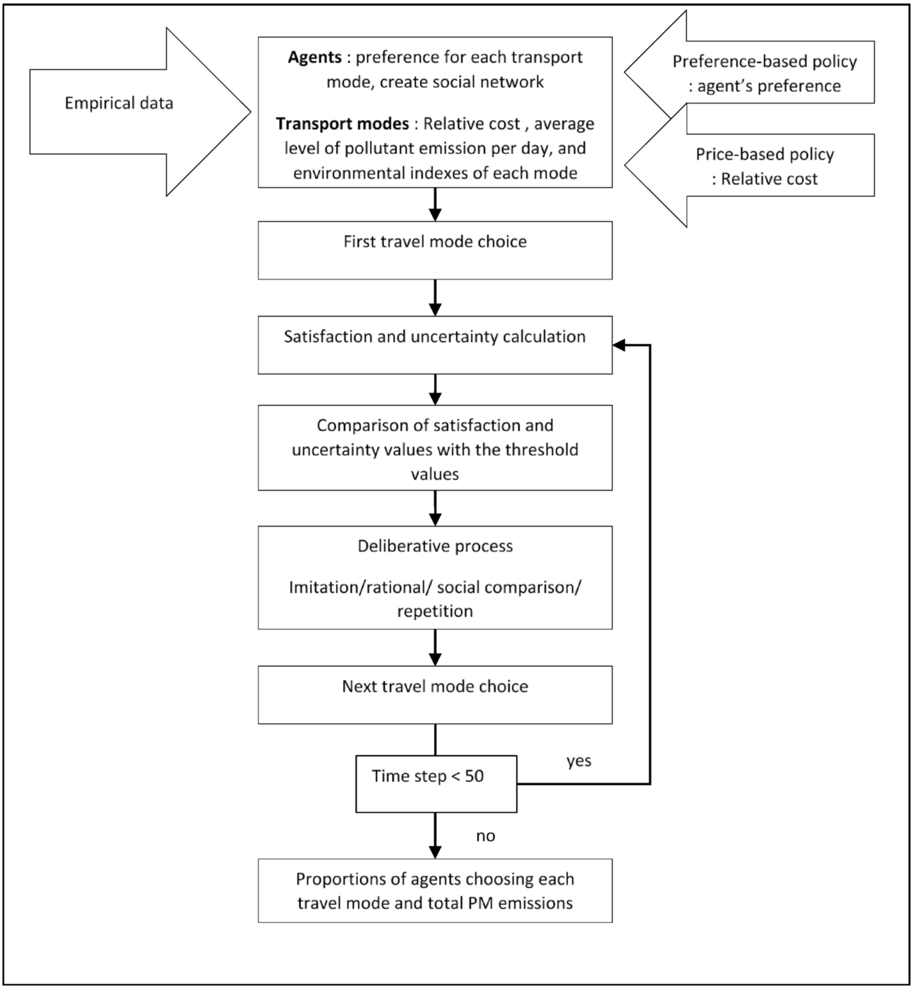

Fig. 5 TransportVarese model diagram (Adopted from Maggi and Vallino (2021)

In the decision-making process, agents choose a travel mode corresponding to one trip. The model assumes that agents use a deliberative process to make mode choice decisions. This process is introduced by Janssen and Jager (2002). In this process, agents select the travel mode based on total need satisfaction and uncertainty level. The total satisfaction of agent i choosing travel mode k (N_{ik}) is defined as the weighted sum of personal needs (N_{ik}^p) and social satisfaction (N_{ik}^s) divided by the relative price (r_k) as described in Eq. 1. Personal satisfaction is estimated based on the preference value corresponding to the mode choice in past time-step. Social satisfaction is calculated based on the proportion of agents in the neighbourhood choosing the same travel mode as the agent. β_i is an agent parameter randomly distributed between 0 and 1 to reflect the weight each agent gives to two satisfaction components.

$$N_{ik} = \frac{\beta_i N_{ik}^s + (1 - \beta_i) N_{ik}^p}{r_k} \tag{1}$$

The uncertainty level reflects the variation of the agent's total satisfaction over time, and it is estimated as described in Eq. 2. $N_{ik(t)}$ is the total satisfaction of agent *i* in time-step *t* and $N_{ik(t-1)}$ is the total satisfaction of agent *i* in the previous time step.

$$U_{ik} = \sqrt{\left|N_{ik(t)} - N_{ik(t-1)}\right|} \tag{2}$$

Both parameters have threshold values that lie between 0 and 1. The first one is the minimum satisfaction level (N_{min}) and the second one is the maximum acceptance level (U_{max}) towards uncertainty. At each time step, the agent first determines its level of satisfaction, followed by its level of uncertainty. Based on its position with threshold values, the agent selects one of four possible deliberation processes summarised in Table 4.

Table 4 summary of the deliberative process (from Natalini and Bravo (2014)

Conditions for the process	Process details
$N_i \geq N_{min}$ and $U_i > U_{max}$	*Imitation*: The agent imitates the most adopted choice among the members of its neighbourhood.
$N_i < N_{min}$ and $U_i \leq U_{max}$	*Rationale*: The agent calculates the satisfaction for all travel modes and chooses one that offers the highest satisfaction.
$N_i \geq N_{min}$ and $U_i \leq U_{max}$	*Repetition*: The agent repeats the decision of the previous time step.
$N_i < N_{min}$ and $U_i > U_{max}$	*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 case of a tie, the agent randomly selects one.

The simulation runs until agents no longer change their behaviour. Different combinations of two key parameter values (minimum satisfaction and maximum acceptance level) are used to calibrate the model, and the combination that best reproduces the actual travel mode distribution is used. Maggi and Vallino (2021) found that minimum satisfaction level (N_{min}) = 0.7, and the maximum acceptance level (U_{max}) = 0.4, which led to Varese city's actual mode distribution (44% car, 19% public transport, and 37% bicycle). The calibration also includes findings on the number of time steps the model takes to reach a steady state where agents no longer change their travel modes. Maggi and Vallino (2021) found this value to be 50. They assumed that one trip corresponds to a round trip to a work or study destination and that 50-time steps represent 50 days in real life.

Preference-based policies represent soft travel behaviour interventions among the two policy types explored. The preference-based policies include school education programs, general information campaigns, social learning promotion, diffusion of more information about transport alternatives and Travel Feedback Programs (TFPs) (Maggi and Vallino 2021). To present this policy type, Maggi and Vallino (2021) introduced a parameter (P_q) and it simultaneously decreases commuters' preference towards cars (deduct (P_q) from the initial preference for cars) and increases their preference towards bicycles and buses (add (P_q) to the initial preferences for bicycles and buses). Similar to preference values of agents, the value of this parameter can range from 0 to 1. When the policy induces a change in the initial preference, it changes the satisfaction estimation, affecting the agent's decision-making process and reflecting the influence of the soft intervention. Furthermore, the parameter (P_q) is adjustable between 0 and 1, reflecting different intensity levels of the soft travel interventions. In reality P_q can be quantified as an investment in this type of policy by the relevant stakeholders (Natalini and Bravo 2014). In the "TransportVarese" model, the impact of the policy intervention is assessed by running the model with a policy scenario (set a value for P_q) and then compare the outputs with the basic scenario (no policy—set P_q value to zero). The share of agents choosing three modes and the amount of PM emissions are assessed in each policy scenario and compared with the basic scenario (no policy).

Appendix B: The summary output comparison with Maggi and Vallino (2021)'s model

Table 5 summarizes the basic scenario (no policy) from the modified and original models. In terms of behavioural stages, the majority of the agents were in the early stage (44% precontemplation), late stage (35% maintenance), and middle stage (20% preparation) in the basic scenario.

Table 5 The summary output of the basic scenario (no policy)

Output measure	Output (present study)	Output (Maggi and Vallino 2021)
Travel mode distribution	Car share—44% Bicycle share—37% Public transport share—19%	Car share—44% Bicycle share—37% Public transport share—19%
Total PM emission	343 PM g/trip	340 PM g/trip
Behavioural stages	Pre-contemplation—2223 (44.46%) Contemplation—0 (0.00%) Preparation—1002 (20.04%) Action—3 (0.06%) Maintenance—1772 (35.44%)	–

Acknowledgements The authors would like to acknowledge and thank the Next Generation Energy Systems (NexSys) Partnership Programme for funding this research.

Author contributions Warnakulasooriya Umesh Ashen Lowe: Conceptualization, Visualization, Methodology, Data obtaining, Formal analysis, Investigation, Writing—original draft.Leonhard Lades: Conceptualization, Visualization, Resources, Writing—review & editing, Supervision.Páraic Carroll: Conceptualization, Visualization, Resources, Writing—review & editing, Supervision.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions

Data availability The dataset used for the manuscript was adopted from Maggi & Vallino (2021) and is publicly available here (https://www.comses.net/codebases/5419/releases/1.1.0/). The dataset contains preferen ces (a value range from 0 to 1) for three travel modes (motorised, public transport, and non-motorised) for 5,000 agents who were representative of the City of Varese, Italy.

Declarations

Conflict of interests The authors declare no conflict of interests.

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