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Diffusion of connected and autonomous vehicles concerning mode choice, policy interventions and sustainability impacts: A system dynamics modelling study

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A R T I C L E I N F O

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A B S T R A C T

Connected and autonomous vehicles (CAV) have seen a rapid development over the past decade. However, wide diffusion of high level CAVs is still decades to come, and will depend on many technological, policy and public acceptance factors. Merging a traditional Bass Diffusion Model with a discrete choice model in a system dynamics approach, this study modelled CAV diffusion from 2020 to 2070 in the UK, considering mode choices of CAV private car, CAV car/ride sharing and CAV bus, their possible impacts on road network performance and sustainability, and the feedback of these impacts to CAV diffusion. Results of this study suggest that without interventions CAV diffusion will start to increase rapidly from 2035, and reach market saturation of 98% in around 2057. CAV diffusion will lead to reductions in average travel time, average travel cost, carbon emission and traffic accident. Training campaign, which prepares the general public to be ready for CAVs, is more effective in accelerating CAV diffusion than marketing campaign, which mainly targets the innovators and early adopters. Promoting shared CAVs and CAV public transport can contribute to more sustainable and more affordable mobility with CAVs, although this may lead to smaller CAV market size in terms of CAV sale, and the market size may reduce at a higher rate than sustainability enhancement.

1. Introduction

Connected and autonomous vehicle (CAV) is becoming a reality after a rapid acceleration in investment and development over the past decade. Level 1 and Level 2 driving automation, defined by SAE International (2021) as systems with driver support features such as lane centring and adaptive cruise control, have already been available in the market for several years. In more recent years, several car manufacturers have delivered Level 3 systems to the market, which can take over driving tasks in designated areas and conditions without the need of constant driver vigilance. In 2020, Waymo launched its Level 4 driverless taxi service in the suburbs of Phoenix, US, and the taxis do not require a human driver behind the wheel. Level 5 systems will have all Level 4 features without location or condition limits. However, market-ready technologies for high level automation remain scarce, and wide diffusion of Level 4 and Level 5 CAVs is still decades to come (Litman, 2021).

The diffusion of CAVs over time will depend on many technological, policy and public acceptance factors. Extensive research has been done to simulate possible diffusion scenarios, predict their timings, and explore how policy makers and industry professionals can provide supports to stimulate the diffusion. Using a Bass model calibrated to electric vehicles sale data, Lavasani et al. (2016) forecasted that the US CAV market will be saturated by around 2060 and approximately 87 million CAVs will have been sold by then, given 116 million households. Also using a Bass model but with data from a stated preference survey, Shabanpour et al. (2018) modelled adoption timing of CAVs in the Chicago metropolitan area, and predicted that the likelihood of an average resident to eventually adopt a CAV is 71.3%, but timing will very much depend on individuals' socio-demographic characteristics, attitudes towards CAVs and land use patterns associated with them. Talebian and Mishra (2018) forecasted CAV adoption among employees of the University of Memphis by integrating a Bass model with an agent-based model. Their results show that with a 5% annual reduction rate of automation cost, only 15% of the University employees will adopt CAVs by 2050, but it can increase to 90% with a 20% cost

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reduction rate. Using a multinomial logit model with survey data, Bansal and Kockelman (2017) forecasted that market penetration of Level 4 CAVs in the US by 2045 will vary from 24.8% to 87.2% depending on drop rate of CAV price, increase rate of people's willingness to pay, and regulations on vehicle production.

However, these studies focused only on private CAVs, while shared CAVs and CAV public transport are also expected to be important modes of CAVs, if not more dominant, and with higher potential for equity and sustainability (Abe, 2019; Krueger et al., 2016; Pigeon et al., 2021). In this regard, Nieuwenhuijsen et al. (2018) considered CAV carsharing in their CAV diffusion study. Using the Netherlands as a case study, and a System Dynamics model with interactive components of CAV technology maturity, purchase price, perceived utility, fleet size, and car carsharing demand, their study shows that growths of Level 4 and Level 5 CAVs remain slow and only reach 34% of the total fleet around 2100, and the total fleet size starts to decrease from around 2050 due to the rise of carsharing. The study also tested scenarios that stimulate CAV adoption, and in the most radical scenario, Level 5 CAVs reach as high as 99% of total fleet around 2100.

However, like most other studies, Nieuwenhuijsen et al. (2018) did not consider the impacts that the resulted CAVs diffusion would have on the road networks, and consequently on people's travel behaviours and sustainability. For example, CAVs can have potential mobility impacts on travel demand, congestion, mode share, traffic accidents, and accessibility (Harper et al., 2016; Luttrell et al., 2015; Stanek et al., 2017; Soteropoulos et al., 2019); environmental impacts on energy efficiency, carbon emission, air pollution and noise (Rojas-Rueda et al., 2020; Stead and Vaddadi, 2019; Wadud et al., 2016); socio-economic impacts on mobility equity, labour market, government revenue from tax, and local business and economic development (Nikitas et al., 2021; Sparrow and Howard, 2020; Terry and Bachmann, 2019). Including these impacts could enhance the accuracy of diffusion prediction by feeding these impacts back to the diffusion process. More importantly, it would provide insights for policy decisions that not only stimulate CAV diffusion, but diffusion in ways that benefit the whole society in the long run.

Many studies have quantitatively modelled some of these CAV impacts (May et al., 2020; Soteropoulos et al., 2019). Results of these studies suggest that directions and extents of CAV impacts can be very different, even opposite, and will very much depend on the choice of CAV modes. Nevertheless, these studies are typically based on traditional integrated land use and transport models, and defined CAV market penetrations as exogenous modelling inputs (Hawkins and Habib, 2019). Hence, while they are helpful for projecting final consequences of given CAV diffusion outcomes, they did not model CAV diffusion over time and can only provide limited insights for policy design that promotes favourable CAV diffusion.

Therefore, this study aims to contribute to this knowledge gap, by modelling CAV diffusion over time, considering mode choices of CAV private car, CAV car/ride sharing and CAV bus, their possible impacts on road network performance and sustainability, and the feedback of these impacts to CAV diffusion. This study merges a traditional Bass Diffusion Model (Bass, 1969) with a discrete choice model using a system dynamics approach. It will help understand the dynamics between user acceptance, CAV adoption, mode share and their society-wide impacts, and to inform better policy interventions.

2. Method

2.1. Modelling approach

This study used System Dynamics (SD) to simulate the diffusion of CAVs. SD is a method to describe, model, simulate and analyse dynamic feedback systems (Pruyt, 2013). It has been developed since the pioneering work of Forrester (1961), and it is the application of system control principles and techniques to the studies of organisational, social, economic and/or environmental problems (Forrester, 1961; Pruyt, 2013). With the capability of addressing dynamic feedback loops between interactive components in complex innovation diffusion systems, SD has been applied in innovation diffusion in a wide range of fields, e.g., renewable energy (Markard et al., 2016), food industry (Horvat et al., 2020), mobile apps (Harrison, et al., 2020), and electric vehicles (Santa-Eulalia et al., 2011; Shepherd et al., 2012; Struben and Sterman, 2008).

Nieuwenhuijsen et al. (2018) applied SD on CAV diffusion, although only focusing on private CAVs. Their choice of SD over Agent-Based Modelling was justified by that there was less knowledge about individual behaviours in possible CAV diffusion processes over a long time horizon, but higher certainty about aggregated behaviours, drawing on results from both aggregated and disaggregated studies, and observations from existing similar systems. Hence, simulating system behaviours at an aggregated level using SD would be more feasible for studying CAV diffusion.

2.2. Model overview

Our SD model used the Bass Diffusion Model (Bass, 1969) as the core structure. The Bass Diffusion Model has been widely used for studying innovation diffusion, including diffusion of CAVs (Lavasani et al., 2016; Shabanpour et al., 2018; Talebian and Mishra, 2018). It describes the process of how an innovation is adopted by new users either as innovators or as imitators. Innovators adopt the innovation because of their desire to innovate, and their adoption rate is influenced by advertising effect; while imitators adopt the innovation because of the need to imitate the rest of the society, and their adoption rate is influenced by word-of-mouth effect, i.e., their contacts with existing users. Equation (1) gives the basic model formulation of Bass model, which leads to an S-shaped curve of cumulative number of adopters over time.

$$\frac{f(t)}{1-F(t)}=p+qF(t) \tag{1}$$

where.

- $F(t)$ is the cumulative adopters (as a fraction of the total potential market) at time t
- $f(t)$ is the new adopters (as a fraction of the total potential market) at time t
- p is the coefficient of innovation
- q is the coefficient of imitation

The advantages of Bass model are that it considers the influence of market size and user behaviour, and the coefficients can be calibrated using real-world data or historical data of diffusions of similar innovations, which can also be updated easily when better data or knowledge become available (Lavasani et al., 2016).

Adding to this Bass model, our SD model was extended with a discrete choice model to include three modes of CAVs: CAV private car, CAV car/ride sharing and CAV bus, as well as components to include impacts of CAV diffusion on mobility which feeds back to CAV adoption and mode choice. Fig. 1 shows the overview of the SD model with key components.

In this model, potential users become willing to consider CAVs by the desire to innovate, or by the need to imitate others. Those who are willing to consider CAVs will choose from CAVs of different modes or remain the choice of non-CAV, depending on the utility of each option, considering travel time and travel cost. Every certain time periods, users of each mode will reconsider their choices. Number of users of each mode hence increases with adoption and decreases with reconsideration. Utility of each mode is influenced by CAV technology advance and road network performance. CAV technology advance accumulates overtime, and the rate is influenced by R&D investment and CAV market

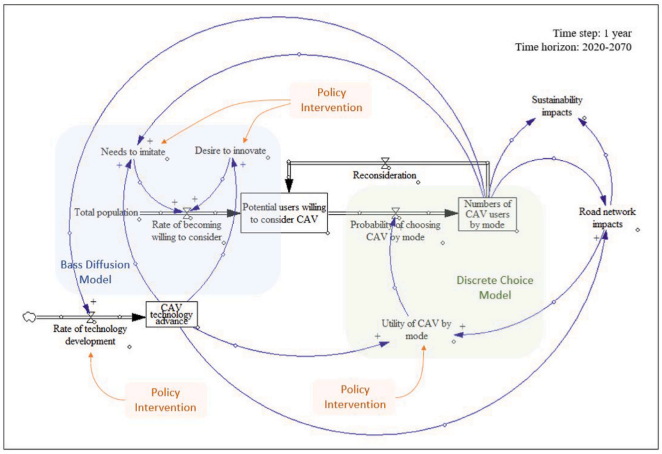

Fig. 1. Overview of the SD model with key components.

size. Road network performance is influenced by CAV technology advance, and travel behaviour which is determined by number of users of each mode. Sustainability impacts of CAV uptake can also be calculated based on road network performance and number of users of each mode. With this model, policy interventions can be tested by adding them as exogenous inputs to change rate of willingness to consider CAVs (e.g., marketing and training), rate of technology advance (e.g., R&D investment), and utilities of different modes (e.g., subsidies and road priority).

The model was implemented in Vensim DSS. The time step for simulation was 1 year and the time horizon was from 2020 to 2070. The UK was used as the case country and its population of 67.22 million in 2020 (World Bank, 2022) was used as the total population in the model, i.e., the total potential market. Population growth was not modelled so effects of CAV diffusion on total number of CAV users, total fleet size, total carbon emission, etc. Can be more easily traced over time. The model focused on passenger transport and did not include freight transport.

2.3. Model components

This section describes the model in more detail in relation to the key components, equations and constants. Constant values are provided and explained in the Appendix.

2.3.1. Innovation diffusion

The innovation diffusion component of this SD model used the Bass diffusion model as described in section 2.2. The innovation coefficient p of 0.001 and imitation coefficient q of 0.341865, estimated for CAV diffusion by Lavasani et al. (2016), were used in this model as the bases for innovation effect and imitation effect. We assumed both innovation effect and imitation effect can be enhanced by CAV technology advance, as a result of overall improvement on e.g. perceived safety, perceived usefulness, perceived ease of use brought about by technology advance. We further assumed the innovation effect can be enhanced by marketing, e.g., through advertisements innovators become more aware of or more interested in CAVs; and the imitation effect can be enhanced by training, e.g., after training imitators become more confident in using CAVs and hence more likely to try them to following other users. Hence:

$$in = p * (1 + TA * eta_{in} + mkt * me) \tag{2}$$

where in is the innovation effect; TA is a dimensionless variable of CAV technology advance, with 0 means no CAV technology and 1 means the most advanced technology achievable (see Section 2.3.4); eta_{in} is a constant of the extent to which technology advance can enhance innovation effect; mkt is a dimensionless variable of marketing activity intensity, with 0 means no marketing activity and 1 means maximum marketing activities; and me is a constant of the extent to which marketing can enhance innovation effect.

$$im = q * (1 + TA * eta_{im} + trn * te) \tag{3}$$

where im is the imitation effect, eta_{im} is a constant of the extent to which technology advance can enhance imitation effect; trn is a dimensionless variable of training activity intensity, with 0 means no training activity and 1 means maximum training activities; and te is a constant of the extent to which training can enhance imitation effect.

2.3.2. User choice

Potential users who are willing to consider CAVs will choose from CAV private car, CAV car/ride sharing and CAV bus, or remain the choice of non-CAV. Their choices will depend on the utility of each option, and the choices are simulated at population level, i.e., percentage of potential users choosing each option at each year. It is common that every now and then people will change their travel mode. So we assume a certain percentage of users of each option will reconsider their choice every year. Hence:

$$UN_i = \int r_i - rrc_i \tag{4}$$

where UN_i is the number of users of option mode i; r_i is rate of people becoming users of option mode i, in person/year; and rrc_i is rate of users of option mode i reconsidering their options, i.e., returning to the status of potential users who are willing to consider CAVs, in person/year

$$r_i = PN_{wc} * pctu_i \tag{5}$$

$$rrc_i = UN_i * rc_i \tag{6}$$

where PN_{wc} is number of potential users who are willing to consider CAVs, calculated using the base Bass model (Eq (1)), the innovation (Eq (2)) and imitation effects (Eq (3)), and adjusted by CAV users reconsidering their choices; $pctu_i$ is percentage of potential users choosing option mode i; and rc_i is a constant of percentage of users of option mode i reconsider choices.

$$pctu_i = \frac{e^{u_i}}{\sum e^{u_i}} \tag{7}$$

where u_i is the utility of option mode i.

Utility of each option mode can be influenced by travel time, travel cost, comfort, safety, etc (Liu et al., 2019a). Due to uncertainty and measuring difficulty in these utility attributes for CAVs, we only consider travel cost and travel time, which are the two highly influential attributes (Hensher and Rose, 2007; Winter et al., 2017). Hence:

$$u_i = \beta_{tt} * tt_i + \beta_{tc} * tc_i + asc_i \tag{8}$$

where tt_i, tc_i and asc_i are travel time, travel cost and alternate specific constant of option mode i, β_{tt} and β_{tc} are travel time and travel cost coefficients. The alternate specific constants represent unobserved preference.

2.3.3. Travel time and travel cost

Consistent units, i.e., minute per trip for travel time and £ (2020 value) per trip for travel cost, were used in the model, with an assumed 5-mile distance for all trips. This was necessary to enable the utility-based mode choice. The 5-mile distance was chosen since most people's daily trips are likely to be under 5 miles. According to Department for Transport (2022), 68% of all trips and 57% of car trips in England in 2019 were under 5 miles. However, with such a setting, our model may underestimate adoption of CAVs, since CAVs are envisaged to be highly attractive for long-distance trips (LaMondia et al., 2016; Perrine et al., 2020). This should be kept in mind when using our modelling results.

2.3.3.1. Travel time of CAV private car. Travel time of CAV private car includes in-vehicle time and parking time. For in-vehicle time, as CAV technology develops, CAV market penetration increases and mode share changes, network speed will change which will affect in-vehicle time. For parking time, one of the advantages of CAVs is that they do not need to be parked. For example, they can drive themselves to a nearby parking space or back home after dropping off the users at destinations. However, such use cases will only be possible when technology has reached a certain advance level. We assumed it to be 0.5 given the 0–1 scale of our CAV technology advance variable, considering that such use cases could be possible with Level 4 CAVs, and the 6 SAE levels are not linear with higher levels require more technology advance. We also assume on average parking time can only be reduced up to a certain percentage instead of 100%, since there may still be cases where parking is necessary. Finally, we assume marginal time reduction effect decreases as CAV technology develops. Hence:

$$tt_{pc} = ivt_{pc} + pt_{pc} \tag{9}$$

where tt_{pc} is CAV private car travel time; ivt_{pc} is the in-vehicle time; and pt_{pc} is the parking time.

$$ivt_{pc} = ivti_{pc} * \frac{nsi}{ns} \tag{10}$$

where $ivti_{pc}$ is a constant of initial CAV private car in-vehicle time, i.e., at the initial time step of 2020; ns is network speed; and nsi is a constant of initial network speed in 2020. Calculation of network speed is described in Section 2.3.5.

$$pt_{pc} = pti_{pc} * \left(1 - ta_{pc-pt}\right) \tag{11}$$

where pti_{pc} is a constant of initial CAV private car parking time in 2020, $ta_{pc\text{-}pt}$ is reduction in parking time as CAV technology develops

$$ta_{pc-pt} = \begin{cases} eta_{pc-pt} * TA^{pta_{pc-pt}}, if\ TA > 0.5 \\ 0, otherwise \end{cases} \tag{12}$$

where $eta_{pc\text{-}pt}$ is a constant of the maximum parking time reduction extent that can be achieved with CAV technology advance; $pta_{pc\text{-}pt}$ is a constant of the power that TA is raised to, with a value between 0 and 1, to simulate the decrease of marginal time reduction as CAV technology develops.

2.3.3.2. Travel cost of CAV private car. CAV private car travel cost consists of car purchase cost and usage cost. For purchase cost, we split it into base cost for the vehicle and added cost for vehicle automation (Shabanpour et al., 2018). This added cost will reduce as CAV technology develops, and we use a learning curve to define this reduction effect (Nieuwenhuijsen et al., 2018). To calculate cost per trip, the purchase is divided by the number of trips over a car's lifespan. For usage cost, the per trip cost will reduce up to a certain extent as CAV technology develops, e.g., by reducing fuel, insurance and maintenance costs (Bösch et al., 2018). The same learning curve is also used to define this reduction effect. Hence:

$$tc_{pc} = \frac{pc_{pc}}{lt_{pc}} + uc_{pc} \tag{13}$$

where tc_{pc} is CAV private car travel cost; pc_{pc} is CAV private car purchase cost; lt_{pc} is a constant of number of trips over its lifespan; and uc_{pc} is the usage cost per trip.

$$pc_{pc} = pc_{n-cav} + apci * \left(\frac{TA}{TAi}\right)^{-le} \tag{14}$$

where $pc_{n\text{-}cav}$ is a constant of base purchase cost of the vehicle, i.e., purchase cost of a conventional car; $apci$ is a constant of initial added cost for vehicle automation in 2020; TAi is initial CAV technology advance in 2020; and le is a constant of the learning elasticity which defines the rate of cost reduction by technology advance.

$$uc_{pc} = uci_{pc} * \left(1 - ta_{pc-uc}\right) \tag{15}$$

where uci_{pc} is a constant of initial CAV private car usage cost in 2020; $ta_{pc\text{-}uc}$ is the cost reduction as CAV technology develops.

$$ta_{pc-uc} = eta_{pc-uc} * \left(1 - \left(\frac{TA}{TAi}\right)^{-le}\right) \tag{16}$$

where $eta_{pc\text{-}uc}$ is a constant of the maximum CAV private car usage cost reduction extent that can be achieved with CAV technology advance.

2.3.3.3. Travel time of CAV car/ride sharing. Travel time of CAV car/ride sharing consists of in-vehicle time and waiting time. Both the in-vehicle time and waiting time will be affected by network speed change in the same way as expressed in Eq (10). Only waiting time will be affected by CAV technology advance, e.g., through optimised service planning. We assume the waiting time reduction is up to a certain extent and the marginal reduction effect decreases as CAV technology develops. Hence:

$$tt_{cs} = ivt_{cs} + wt_{cs} \tag{17}$$

where tt_{cs} is CAV car/ride sharing travel time; ivt_{cs} is the in-vehicle time; and wt_{cs} is the waiting time.

$$ivt_{cs} = ivti_{cs} * \frac{nsi}{ns} \tag{18}$$

where $ivti_{cs}$ is a constant of initial CAV car/ride sharing in-vehicle time in 2020.

$$wt_{cs} = wti_{cs} * \frac{nsi}{ns} * (1 - ta_{cs-wt}) \tag{19}$$

where wti_{pc} is a constant of initial CAV car/ride sharing waiting time in 2020, $ta_{cs\text{-}wt}$ is reduction in waiting time as CAV technology develops.

$$ta_{cs-wt} = eta_{cs-wt} * TA^{pta_{cs-wt}} \tag{20}$$

where $eta_{cs\text{-}wt}$ is a constant of the maximum waiting time reduction extent that can be achieved with CAV technology advance; $pta_{cs\text{-}wt}$ is a constant of the power that TA is raised to, with a value between 0 and 1, to simulate the decrease of marginal time reduction as CAV technology develops.

2.3.3.4. Travel cost of CAV car/ride sharing. CAV car/ride sharing travel cost will reduce up to a certain extent as CAV technology advances. We use the same learning curve as used for CAV private car travel cost to define the reduction rate. The cost will also reduce up to a certain extent as number of users grows, and we assume the marginal reduction effect decreases as number of users grows. Hence:

$$tc_{cs} = tci_{cs} * (1 - ta_{cs-tc}) * (1 - un_{cs-tc}) \tag{21}$$

where tc_{cs} is CAV car/ride sharing travel cost; tci_{cs} is a constant of initial travel cost in 2020; $ta_{cs\text{-}tc}$ is the cost reduction as CAV technology develops; $un_{cs\text{-}tc}$ is the cost reduction as CAV car/ride sharing user number grows.

$$ta_{cs-tc} = eta_{cs-tc} * \left(1 - \left(\frac{TA}{TAi}\right)^{-le}\right) \tag{22}$$

where $eta_{cs\text{-}tc}$ is a constant of the maximum CAV car/ride sharing travel cost reduction extent that can be achieved with CAV technology advance.

$$un_{cs-tc} = eun_{cs-tc} * \left(\frac{UN_{cs}}{pop}\right)^{pun_{cs-tc}} \quad (23)$$

where $eun_{cs\text{-}tc}$ is a constant of the maximum CAV car/ride sharing travel cost reduction extent that can be achieved with user number growth; UN_{cs} is number of CAV car/ride sharing users; pop is a constant of the total modelling population; $pun_{cs\text{-}tc}$ is a constant of the power that the user share is raised to, with a value between 0 and 1, to simulate the decrease of marginal cost reduction as user number grows.

2.3.3.5. Travel time of CAV bus. Travel time of CAV bus consists of in-vehicle time, waiting time and walking time to/from bus stops. Both the in-vehicle time and waiting time will be affected by network speed change in the same way as expressed in Eq (10). Both waiting time and walking time will be reduced up to a certain extent by CAV technology advance, e.g., through optimised service planning and on-demand bus service. Hence:

$$tt_{pt} = ivt_{pt} + wt_{pt} + wk_{pt} \quad (24)$$

where tt_{pt} is CAV bus travel time; ivt_{pt} is the in-vehicle time; wt_{pt} is the waiting time, and wk_{pt} is walking time to/from bus stops

$$ivt_{pt} = ivti_{pt} * \frac{nsi}{ns} \quad (25)$$

where $ivti_{pt}$ is a constant of initial CAV bus in-vehicle time in 2020.

$$wt_{pt} = wti_{pt} * \frac{nsi}{ns} * \left(1 - ta_{pt-wt}\right) \quad (26)$$

$$wk_{pt} = wki_{pt} * \left(1 - ta_{pt-wk}\right) \quad (27)$$

where wti_{pt} and wki_{pt} are constants of initial CAV bus waiting time and walking time in 2020, $ta_{pt\text{-}wt}$ and $ta_{pt\text{-}wk}$ are reductions in waiting time and walking time as CAV technology develops.

$$ta_{pt-wt} = eta_{pt-wt} * TA^{pta_{pt-wt}} \quad (28)$$

$$ta_{pt-wk} = eta_{pt-wk} * TA^{pta_{pt-wk}} \quad (29)$$

where $eta_{pt\text{-}wt}$ and $eta_{pt\text{-}wk}$ are constants of maximum waiting time and walking time reduction extents that can be achieved with CAV technology advance; $pta_{pt\text{-}wt}$ and $pta_{pt\text{-}wk}$ are constants of powers that TA is raised to, with a value between 0 and 1, to simulate the decrease of marginal time reductions as CAV technology develops.

2.3.3.6. Travel cost of CAV bus. CAV bus travel cost will reduce up to a certain extent as CAV technology advances, with reduction rate defined by the same learning curve used for travel costs of CAV private car and CAV car/ride sharing. The cost will also reduce up to a certain extent as number of users grows, and we assume the marginal reduction effect decreases as number of users grows. Hence:

$$tc_{pt} = tci_{pt} * \left(1 - ta_{pt-tc}\right) * \left(1 - un_{pt-tc}\right) \quad (30)$$

$$ta_{pt-tc} = eta_{pt-tc} * \left(1 - \left(\frac{TA}{TAi}\right)^{-le}\right) \quad (31)$$

$$un_{pt-tc} = eun_{pt-tc} * \left(\frac{UN_{pt}}{pop}\right)^{pun_{pt-tc}} \quad (32)$$

The equations are equivalent to Eq (21), Eq (22) and Eq (23) for travel cost of CAV car/ride sharing, with parameters related to CAV car/ride sharing replaced with parameters related to CAV bus.

2.3.3.7. Travel time of non-CAV option. Weighted average of travel times of non-CAV private cars, non-CAV car/ride sharing and non-CAV bus is used for travel time of non-CAV option. Components of travel times of non-CAV modes are the same as their CAV counterparts. Given the much smaller proportions of people who use cycling, walking and/or rail as main travel modes in the UK (Department for Transport, 2021a), and the complications in calculating their utilities, we did not include them when calculating utility of the non-CAV option. Hence:

$$tt_{n-cav} = w_{n-pc} * tt_{n-pc} + w_{n-cs} * tt_{n-cs} + w_{n-pt} * tt_{n-pt} \quad (33)$$

where $tt_{n\text{-}cav}$ is travel time of non-CAV option; $tt_{n\text{-}pc}$, $tt_{n\text{-}cs}$ and $tt_{n\text{-}pt}$ are travel time of non-CAV private cars, non-CAV car/ride sharing and non-CAV bus; and $w_{n\text{-}pc}$, $w_{n\text{-}cs}$ and $w_{n\text{-}pt}$ are constants of weights applied to them.

$$tt_{n-pc} = ivti_{n-pc} * \frac{nsi}{ns} + pti_{n-pc} \quad (34)$$

where $ivti_{n\text{-}pc}$ and $pti_{n\text{-}pc}$ are constants of initial non-CAV private car in-vehicle time and parking time.

$$tt_{n-cs} = \left(ivti_{n-cs} + wti_{n-cs}\right) * \frac{nsi}{ns} \quad (35)$$

where $ivti_{n\text{-}cs}$ and $wti_{n\text{-}cs}$ are constants of initial non-CAV car/ride sharing in-vehicle time and waiting time.

$$tt_{n-pt} = \left(ivti_{n-pt} + wti_{n-pt}\right) * \frac{nsi}{ns} + wki_{n-pt} \quad (36)$$

where $ivti_{n\text{-}pt}$, $wti_{n\text{-}pt}$ and $wki_{n\text{-}pt}$ are constants of initial non-CAV bus in-vehicle time, waiting time and walking time to/from bus stops.

2.3.3.8. Travel cost of non-CAV option. Weighted average of travel costs of non-CAV private cars, non-CAV car/ride sharing and non-CAV bus is used for travel cost of non-CAV option. Since the cost components of these non-CAV modes will not be affected by CAV technology advance, and users shares of car/ride sharing and bus are relatively small (Department for Transport for London, 2022) which means variations in their user numbers will be small and are unlikely to affect travel costs very much, constant values are used for their travel costs in the model. Hence:

$$tc_{n-cav} = w_{n-pc} * tc_{n-pc} + w_{n-cs} * tc_{n-cs} + w_{n-pt} * tc_{n-pt} \quad (37)$$

where $tc_{n\text{-}cav}$ is travel cost of non-CAV option; and $tc_{n\text{-}pc}$, $tc_{n\text{-}cs}$ and $tc_{n\text{-}pt}$ are constants of travel costs of non-CAV private cars, non-CAV car/ride sharing and non-CAV bus.

2.3.4. CAV technology advance

In our SD model, CAV technology advance is a dimensionless variable with 0 means no CAV technology and 1 means the most advanced technology achievable. The technology advance starts from an assumed initial level of 0.1 in 2020 and accumulates overtime depending on the rate of technology development. The rate of technology development is determined by R&D investment and knowledge transfer from investment.

We assume an initial R&D investment per year and it will increase as number of CAV users grows. The increases by user numbers are different for the three CAV modes, since user numbers that can be served per vehicle are different for the three modes. We also assume marginal investment increase per user reduces as number of users grows. The R&D investment converts to CAV technology advance through knowledge transfer, i.e., increase in CAV technology advance per unit R&D investment (Nieuwenhuijsen et al., 2018).

Finally, the rate of technology development is multiplied by technology gap, which can be expressed as (1 – technology advance). This means that when technology gets more matured, it requires more knowledge to make per unit increase in technology advance (Nieuwenhuijsen et al., 2018). Hence:

$$TA = \int r_{ta} \tag{38}$$

$$r_{ta} = \left(rdi + rd_{pc} + rd_{cs} + rd_{pt}\right) * kt * (1 - TA) \tag{39}$$

where r_{ta} is rate of technology development per year; rdi is a constant of the base R&D investment per year, rd_{pc}, rd_{cs} and rd_{pt} are additional R&D investments per year from the markets of CAV private car, CAV car/ride sharing and CAV bus respectively; kt is knowledge transfer.

$$rd_{pc} = mrd_{pc} * \left(\frac{UN_{pc}}{pop}\right)^{pun_{pc-rd}} \tag{40}$$

$$rd_{cs} = mrd_{cs} * \left(\frac{UN_{cs}}{pop}\right)^{pun_{cs-rd}} \tag{41}$$

$$rd_{pt} = mrd_{pt} * \left(\frac{UN_{pt}}{pop}\right)^{pun_{pt-rd}} \tag{42}$$

where mrd_{pc}, mrd_{cs} and mrd_{pt} are constants of the maximum additional R&D investments per year from the markets of CAV private car, CAV car/ride sharing and CAV bus respectively, when they each has 100% market penetration; $pun_{cs\text{-}rd}$, $pun_{cs\text{-}rd}$ and $pun_{cs\text{-}rd}$ are constants of the powers that the user share is raised to, with a value between 0 and 1, to simulate the decrease of marginal investment increase per user as user number grows.

2.3.5. CAV road network impacts

2.3.5.1. Vehicle fleet size. Vehicle fleet size, including CAVs and non-CAVs, is determined by number of users of each of the four option modes, and number of users that each vehicle can serve in each option mode. Hence:

$$fs_{all} = \sum fs_i \tag{43}$$

where fs_{all} is total vehicle fleet size, fs_i is fleet size of option mode i.

$$fs_i = \frac{UN_i}{unp_i} \tag{44}$$

where UN_i is number of users of option mode i, unp_i is a constant of number of users that each vehicle of option mode i can serve.

2.3.5.2. Vehicle mile travelled. Vehicle miles travelled (VMT) is calculated as the ratio compared to the initial level in 2020. According to Wadud et al. (2016), VMT will increase with the diffusion of CAV private cars and CAV car/ride sharing due to travel cost reduction and new users (e.g., the disabled, elderly and children), and on the other hand, decrease due to new mobility services enhanced by CAVs such as car/ride sharing. We also assume that VMT will decrease due to mode shift to CAV buses. The overall VMT increase or decrease will depend on shares of users of the four option modes in total population. Hence:

$$vmt = vmt_{pc-cs} + vmt_{pt} + vmt_{n-cav} \tag{45}$$

where vmt is total VMT as the ratio compared to the initial level in 2020; $vmt_{pc\text{-}cs}$ is VMT from CAV car and CAV car/ride sharing users; vmt_{pt} is VMT from CAV bus users; and $vmt_{n\text{-}cav}$ is VMT from non-CAV users.

$$vmt_{pc-cs} = vmtc_{pc-cs} * \frac{UN_{pc} + UN_{cs}}{pop} * \left(1 - vmtc_{cs} * \frac{UN_{cs}}{UN_{pc} + UN_{cs}}\right) \tag{46}$$

Where $vmtc_{pc\text{-}cs}$ is a constant of the maximum VMT change that CAV private car and CAV car/ride sharing can lead to, i.e., when all users become CAV private car or CAV car/ride sharing users; $vmtc_{cs}$ is a constant of the maximum VMT reduction effect of CAV car/ride sharing.

$$vmt_{pt} = vmtc_{pt} * \frac{UN_{pt}}{pop} \tag{47}$$

where $vmtc_{pt}$ is a constant of the maximum VMT change that CAV bus can lead to.

$$vmt_{n-cav} = \frac{UN_{n-cav}}{pop} \tag{48}$$

2.3.5.3. Network speed and flow. Highways Agency (2002) defines the relationship between network speed and flow on urban roads in typical non-central areas as:

$$ns = 48.5 - 30 * \frac{nf}{1000} \tag{49}$$

where ns is network speed in km/h, and nf is net work flow in vehicle/hour/lane and is capped at 800 (Highways Agency, 2002).

We assume network flow will increase as total vehicle fleet size and VMT increase. Hence:

$$nf = nfi * \frac{fs_{all}}{fsi_{all}} * vmt \tag{50}$$

where nfi is initial network flow in 2020, calculated using the constant of initial network speed and Eq (49); and fsi_{all} is initial total fleet size in 2020, calculated using Eq (43).

2.3.5.4. Traffic accident. Traffic accident is calculated as the ratio compared to the initial level in 2020. CAVs are expected to reduce traffic accidents, since more than 90% of serious vehicle crashes were attributed to human errors (US Department of Transportation, 2018). We assume the reduction effect is linear to percentage of CAVs in total fleet and CAV technology advance. On the other hand, traffic accident will be affected by VMT, i.e., the more vehicles travel, the more traffic accidents are likely to happen, and we also assume a linear relationship between them. Hence:

$$ac = (1 - ar) * vmt \tag{51}$$

where ac is traffic accident as the ratio compared to the initial level in 2020; ar is traffic accident reduction by CAVs.

$$ar = ear * \frac{fs_{cav}}{fs_{all}} * TA \tag{52}$$

where ear is a constant of the maximum accident reduction extent that can be achieved by CAVs, i.e., when all vehicles are CAVs and with the most advanced CAV technology; fs_{cav} is the fleet size of CAVs.

2.3.6. Energy intensity and carbon emission

Energy intensity is calculated as the ratio compared to the initial level in 2020. CAVs have the potential to reduce transport energy intensity by e.g., automated eco-driving, platooning, right-sizing of vehicles and de-emphasised performance (Wadud et al., 2016). We assume the reduction effect is linear to percentage of CAVs in total fleet and CAV technology advance. Hence:

$$ei = (1 - er) \tag{53}$$

where ei is energy intensity as the ratio compared to the initial level in 2020; er is energy intensity reduction by CAVs.

$$er = eer * \frac{fs_{cav}}{fs_{all}} * TA \tag{54}$$

where eer is a constant of the maximum energy intensity reduction extent that can be achieved by CAVs, i.e., when all vehicles are CAVs and with the most advanced CAV technology.

Carbon emission is also calculated as the ratio compared to the initial level in 2020. Schipper (2002) defined four major drivers of transport carbon emissions as activity level, modal share, energy intensity and fuel carbon content. Since activity level and modal share combined can be represented by VMT (Wadud et al., 2016), and fuel carbon content is exogenous to the model and not addressed in this study, carbon emission is calculated by:

$$ce = vmt * ei \tag{55}$$

where *ce* is carbon emission.

2.4. Scenario design and key indicators

Six intervention scenarios, in addition to the base scenario, were designed to explore the effects of R&D investment, marketing and training campaigns, which are intended to stimulate CAV technology development and public acceptance; and the effects of policies to boost utilities of CAVs of different modes, which are intended to stimulate CAV adoption and will affect CAV mode share. The six intervention scenarios are.

- R&D investment increase: more R&D investment to accelerate CAV technology development.
- Marketing campaign: more marketing activities to promote the exposure and attractiveness of CAVs to the public, in particular, to the innovators and early adopters.
- Training campaign: more training activities to enhance people's familiarity to CAVs and confidence in using them, when they need to imitate the rest of the society.
- CAV overall boost: policy interventions to support the use of all CAVs, e,g., subsidies and road priority for all CAV use, aiming to stimulate the diffusion of all CAVs regardless of mode.
- CAV shared mobility boost: policy interventions to support the use of shared CAVs and CAV public transport, e,g., subsidies and road priority for their use, aiming to stimulate the diffusion of shared CAVs for sustainability.
- CAV public transport boost: policy interventions to support the use of CAV public transport, e,g., subsidies and road priority for its use, and discourage the use of private CAVs, aiming to stimulate sustainable diffusion of CAVs in a more radical approach.

Table 1 lists the six intervention scenarios and changes in some model variables to simulate interventions taken in each scenario. These changes were specified to reflect intended effects of the interventions, relative to the settings in the base scenario with reasonable variation scales.

Indicators calculated in the model and used to assess the success of CAV diffusion and effectiveness of interventions include number of CAV users, CAV fleet size and CAV market penetration. The model also calculates indicators that reflect wider impacts of CAVs. These indicators include average travel time and average travel cost for the whole population, total carbon emission and total traffic accidents, which are related to the Sustainable Urban Mobility Indicators developed by European Commission (2020), e.g., commuting travel time, affordability of public transport, congestion and delays, energy efficiency, greenhouse gas emissions and road deaths. Table 2 lists these indicators.

3. Results

3.1. CAV diffusion

3.1.1. CAV diffusion in the base, training, marketing and investment scenarios

Fig. 2 shows CAV diffusion in terms of user numbers over the simulation period, i.e., numbers of CAV private car, CAV car/ride sharing and CAV bus users, and percentage of CAV users in total population. In the base scenario, users of all modes grow slowly in the first 15 years, and then experience a rapid growth from 2035 to 2055. This is the period when the imitation effect becomes the dominant and powerful driver of user acceptance, i.e., when there are enough CAV users to influence non-users and the number of non-users is still large. The growth slows down from around 2052, and percentage of CAV users in total population reaches the saturate level of 98% in around 2057.

CAV private car is the dominant mode with 56.13 million users by 2070, accounting for 84% of the total population. Numbers of CAV car/ride sharing and CAV bus users reach their maximum of 4.45 million and 9.14 million in 2053, and then decline to 3.21 million and 6.43 million in 2070. The declines are due to the setting in the SD model that CAV car/ride sharing and CAV bus users are more likely to reconsider their choices than CAV private car users. This is further discussed in Section 3.3.2.

While marketing campaign and investment increase do not make much difference, training campaign accelerates CAV user growth from 2035, researching the saturate level of 98% earlier in around 2052. This is in line with the typical innovation diffusion pattern that the imitation effect is the main driver of diffusion, since usually only a small

Table 2
Indicators of CAV diffusion and CAV impacts.

CAV diffusion indicators	CAV impact indicators
Number of CAV private car users	Average travel time
Number of CAV car/ride sharing users	Average travel cost
Number of CAV bus users	Carbon emission
Percentage of CAV users in total population	Traffic accident
Fleet size of CAVs	
Percentage of CAVs in total vehicle fleet	

Table 1
The six intervention scenarios and changes in model variables.

	Training activity intensity	Marketing activity intensity	R&D investment	CAV private car travel cost	CAV private car travel time	CAV car/ride sharing travel cost	CAV car/ride sharing travel time	CAV bus travel cost	CAV bus travel time
Training campaign	+1	0	0	0	0	0	0	0	0
Marketing campaign	0	+1	0	0	0	0	0	0	0
R&D investment increase	0	0	+£1.2 billion/year	0	0	0	0	0	0
CAV overall boost	0	0	0	-£0.5/trip	−1.5 min/trip	-£0.5/trip	−1.5 min/trip	-£0.25/trip	−5 min/trip
CAV shared mobility boost	0	0	0	0	0	-£3/trip	−2 min/trip	-£0.5/trip	−10 min/trip
CAV public transport boost	0	0	0	+£2/trip	+3 min/trip	0	0	-£1/trip	−15 min/trip

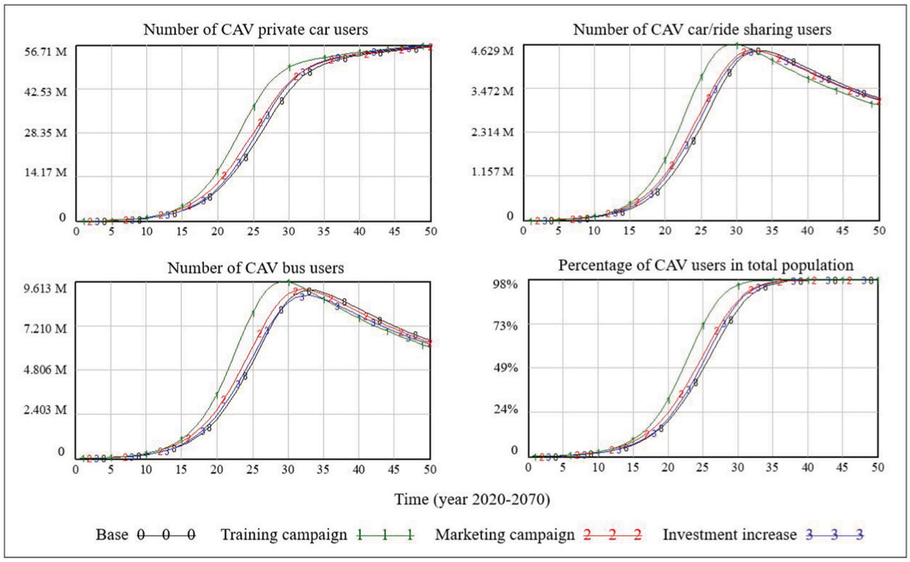

Fig. 2. Numbers of CAV private car, CAV car/ride sharing and CAV bus users and percentage of CAV users in total population in the base, training, marketing and investment scenarios.

proportion of the population are innovators (Rogers, 2010). This indicates that preparing the general public to be ready for CAV is important for CAV diffusion.

Fig. 3 shows CAV diffusion in terms of fleet sizes over the simulation period, i.e., fleet size of CAVs, fleet size of total vehicles and percentage of CAVs in total vehicle fleet. Fleet size of CAVs reflects the growth pattern of CAV users, in particular, CAV private car users, since CAV car/ride sharing and CAV bus serve much more users per vehicle. In the base, marketing campaign and investment increase scenarios, fleet size of CAVs reaches around 34 million after a rapid growth from 2035 to 2055 due to rapid CAV diffusion. It continues to grow at a reduced rate after 2055 and reaches 37.5 million in 2070. This is because many CAV car/ride sharing and CAV bus users switch to private cars from 2055. In the training campaign scenario, fleet size of CAV reaches 34 million earlier in 2051, but it also ends up at around 37.5 million in 2070.

Fleet size of total vehicles remains largely unchanged at around 35 million in all the four scenarios till 2050. This is because mode share among new CAV users remains similar to the initial non-CAV mode share during this period, making the user-vehicle ratio largely unchanged at total fleet level. The fleet size then increases steadily to around 38 million in 2070, as many CAV car/ride sharing and CAV bus users switch to CAV private cars.

Percentage of CAVs in total vehicles mirrors the pattern of percentage of CAV users in total population, reaching the saturate level of 98% in around 2052 in the training campaign scenario and around 2057 in the other three scenarios.

3.1.2. *CAV diffusion in the base and CAV boost scenarios*

Fig. 4 shows numbers of CAV private car, CAV car/ride sharing and CAV bus users and percentage of CAV users in total population in the base and the three CAV boost scenarios. The overall boost does not show a clear impact on user choice, since utilities of all the three modes are improved in a balanced manner and hence probability of choosing among them are not very much affected. CAV shared mobility boost, with which utilities of CAV car/ride sharing and CAV bus are improved while CAV private car is unaffected, sees CAV private car users reduce to 49.67 million in 2070 as compared to 56.13 million in the base scenario, and CAV car/ride sharing and CAV bus users increase to 5.89 million and 9.96 million in 2070 as compared to 3.21 million and 6.43 million respectively in the base scenario. CAV public transport boost, with which utilities of CAV private car is reduced and CAV bus is further improved, sees CAV private car users reduce to 40.49 million in 2070,

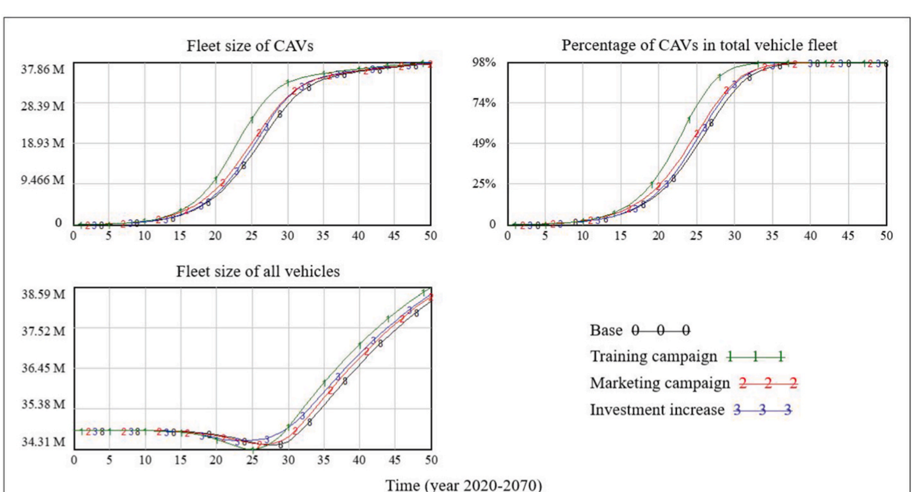

Fig. 3. Fleet size of CAVs, fleet size of total vehicles and percentage of CAVs in total vehicle fleet in the base, training, marketing, and investment scenarios.

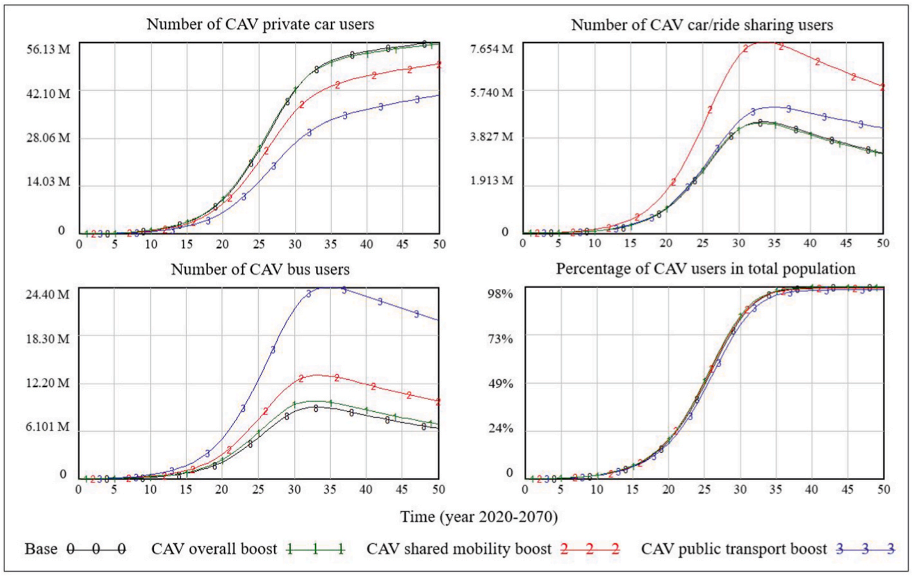

Fig. 4. Numbers of CAV private car, CAV car/ride sharing and CAV bus users and percentage of CAV users in total population in the base and CAV boost scenarios.

CAV car/ride sharing users increase slightly to 4.22 million in 2070, while CAV bus users experience a large increase to 20.21 million in 2070.

The growth patterns of CAV users in the three CAV boost scenarios however remain the same as those in the base scenario, i.e., while number of CAV private car users continues to grow after 2053 although at a reduced rate, numbers of CAV car/ride sharing and CAV bus users reach their maximum in 2053 and then start to decline. In total, percentage of CAV users in total population sees largely the same growth curves in the three CAV boost scenarios as in the base scenario, reaching the saturate level of 98% in around 2057.

Fig. 5 shows fleet size of CAVs, fleet size of total vehicles and percentage of CAVs in total vehicle fleet in the base and the three CAV boost scenarios. Fleet size of CAVs in the CAV overall boost scenario is similar to that in the base scenario, reaching 33.55 million after a rapid growth from 2035 to 2055 due to rapid CAV diffusion, and then continuing to grow to 37.16 million in 2070. Fleet size of CAVs is smaller in the CAV shared mobility boost and CAV public transport boost scenarios, reaching 28.93 million and 22.38 million in 2055, and 33.21 million and 27.11 million in 2070 respectively.

Fleet size of total vehicles in the CAV overall boost scenario is again similar to that in the base scenario. It sees some reductions in the CAV shared mobility and public transport boost scenarios, ending at 34.09 million and 28.30 million respectively in 2070, which are both lower than the initial size of 34.81 million in 2020.

Percentages of CAVs in total vehicle fleet in the CAV overall boost and CAV shared mobility boost scenarios are similar to the base scenario, and mirror the pattern of percentage of CAV users in total population, reaching the saturate level of 98% in around 2057. The percentage is slightly lower in the CAV public transport boost scenario, reaching the saturate level of 96% in around 2060.

3.2. CAV impacts

3.2.1. CAV impacts in the base, training, marketing and investment scenarios

Fig. 6 shows key CAV impacts calculated in this study, i.e., average travel time, average travel cost, total carbon emission and total traffic

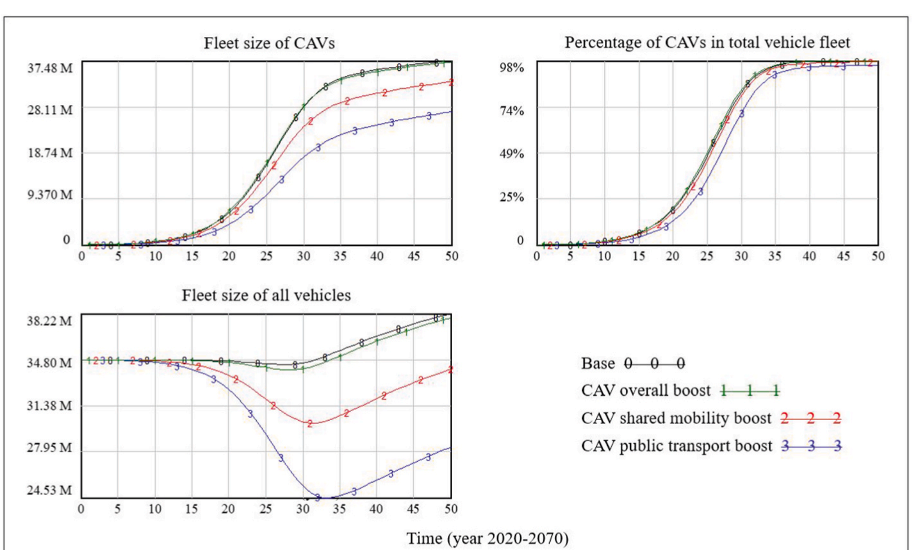

Fig. 5. Fleet size of CAVs, fleet size of total vehicles and percentage of CAVs in total vehicle fleet in the base and CAV boost scenarios.

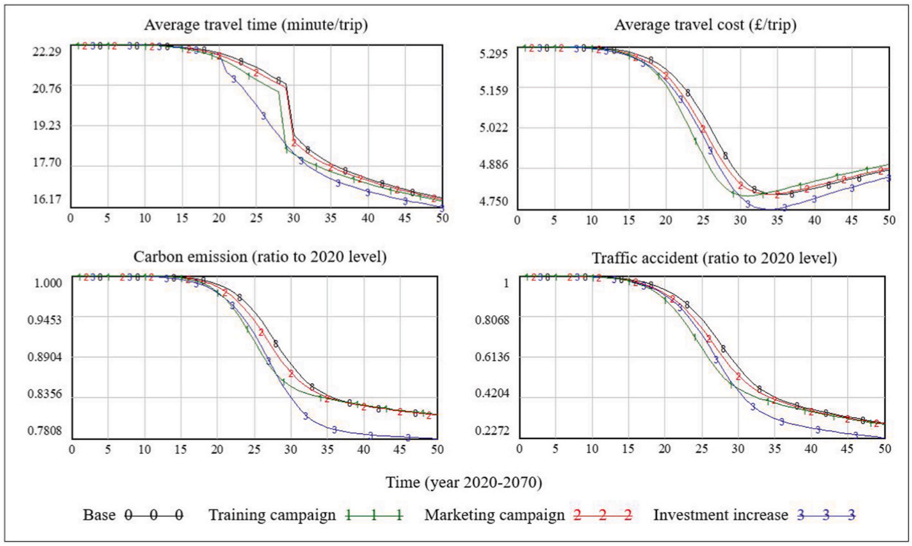

Fig. 6. Average travel time, average travel cost, carbon emission and traffic accidents in the base, training, marketing and investment scenarios.

accidents in the base, training, marketing and investment scenarios. Average travel time remains largely constantly at around 22.3 min/trip in the first 20 years in all the four scenarios. It starts to reduce from 2040, with a rapid drop from around 20.5 to 18.5 min/trip over 2049 to 2050 in the base, marketing and training scenarios. This is caused by the availability of self-parking function of CAVs which reduces CAV private car parking time. The reduction is smoother in the investment scenario where the self-parking function was achieved earlier when number of CAV private car users is not yet dominant, and hence the sudden parking time reduction only gradually becomes obvious over the 10 years from 2020 to 2030 during which number of CAV private car users enjoys a rapid growth. By 2070, average travel time drops to around 16.5 min/trip in all the four scenarios.

Average travel cost is similar across the four scenarios. It remains constant at around £5.30/trip during the first 15 years, and then drops to £4.8/trip in around 2053. The drop over this period is due to the continuous reductions of travel costs of CAV private car, CAV car/ride sharing and CAV bus, and the rapid growths of their users. After that, average travel cost grows slowly to around £4.90/trip in 2070 in all the four scenarios. The growth is due to many CAV car/ride sharing and CAV bus users shifting to CAV private cars of which the travel cost is higher.

Carbon emission decreases over the simulation period in all the four scenarios. The reduction mainly occurs during the 15 years from 2040 to 2055 when rapid CAV diffusion occurs. By 2070, carbon emission reduces to 0.81 in the base, marketing and training scenarios, and further to 0.78 in the investment scenario, as a result of higher CAV technological advance that further reduces CAV energy intensity.

Traffic accident also reduces in an inverse S-shape pattern, following the S-shaped CAV diffusion, and the effects of marketing campaign, training campaign and R&D investment increase are similar to those on carbon emission. Traffic accident reduces to 0.30 in the base, marketing and training scenarios, and further to 0.23 in the investment scenario.

3.2.2. CAV impacts in the base and CAV boost scenarios

Fig. 7 shows the key CAV impacts in the base and the three CAV boost scenarios. Average travel time shows a similar reduction pattern as described in section 3.2.1 but with more variation across scenarios due to larger differences in numbers of users of different option modes. As a result, average travel time in 2070 is shortest in the CAV overall boost

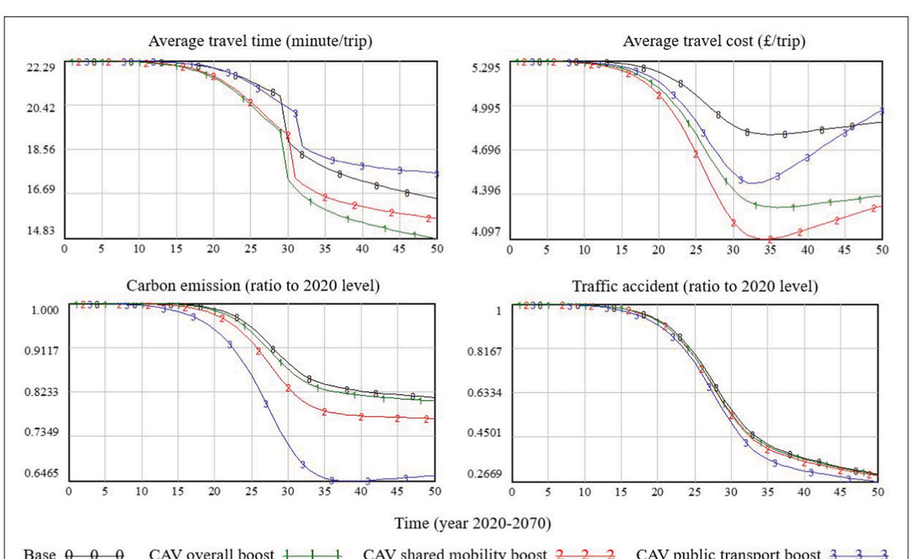

Fig. 7. Average travel time, average travel cost, carbon emission and traffic accidents in the base and CAV boost scenarios.

scenario (14.8 min/trip) and longest in the CAV public transport boost scenario (17.6 min/trip).

Similarly, reductions in travel cost vary across the scenarios. The CAV shared mobility boost scenario sees the largest reduction, reaching the lowest cost of £4.10/trip in 2054, £0.70 lower than the lowest in the base scenario. Noticeably, due to increased travel cost of CAV private car in the CAV public transport boost scenario, the scenario sees a much steeper increase in travel cost from around 2052 as shifts to CAV private car increase. As a result, average travel cost increased to £5.00/trip in 2070 in this scenario, £0.1 higher than that in the base scanrios.

Larger variation is also seen for carbon emission reduction. With more people using public transport, the CAV public transport boost scenario sees the largest reduction to 0.66 in 2070, compared to 0.81 in the base scenario. Reductions in traffic accidents remain similar across the four scenarios.

3.3. Sensitivity tests

Many of the results in Sections 3.1 and 3.2 are sensitive to the values of constants used in the SD model. Since many of the constant values were based on literature and assumptions (see Appendix), and there is currently little CAV usage data available for calibration, the SD model was subjected to sensitivity tests. To do the tests, each of all model constant was varied univariately by ±20%, which is a commonly applied range for sensitivity test (Sterman, 2000), and changes in four key output variables, i.e., Number of CAV private car users, Number of CAV car/ride sharing users, Number of CAV bus users and Carbon emission, were recorded. These sensitivity tests were conducted in the context of the base scenario.

3.3.1. Overall test results

Table 3 shows sensitive results where the ±20% change in a constant causes noticeable changes in any of the four key output variables. Numbers of CAV users of all modes are sensitive to the base imitation coefficient q. This further highlights the importance of improving public acceptance of and readiness for CAVs in accelerating CAV diffusion.

Numbers of CAV car/ride sharing users and CAV bus users are sensitive to some constants that affect travel time and travel cost of different options. This raises concerns on the robustness of the modelling results on mode share, but on the other hand, indicates the potential of policy interventions on travel time and travel cost to promote more sustainable mode share. Number of CAV private car users, which accounts for the majority of the total population, is not sensitive to these constants, hence modelling results on overall CAV diffusion is more robust.

Numbers of CAV car/ride sharing users and CAV bus users are also sensitive to percentages of users reconsidering choice every year. This is discussed in more detail in Section 3.3.2.

Carbon emission is sensitive to *eer,* the maximum energy intensity reduction *extent*, and to $vmt_{pc\text{-}cs}$, the maximum VMT change that CAV private car and CAV car/ride sharing can lead to. Since there are still uncertainties on these constants, the modelling results on carbon emission need to be used with caution.

3.3.2. Sensitivity to user reconsideration

In this SD model, we assume that every year, 1% of CAV private car users and 5% of CAV car/ride sharing and CAV bus users will reconsider their choice. This leads to declines in number of CAV car/ride sharing users and CAV bus users in the later stage of the simulated period. This is because as the cumulative numbers of their users increases, the numbers of their users reconsidering choice also increase, and only a small proportion of them will return to these two modes since the utility of CAV private car is constantly higher. On the other hand, number of potential new users is decreasing. So from a certain time point, cumulative numbers of CAV car/ride sharing users and CAV bus users start to decrease. With an extended simulation period of 200 years (2020–2220), it shows that an equilibrium will be reached around 2170 in the base scenario, with numbers of CAV private car users, CAV car/ride sharing users and CAV bus users settling down at 61.66 million, 1.56 million and 2.86 million respectively.

To further understand the impacts of this reconsideration setting, we tested four more different settings: a. 1% for CAV private car, 2% for CAV car/ride sharing and CAV bus; b. All 5%; c. All 1%; d. All 0%.

Table 3
Results of sensitivity tests where changes in input constants cause noticeable changes in key output variables.

Constants	Sensitivity test input constant base values	Changes in key output variables			
		Number of CAV private car users	Number of CAV car/ride sharing users	Number of CAV bus users	Carbon emission
Base imitation coefficient (q)	0.341865	−27%–15%	−26%–10%	−26%–11%	
Initial CAV bus in-vehicle time ($ivti_{pt}$)	29 min/trip			−20%–24%	
Initial CAV car/ride sharing in-vehicle time ($ivti_{cs}$)	11.86 min/trip		−11%–12%		
Initial CAV car/ride sharing travel cost (tci_{cs})	£8.536/trip		−19%–24%		
Initial CAV private car in-vehicle time ($ivti_{pc}$)	11.86 min/trip		−8%–9%	−9%–9%	
Initial CAV private car usage cost (uci_{pc})	£5.2/trip		−16%–18%	−16%–19%	
Percentage of CAV bus users reconsider choice (rc_{pt})	5%/year			−15%–18%	
Percentage of CAV car/ride sharing users reconsider choice (rc_{cs})	5%/year		−15%–19%		
The maximum CAV car/ride sharing travel cost reduction extent that can be achieved with CAV technology advance ($eta_{cs\text{-}tc}$)	60%		−10%–11%		
The maximum energy intensity reduction extent that can be achieved by CAVs (eer)	43%				−12%–12%
The maximum VMT change that CAV private car and CAV car/ride sharing can lead to ($vmt_{pc\text{-}cs}$)	1.42				−20%–20%

Results are shown in Fig. 8. It shows that with a reduced reconsideration rate of 2%, declines of numbers of CAV car/ride sharing and CAV bus users slow down a lot. With equal reconsideration rate as CAV private car users, the declines are avoided. The implication is that, to achieve sustainable mode share more effectively, apart from enhancing utilities of sustainable modes, it is also important to build loyalty of their users, e.g., by introducing customer loyalty programmes.

3.4. Results summary

The simulation results suggest that without interventions, i.e., in the base scenario, number of CAV users will start to increase rapidly from around 2035, and reaches a saturation level of 98% of the total population of 67.22 million in the UK in around 2057. Among these CAV users, more than 80% are CAV private car users. Fleet size of CAVs reaches 37.5 million in 2070, which is also 98% of total vehicles. Training campaign, which prepares the general public to be ready for CAVs and encourages their decisions to imitate the emerging norms, accelerates CAV diffusion, and the market saturation of 98% is researched earlier in 2052. Marketing campaign, which enhances early adopters' desire to innovate regardless of the rest of the society, and R&D investment increase, which accelerates CAV technology development, do not make much difference to the diffusion process. The three CAV boost interventions do not make much difference to user penetration. They do change the shares of the three CAV modes and hence fleet size of CAVs and fleet penetration. In particular, with CAV public transport boost, fleet size of CAVs reaches only 27.1 million, accounting for 96% of total vehicles.

Regarding the wider impacts of CAVs, average travel time and average travel cost reduce from 22.3 min and £5.3 per trip in 2020 to 16.5 min and £4.9 per trip in 2070 in the base scenario. Carbon emission reduces by 19% and traffic accidents reduces by 70%. Training and marketing campaigns that enhance user acceptance rate do not make much difference to these CAV impacts. R&D investment increase which enhances CAV technology advance further reduces carbon emission and traffic accidents by small percentages. The three CAV boost interventions have stronger effects on CAV impacts. In particular, in the CAV public transport boost scenario, with higher shares of bus and car/ride sharing users, carbon emission reduces by 34% in 2070.

4. Discussion and policy recommendations

As shown in our results, CAV diffusion will be very slow in the beginning (Figs. 2–5). This is partly because CAV technology is not mature enough in the beginning and hence utility of CAVs is not particularly high, but more importantly, most people would be reluctant to accept radical innovations and changes (Othman, 2021; Rogers, 2010). Marketing activities especially advertising that encourages people's desire to innovate, e.g., by inspiring their technological motivation and/or responds to their environmental concern, would be most effective in the early stage of innovation diffusion to encourage the innovators and early adopters to accept and adopt CAVs. These people as CAV users can then influence the rest majority of the population. However, as shown in our results, effects of such interventions on overall CAV diffusion are unlikely to be strong (Figs. 2 and 3), since imitation effect, instead of innovation effect, is the main driver of innovation adoption according to the Bass diffusion theory (Bass, 1969).

To stimulate the imitation effect and accelerate CAV diffusion, i.e., to encourage the rest majority of the population to follow existing CAV users and the emerging social norms, it would be very helpful to provide training programmes and organise education campaigns to develop people's trust and familiarity to CAVs, as well as to relevant infrastructure, services, rules and regulations, so they can feel confident and comfortable to try CAVs when they need to imitate the others (Kaur and Rampersad, 2018; Liu et al., 2019b).

Promoting shared CAVs and CAV public transport will reduce fleet size of CAVs (Fig. 5), which from certain perspectives discourages CAV diffusion. However, this is unlikely to reduce or delay CAV market penetration very much in terms of percentage of CAV users in total population and percentage of CAVs in total fleet (Figs. 4 and 5). On the other hand, promoting shared CAVs and CAV public transport contributes to more sustainable mobility with larger reductions in carbon emission (Fig. 7). The extents of fleet size and carbon emission reductions will depend on policy intensity. Comparing our base and the most radical scenarios, 27.7% reduction in fleet size (37.5 million VS 27.1 million) comes with a benefit of 18.5% reduction in carbon emission (0.81 V S 0.66). Policy makers need to assess whether such trade-off is beneficial for all. With large enough user groups, shared CAVs also have the advantage of lowering travel cost without compromising travel time too much (Fig. 7).

To encourage more people to use shared CAVs and CAV public transport, interventions are needed to enhance their utilities, e.g., by providing subsidies to reduce their travel cost and road priority to reduce their travel time, or on the other hand, implementing restrictions on road use and higher tax for CAV private cars to reduce their utility (Haboucha et al., 2017). As shown in the sensitivity test results, it is also

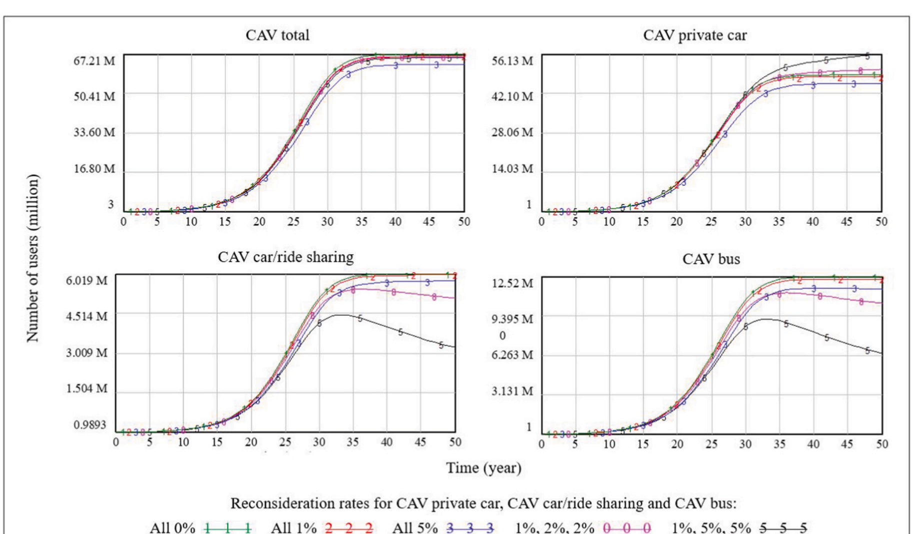

Fig. 8. Numbers of CAV private car, CAV car/ride sharing and CAV bus users in the base scenario with different reconsideration settings.

important to build loyalty of the users of shared CAVs and CAV public transport, e.g., by introducing customer loyalty programmes, to maintain their high mode shares in the long run.

Technology development is critical for achieving these positive impacts. In particular, as shown in our results, without sufficient R&D investment to stimulate technology development, CAVs may not be able to reach their full potential in carbon emission and traffic accident reductions (Fig. 6), despite an almost full market penetration.

5. Conclusions

Using a system dynamics based model and the Bass innovation diffusion theory, this study explored CAV user acceptance and diffusion over time from 2020 to 2070 in the UK, considering choices of CAV private cars, CAV car/ride sharing and CAV buses. The study also included wider mobility impacts of CAV diffusion, and how these in return influence CAV users acceptance and diffusion. A list of indicators for CAV diffusion and CAV impacts were tested in six scenarios in addition to the base scenario, to assess the long-term impacts of possible interventions that are designed to stimulate CAV diffusion and to optimise CAV impacts.

The simulation results suggest that without interventions CAV diffusion will be slow before 2035, and then increase rapidly and reach market saturation of 98% in around 2057. CAV diffusion will lead to reductions in average travel time, average travel cost, carbon emission and traffic accident.

Training campaign that prepares the majority of the population to be ready for CAVs is more effective than marketing campaign in accelerating CAV diffusion. Promoting shared CAVs and CAV public transport can contribute to more sustainable and more affordable mobility with CAVs, although this may lead to smaller CAV market size in terms of CAV sale, and the market size may reduce at a higher rate than sustainability enhancement.

The study however has some limitations. We did not include long-distance travels and competition of CAVs with travel modes such as rail and aviation, and we focused on passenger transport so did not include CAV diffusion in freight transport. These may lead to underestimation of CAV diffusion in our study. Also, not all potential CAV impacts and feedback loops were considered, e.g., impact on labour market and their feedback to public acceptance, and adding them into the SD model may change the simulation results in different directions. Hence, the absolute forecasts should not be seen as the primary outputs of the study, rather, it is the comparative analysis of the modelled factors of interest that is most useful. Moreover, like most other SD models, if not all, this SD model is based on many assumptions as described in Section 2 and in the appendix, due to lack of existing CAV market data and uncertainties in CAV technology and policy development. Hence, results need to be interpreted and used with caution. Nevertheless, sensitivity tests show that key model behaviours are robust and results are reliable for qualitative policy implications. As more and more CAV data become available, the model can be further calibrated and optimised to improve simulation accuracy.

Authorship statement

Like JIANG: Conceptualization; Methodology; Data curation; Formal analysis; Visualization; Writing - original draft; Writing - review & editing.

Haibo CHEN: Funding acquisition; Project administration; Conceptualization; Methodology; Formal analysis; Writing - review & editing.

Evangelos PASCHALIDIS: Methodology.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix. Model constants

Notation	Constant	Unit	Value	Justification and/or assumption
apci	Initial CAV private car added purchase cost	£	16,330	Adopted from Shabanpour et al. (2018) which used an added purchase price of $20,000 in 2025.
asc_{cs}	Alternate specific constant of CAV car/ride sharing in utility function	Dimensionless	−2.11	Calibrated so that the probabilities of choosing CAV private car, CAV car/ride sharing and CAV bus, with travel time and travel cost at their non-CAV counterparts' levels, are the same as the current share of frequent private car users, taxi and car sharing users and bus users in England. More detail provided in justification for $w_{n\text{-}cs}$, $w_{n\text{-}pc}$ and $w_{n\text{-}pt}$.
$asc_{n\text{-}cav}$	Alternate specific constant of non-CAV option in utility function	Dimensionless	−0.31	Weighted-average of the alternate specific constants for the three CAV options. See $w_{n\text{-}cs}$, $w_{n\text{-}pc}$ and $w_{n\text{-}pt}$ for the weights
asc_{pc}	Alternate specific constant of CAV private car in utility function	Dimensionless	0	CAV private car was modelled as reference option in our model, following the approach in Hensher and Rose (2007).
asc_{pt}	Alternate specific constant of CAV bus in utility function	Dimensionless	−1.12	The same as for asc_{cs}
β_{tc}	Travel cost coefficient in utility function	Dimensionless	−0.2	Adopted from Hensher and Rose (2007)
β_{tt}	Travel cost coefficient in utility function	Dimensionless	−0.04	Adopted from Hensher and Rose (2007)
ear	The maximum accident reduction extent that can be achieved by CAVs	Dimensionless	0.9	According to US Department of Transportation (2018), more than 90% of serious vehicle crashes were attributed to human errors. We hence assume the 90% maximum reduction extent.
eer	The maximum energy intensity reduction extent that can be achieved by CAVs	Dimensionless	0.43	Mid value of energy intensity reduction by CAV through automated eco-driving, platooning, right-sizing of vehicles and de-emphasised performance, estimated in Wadud et al. (2016).
$eta_{cs\text{-}tc}$	The maximum CAV car/ride sharing travel cost reduction extent that can be achieved with CAV technology advance	Dimensionless	0.6	Assumption. Much higher than the 0.2 reduction extent for CAV private car usage cost (see $eta_{pc\text{-}uc}$), since automation can further

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Notation	Constant	Unit	Value	Justification and/or assumption
				reduce driver cost and operation cost for car/ride sharing companies.
$eta_{cs\text{-}wt}$	The maximum waiting time reduction extent that can be achieved with CAV technology advance	Dimensionless	0.2	Assumption
eta_{im}	The extent to which technology advance can enhance imitation effect	Dimensionless	0.3	Assumption
eta_{in}	The extent to which technology advance can enhance innovation effect	Dimensionless	0.3	Assumption
$eta_{pc\text{-}pt}$	The maximum parking time reduction extent that can be achieved with CAV technology advance	Dimensionless	0.8	We assume parking time can only be reduced by up to 80% instead of 100%, since there may still be cases where parking is necessary.
$eta_{pc\text{-}uc}$	The maximum CAV private car usage cost reduction extent that can be achieved with CAV technology advance	Dimensionless	0.2	Possible usage cost reductions with vehicle automation are uncertain, e.g., fule cost −10%, insurance cost −50% (Bösch et al., 2018). We assume that CAV technological advance can reduce CAV PC usage cost by up to 20%.
$eta_{pt\text{-}tc}$	The maximum CAV bus travel cost reduction extent that can be achieved with CAV technology advance	Dimensionless	0.4	We assume the reduction extent is between the extents for CAV private car and CAV bus, since for CAV bus, the reduction from driver cost and operation cost is likely to be smaller than that of CAV car/ride sharing, given the smaller fleet size needed for bus service.
$eta_{pt\text{-}wt}$	The maximum waiting time reduction extent that can be achieved with CAV technology advance	Dimensionless	0.5	Assumption
$eta_{pt\text{-}wk}$	The maximum walking time reduction extent that can be achieved with CAV technology advance	Dimensionless	0.5	Assumption
$eun_{cs\text{-}tc}$	The maximum CAV car/ride sharing travel cost reduction extent that can be achieved with user number growth	Dimensionless	0.25	Assumption
$eun_{pt\text{-}tc}$	The maximum CAV bus travel cost reduction extent that can be achieved with user number growth	Dimensionless	0.25	Assumption
$ivti_{cs}$	Initial CAV car/ride sharing in-vehicle time	Minute/trip	11.86	Calculated based on the 5-mile trip distance and the average speed of 25.3 mph on local 'A' roads in England in 2019 (Department for Transport, 2021b).
$ivti_{n\text{-}cs}$	Initial non-CAV car/ride sharing in-vehicle time	Minute/trip	11.86	The same as $ivti_{cs}$
$ivti_{n\text{-}pc}$	Initial non-CAV private car in-vehicle time	Minute/trip	11.86	The same as $ivti_{cs}$
$ivti_{n\text{-}pt}$	Initial non-CAV bus in vehicle time	Minute/trip	29	According to the buses performance data from Transport for London (2022), average bus speed in Greater London in 2018/19 was 9.3 mph. Given the trip length of 5 miles, of which we assume 0.5 mile is walk to and from bus stops, initial in-vehicle time of CAV bus is 29 min
$ivti_{pc}$	Initial CAV private car in-vehicle time	Minute/trip	11.86	The same as $ivti_{cs}$
$ivti_{pt}$	Initial CAV bus in vehicle time	Minute/trip	29	the same as $ivti_{n\text{-}pt}$
le	learning elasticity	Dimensionless	0.5	Adopted from Nieuwenhuijsen et al. (2018). So with every doubling of technological advance, cost will be reduced by around 30% (1–70.7%).
lt_{pc}	Number of trips over a CAV private car's lifespan	Dimensionless	40,000	Calculated based on the 5-mile trip distance and the average total milage of 200,000 miles of a private car over its lifespan (Ford, 2012).
mrd_{cs}	Maximum R&D investment from CAV car/ride sharing market	£/year	480 million	Given the large number of users per vehicle can serve in the case of car/ride sharing, car sales will drop so R&D investment will be lower than from CAV private car market. We assume 1/5. See mrd_{pc}.
mrd_{pc}	Maximum R&D investment from CAV private car market	£/year	2.4 billion	We assume that when market penetration of CAV private car reaches 100%, R&D investment receives an additional £2.4 billion per year, three times the base level.
mrd_{pt}	Maximum R&D investment from CAV bus market	£/year	240 million	Given the large number of users per bus vehicle can serve, car sales will drop so R&D investment will be lower than from CAV private car market. We assume 1/10.
me	The extent to which marketing can enhance innovation effect	Dimensionless	0.3	Assumption
nsi	Initial network speed in 2020	mph	25.3	Average speed on local 'A' roads in England in 2019 was 25.3 mph (Department for Transport, 2021b).
p	Base innovation coefficient p	Dimensionless	0.001	Adopted from Lavasani et al. (2016)
$pc_{n\text{-}cav}$	Purchase cost of a conventional private car	£	23,185	Average mid size car price in 2021 in the UK is £23,185 (NimbleFins, 2021)
pop	Total population	person	67.22 million	The total UK population in 2020 (World Bank, 2022)
$pta_{cs\text{-}wt}$, $pta_{pc\text{-}pt}$, $pta_{pt\text{-}wt}$, $pta_{pt\text{-}wk}$	The power that CAV technology advance is raised to, to simulate the decrease of marginal time reduction, including CAV car/ride sharing waiting time, CAV private car parking time, CAV bus waiting time and walking time, as CAV technology develops.	Dimensionless	0.5	Assumption
$pti_{n\text{-}pc}$	initial non-CAV private car parking time	Minute/trip	5	Average search time for parking in UK is 7.5 min (INRIX, 2017). Considering there is extra time for access to and egress from parking space, while return trips do not usually need to search for parking, we assume 5 min for parking time.
pti_{pc}	Initial CAV private car parking time in 2020	Minute/trip	5	The same as $pti_{n\text{-}pc}$
$pun_{cs\text{-}rd}$, $pun_{pc\text{-}rd}$, $pun_{pt\text{-}rd}$	Powers that the user share is raised to, to simulate the decrease of marginal investment increase per user from CAV	Dimensionless	0.5	Assumption

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Notation	Constant	Unit	Value	Justification and/or assumption
	car/ride sharing, private car and bus markets, as user number grows			
$pun_{cs\text{-}tc}$, $pun_{pt\text{-}tc}$	Power that user share is raised to, to simulate the decrease of marginal travel cost reductions of CAV car/ride sharing and CAV bus, as user numbers grow.	Dimensionless	0.5	Assumption
q	Base imitation coefficient q	Dimensionless	0.341865	Adopted from Lavasani et al. (2016)
rc_{cs}	Percentage of CAV car/ride sharing users reconsider choice	100%/year	0.05	Assumption
rc_{pc}	Percentage of CAV private car users reconsider choice	100%/year	0.01	Assumption
rc_{pt}	Percentage of CAV bus users reconsider choice	100%/year	0.05	Assumption
rdi	Base R&D investment	£/year	1.2 billion	Estimation based on global investments on CAV over the last 10 years.
$tc_{n\text{-}cs}$	Travel costs of non-CAV car/ride sharing	£/trip	8.536	Given Uber's cost structure of £1.35 base fare, £0.1 per minute and £1.2 per mile (Taxi How Much, 2022), a 5-mile trip with an 11.86 min trip time would cost £8.536.
$tc_{n\text{-}pc}$	Travel costs of non-CAV private cars	£/trip	5.78	Calculated based on the conventional car purchase cost of £23,185, usage cost of £5.2 per trip and lifespan trip of 40,000. See $pc_{n\text{-}cav}$, uci_{pc} and lt_{pc} for more detail.
$tc_{n\text{-}pt}$	Travel costs of non-CAV bus	£/trip	2	We assume £2 per trip, which was the First Bus single adult ticket for trips within West Yorkshire (UK) in 2021.
tci_{cs}	Initial CAV car/ride sharing travel cost	£/trip	8.536	Assumed to be the same as $tc_{n\text{-}cs}$, since users are unlikely to pay more for, e.g., an Uber without a driver than for an Uber with a driver, and that automation adds capital cost to service providers but reduces operation cost at the same time.
tci_{pt}	Initial CAV bus travel cost	£/trip	2	Assumed to be the same as $tc_{n\text{-}pt}$, for the same reason as tci_{cs}.
te	The extent to which training can enhance imitation effect		0.3	Assumption
uci_{pc}	Initial CAV private car usage cost	£/trip	5.2	Average cost to run a car in the UK in 2021 was £1977 per year excluding purchase and depreciation (NimbleFins, 2021). Average number of trips per person per year using private car/van as a driver was 380 in England in 2019 (Department for Transport, 2021c). We assume initial CAV private car usage cost is the same as that of conventional private cars.
unp_{cs}	Number of users per car/ride sharing vehicle	person	100	Monitor Deloitte (2017) reported 125 users per car with free-floating car sharing and 45 users per car with stationary car sharing in Germany. We hence assumed that each car/ride sharing vehicle can serve 100 users.
unp_{pc}	Number of users per private car vehicle	person	1.5	According to Department for Transport (2020a), number of cars per household among those with at least one car was 1.59 in 2018/19 in England. Given that the average household size was 2.4 in 2020 in the UK (Office for National Statistics, 2021), we assumed that each private car can serve 1.5 users.
unp_{pt}	Number of users per bus vehicle	person	261	According to Department for Transport (2021a), frequent bus users in England in 2019 is 15% of the total population which was 56,286,961 (Office for National Statistics, 2020), and there were 32,300 buses used by local operators in England in 2019/20 (Department for Transport, 2020b), we thus calculated that each bus can serve 261 users.
$vmtc_{cs}$	The maximum VMT reduction effect of CAV car/ride sharing	Dimensionless	0.1	According to Wadud et al. (2016), VMT will decrease due to new mobility services enhanced by CAVs such as ride sharing, and the mid-value of the estimated decrease is 10%.
$vmtc_{pc\text{-}cs}$	The maximum VMT change that CAV private car and CAV car/ride sharing can lead to	Dimensionless	1.42	According to Wadud et al. (2016), VMT will increase with CAVs due to travel cost reduction and new users (e.g., the disabled, elderly and children), and the mid-value of the estimated increase is to reach 142% of current level.
$vmtc_{pt}$	The maximum VMT change that CAV bus can lead to	Dimensionless	0.15	According to Department for Transport (2021d, 2021e), vehicle km on local bus service in Great Britain in 2018/19 was 2.316 billion, while passenger km was 27.3 billion. So for bus, vehicle km per passenger km was 0.085. According to Department for Transport (2021f, 2021g), vehicle km of all road passenger vehicles in Great Britain in 2018 was 447.1 billion, while passenger km was 767 billion. So for road passenger vehicles, vehicle km per passenger km was 0.583. Given the above, we assume that if all current road passengers shift mode to CAV bus, VMT will reduce to 0.085/0.583 which is 15% of current level.
$w_{n\text{-}cs}$	Weight applied to values related to car/ride sharing to calculate weighted average values for the non-CAV option	Dimensionless	0.056	According to Department for Transport (2021a), percentages of frequent private car users, taxi users and bus users were 69%, 2% and 15% in 2019 in England. According to Statista (2021), car-sharing user penetration in the UK is 2.8% in 2021. So the weights used are 69 : 5: 15, which are 0.775 : 0.056 : 0.169 when normalised to 1.
$w_{n\text{-}pc}$	Weight applied to values related to private cars to calculate weighted average values for the non-CAV option	Dimensionless	0.775	
$w_{n\text{-}pt}$	Weight applied to values related to buses to calculate weighted average values for the non-CAV option	Dimensionless	0.169	
$wki_{n\text{-}pt}$	Initial non-CAV bus walking time	Minute/trip	10	Giving the assumed 0.5 mile walking to and from bus stops, and average adult walking speed of 3–4 mph, walking time of 10 min is used.
wki_{pt}	Initial CAV bus walking time	Minute/trip	10	The same as $wki_{n\text{-}pt}$
wti_{cs}	Initial CAV car/ride sharing waiting time	Minute/trip	5	Assumption
$wti_{n\text{-}cs}$	Initial non-CAV car/ride sharing waiting time	Minute/trip	5	The same as wti_{cs}
$wti_{n\text{-}pt}$	Initial non-CAV bus waiting time	Minute/trip	10	Assumption
wti_{pt}	Initial CAV bus waiting time	Minute/trip	10	The same as $wti_{n\text{-}pt}$

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