Journal of Transport & Health 37 (2024) 101830

Contents lists available at ScienceDirect

Journal of Transport & Health

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

Influencing transport-health interactions through incentivised mode switch using new data and models

Gillian Harrison *, Yuanxuan Yang, Keiran Suchak, Susan M. Grant-Muller, Simon Shepherd, Frances C. Hodgson

Institute for Transport Studies, University of Leeds, Leeds, LS2 9JT, UK

ARTICLE INFO

Keywords:
Transport
Health
System dynamics
Causal loop diagram
Spatial microsimulation
Agent-based modelling

ABSTRACT

Introduction: In this study we present a 'proof-of-concept' model using novel model integration and new forms of data that addresses the research question, *How does incentivising a change in travel mode to reduce personal car use impact health?* We focus on simple transport-health interactions between switching between car and bus: the exposure to activity and pollution linked to these modes and how these changes effect health status, which in turn influences the mode choice.

Methods: We identify a basic causal loop diagram of key conceptual feedback between mode choice and health status (related to exposure to activity and pollution). From this we build a simple system dynamics stock and flow simulation model, with data input from spatial microsimulation synthetic populations derived from 'track and trace' data as the output from an agent-based model. We then analyse scenarios of mode shift incentivised by bus fare reduction and bus frequency increase.

Results: In the tested scenarios of this novel modelling approach, we identify that a reduction in bus fare or increase in bus frequency could incentivise a shift from car to bus which would result in a small decrease in relative risk of all causes mortality. Reducing bus fare in particular could provide both health and financial benefits for the most deprived communities.

Conclusions: This modelling approach presented in this data is a promising new method for the study of complex transport-health interactions. From our prototype model we have identified the impacts of mode shift on health status through exposure to pollution and activity, using unique feedbacks that are unaccounted for in conventional models.

1. Introduction

Mobility systems influence public health in numerous ways (see for example (Glazener et al., 2021; Cooper et al., 2019; van Schalkwyk and Mindell, 2018):), and this is reflected in recent transport policy priorities across the world (DfT, 2023; EC, 2020; DOT, 2022). Furthermore, the health of an individual can influence their choice of transport mode. Thus, academic research on the interactions between transport and health is an established and increasingly topical field, and more recently various aspects of these have been addressed using system dynamics (SD), as discussed by Harrison et al. (2021).

* Corresponding author.
E-mail address: G.Harrison@leeds.ac.uk (G. Harrison).

https://doi.org/10.1016/j.jth.2024.101830
Received 21 July 2023; Received in revised form 8 April 2024; Accepted 13 May 2024
Available online 23 May 2024

This study adds to the literature by describing a simple simulation model that addresses the research question; *How does incentivising a change in travel mode to reduce personal car use impact health?* In particular we have focused on physical activity and emissions related health and two forms of policy (bus fare reduction and bus frequency). Based on the findings of previous work (Harrison et al., 2021, 2022), this model is a simple prototype model, whose purpose is two-fold.

- A simple stand-alone representation of mode choice between bus and sole-occupancy conventionally fuelled private car (including walking access and egress), and their effects on population health related to pollution and activity
- A component of a proof of concept model, integrated with an Agent-Based Model and Spatial Micro Simulation using finely grained, individual-level new and emerging data.

This paper will introduce the SD model. In the next section we provide a brief background to the study, covering system dynamics, transport and health, and new and emerging data. Then the SD model is described before we discuss our results and present our conclusions.

2. Background

2.1. System dynamics

System Dynamics (SD) modelling has been used in a wide range of applications to study the influence of feedbacks and unintended consequences of complex dynamic systems. The methodology involves both qualitative ("causal loop diagram") and quantitative ("stock flow simulation model") steps, following a five-stage modelling process, described by Harrison et al. (2021) after Sterman (2000). This paper focuses on the latter three steps: model formulation, model testing and policy formulation and evaluation.

SD is being increasingly used as a tool within both health care applications (Hirsch et al., 2015) and transport research, consultancy and policy-making (Shepherd, 2014). The use of SD in understanding transport-health interactions is less well covered. Harrison et al. (2021) identified just over 20 publications of transport-health SD studies covering air pollution, road safety, active transport, road traffic noise and multiple impacts. More recently there have also been studies considering urban mobility and resilience during the pandemic (Lara et al., 2023; Gorji et al., 2023; Zhang and Wang, 2023). This study builds on the findings and structures of the previous models discussed by Harrison et al. (2021) who used them as a basis of a causal loop diagram (CLD) considering the trade-offs and synergies between different types of health impacts within the transport-health system, which was further refined through expert engagement and presented in Harrison et al. (2022).

2.2. Transport and health interactions

Interactions between transport and health are increasingly studied and understood (Widener and Hatzopoulou, 2016), often measured using health impact assessments (Nieuwenhuijsen et al., 2020), and increasingly recognised to have diverse impacts across different regions and socio-demographic groups (Lu et al., 2022; Mueller et al., 2018; Oviedo et al., 2022). Therefore, developing public health policy in the context of transport is essential (Milne, 2012). Some key established pathways include air quality, activity, noise, access to health-care, road safety, well-being and more recently, exposure to communicable disease in-vehicle or across regions (Muley et al., 2020) and indoor air quality (AQEG, 2022). Furthermore, understanding and managing these impacts are critical to addressing social inequalities (Hosking et al., 2022).

Transport-health interaction studies have been dominated by 1) traffic-related air pollution and respiratory health (Boogaard et al., 2023) and 2) benefits of active travel (Saunders et al., 2013), though it's increasingly recognised that the interactions cover both (or even broader) health aspects with multiple feedbacks (Mueller et al., 2015), which a system dynamics approach is able to reflect. This model focuses on 1) and 2) in the first instance but can be used as a base on which other interactions can be added.

2.3. New and emerging data

The development of a digitised and connected society means that more data than ever is collected about individuals, their transport behaviour and characteristics. Types of new and emerging data forms (sometimes referred to as "big data" or 'digital footprints') that are useful to transport research and planning include ticketing transactions, Automatic Number Plate Recognition (ANPR), CCTV, and mobile phone data (e.g. network connections, social media and GPS tracking) (Budnitz et al., 2021; Harrison et al., 2020). New data forms are vital to the better understanding of transport systems and in the development of sustainable and equitable transport policy (Tranos and Mack, 2019). The use of such data in transport modelling is being increasingly explored (Milne and Watling, 2019) and can be especially useful for developing synthetic populations through spatial micro-simulation. The populations can then be utilised in transport-related modelling such as agent-based modelling and system dynamics (Wu et al., 2022; Odiari and Birkin, 2022), as we do in this study.

3. SD model description

3.1. Conceptual feedbacks

Harrison et al. (2021) reviewed existing system dynamics models of transport and health, in order to create a causal loop diagram (CLD) of trade-offs between health impacts within the transport-health system, whereas Harrison et al. (2022) refined this CLD through expert engagement and extended it to consider how new and emerging data forms improve understanding of mobility behaviours and related health outcomes. Drawing from these studies, we consider the feedbacks between health and mode choice. Assuming a simple case of just bus and car, with walking for access and egress, we do not aim to capture all feedbacks, but focus on key exposures to activity and transport related pollution. From this, we have developed the CLD shown in Fig. 1 and Table 1. Links are evidenced later in this paper where we describe how we have implemented them in the quantified model. There are ten feedback loops, six of which are balancing and four reinforcing. Although we will not discuss all of these here, it is worth highlighting the key feedbacks in relation to *Health Status*. R2, R3, B3, all capture the influence of *Bus Trips* on *Exposure to Activity* that effects *Health Status*. If this number of *Bus Trips* increase, then so will the *Weekly Walking Time* (as this is assumed to be higher than for car trips), which in turn means an increase in *Exposure to Activity* that (with some time lag) can improve the *Health Status*. For R3 we then assume that this improvement in *Health Status* increases to the *Willingness to Consider* the bus (as a healthier individual may have less barriers to bus travel), which therefore increases the number of *Bus Trips* – hence a reinforcing effect. Similarly, when starting with an increase in *Bus Trips*, in R2 the improvement in *Health Status* leads to an increase in *Walking Speed* (again as the individual is healthier), meaning the overall *Bus Time* of the journey is lower and the bus choice is more attractive thus increasing *Bus Trips*. B3 also follows through the *Walking Speed*, but with the assumption that the increased walking speed could also decrease the overall journey *Car Time* in the same way, which would increase the number of *Car Trips*, and subsequent congestion that would itself increase *Bus Time* making bus trips less attractive, leading to fewer *Bus Trips*. Thus, R2 and B3 are in competition and the dominant loop will be dependent on the marginal time differences of the increased *Walking Speed* in comparison to the overall journey times and the effect of congestion. In addition to the direct feedback of *Bus Trips* on *Activity Exposure*, there is also a balancing loop, B6, which is similar to R2 and B3. Here, we assume that the increase in *Walking Speed* from improved *Health Status* leads to a decrease in *Walking Time* that reduces the *Exposure to Activity* (though the impact on the quicker walking speed isn't captured here), though as a balancing loop this may dampen the effect of R3. The second health impact that we consider in this CLD is the exposure to pollution. This is assumed in the CLD to be influenced by two variables – emissions and walking time. In our simulation model we do not include the walking time link to pollution exposure due to lack of available data so will not discuss those feedbacks in detail here. What is of interest is the loop B2. If we start with an increase in *Car Trips*, we would expect an increase in *Congestion*, which would in turn increase *Emissions* (not represented directly is the impact of the number of car trips on emissions). The increased *Emissions* would increase the concentration of pollutants in the air thus the *Exposure to Pollution* that would lead (with a time lag) to a decrease in *Health Status*. As discussed in previous loops, this would decrease *Walking Speed*, which would increase the total journey *Car Time*, thus decreasing the number of *Car Trips* as its attractiveness decreases. When comparing the effects of pollution and activity, it is important to note that the relative dominance of each loop is sensitive to the details of a specific trip, as well as to the time lags associated with the impact of the exposure on *Health Status*.

3.2. Case study: transport-health interactions arising from incentivised mode switch

We model a simple case of mode choice between car and bus for two communities in the Newcastle city region, involving travel from home to a city centre location. We focus on a binary mode choice for simplification and choose the switch from car to bus (rather than active travel), as we have a particular interest in the health benefits of bus (which is less researched than active travel as stated

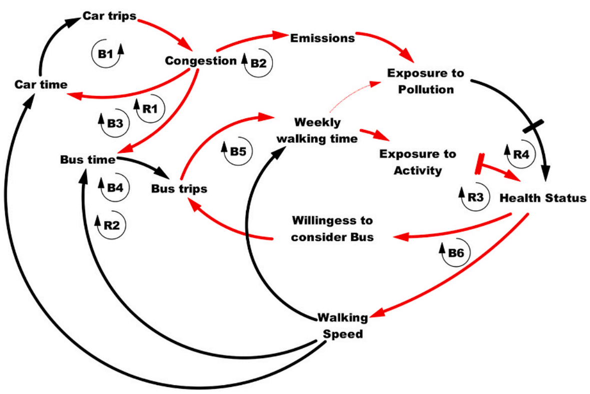

Fig. 1. Key Conceptual feedbacks between health status and mode choice related to explore to activity and pollution (red link = positive (change in same direction); black link = negative (change in opposite direction)). Cross marks on a link indicate a time lag. Assumptions: car trips have negligible impact on overall walking time; bus trips have negligible impact on congestion; Bus emissions not considered; Walking time > Exposure to Pollution is a dashed line as not represented in main model due to lack of data.

Table 1
Feedback loops.

B1	Car trips (+) > Congestion (+) > Car time (−) > Car trips
B2	Car trips (+) > Congestion (+) > Emissions (+) > Exposure to Pollution (−) > ^{DELAY}Health Status (+) > Walking Speed (−) > Car time (−) > Car trips
B3	Car trips (+) > Congestion (+) > Bus time (−) > Bus trips (+) > Weekly walking time (+) > Exposure to Activity (+) > ^{DELAY}Health Status (+) > Walking Speed (−) > Car time (−) > Car trips
B4	Bus trips (+) > Weekly walking time (+) > Exposure to Pollution (−) > ^{DELAY}Health Status (+) > Walking Speed (−) > Bus time (−) > Bus trips
B5	Bus trips (+) > Weekly walking time (+) > Exposure to Pollution (−) > ^{DELAY}Health Status (+) > WtC Bus (+) > Bus trips
B6	Health Status (+) > Walking Speed (−) > Weekly walking time (+) > Exposure to Activity (+) > ^{DELAY}Health Status
R1	Car trips (+) > Congestion (+) > Bus time (−) > Bus trips (+) > Weekly walking time (+) > Exposure to Pollution (−) > ^{DELAY} Health Status (+) > Walking Speed (−) > Car time (−) > Car trips
R2	Bus trips (+) > Weekly Walking time (+) > Exposure to Activity Exposure (+) > ^{DELAY}Health Status (+) > Walking Speed (−) > Bus time (−) > Bus trips
R3	Bus trips (+) > Weekly walking time (+) > Exposure to Activity (+) > ^{DELAY}Health Status (+) > WtC Bus (+) > Bus trips
R4	Health Status (+) > Walking Speed (−) > Weekly walking time (+) > Exposure to Pollution (−) > ^{DELAY}Health Status

previously) and as part of a broader research agenda which considers a wider range of health exposure and trade-offs than we present here (including in-carriage virus exposure (Bell et al., 2023; Aranega-Bou et al., 2023)). Furthermore, the model and data we had access to for developing this prototype model was more reliable with regards to bus than active travel. The rationale for the choice of Newcastle as a case study is two-fold. Firstly, the city has significant extremes in terms of wealth and deprivation, which highlight the inequalities in existing health status amongst the population. These health status inequalities were of interest in terms of being able to understand the distribution of any health status impacts arising from the transport policies. In particular, Gosforth is a relatively affluent area north of the city centre, whereas Walker is more deprived and to the south-east. Secondly, existing high-resolution smartphone app 'track and trace' data was available for the Newcastle city region from other research studies concerned with travel choice and the resulting impacts (EU funded EMPOWER project, 2015–18: SMART app and UKRI funded TRACK project, 2020–23: Sesamo app), allowing the characterisation of agents' choices within the modelling process. Track and Trace apps are able to automatically sense user's travel behaviours in detail, providing information such as trip destination types and departure time. Focusing on Gosforth and Walker, the populations in each community are characterised by a number of demographic variables: age, sex, income, social grade, household car access and health status (Table 2). The synthetic population was built spatially using spatial microsimulation (SMS) and data from the UK 2011 Census (ONS, 2011) and 2016 Health Survey for England (NHS, 2016). SMS is a method for creating, analysing and modelling of individual level data allocated to geographic zones (Lovelace and Dumont, 2016). SMS has been widely used in the public health domain for estimating and understanding health over space and time (Smith et al., 2021) and in transport research (Lovelace et al., 2014; O'Donoghue et al., 2014). One important application of SMS is to create a realistic synthetic population for each area, closely matching aggregate level constraints. The process typically assigns individuals from survey data to administrative zones, aligning with constraint variables shared between zone (e.g. Census) and individual data. Additionally, when individual survey samples contain extra target variables that are not in aggregate data (Census), this method can simulate and bring such information to the local level (Wu et al., 2022). For instance, constraint variables in the SMS model, including age, gender, education, economic activity, social grade, marital status, health, car ownership, and children's dependency in the household, influence the probability distribution of household income in different areas (which is only available in the survey dataset). Both Census and Health Survey for England data provide variable on self-reported general health status; therefore, it is used as an important constraint in the SMS. The implementation of SMS applied Iterative Proportional Fitting algorithm at output area level and generated synthetic populations in the Gosforth and Walker areas. The synthetic population was further enriched with the individual, high-resolution, smartphone track and trace mobility data. Mobility enrichment was implemented using Propensity Score Matching (Morrissey et al., 2015; Spooner et al., 2021), depending on sociodemographic information (age and gender). Following enrichment, each individual was characterised with different departure times for working (commuting) trips and shopping trips. The individual characteristics and travel behaviours then formed inputs to an Agent Based Model (ABM). The ABM simulates a daily return journey from these two zones to Newcastle city centre; this included their changes of mode between walking (for access/egress) and car/bus where appropriate during their trips. The ABM assumes there is no trip chaining or mode switching en-route. The resultant trips from the ABM are then used to calibrate initial trips in the system dynamics model described in the following sections.

Table 2
Model Subscripts (categories based on UK Census categories).

Subscript	Values
Income	<£20,000; £20,000 to £40,000; £40,000 to £60,000; £60,000 to £80,000; >£80,000
Sex	Female; Male
Social Grade[a]	AB; C1; C2; DE
Zone	Walker; Gosforth
Age	16-19; 20–29; 30–39; 40–49; 50–59; 60+
Household Car Access	Car; No Car
Health Status	Below (very bad and bad); Fair; Above (good and very good)

[a] AB: Higher & intermediate managerial, administrative, professional occupations; C1: Supervisory, clerical & junior managerial, administrative, professional occupations; C2: Skilled manual occupations; DE: Semi-skilled & unskilled manual occupations, Unemployed and lowest grade occupations.

3.3. Rationale for integration between SD and ABM

ABMs are ideal tools for representing behaviours and spatial movements of individuals within a system, so may appear to be the appropriate tool for our problem. However, our interest is centred around the complex feedbacks between transport choices and health, which evolve over long timescales (in order of magnitude of a year). ABMs can be computationally intense, and to develop an ABM for the year-long timescale required to capture health impacts whilst also capturing temporally granular information about individual trips (at second/minute time-steps) would require significant computational resources (including unrealistically long run-times), especially considering the many scenarios we wish to test. SD has been developed to capture complex feedbacks over long periods of time, with each simulation taking a matter of minutes, though we appreciate that SD requires the aggregation of individual data, thus losing some of the granularity pertinent to health. As such, we designed our prototype method to capture the benefits of both modelling approaches, whilst minimising the drawbacks. An iterative process of data transfer between the models has been designed and is discussed in another paper (currently under review), whilst this paper focuses on the SD model.

3.4. SD model features

The model is set to run for a year (52 weeks). This was chosen as a period where we could expect small changes in health to occur as a result of accumulated instances of behaviour change prompted by policy interventions (Woolf-May et al., 1999; Manisalidis et al., 2020; Ahmadi et al., 2024)The time-step is 0.0625 weeks, to reflect approximately half a day. The model was developed and simulated using Vensim DSS (5.7a), and full model equations are available in Appendix 2.

The core structure of the model is drawn from the well-established MARS model (Pfaffenbichler et al., 2008), where mode choice is based on the comparative friction factors related to the respective modes. The MARS model is a complex transport-land use interaction model, developed to allow numerous mode choices across a city/region population. The population is divided into several population sub-groups as set out in Table 2, with journey choices and resultant health impacts simulated for each compound sub group [Zone, Car Ownership, Sex, Age, Health Status, Social Grade]. Journeys being made for commute purposes and other trips are calculated within a limited time budget per person per day. The origin and destination zones for the trip are determined by an attraction matrix. The complexities and detail of the MARS model are not required for our purposes and we refer the reader to Pfaffenbichler (2003) should they require this. Rather, in this paper we will highlight the elements of MARS used in our simple model.

3.5. Mode choice

In our model we focus on only two modes – car or bus, with an assumption that these are alternatives for the same trip from the home zone to the city centre. Specific routes are simulated in the associated ABM so are not the concern of this aggregated SD model. The total trips from each zone every week for each population group is calibrated to the initial trips (generated through linking SMS and ABM) for each zone through a coefficient of the friction factors (FF) for each mode (see 3.5 and 3.6). We assume that this total number of trips does not change over the course of the year. From this the desired share of trips that are bus or car are determined using logit choice (Equation 1) of the FFs. Populations without access to a car do not have the car choice (i.e. their trips must be by bus).

Equation 1: Number of desired weekly trips made by mode by each population sub-group

$$DT_m = TT * \left. \frac{1/FF_m}{\sum 1/FF_m} \right)$$

DT_m = Desired weekly Trips by mode m.
TT = Total Trips.
FF_m = Friction Factor of mode m.
NOTE: For all equations, full subscripts are: [Zone, Car Access, Sex, Age, Health Status, Social Grade]

The desired trips are then translated into the actual trips per week (Equation 2), which are modelled as a stock, through a goal seeking archetype. We assume a time lag (or adjustment time) is required for behavioural change, and this is set at 4 weeks in the base model, and that there is no attrition once behaviour changes (unless there are further external influences).

Equation 2: Number of weekly trips made by mode by each population sub-group

$$T_m = \int_0^t \Delta T_m \ ; \ (t_0 : IT_m)$$

T_m = Weekly Trips by mode m.
IT_m = Initial Trips by mode m.
ΔT_m = Rate of change in Trips by mode m.
T_0 = Initial Time.

3.6. Bus friction factor

A bus trip is assumed to consist of four stages: Walk to bus stop; Wait at bus stop; Time on bus; Walk from bus stop to final destination. Change time could form another component but in our simple model we assume direct journeys. Based on the MARS model, the Friction Factor (FF) (Equation 3) is a function of time and consists of a time element and a cost element, and are a perceived expense of the journey (Pfaffenbichler (2003) based on Walther et al. (1997)). In addition to this in our model we include a willingness to consider element - based on the change in relative risk (as a proxy for a health status). Although time resistance is captured in the FF by subjective values and cost resistance with a calibrated coefficient relative to household income, this additional willingness to consider reflects how a change in health status may cause additional resistance (related to ability and affordability). This is based on an understanding that poorer health and associated mobility issues lead to transport difficulties (Luiu and Tight, 2021), which would deter individuals from considering bus as an option. However, as previously mentioned, those without access to a car are only able to choose bus.

Equation 3: Friction Factor for Bus in choice model

$$FF_B = \left(at \times SV_{at} + wt \times SV_{wt} + ivt \times SV_{ivt} + et \times SV_{et} + \frac{C_B}{\alpha \times HI} \right) \times \Delta HS$$

FF_B = Bus Friction Factor (minutes)
at = Access time.
SV_{at} = Subjective Value of access time.
Wt = Wait time.
SV_{wt} = Subjective Value of waiting time
ivt = In-vehicle time.
SV_{ivt} = Subjective Value of in-vehicle time
et = Egress time.
SV_{et} = Subjective Value of egress time.
CB = Cost of Bus.
HI = Household Income
α = Co-efficient (calibrated to initial data)
HS = Health Status.

The access and egress times are dependent not only on distance (a constant input that, for simplification, is an average for each zone) but also the average walking speed (see later). The in-vehicle time for the bus is influenced by the speed of the bus and the time lost at bus stops. Both of these are dependent on the car speed (see later), and the time loss is also dependent on the bus occupancy. As this is a simple model we do not account for the bus timetable. The occupancy is in relation to the initial occupation and also determines the subjective value of in vehicle time.

The cost of the bus is based on the actual bus fare, though can be increased if bus occupancy is too high to reflect the inconvenience of overcrowding. It is also sensitive to a willingness-to-pay co-efficient, α, that is calibrated to the initial trip data but also to average household income of the population in each zone.

3.7. Car friction factor

Car trips FF have the same fundamental elements as bus trips, with some minor differences. With a car trip there is no waiting time element of the journey, and access walking time (from home) is assumed to be negligible, though egress time (from car parks) could be non-negligible and is included. The in-vehicle time for the car is determined by car speed and the subjective value is influenced by the level of congestion. The car speed (Equation 4) is determined by free-flow speed and changes in demand on the road (i.e. number of car trips). Finally, there is no willingness to consider effect from a change in health.

Equation 4: Car speed

$$S = \frac{S_{FF}}{1 + av \times DF^{bv}}$$

S = Speed.
S_{FF} = Free Flow Speed
av/bv = Co-efficients.
DF = Demand Factor.

The cost component of the car consists of fuel cost (based on price and consumption due to the distance travelled) as well as other per km costs (e.g. insurance, maintenance) and any parking costs associated with the trips.

3.8. Health

In this simple model, transport mode choice influences health through two pathways: activity exposure (walking – access to a bus stop and egress from either a bus stop or car park) and pollution exposure (whilst walking). Pollution is limited to PM2.5 due to availability of data and is based only on a change in car tailpipe emissions. This is based on the mechanisms of the Integrated Transport and Health Impact model (ITHIM) (Woodcock et al., 2013; Maizlish et al., 2013).

3.8.1. Physical activity health impact

The average weekly walking time of each subscripted set of the population (Zone, Car Access, Sex, Age, Health Status, Social Grade) consists of the access and egress walking time from both car and bus (Table 3). These are calculated from the walking speeds and access/egress walking distances. The walking speeds of average health by different age and gender have been identified using Track and Trace app data (see 3.2), based on real world walking speeds of the relevant population groups. Speeds for below and above average are assumed to be ± 30% of the average speed. Though this is based on studies concerning older adults we take what we feel to be a high-end realistic estimate for the whole population (Middleton et al., 2015; Studenski et al., 2011).

The average access/egress walking time (in hours) for each sub-population is aggregated across all bus and car trips per week. The exposure arising from physical activity in each trip (in MET-h, Equation 5), is determined from the METs associated with walking speed (Ainsworth et al., 2000) and duration. This approach is derived from the method adopted in the ITHIM and for average travel times in each demographic.

Equation 5: Calculation of MET-h

$$METh = MET_{s,m} \times T$$

MET-h = Energy expenditure (Hours of Metabolic Equivalent of Task)

MET_{sm} = Metabolic Equivalent of Task at a specific speed, s, on specific mode, m.

T = Time.

In addition to the MET-h from active travel, Woodcock et al. (2009) also presume that non-activity METs explain variation in health outcomes (with the exception of Diabetes and the Cardiovascular Diseases. WhoseThe Relative Risks were based on walking alone, whereas other diseases were from studies considering physical activity from multiple domains). In the original ITHIM, (Woodcock et al., 2009) derived the non-travel physical activity MET-h from the 2008 Health Survey of England (NCSR, 2003).

The latest HSE data available at the time of our model development was 2014 (NCSR, 2015), so this was updated, using a slightly different method from Woodcock et al. (2009), as detailed in Appendix 2, resulting in the data in Table 4.

The ITHIM then calculates a Relative Risk (RR) of disease resulting from a certain level of exposure to physical activity, using Equation 6.

Equation 6: RR of physical activity

$$RR_{PA,x,t} = {RR_{1MET}}^{{E_x}^{\alpha}}$$

$RR_{PA,x,t}$ = Relative Risk of disease from Physical Activity for population x at time t.

RR_{1MET} = Relative Risk of disease from 1 MET

E_x = Exposure to activity of sub-population x

a = Co-efficient.

The exposure is the average weekly person MET-h resulting from active travel plus non-travel related activity. Additionally, Woodcock applied a minimum threshold of 2.5 MET-h/week to assume any benefit from physical activity. If an individual has a total (travel + non-travel) weekly MET-h of less than 2.5, the MET-h applied is equal to a minimum 0.1 MET-h. In the original ITHIM, various diseases were considered, but for simplicity in this model we only consider "all-cause mortality", with values of 0.25 for the transformational alpha coefficient and RR_{1MET} was 0.89. In future models we can adapt to consider disease specific RRs. In our model, the RR of the weekly exposure in each week (Time = t) is then compared to the initial (Time = 0) RR to give the physical activity health impact for that week.

3.8.2. Pollution-exposure health impact

The total car miles travelled across the whole population is aggregated from the number of trips and trip distances. For the purpose of the simple model, bus mileage (and associated pollution) are not considered and it is assumed that all individuals will be exposed to all emissions during the walking portion of their trip. Emissions are represented by PM2.5, as per the ITHIM. The PM2.5 concentration

Table 3
Health status and walking speeds (m/s) by age and sex, derived from Sesamo App data (1103 users over 14 months resulting in 206,162 trips).

Sex	Health Status	Age					
		16–19	20–29	30–39	40–49	50–59	Over 60
Female	Below	0.82	0.80	0.79	0.76	0.74	0.74
	Fair	1.17	1.14	1.13	1.09	1.06	1.05
	Above	1.52	1.49	1.47	1.42	1.37	1.37
Male	Below	0.85	0.85	0.84	0.82	0.78	0.75
	Fair	1.21	1.22	1.20	1.17	1.11	1.07
	Above	1.58	1.59	1.56	1.53	1.45	1.39

Table 4
Non Travel MET-Hr, derived from (Ainsworth et al., 2000; NCSR, 2015).

Sex	Health Status	Non-travel METh					
		16–19	20–29	30–39	40–49	50–59	Over 60
Female	below	15.83	16.45	17.97	18.20	15.70	12.21
	fair	33.71	32.06	31.17	32.24	30.75	15.78
	above	59.54	55.55	52.41	54.29	52.79	24.62
Male	below	16.19	15.62	15.29	14.87	14.41	11.03
	fair	60.77	59.46	55.48	53.10	49.29	25.89
	above	109.30	105.76	97.96	94.06	87.17	44.74

($\mu g/m^3$) in any week can be calculated from the initial concentration and any change in Vehicle Miles Travelled (VMT) relative to the initial weekly VMT, following Equation 3. The initial PM2.5 concentration was taken as 9.3 $\mu g/m^3$, as per the original ITHIM data that we had, which was for the San Francisco Bay Area of California (Maizlish et al., 2013) as the value for the Newcastle region was not available at the time of study. We accept any differences between these regions as a compromise in the proof of concept of this model.

Equation 8: Concentration of PM2.5

$$C_{PM2.5,t} = C_{PM2.5,T=0} - 3.17 \times \Delta VMT + 0.23$$

$C_{PM2.5,t}$ = Concentration in air of $PM_{2.5}$ at time, t.
$C_{PM2.5,t}$ = Concentration in air of $PM_{2.5}$ at initial time.
ΔVMT = Change in Vehicle Miles Travelled from initial time to time, t.
Thus, the relative risk of disease (for all-cause mortality) is determined using Equation 9.

Equation 9: RR of pollution exposure for sub population x

$$RR_{PM,x,t,} = e^{RR_{PM,x,T=0}} \times (\Delta C_{PM})$$

$RR_{PM,x,t}$ = Relative Risk of disease from exposure to Particulate Matter for population x at time t.
$RR_{PM,x,T=0}$ = Relative Risk of disease from exposure to Particulate Matter for population x at initial time.
ΔC_{PM} = Change in concentration in air of $PM_{2.5}$ from initial time to time, t.

3.8.3. Change in relative risk

In this model to understand health impacts we consider the change in relative risk (RR) of all cause mortality at each time step relative to an initial value of 1. An improvement in health is indicated by a reduction in RR. It is different from the population category of health status, which is applied to separate the population in sub-groups. The rate of change in RR from time = 0 of the population sub-group to time = t is then calculated through a goal seeking archetype, as the product of the change in RR from pollution exposure and physical activity exposure over an adjustment time (T_{adj}) of 6 weeks, feeding into a stock of RR. For this initial model, there isn't a consequential change to health status category which is a limitation of the model. However this could be considered as refinement in future model development.

Equation 10: Change in relative risk

$$RR_{x,t} = \int_0^t \frac{\left(\left(RR_{PA,x,t}/RR_{PA,x,T=0} \times RR_{PM,x,t}/RR_{PM,x,T=0}\right) - RR_{x,t}\right)}{T_{adj}} ;$$

$$\left(t_0 = RR_{PA,x,T=0} \times RR_{PM,x,T=0} = 1\right)$$

$RR_{,x,t}$ = Overall Relative Risk of disease for population x at time t.
$RR_{PA,x,T=0}$ = Relative Risk of disease from Physical Activity for population x at initial time.
$RR_{PA,x,t}$ = Relative Risk of disease from Physical Activity for population x at time t.
$RR_{PM,x,t}$ = Relative Risk of disease from exposure to Particulate Matter for population x at time t.
$RR_{PM,x,T=0}$ = Relative Risk of disease from exposure to Particulate Matter for population x at initial time.
T_{adj} = Adjustment Time.

3.8.4. Walking speed feedback

The walking speed of each sub-population is assumed to be affected by the change in health, as a product of the change in RR and walking speed. This is based on literature that suggests that walking speeds are associated with health (Middleton et al., 2015; Studenski et al., 2011). We accept that the calculation may be crude but were unable to find an established relationship in the literature that we could apply in our model.

4. Results and discussion

We run the model for 52 weeks at a time step of 0.0625 weeks. Under baseline conditions, there is no change in travel behaviour – the friction factors and thus the mode choice are constant. As such, there is no change in health. We test two forms of policy that could encourage the uptake of public transport: fare and frequency, introducing reductions over differing time periods, as set out in Table 5. As only households with access to a car can make a choice between bus and car in our model, we focus on this population in our results.

For bus fares, the initial (baseline) fare was £2.25, based on actual bus fares at the time of analysis in the area (half of a "Day Rider" ticket – noting that this study was carried out prior to the UK Wide £2 bus fare initiative). Thus, the reduction by 25% is to £1.69, by 50% is £1.13 and by 75% is £0.56. For the bus frequency, which affects the waiting time, the initial (baseline) headway time is 10 min, based on actual data from Google Maps and MOOVIT (2022). This translates in the MARS model to a waiting time of just over 4 min, with a 25% reduction to 7.5 min (3 min waiting time), 50% to 5 min (2 min waiting time) and 75% to 3.5 min (<1 min waiting time). The initial figure is reflective of an actual average waiting time of 3–15 min, though we accept this is on the low side (Mishalani et al., 2006), and we also recognise that these times are clearly unrealistic. However the purpose of our model is to show illustrative sensitivities rather than designed to reflect real policy. The reduction %'s and times are somewhat arbitrary rather than reflecting any proposed policy, but were selected on the basis of being both reasonable and extreme examples in order to test the response of the model to granularity in the policy changes.

4.1. Change in weekly bus trips by zone with household car access

As shown in Fig. 2, a fare reduction can increase weekly bus trips over the course of a year by those with household car access by up to 45% in Walker, almost 40% in Gosforth, or around 40% overall, compared to the initial weekly bus trips. To put this into perspective, the recommended UK commute bus fare elasticity is between −0.3 and −0.85 (Dunkerley et al., 2021). This range of impact from around 10% increase for a 25% price reduction to 45% increase for a 75% reduction represents a price elasticity between −0.4 and −0.6 so within the expected range. As we consider only households with car access we may consider that the most price sensitive are not within this population as they would not be able to purchase a car. The larger impact in Walker is as expected due to the higher price sensitivity of that community.

Changing the frequency of the bus services has a much smaller impact on weekly bus trips for those with household car access, despite an unrealistically high frequency in the extreme case. As seen in Fig. 3, there is a range of between a 1% increase in trips for a 25% frequency increase in Walker, and almost 4.5% increase for 75% more frequent bus trips in Gosforth. This is comparable to a previous MARS modelling study, which identified a 4% increase in public transport trip-km for a 50% increase in frequency (May et al., 2005), though admittedly somewhat lower than reported wait time elasticities of between −0.39 and −1.17 (Preston (2000) in Balcombe et al. (2004)). Contrary to the impact of fare reductions, Gosforth has a larger impact from frequency increases than Walker. This is probably due that community having a shorter bus distance so the lower waiting time makes a greater proportional impact on the overall time friction factor.

4.2. Total annual change in bus trips by zone with household car access

The impact on total bus trips across the year is more noticeable than weekly trips discussed in the previous section. Unsurprisingly, we can see in Fig. 4 that the largest modal change can be seen when the largest reduction (75%) is made for the longest period (from Week 4) (Fare 7), but also how the delay in implementing the largest reduction can have a significant impact on the change over the year – if the fare reduction is not introduced until week 40 (Fare 9) then the resultant total change can be less than an earlier, lower reduction (Fares 1,4,5,10, 12–15), thus delaying the potential positive impacts on health. Only Fares 2, 6 and 3 result in a lower impact.

Table 5
Policy scenarios.

	% reduction from initial value at start time	% reduction from initial value at end time	Start Week	End Week
Policy 1	25	25	4	n/a
Policy 2			20	
Policy 3			40	
Policy 4	50	50	4	
Policy 5			20	
Policy 6			40	
Policy 7	75	75	4	
Policy 8			20	
Policy 9			40	
Policy 10	25	50	4	20
Policy 11			20	40
Policy 12		75	4	20
Policy 13			20	40
Policy 14	50		4	20
Policy 15			20	40

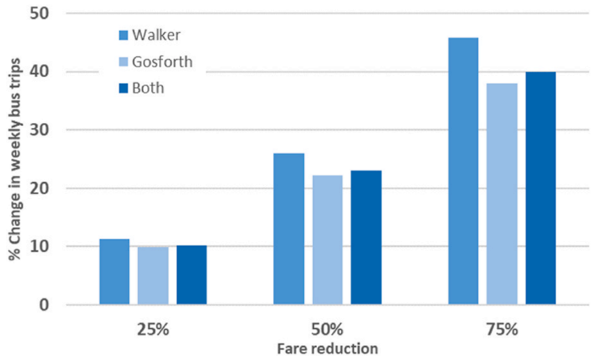

Fig. 2. Change in weekly bus trips (Week 0 vs Week 52) due to fare change across population with household car access (Compared to initial weekly bus trips).

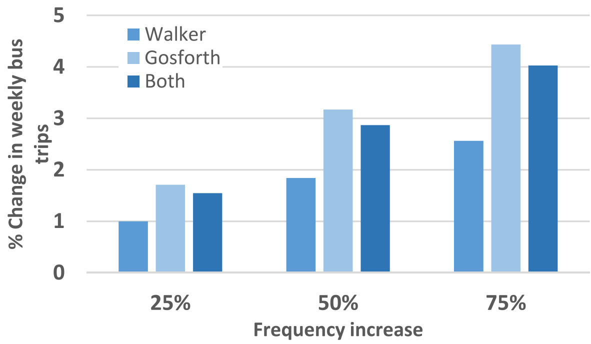

Fig. 3. Changes in weekly bus trips (Week 0 vs Week 52) due to frequency change across population with household car access (Compared to initial weekly bus trips).

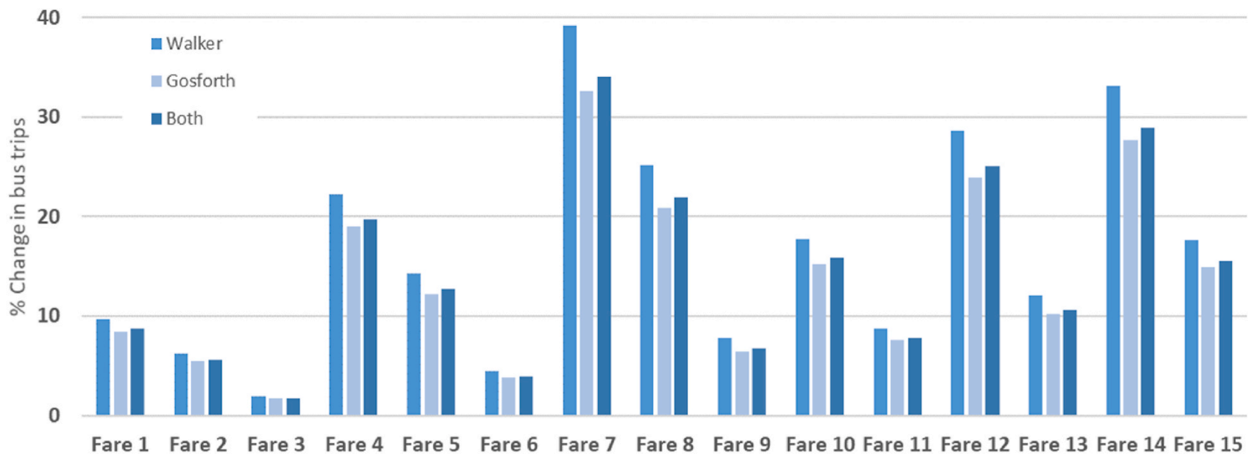

Fig. 4. Total annual change in total bus trips across population with household car access by fare reduction (success in order: 7, 14, 12, 8, 4, 10, 15, 5, 13, 1, 11, 9, 2, 6, 3).

If we assume that the government is subsidising the fare reduction, then we can also look at the cost per trip shifted (Fig. 5). We account for the whole population, as those without household car access will also benefit from the reduced fares. The most successful policy (Fare 7) is also the most efficient policy at just over £9 invested per trip. Conversely, the least successful policies are also the least efficient, suggesting that there may be a false economy in small reductions. There will of course, be a limit to budget available. Fare 7, despite being the most efficient is also the most expensive at nearly £0.25M.

Frequency reductions have a similar pattern of impact as fare reduction (Fig. 6), with some subtle differences. If policies are ranked by success, we see that policies 4 and 8, 1 and 13, and 2 and 9 appear in the opposite order to the fare policy results (Fig. 4). As a hypothetical scheme to increase frequency, we don't have approximate costs to consider in the same way as the bus fare subsidies.

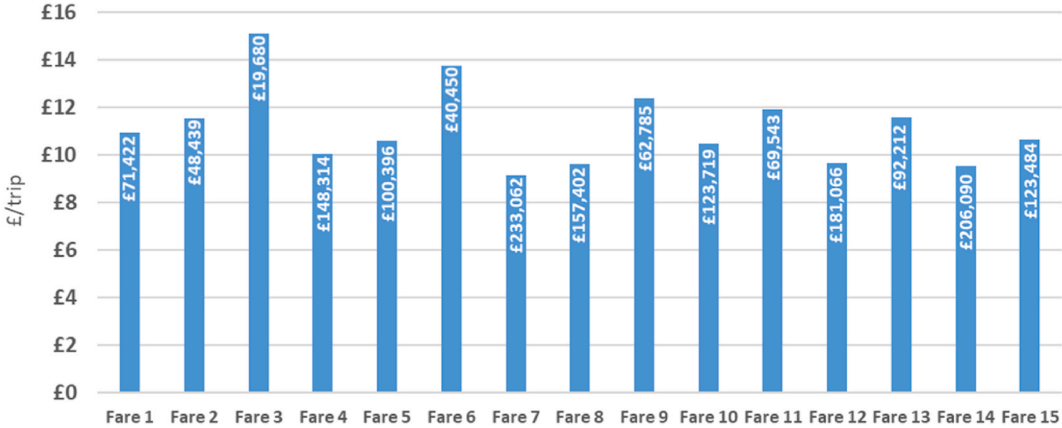

Fig. 5. Cost per bus trip increase across whole population (data label is total invested on bus trip subsidies across the population).

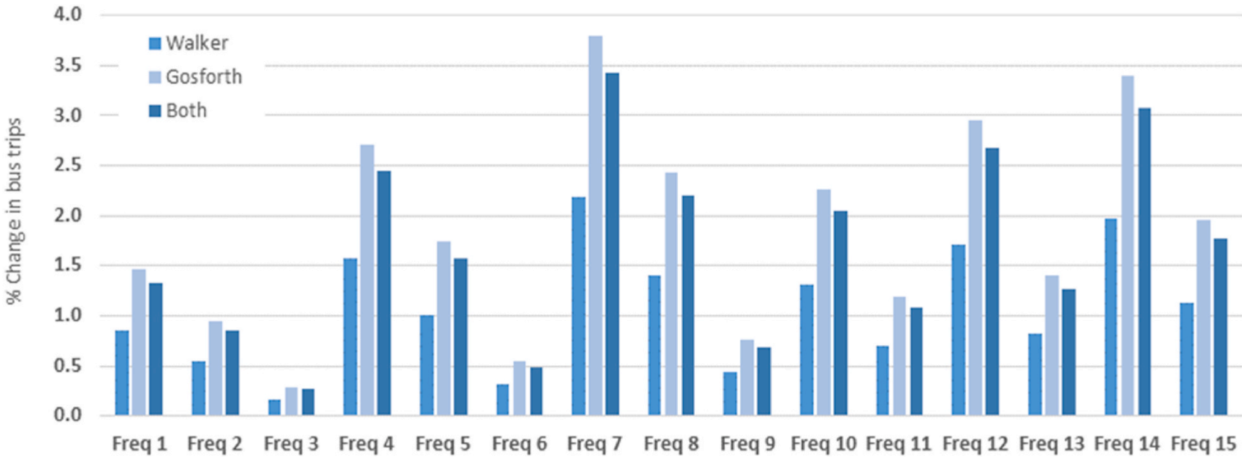

Fig. 6. Total annual change in bus trips across population with household car access by frequency reduction (success in order: 7, 14, 12, 4, 8, 10, 15, 5, 1, 13, 11, 2, 9, 6, 3.

4.3. Total annual change in bus trips and health by socio-demographic groups with household car access

In the previous sections, we have presented the results for the aggregate population with household car access in each zone for each of the policies. When we consider the results at a more disaggregated population level, accounting for general health and social group of just those who shifted mode, we see micro-changes in the health impacts of mode shift more clearly, as these sub-groups may increase or decrease their bus trips.

Figs. 7 and 8 show this change for bus trips and relative risk relevant to an average individual in each sub-group (averaged across age and sex), for the most successful Fare policy (7). Relative risk is for all cause mortality. We can clearly see that the least affluent socio-economic groups,[1] DE, who are most price sensitive make the greatest change in bus trips in each health status category, and that the Fair and Above average health status groups make larger changes than the Below average health group. This is because the Below average health status groups tend to take less trips overall, so have fewer additional trips they can take. Seeing how this translates to change in health, although the impact may be minimal, we see that in general the change in health follows the change in bus trips. Therefore, the lower socio-economic groups in each health category witness the greatest benefits. On the other hand the Below average health status sub-groups have the smallest health increase across health status categories.

The distribution of the Frequency 7 intervention shown in Fig. 9 (bus trips) and Fig. 10 (relative risk) has quite a different pattern to that of the Fares. Here we see that the lower socio-economic groups benefit the least. Though similar to the fare policy, the middle health status group stand to benefit more than other health status groups. Those in the below average health status have similar

[1] AB: Higher & intermediate managerial, administrative, professional occupations; C1: Supervisory, clerical & junior managerial, administrative, professional occupations; C2: Skilled manual occupations; DE: Semi-skilled & unskilled manual occupations, Unemployed and lowest grade occupations.

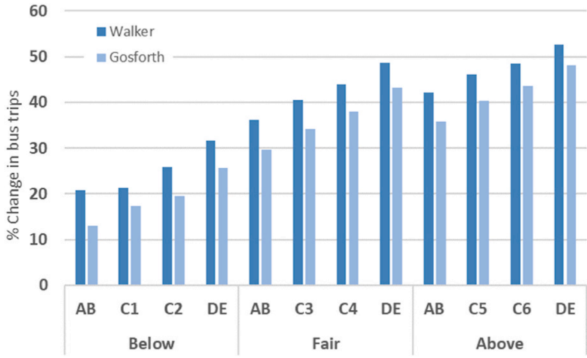

Fig. 7. Percentage change in bus trips under Fare 7 by socio-demographic group of car users (change is averaged across age and sex).

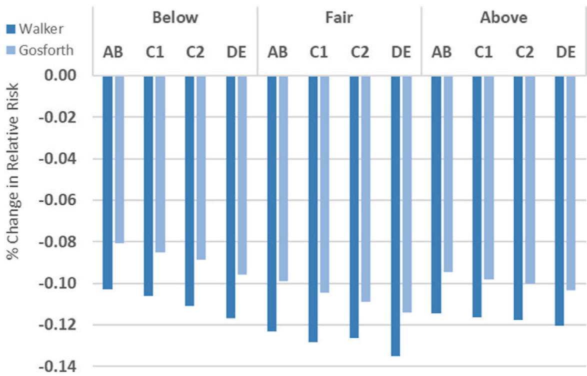

Fig. 8. Percentage change in relative risk under Fare 7 by socio-demographic group of car users (change is averaged across age and sex).

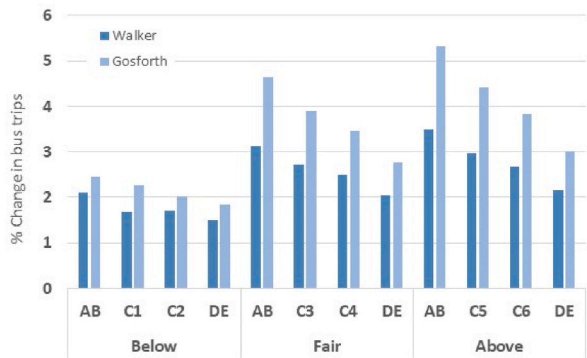

Fig. 9. Percentage change in bus trips under Frequency 7 by socio-demographic group (change is weight averaged across age and sex).

changes in health regardless of socio-economic group (presumably as there is limited issue with price sensitivity in the frequency policy), yet the impact on willingness to consider bus must have a dominant effect here. As already identified, Gosforth benefits more by the Frequency policy than Walker, but interestingly, the more affluent groups within both zones also benefit more. This occurs because the reduction in waiting time in some cases leads to the time portion of the friction factor being lower than the cost portion, reducing the influence of the price sensitivity. As at the start of the simulation the more affluent groups have fewer weekly bus trips than the least affluent, and the cost element does not change but remains restrictive to the least affluent. They therefore stand to be more influenced by the now dominant time element. In comparison to the Fare policy, this may not be a favourable choice in terms of social equity as it stands to benefit those better off more than those worse off.

4.4. Effect of combined policies

Finally, by combining the two most ambitious policies, Fare 7 and Frequency 7, we find that the two policies can reinforce each other creating a greater overall impact than each individual policy, which is still within the range of generalised journey time

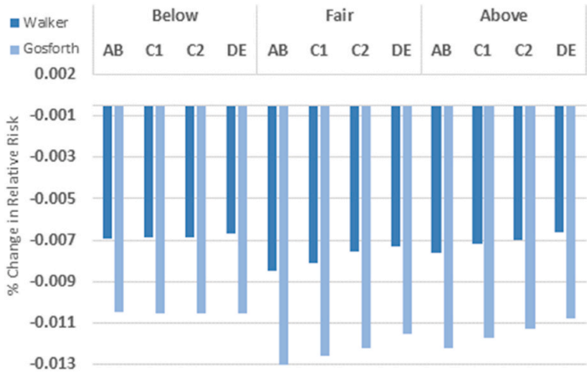

Fig. 10. Percentage change in relative risk under Frequency 7 by socio-demographic group (change is averaged across age and sex).

Table 6
Final Change in Weekly Bus Trips of population with household car access.

	Walker	Gosforth	Both
Fare 7	+149	+420	+569
Freq 7	+8	+49	+57
Fare 7 Freq 7	+169	+520	+689

elasticities for bus of −1.05 to −1.15 (Dunkerley et al., 2021), though not to the extent of if both policies were independent (Table 6, Table 7 and Fig. 11). Although changes in relative risk are relatively small, this may be expected over the short time period, which would only have acute effects on health. When we compare the impacts of the mixed scenario on socio-economic groups (Fig. 11), the pattern reflects the dominance of fare effects as we see that there is limited additional benefit from the frequency policy (Fig. 10) on top of the impacts of the fare policy (Fig. 8).

In Table 8 we present distribution data on the car-owning populations of Walker (left) and Gosforth (right) by socio-economic class (Columns: AB, C1, C2, DE) and health status (Rows: Below, Fair, Above) at the initial time - i.e. before any policy interventions. 8(a) shows the total (synthetic) population in each sub-category. 8(b) and 8(c) show the percentage of the overall and zone populations in each sub-category. 8(d) shows the percentage of population within the three health statuses by socio-economic class population in each zone, whereas 8(e) shows the percentage of population within the four socio-economic classes by health status. The colour grading in each sub-table shows the range from lowest (red) to highest (green).

Table 7
Final change in relative risk of population with household car access.

	Walker	Gosforth	Both
Base	1	1	1
Fare 7	0.9990	0.9992	0.9991
Freq 7	0.9999	0.9999	0.9999
Fare 7 Freq 7	0.9989	0.9990	0.9989

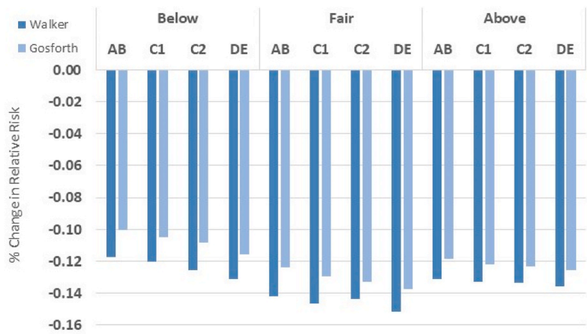

Fig. 11. Percentage change in relative risk under mixed scenario (Fare 7 & Frequency 7) by socio-demographic group (change is representative of a single individual with household car access).

Table 8
Study population with household car access in the two zones (colour graded from red being lowest to green being highest in each sub-table).

		Walker					Gosforth				
		Socio-Economic Class (SEC)									
	Health Status	AB	C1	C2	DE	All	AB	C1	C2	DE	All
8(a) Population (no.)	Below	2	5	8	15	30	13	13	6	12	44
	Fair	10	10	18	30	68	64	29	16	35	144
	Above	61	52	77	109	299	622	226	127	177	1152
	All	73	67	103	154	397	699	268	149	224	1340
8(b) % of Overall Population	Below	0.1	0.3	0.5	0.9	1.7	0.7	0.7	0.3	0.7	2.5
	Fair	0.6	0.6	1.0	1.7	3.9	3.7	1.7	0.9	2.0	8.3
	Above	3.5	3.0	4.4	6.3	17.2	35.8	13.0	7.3	10.2	66.3
	All	4.2	3.9	5.9	8.9	n/a	40.2	15.4	8.6	12.9	n/a
8(c) % of Zone Population	Below	0.5	1.3	2.0	3.8	7.6	1.0	1.0	0.4	0.9	3.3
	Fair	2.5	2.5	4.5	7.6	17.1	4.8	2.2	1.2	2.6	10.7
	Above	15.4	13.1	19.4	27.5	75.3	46.4	16.9	9.5	13.2	86.0
	All	18.4	16.9	25.9	38.8	n/a	52.2	20.0	11.1	16.7	n/a
8(d) % of Zone SEC	Below	2.7	7.5	7.8	9.7	n/a	1.9	4.9	4.0	5.4	n/a
	Fair	13.7	14.9	17.5	19.5		9.2	10.8	10.7	15.6	
	Above	83.6	77.6	74.8	70.8		89.0	84.3	85.2	79.0	
8(e) % of Zone Health	Below	6.7	16.7	26.7	50.0	n/a	29.5	29.5	13.6	27.3	n/a
	Fair	14.7	14.7	26.5	44.1		44.4	20.1	11.1	24.3	
	Above	20.4	17.4	25.8	36.5		54.0	19.6	11.0	15.4	

By looking at this initial data we can make some assessment on the potential benefits of our interventions based on the results already presented that could support decisions on where limited resources to improve health outcomes could be focused. We can see from 8(a) and 8(b) that Gosforth has not only a higher population than Walker, but also account for two thirds of the population that are already in above average health (with half of that population in the highest SEC). In Walker we see that the lowest socio-economic group, DE, which has the most people with above average health status, is also the largest group. If the concern of the policy is not just to benefit the most vulnerable but also the biggest group then this policy would be desirable. Furthermore, in 8(c) we can see that Gosforth has a healthier population than Walker, with 85% of the population of above average health compared to only 75% in Walker, which also has over twice the portion of those in below average health compared to Gosforth, further reinforcing that a policy that favours Walker may be preferable. Although health status by SEC shows similar patterns in both zones (8(d)), Gosforth once again shows above average health status higher than Walker, and below average health status to be lower, in all SECs. On the other hand, 8 (e) shows SEC by health status, which would seem for both zones to correlate with the most populous SEC in each zone. What should also be noted is that although Walker has a much lower total population (847) than Gosforth (1680), it also has substantially lower household car access than Gosforth, which is 47% compared to 80%, so the choice to shift to bus (and the related benefits) is available to a higher portion of the population in that area. As such, we must be wary that a large portion of who we can consider most vulnerable are not directly considered within our results, but could also benefit substantially from the reduced fares and/or increased frequency.

5. Conclusions

This simple system dynamics (SD) model was established to demonstrate how causal feedbacks identified in previous research can be developed into a simple working tool for assessing policy interventions related to transport and health. Alongside this, we demonstrate the potential benefits of integrating SD with spatial micro-simulation development of synthetic populations and agent based modelling. In future work, we plan to integrate further with the ABM to run for longer and more dynamic time scales, as well as developing more detailed policy scenarios.

Our results suggest that policies aimed at reducing bus fare and increasing bus frequency can stimulate a mode shift from car to bus with resultant impacts on health, albeit small, and the policy interventions tested may provide benefits to the most deprived communities. In our case the shift from car to bus would involve an increase of 700m walking per day per person, which is some way off the often mooted "10,000" steps (approx. 7.5–8 km) that studies suggest may reduce mortality risk (del Pozo Cruz et al., 2022). However, other sources suggest that 10,000 steps are not required, and it may be more in the range of an additional 10 min of walking time per trip, which is recommended as having health benefits if carried out daily (NHS, 2021), or 150 min of moderate-to-vigorous aerobic activity a week (Garcia et al., 2023), or short bouts (Woolf-May et al., 1999) as is indeed any increase in walking (Lee and Buchner, 2008), especially if they are already in a poorer state of health (Ahmadi et al., 2024). This is particularly important for those who are in the lowest socio-economic group, who may benefit most from the policies tested. However, it should be noted that as those groups tend to travel less the opportunities for improved health through transport mode switch may be more limited than other groups. The associated reduction in transport related air pollution provides additional benefits through reduction of both acute and chronic cardio-vascular and respiratory affects, even if the short term (Manisalidis et al., 2020). What we don't capture (yet) in this model are additional mode choices (e.g. walking, cycling, rail) and other transport-health interactions – both positive, such as the improvement in wellbeing commonly associated with increased activity, and negative, such as the increased exposure to pollution whilst walking (which is in the CLD but not the simulation model) or even other transport-health interactions such as the exposure to disease whilst using public transport. Nor do we capture if the increased walking (or health benefits) arising from the modal shift may lead to other activity-related behaviour change. In future developments of the model, it would be interesting to consider these limitations and include further incentives, modes and exposures, for a broader picture of health impacts. This could be further improved by considering longer time-periods and specific diseases, as well as capturing the transition between different health status. However, the findings of this paper are an encouraging start to the further development of new types of models and model integration for the understanding of transport-health interactions utilising new and emerging forms of data.

Financial disclosure

This work was funded by the Alan Turing Institute under Grant number R-LEE-006 ("KARMA") and the EPSRC under Grant Number EP/V032658/1 ("TRACK").

CRediT authorship contribution statement

Gillian Harrison: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Yuanxuan Yang:** Writing – review & editing, Methodology, Data curation. **Keiran Suchak:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Susan M. Grant-Muller:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Simon Shepherd:** Writing – review & editing, Investigation. **Frances C. Hodgson:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank the wider KARMA and TRACK project teams and Dr Adam Martin (School of Medicine, University of Leeds) for their contribution to the development of this model and comments on previous drafts of this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jth.2024.101830.

References

Ahmadi, M.N., Rezende, L.F.M., Ferrari, G., Cruz, B.D.P., Lee, I.-M., Stamatakis, E., 2024. Do the Associations of Daily Steps with Mortality and Incident Cardiovascular Disease Differ by Sedentary Time Levels? A Device-Based Cohort Study, vol. 58, pp. 261–268.

Ainsworth, B.E., Haskell, W.L., Whitt, M.C., Irwin, M.L., Swartz, A.M., Strath, S.J., O'brien, W.L., Bassett, D.R., Schmitz, K.H., Empliancourt, P.O., Jacobs, D.R., Leon, A.S., 2000. Compendium of Physical Activities: an update of activity codes and MET intensities. Med. Sci. Sports Exerc. 32, S498–S516.

AQEG, 2022. Indoor air quality. Air Quality Expert Group. Prepared for. Department for Environment, Food and Rural Affairs (Scottish Government; Welsh Government; and Department of Agriculture, Environment and Rural Affairs in Northern Ireland).

Aranega-Bou, P., Pottage, T., Fenwick, A., D'costa, W., Brown, N.F., Yaxley, N., King, M.-F., Parker, S.T., Miller, D., López-García, M., Noakes, C.J., Moore, G., Bennett, A., 2023. A 17-month Longitudinal Environmental Sampling Study Carried Out on Public Transport Vehicles Operating in England during the COVID-19 Pandemic Identified Low Levels of SARS-CoV-2 RNA Contamination. 2023, 12.20, 23300219.

Balcombe, R., Mackett, Er, Paulley, N., Preston, J., Shires, J., Titheridge, H., Wardman, M., White, P., 2004. In: TRL (Ed.), The Demand for Public Transport: a Practical Guide. Report TRL593. Available from: https://trl.co.uk/uploads/trl/documents/TRL593%20-%20The%20Demand%20for%20Public%20Transport.pdf. (Accessed 17 May 2023).

Bell, D.S., James, P., López-García, M., 2023. Social Distance Approximation on Public Transport Using Stereo Depth Camera and Passenger Pose Estimation, vol. 23, p. 9665.

Boogaard, H., Samoli, E., Patton, A.P., Atkinson, R.W., Brook, J.R., Chang, H.H., Hoffmann, B., Kutlar Joss, M., Sagiv, S.K., Smargiassi, A., Szpiro, A.A., Vienneau, D., Weuve, J., Lurmann, F.W., Forastiere, F., Hoek, G., 2023. Long-term exposure to traffic-related air pollution and non-accidental mortality: a systematic review and meta-analysis. Environ. Int. 176, 107916.
Budnitz, H.D., Tranos, E., Chapman, L., 2021. Transport modes and big data. In: VICKERMAN, R. (Ed.), International Encyclopedia of Transportation. Elsevier, Oxford.
Cooper, E., Gates, S., Grollman, C., Mayer, M., Davis, B., Bankiewicz, U., Khambhaita, P., 2019. Transport, health, and wellbeing: an evidence review for the Department for Transport. Available online: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/847884/Transport_health_and_wellbeing.pdf.
Del Pozo Cruz, B., Ahmadi, M.N., Lee, I.-M., Stamatakis, E., 2022. Prospective associations of daily step counts and intensity with cancer and cardiovascular disease incidence and mortality and all-cause mortality. JAMA Intern. Med. 182, 1139–1148.
DFT, 2023. DfT Areas of Research Interest 2023. Available from: https://www.gov.uk/government/publications/dft-areas-of-research-interest/areas-of-research-interest-2023.
DOT, 2022. U.S. Department of transportation strategic plan FY 2022-2026. Available from: https://www.transportation.gov/sites/dot.gov/files/2022-04/US_DOT_FY2022-26_Strategic_Plan.pdf.
Dunkerley, F., Rohr, C., Wardman, M., 2021. Elasticities for travel demand: recent evidence. In: VICKERMAN, R. (Ed.), International Encyclopedia of Transportation. Elsevier, Oxford.
EC, 2020. Sustainable and Smart Mobility Strategy – putting European transport on track for the future. In: COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, T. C., THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS COM(2020) 789 FINAL. Available from: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52020DC0789.
Garcia, L., Pearce, M., Abbas, A., Mok, A., Strain, T., Ali, S., Crippa, A., Dempsey, P.C., Golubic, R., Kelly, P., Laird, Y., Mcnamara, E., Moore, S., Sa, T.H.D., Smith, A. D., Wijndaele, K., Woodcock, J., Brage, S., 2023. Non-occupational physical activity and risk of cardiovascular disease, cancer and mortality outcomes: a dose–response meta-analysis of large prospective studies, 57, 979–989.
Glazener, A., Sanchez, K., Ramani, T., Zietsman, J., Nieuwenhuijsen, M.J., Mindell, J.S., Fox, M., Khreis, H., 2021. Fourteen pathways between urban transportation and health: a conceptual model and literature review. J. Transport Health 21, 101070.
Gorji, M.-A., Shetab-Boushehri, S.-N., Akbarzadeh, M., 2023. Evaluation and improvement of the resilience of a transportation system against epidemic diseases: a system dynamics approach. Transport Pol. 133, 27–44.
Harrison, G., Grant-Muller, S.M., Hodgson, F.C., 2020. New and emerging data forms in transportation planning and policy: opportunities and challenges for "Track and Trace" data. Transport. Res. C Emerg. Technol. 117, 102672.
Harrison, G., Grant-Muller, S.M., Hodgson, F.C., 2021. A review of transport-health system dynamics models. J. Transport Health 22.
Harrison, G., Grant-Muller, S.M., Hodgson, F.C., 2022. Understanding the influence of new and emerging data forms on mobility behaviours and related health outcomes. J. Transport Health 24, 101335.
Hirsch, G., Homer, J., Tomoaia-Cotisek, A., 2015. System dynamics applications to health and health care—introduction. Syst. Dynam. Rev. (Special Virtual Issue: https://onlinelibrary.wiley.com/page/journal/10991727/homepage/VirtualIssuesPage.html#Health).
Hosking, J., Braubach, M., Buss, D., Khayesi, M., Filho, V.P., De Sá, T.H., 2022. Towards a global framework for transport, health and health equity. Environ. Int. 169, 107472.
Lara, D.V.R., Pfaffenbichler, P., Rodrigues Da Silva, A.N., 2023. Modeling the resilience of urban mobility when exposed to the COVID-19 pandemic: a qualitative system dynamics approach. Sustain. Cities Soc. 91, 104411.
Lee, I.M., Buchner, D.M., 2008. The importance of walking to public health. Med. Sci. Sports Exerc. 40, S512–S518.
Lovelace, R., Ballas, D., Watson, M., 2014. A spatial microsimulation approach for the analysis of commuter patterns: from individual to regional levels. J. Transport Geogr. 34, 282–296.
Lovelace, R., Dumont, M., 2016. Spatial Microsimulation with R, first ed. Chapman and Hall/CRC, New York.
Lu, C., Adger, W.N., Morrissey, K., Zhang, S., Venevsky, S., Yin, H., Sun, T., Song, X., Wu, C., Dou, X., Zhu, B., Liu, Z., 2022. Scenarios of demographic distributional aspects of health co-benefits from decarbonising urban transport. Lancet Planet. Health 6, e461–e474.
Luiu, C., Tight, M., 2021. Travel difficulties and barriers during later life: evidence from the national travel survey in England. J. Transport Geogr. 91, 102973.
Maizlish, N., Woodcock, J., Co, S., Ostro, B., Fanai, A., Fairley, D., 2013. Health cobenefits and transportation-related reductions in greenhouse gas emissions in the San Francisco Bay area. Am. J. Publ. Health 103, 703–709.
Manisalidis, I., Stavropoulou, E., Stavropoulos, A., Bezirtzoglou, E., 2020. Environmental and health impacts of air pollution: a review. Front. Public Health 8, 14.
May, A.D., Shepherd, S.P., Emberger, G., Ash, A., Zhang, X., Paulley, N., 2005. Optimal Land Use–Transport Strategies:Methodology and Application to European Cities, pp. 129–138, 1924.
Middleton, A., Fritz, S.L., Lusardi, M., 2015. Walking speed: the functional vital sign. J. Aging Phys. Activ 23, 314–322.
Milne, D., Watling, D., 2019. Big data and understanding change in the context of planning transport systems. J. Transport Geogr. 76, 235–244.
Milne, E.M.G., 2012. A public health perspective on transport policy priorities. J. Transport Geogr. 21, 62–69.
Mishalani, R.G., Mccord, M.M., Wirtz, J., 2006. Passenger wait time perceptions at bus stops: empirical results and impact on evaluating real-time bus arrival information. J. Public Transport. 9, 89–106.
MOOVIT, 2022. Moovit global public transport report 2022. Available online: https://moovitapp.com/insights/en/Moovit_Insights_Public_Transit_Index-countries. (Accessed 5 May 2023).
Morrissey, K., Clarke, G., Williamson, P., Daly, A., O'donoghue, C., 2015. Mental Illness in Ireland: Simulating its Geographical Prevalence and the Role of Access to Services, vol. 42, pp. 338–353.
Mueller, N., Rojas-Rueda, D., Cole-Hunter, T., De Nazelle, A., Dons, E., Gerike, R., Götschi, T., Int Panis, L., Kahlmeier, S., Nieuwenhuijsen, M., 2015. Health impact assessment of active transportation: a systematic review. Prev. Med. 76, 103–114.
Mueller, N., Rojas-Rueda, D., Khreis, H., Cirach, M., Milà, C., Espinosa, A., Foraster, M., Mceachan, R.R.C., Kelly, B., Wright, J., Nieuwenhuijsen, M., 2018. Socioeconomic inequalities in urban and transport planning related exposures and mortality: a health impact assessment study for Bradford, UK. Environ. Int. 121, 931–941.
Muley, D., Shahin, M., Dias, C., Abdullah, M., 2020. Role of Transport during Outbreak of Infectious Diseases: Evidence from the Past, vol. 12, p. 7367.
NCSR, 2003. Health Survey for England, 2003. National Centre for Social Research for the Department of Health.
NCSR, 2015. Health Survey for England 2014. National Centre for Social Research for the Department of Health.
NHS, 2016. 2016 health survey for England. Available from: https://digital.nhs.uk/data-and-information/publications/statistical/health-survey-for-england/health-survey-for-england-2016. (Accessed 16 May 2023).
NHS, 2021. Physical activity guidelines for adults aged 19 to 64 [Online]. https://www.nhs.uk/live-well/exercise/exercise-guidelines/physical-activity-guidelines-for-adults-aged-19-to-64/:NationalHealthServiceUK.
Nieuwenhuijsen, M.J., Khreis, H., Mueller, N., Rojas-Rueda, D., 2020. Chapter fourteen - health impact assessment of transport planning and policy. In: Nieuwenhuijsen, M.J., Khreis, H. (Eds.), Advances in Transportation and Health. Elsevier.
O'donoghue, C., Morrissey, K., Lennon, J., 2014. Spatial microsimulation modelling: a review of applications and methodological choices. Int. J. Manag. 7, 26–75.
Odiari, E., Birkin, M., 2022. Simulating micro-level attributes of railway passengers using big data. J. Urban Mobil. 2, 100027.
ONS, 2011. 2011 UK Census. Available from: https://www.ons.gov.uk/census/2011census. (Accessed 16 May 2023).
Oviedo, D., Sabogal, O., Villamizar Duarte, N., Chong, A.Z.W., 2022. Perceived liveability, transport, and mental health: a story of overlying inequalities. J. Transport Health 27, 101513.
Pfaffenbichler, P., 2003. The Strategic, Dynamic and Integrated Urban Land Use and Trasnport Model MARS (Metropolitan Activity Relocation Simulator). PhD Thesis. Technische Universitat Wien.

Pfaffenbichler, P., Emberger, G., Shepherd, S., 2008. The integrated dynamic land use and transport model MARS. Network. Spatial Econ. 8, 183–200.
Preston, L.A.T.J., 2000. Analysis of demand for bus services. In: Oxford, T.S.U.U.O (Ed.), Final Report.
Saunders, L.E., Green, J.M., Petticrew, M.P., Steinbach, R., Roberts, H., 2013. What are the health benefits of active travel? A systematic review of trials and cohort studies. PLoS One 8, e69912.
Shepherd, S.P., 2014. A review of system dynamics models applied in transportation. Transport. Bus.: Transport Dynam. 2, 83–105.
Smith, D.M., Heppenstall, A., Campbell, M., 2021. Estimating Health over Space and Time: A Review of Spatial Microsimulation Applied to Public Health, vol. 4. *J* [Online].
Spooner, F., Abrams, J.F., Morrissey, K., Shaddick, G., Batty, M., Milton, R., Dennett, A., Lomax, N., Malleson, N., Nelissen, N., Coleman, A., Nur, J., Jin, Y., Greig, R., Shenton, C., Birkin, M., 2021. A dynamic microsimulation model for epidemics. Soc. Sci. Med. 291, 114461.
Sterman, J.D., 2000. Chapter 3: the modelling process. In: Sterman, J.D. (Ed.), Business Dynamics: Systems Thinking and Modelling for a Complex World. McGraw-Hill Higher Education, Boston.
Studenski, S., Perera, S., Patel, K., Rosano, C., Faulkner, K., Inzitari, M., Brach, J., Chandler, J., Cawthon, P., Connor, E.B., Nevitt, M., Visser, M., Kritchevsky, S., Badinelli, S., Harris, T., Newman, A.B., Cauley, J., Ferrucci, L., Guralnik, J., 2011. Gait speed and survival in older adults. JAMA 305, 50–58.
Tranos, E., Mack, E., 2019. Big data: a new opportunity for transport geography? J. Transport Geogr. 76, 232–234.
Van Schalkwyk, M.C.I., Mindell, J.S., 2018. Current issues in the impacts of transport on health. Br. Med. Bull. 125, 67–77.
Walther, K., Oetting, A., Vallee, D., 1997. Simultane Modellstruktur fur die Personenverkehrsplanung auf der Basis eines neuen Verkehrswiderstands. Veroffenttlinichungen des Verkehrswissenscheftlichen Instituts der Rheinisch-Westfalischen Technischen Hochschule Aachen 52.
Widener, M.J., Hatzopoulou, M., 2016. Contextualizing research on transportation and health: a systems perspective. J. Transport Health 3, 232–239.
Woodcock, J., Edwards, P., Tonne, C., Armstrong, B.G., Ashiru, O., Banister, D., Beevers, S., Chalabi, Z., Chowdhury, Z., Cohen, A., Franco, O.H., Haines, A., Hickman, R., Lindsay, G., Mittal, I., Mohan, D., Tiwari, G., Woodward, A., Roberts, I., 2009. Public health benefits of strategies to reduce greenhouse-gas emissions: urban land transport. Lancet 374, 1930–1943.
Woodcock, J., Givoni, M., Morgan, A.S., 2013. Health impact modelling of active travel visions for England and wales using an integrated transport and health impact modelling tool (ITHIM). PLoS One 8, e51462.
Woolf-May, K., Kearney, E.M., Owen, A., Jones, D.W., Davison, R.C.R., Bird, S.R., 1999. The efficacy of accumulated short bouts versus single daily bouts of brisk walking in improving aerobic fitness and blood lipid profiles. Health Educ. Res. 14, 803–815.
Wu, G., Heppenstall, A., Meier, P., Purshouse, R., Lomax, N., 2022. A synthetic population dataset for estimating small area health and socio-economic outcomes in Great Britain. Sci. Data 9, 19.
Zhang, J., Wang, T., 2023. Urban resilience under the COVID-19 pandemic: a quantitative assessment framework based on system dynamics. Cities 136, 104265.