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Mode choice in metropolitan areas: Impacts of automation and electrification

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A B S T R A C T

Urban mobility patterns might radically change due to electrification and automation. This paper investigates mode choice in Sweden when introducing electric and automated private cars, electric and autonomous buses in regular service, and private electric bikes. Mode choice is investigated by using a multinomial logit model of short-distance trips in metropolitan areas calibrated to the Swedish National Travel Survey. The model considers relationships between trip length, travel speed and access-egress times for all modes and is used for analysing future scenarios up to 2050. The new technologies affect driving costs, travel time costs, travel speed and access times, which in turn impact mode choice. The results show that when autonomous technology is used within a transport system similar to the current one (e.g., mainly private car ownership and a required license to drive), the effect on modal shares of trips and passenger-kilometres is limited. For example, the distance modal share of car drivers increases from 55.3 % to 61.3 % in 2050. The limited impact can partly be explained by the fact that the impact of new technology on generalised travel cost is limited, and partly by the fact that the multinomial logit model yields mode-specific constants, which causes the model to be relatively insensitive to changes in technology. Finally, the turn-over rate in a car fleet is typically lower than for both buses and bikes. Overall, it seems unlikely that mobility patterns with radically change with electric and autonomous cars without additional changes to ownership structures and car accessibility.

1. Introduction

Autonomous and electric cars are perceived as possible game-changers. Autonomous cars are expected to lower travel time costs compared to driving a conventional car (Wadud et al., 2016; Steck et al., 2018; Correia et al., 2019), and the total cost of ownership of electric cars is now lower than the cost of owning a conventional car in many parts of Europe (LeasePlan, 2022). Combining these two technologies has the potential to greatly lower travel costs. The generalised travel time cost (GTC) is widely used in transport demand analysis and determines the attractiveness of a mode in mode choice modelling (Ortúzar and Willumsen, 2011). Lower time travel costs with autonomous vehicles (AVs) and lower fuel costs with electric vehicles (EVs) will both decrease the GTC and increase the attractiveness of cars compared to other modes.

However, electrification is also increasing for other modes of transport. Electric bus sales are increasing rapidly in China, Europe and the US (IEA, 2022). Likewise, electric bike (e-bike) sales are growing and reached 5 million units in Europe in 2021 (Confederation of the European Bicycle Industry, 2022) and there is evidence of a substitution effect between e-bikes and cars (Bourne et al., 2020). If the comfort increases with e-bikes or electric buses, the GTC will decrease and thus increase their mode competitiveness.

While there are several studies looking at autonomous small shuttle buses as feeder services (Chee et al., 2020; Kassens-Noor et al., 2020; Mouratidis and Cobeña Serrano, 2021), an identified research gap is the impact of autonomous buses in regular line service (Azad et al., 2019). In the current transport system, line service buses are more common than feeder services, and the impact of autonomous technology in such buses is of interest to e.g., public transport authorities and city planners. In addition to the lack of autonomous bus research, there are also few studies considering the simultaneous introduction of AVs in competing modes of transport. Moreover, there is a lack of modelling studies that include the effects of partly automated vehicles. Partly automated vehicles are closer to introduction, and it is still unclear if or when fully autonomous cars will be available (Carter, 2023). Hence, the effect of

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lower degrees of automation deserves more attention. Finally, many of the current studies (including those of autonomous cars) do not take access time, i.e. the time spent walking to the car, for different types of AVs into consideration. As out-of-vehicle costs like parking costs or walking time can be important in modal choice (Feeney, 1989), including these factors can be significant in a mode choice model. Still, little is known about time spent walking to and from car parking compared to time access-egress time for public transport. To sum up, more research is needed on regular autonomous buses, competition between different types of AVs, mode impact of lower levels of automation, and inclusion of out-of-vehicle factors for autonomous cars.

This paper aims to address identified research gaps by i) exploring mode competition between private cars, buses in regular service, and private bikes in metropolitan areas with an increased share of autonomous and electric vehicles, and ii) including both partly and fully autonomous vehicles. We also provide insights to model sensitivity to GTC by using likelihood profiling. Finally, this paper provides empirical estimates of access times and vehicle speeds that could be used in future studies of AV and EV scenarios.

We explore mode competition by modelling future mode choice with a multinomial logit choice (MNL) model estimated from the Swedish National Travel Survey (NTS) in metropolitan areas in Sweden. The NTS is also used derive trip characteristics such as trip lengths and frequency, access-egress time and travel speeds. Fleet turnover models are developed for cars, buses and bikes to study the diffusion of EVs and AVs. The introduction rate of AVs as well as the reduction of GTC are derived from literature.

The remainder of this paper is structured in five sections. Section 2 starts with a brief literature review covering travel time costs (TTC) and mode competition with autonomous vehicles. Section 3 describes the dataset and methods used to develop the mode choice model. Section 4 outlines future scenarios for autonomous and electric vehicles and presents the scenario model results. Finally, Sections 5 and 6 discuss the results, possible implications, and conclusions.

2. Literature review

This section provides an overview of previous research on AV travel and mode competition with AVs. The purpose is to elaborate on gaps in the literature and to summarise findings on autonomous buses. As no major changes to how public transport operates are assumed, studies focusing on on-demand services are excluded from the review. Although shared robot-taxis are commonly featured in AV research, privately owned vehicles will likely remain competitive due to low use costs combined with a continued acceptance of high fixed costs (Bösch et al., 2018; Wadud and Chintakayala, 2021; Wadud and Mattioli, 2021).

2.1. Travel time costs and willingness-to-travel in autonomous vehicles

It is commonly assumed that the travel time cost (TTC)[1] will decrease with the introduction of AVs. For cars, this is due to lower driving stress already at lower levels of automation and even more so with the prospects of using time in the car for other activities, e.g., working. Steck, et al (Steck et al., 2018). used a stated-choice experiment looking at commuting trips. The respondents reported a 30 % lower TTC for private car trips and a 10 % lower TTC for shared car trips compared to conventional driving. Another study using a stated-preference survey found a similar decrease in commuting by car (26 %) but an increased TTC for leisure travel (+9 %) (Correia et al., 2019). Kolarova, et al (Kolarova et al., 2019). found a TTC reduction of 41 % for commuting and no change for leisure travel.

Szimba and Hartmann (Szimba and Hartmann, 2020) instead estimated the benefit of re-purposing time in the car by comparing the willingness-to-pay (WTP) for using additional services in an AV with how much the car is used during a month. The resulting WTP is about 0.2–0.3 €/day for a level 4 AV and 0.7–0.8 €/day for a level 5 AV (according to the SAE levels of driving automation (Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles, 2021)), which would equal a saving of daily travel time costs by about 5 % and 10 % respectively. The scope of the study is German commuters, and the study also assumes decreased travel time with AVs due to more efficient traffic flows.

Although many studies have focused on fully automated cars, as illustrated by Szimba and Hartmann (Szimba and Hartmann, 2020), lower levels of automation would also reduce driver stress, which would decrease the TTC. Drivers with level 2 AVs had 15.5–19 % longer mean annual vehicle miles travelled (VMT) than drivers without any on-board automation in a study of American drivers (Hardman et al., 2022). Another study of driver assists systems (level 1 and 2) found a VMT increase with an average range of 9.8–18.9 % for driver related features, even though the range was even larger (3.6–40 %) for different subgroups divided by age and gender (Asmussen et al., 2022). Although these numbers are not easily translatable to reductions in TTC, they may at least indicate such a reduction.

There are few estimates of TTC changes for partly or fully autonomous buses. Almlöf, et al (Almlöf et al., 2022a). argue that autonomous buses could have a higher level of comfort due to smoother driving and translate this into the difference of TTC between bus and train and hence assume a 30 % reduction of TTC for fully autonomous buses. Studies of willingness-to-ride automated buses are a little more common, but there is not a clear picture that could be used to derive TTC changes. Mouratidis and Cobeña Serrano (Mouratidis and Cobeña Serrano, 2021) used surveys and interviews with riders in a shuttle bus trial in Oslo. Bus riders overall had a positive intention to use shuttle buses in the future, but negative concerns were the low speed of the bus and discomfort related to abrupt braking. Cartenì (Cartenì, 2020) estimated that bus and taxi riders in Naples had a negative willingness-to-pay for riding an autonomous bus, but concluded that the perceived disutility was likely related to initial unwillingness. Guo, et al (Guo et al., 2021). used a stated-preference survey to investigate bus passenger preferences for automated buses. The scope for this study was shorter trips of either 1 km or 5 km in a variety of settings (weather, unaccompanied travel, crowdedness etc). Their result suggest that bus passenger preferences are similar for automated and conventional buses.

Overall, it seems like willingness-to-ride could be negatively affected by a driverless bus due to concerns for safety or distrust in technology, but also that willingness to ride could increase, particularly among some groups (male, current users of AV technology (Kassens-Noor et al., 2020); Cartenì, 2020; Guo et al., 2021). However, to what extent these preferences will persist if the technology matures and becomes widely adopted remains unclear.

2.2. Autonomous buses and mode competition

The lack of studies on larger size buses has been identified by previous reviews (Azad et al., 2019). In one of few studies of fixed-route bus services, Badia and Jenelius (Badia and Jenelius, 2021) illustrate that fixed-route bus services can remain competitive as feeder solutions to high-capacity public transport compared to DRT or car travel, depending on factors like demand-density and value of time. Hatzenbühler, et al (Hatzenbühler et al., 2020). also study the integration of autonomous buses in a line-based public transport system. Although the work is more related to operator costs and scheduling, lower user costs due to higher frequency service are one of the potential benefits for users. A higher frequency service can both reduce waiting time and redistribute

[1] We use “travel time cost” (TTC) to denote the disutility of travel time. “Value of travel time (VTT) and value of travel time savings (VTTS) are commonly used to denote the same cost. Our choice of using TTC is to avoid any confusion regarding the sign and impact of this disutility (the value of time as a resource is positive, but the utility of travel time is negative).

passenger loads. A second study (Hatzenbühler et al., 2021) looks at network design with (fully) autonomous buses and concludes that the deployment of automated buses together with a network design increases service ridership, but the increase is likely to primarily substitute walking.

A study of both autonomous buses and taxis (Abe, 2019) investigates the competition between private cars, taxis, and public transport in metropolitan Japan. In this study, public transport trip shares fell as automated technology had less impact on the total GTC for public transport compared to private car trips and taxis. Abe (Abe, 2019) assumes that TTC decreased by 30 % for cars but was not changed for buses. The benefit of autonomous buses for users was instead lower fares due to decreased labour costs.

Almlöf, et al (Almlöf et al., 2022b). look at modal competition in Stockholm with automated buses and cars. The modal split in a range of scenarios is an increased use of autonomous cars and a decrease in active transport. Public transport use also decreases in a scenario with automated cars and no change to public transport, but the change was less drastic than for active transport. In a scenario with on-demand public transport as a feeder service, public transport use increased a little (at most a 10 % increase in pkm). The limited changes to public transport use are, according to the authors, the current high service level of public transport in Stockholm, meaning that additional service has a limited impact on use. Increased car use is due to several factors, e.g., assuming that traveling by car is also available for those without a driving licence or their own car. Notably, this study does not assume any changes to the value of travel time for AVs.

3. Travel data and mode choice

3.1. Methodological overview

Firstly, a trip data set representing travel in metropolitan areas was drawn from the Swedish NTS. The dataset is characterised by a discrete distribution of number of trips and average trip length. The NTS is also the source of access-egress time and travel speeds for different modes, which was used to calculate GTC in the second step. Secondly, an MNL model of mode choice was estimated based on NTS data together with additional assumptions of the GTC. Finally, future mode choices were analysed using the MNL model with an assumed introduction of AVs and EVs. We assume that future travel will stay the same in terms of the distribution of trips and trip lengths, i.e., there are no changes regarding destination choice or travel frequency. The main assumptions affecting future mode choice in this study are increased TTC due to higher GDP/capita, decreased TTC for AVs, lower driving costs with an increased share of EVs, and an increased speed with a larger share of e-bikes. A sensitivity analysis is made by varying the most central assumptions regarding the TTC and the estimated MNL cost parameter.

3.2. Trip characteristics in the national travel survey

The trip dataset is derived from the Swedish NTS 2011–2016 (Trafikanalys, 2015b; Trafikanalys, 2015a). A subset of trips was selected based on journey properties. A journey is defined as the sum of trips between two main stays (e.g., home, work). A trip is a movement between two stays with separate activities, and a stage is “a movement making use of one transport mode” (Eurostat, 2018).

The two criteria for trip inclusion were i) journeys starting and ending in the metropolitan regions of Stockholm, Gothenburg, or Malmö, and ii) the total distance of all trips in a journey, i.e., the journey distance is between 5 and 100 km. The criteria aim to select journeys where autonomous buses could theoretically be introduced and where there is reasonable competition between public transport, e-bikes, and car travel in metropolitan areas. The upper bound of 100 km is to exclude long-distance journeys and the lower bound of 5 km is to exclude short journeys where walking and biking are much more competitive. Journeys less than 5 km make up 9 % of passenger-kilometres (pkm) travelled, and journeys longer than 100 km make up 25 % of pkm travelled in the dataset. Hence, the journeys included make up 66 % of the pkm travelled in the dataset. Trips within a journey can still be shorter than 5 km and start or end outside the metropolitan areas. As shown in Table 1, about 30 % of the trips are shorter than 5 km.

The dataset consists of 17 952 journeys and 31 199 trips with 52 528 stages, made by 9 377 respondents. All further analysis is made at trip level.[2] The shortest trip is 100 m and the longest 100 km. For further processing, the trips are grouped into 10 bins by trip length. A summary of the bins can be seen in Table 1, together with data on mode share for trips and transport (pkm) for all trips. The “other mode” trips are mainly pedestrian trips, but also covers “other modes” such as moped, public transport ferries, and trips reported as “mode unknown”.

3.2.1. Access and egress distance and time for different modes

The NTS dataset contains data for each stage of all trips. This information is used to derive access-egress distance and time for all modes, which here is defined as the time spent walking in a trip otherwise mainly made by public transport, car, or bike.

Stage data only contain distance travelled and not travel time, so access-egress time is estimated by assuming a walking speed of 5 km/h applied to all walking stages in a trip. For car drivers, car passengers, and bike trips, the same access-egress time is assumed for all trips regardless of length, as the NTS data only shows a limited increase in walking distances with increased trip distance, see Fig. 1. Public transport trips show an increase in average access-egress time with increased trip length, even though there are large variations within each bin of trips (overall correlation between trip length and access-egress distance only had $r^2 = 0.05$). The resulting access-egress times are estimated to 2.2 min for car drivers, 2.6 min for car passengers, and 2.5 min for cyclists. For public transport, access-egress time increases from 3.9 min for the shortest trips (0–2 km) to 13 min for the longest trips (25–100 km). The inclusion of all walking stages in the analysis means that transfer distances are counted as access-egress time, while waiting time for transfers is included in the travel time.

The resulting access-egress times seem reasonable compared to other estimates. A recent study found access-egress times of 4.1–6 min to local bus stops and 6.6–8.6 min to railway stations in Norwegian cities (Tennøy et al., 2022). A previous literature review of access-egress time for public transport based on NTS-data found mean and median walking times to be in the range of 4–9 min (van Soest et al., 2019). Access-egress time for cars is estimated by e.g. Soto, et al (Soto et al., 2018)., who used surveyed access times to form alternatives in a stated preference experiment on parking preferences. Access time for different types of public parking varied between 4–10 min. However, many trips start or end at home rather than at a public parking spot. Christiansen, et al (Christiansen et al., 2016). found that most Norwegian urban residents have less than 50 m between home and residential parking (which would equal 0.6 min). Adding the low access/egress time at residential parking with the 4–10 min for public parking yields higher estimates than our study, but a large share of car travel consists of trips to destinations where parking can be expected to be closer than the public parking studied by Soto et al. (e.g., workplaces and shopping centres) where access/egress time are significantly lower. Hence, our estimate seems reasonable, although to our knowledge, car access-egress has not previously been studied in Sweden. Finally, we found no studies of access-egress time for bike trips in the literature.

3.2.2. In-vehicle speed

For every trip length bin, the average trip speed and average in-vehicle speed are derived from NTS data, see Fig. 2. In-vehicle speed

[2] Multimodal trips are assigned a main mode based on the mode was been used for the longest distance within the trip (Trafikanalys, 2015b).

Table 1
Overview of trip dataset used in this study. All trips are selected from the Swedish National Travel Survey 2011–2016 and binned into decentiles. The number of trips in each bin is not exactly equal as the number of trips with integer lengths (in km) is generally much larger than other reported trip lengths.

Trip bin lengths (km)	Share of trips	Share of transport (pkm)	Average trip distance (km)	Car driver share (trip)	Car passenger share (trip)	Public transport share (trips)	Bike share (trips)	Other mode share (trips)
0 –2.0	8 %	0.7 %	1.1	39.3 %	8.2 %	4.3 %	4.5 %	43.8 %
2.0 –3.15	8 %	1.9 %	2.8	50.5 %	16.7 %	13.6 %	6.3 %	12.9 %
3.15 –5.0	12 %	4.5 %	4.4	46.2 %	14.8 %	17.8 %	5.4 %	15.9 %
5.0 –6.0	8 %	3.5 %	5.6	44.6 %	13.7 %	26.2 %	4.3 %	11.2 %
6.0 –7.7	9 %	5.2 %	6.9	42.7 %	12.6 %	30.9 %	4.8 %	9.0 %
7.7 –10.0	11 %	8.5 %	9.1	49.4 %	14.7 %	22.3 %	4.6 %	9.0 %
10.0 –12.6	10 %	9.1 %	11.1	48.0 %	12.7 %	34.3 %	1.9 %	3.1 %
12.6 –17.0	11 %	13.8 %	14.9	55.3 %	13.3 %	26.2 %	2.0 %	3.2 %
17.0 –25.0	12 %	21.3 %	20.9	56.6 %	14.6 %	25.0 %	1.1 %	2.8 %
25 –100	11 %	31.4 %	36.1	57.6 %	14.7 %	23.9 %	0.6 %	3.2 %
Total trip share			11.0	**49.1 %**	**13.7 %**	**21.6 %**	**3.7 %**	**12.0 %**
Total transport (pkm) share				**53.1 %**	**14.3 %**	**24.5 %**	**2.2 %**	**5.8 %**

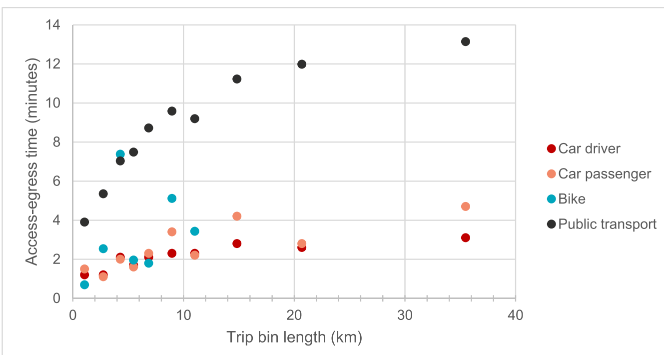

Fig. 1. Total time spent walking in connection to traveling with other modes increases with trip length for all modes in the Swedish National Travel Survey 2011–2016 (Trafikanalys, 2015b; Trafikanalys, 2015a). The more irregular pattern for bike is due to a lower of number of observations. A table of mean values and standard errors is available in Supplementary note 2.

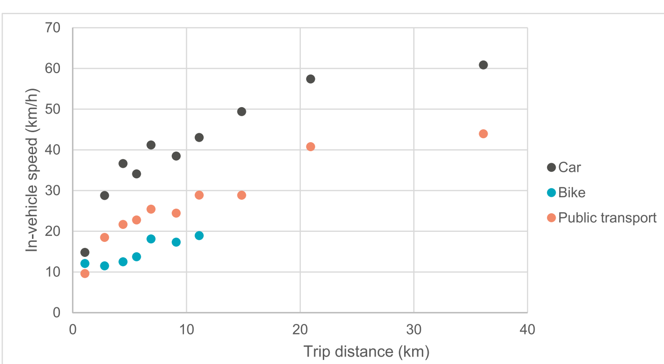

Fig. 2. Average in-vehicle speed by mode for trips in the Swedish National Travel survey for trip decentiles by trip length.

is calculated by dividing the reported trip duration and distance while subtracting time and distance spent in the walking stage of a trip, as calculated in the previous section. As previously mentioned, waiting time for transfers is assumed to be zero. As reported duration and distance in the NTS might not always be consistent, resulting speed data was cleaned from negative and unreasonably high speed. Details on data cleaning are available in Supplementary note 2.

The resulting in-vehicle speeds per trip bin are shown in Fig. 2. Overall, speed increases with trip distance, as expected (Barbosa et al., 2018). The average speed for public transport spans a large range (10–44 km/h). For most trip bins, this is slightly higher than other estimates for public transport trips. Liao, et al (Liao et al., 2020). estimated the average speed for public transport trips in Stockholm to 14.9 km/h. An important difference is that the calculated speeds are in-vehicle speeds and not the average speed for a public transport trip, including access-egress time, which is included in the estimates by, e.g., Liao, et al (Liao et al., 2020). The average vehicle speed of a bus in all urban areas in Sweden is 27 km/h (Ericsson, 2020), and about 20 km/h for urban buses in the Skåne region (including Malmö, which is part of this study) (Jerksjö et al., 2022).

The average speed for a car (15–60 km/h) is in the range of other estimates of Swedish urban car speed, e.g., the average of 50 km/h for all cars within urban areas in Sweden (Ericsson, 2020) or the population weighted trip speed of 37.6 km/h in Stockholm (Liao et al., 2020). The latter also includes a randomly assigned time between 5 and 10 min for parking and access-egress.

Average bike speed stabilises at roughly 18 km/h for trips over 7 km. The average speed for the three longest bins is excluded from the analysis due to few observations. The findings are largely consistent with other estimates of cycling speed calculated by self-reported distance and duration by commuters in Stockholm (Schantz, 2017). The commuters in Schantz's study were slightly faster on average (speeds ranged from 11.6–21.3 km/h among 1661 participants), which seems reasonable considering that the NTS data also include children cycling to school and other trip purposes.

3.3. Choice model parameters and estimation

The discrete choice between a finite set of modes is modelled with MNL (Ortúzar and Willumsen, 2011). In the general form, the choice between modes i by an individual n is made by maximising the mode-dependent utility $U_{n,i}$. We assume two groups with homogenous preferences: individuals with a driving license and access to a car (*car group*), and individuals lacking either a driving licence or household car access (*no-car group*). For each group, the choice between modes i for group n is made by maximising the mode-dependent utility $U_{n,i} = ASC_{n,i} + \beta_n GTC_{n,i} + \varepsilon_{n,i}$. $ASC_{n,i}$ is the alternative specific constant for mode i in group n, which captures mode specific preference attributes, and β is the marginal utility of GTC_i. ε_i is the independent and identically (Gumbel) distributed random residual variable.

Based on the assumption of maximisation of utility and homogenous preferences among decision makers and ε_i follows the characteristics stated above, the probability P_i of choosing mode i is described in Eq. (1).

$$P_i = \frac{e^{ASC_i + \beta GTC_i}}{\sum_{j=1}^{N} e^{ASC_j + \beta GTC_j}} \tag{1}$$

The available modes in this paper are car driver, car passenger, public transport, cycling, and walking. All modes are available for all trips, i.e., we assume no restrictions for availability based on, e.g., trip distance. GTC_i consist of the monetary cost ($Cost_{M,i}$) and the cost of travel time ($Cost_{T,i}$), i.e., $GTC_i = Cost_{M,i} + Cost_{T,i}$. The monetary cost represents the perceived marginal cost by the traveller when making the decision. We assume the marginal cost is equal to the fuel cost and parking cost for car drivers, and that there is no perceived monetary cost for car passengers. The cost of public transport trips is a paid-per trip fee with two levels differentiated by trip length. Cyclists and pedestrians are assumed to have no perceived monetary cost. The assumption means that the monetary cost does not include a levelised capital cost, other operational costs such as insurance or tire wear, or electricity cost for electric bikes. Costs of travel times are calculated by using reported travel and access-egress times in the NTS together with values of travel time cost from the Swedish Cost-Benefit Analysis (CBA) guidelines ASEK 6.0 (Trafikverket, 2016).

3.3.1. Monetary costs

All costs in the parameter estimation were calculated in 2014 value for two reasons: i) 2014 is a midpoint year of the NTS data period of 2011–2016, and ii) costs can easily be compared to the CBA guidelines (Trafikverket, 2016), which have costs in 2014 value.

Public transport costs were not calculated from NTS data, but from other sources used by the Swedish passenger transport model SAMPERS (Schmidt, 2020; Östlund, 2020a, 2020b; Dahl et al., 2019; WSP, 2016). Public transport fares are decided at the county level in Sweden and hence differ in the three regions included in the study. In Stockholm, the same fare applies to the whole county, whereas in Gothenburg and Malmö, the areas included in this study have zoned fares with higher fares for trips across zones. A simplified representation was implemented where trips shorter than 15 km are charged 19.9 SEK[3]/trip and trips longer than 15 km are charged 35.8 SEK/trip. These averages are calculated from the share of trips in each county, the fare in each county for card holders and single trips, and the share of card holders and non-card holders in each county. Calculation details are available in Supplementary note 3.

Fuel costs for car trips in the NTS were estimated by combining the fuel consumption for Swedish petrol and diesel cars, the price of petrol and diesel, and the share of petrol and diesel driving respectively for each year between 2011 and 2016. The resulting cost varied from 1.21 SEK/km in 2011 to 1.02 in 2016. An average of 1.13 SEK/km was used for all car trips in the parameter estimation. Fuel consumption, fuel prices, driving shares, parking fees, and cost calculations are available in Supplementary note 3.

A parking fee of 9.2 SEK was added to each trip. The parking cost was calculated from reported parking costs in the NTS. The same parking cost was used for all car trips, even though the NTS indicated a slightly higher parking cost for Stockholm (11.4 SEK/trip) than for Gothenburg (8.1 SEK/trip) and Malmö (8.2 SEK/trip). Parking in Sweden is typically charged at hourly rates in metropolitan city centres, but free at external shopping malls or for street-parking in residential areas in the outer parts of the metropolitan area. The simplification of using the same parking cost for all trips means this heterogeneity is not represented in the model.

3.3.2. Time costs

The time cost for each trip is calculated by adding the cost of in-vehicle travel time and access-egress travel time:

$$Cost_{T,i} = T_{IVT,i} * TTC_{IVT,i} + \quad T_{access-egress,i} * TTC_{IVT,i} * 1.5 \tag{2}$$

The travel time and access-egress time for each trip with mode i was calculated using trip distance and previously calculated mode speeds. The values of travel time (TTC_{IVT}) used are 72 SEK/h for car drivers, 66 SEK/h for car passengers, 129 SEK/h for cyclists, 56 SEK/h for public transport, and 200 SEK/h for pedestrians. The values are based on CBA values (Trafikverket, 2016) for short-distance travel (<100 km) and weighted for the share of commuting and non-commuting trips. The CBA values are based on the Swedish Value of Time study (Börjesson and Eliasson, 2014), where the value of travel time was estimated with a stated preference survey as the relation between the marginal utility of time and the marginal utility of money, ($\beta_{time}/\beta_{cost}$). The travel time cost values in the SVT study include the differentiation between short and long-distance travel as well as mode-specific travel time valuation. A multiplier of 1.5 was used for access-egress time cost based on TTC for the main mode (Wardman et al., 2016). TTC_{IVT} values are increased by 1.5 % annually, following a 1.5 % annual increase in income per capita and an assumed income elasticity of the time cost equal to 1 (Trafikverket, 2016).

3.3.3. Estimation of mode choice parameters

For all trips in the dataset, GTC_i was calculated for each mode as described in the previous sections. This cost was used in a logistic regression estimating the model parameters β_n and $ASC_{i,n}$ in Eq. (1). BIOGEME 3.2.10 (Bierlaire, 2020) was used in the estimation. The regression was made separately for the *car group* and the *no-car group*.

For trips made by the *car group*, *car driver* was considered the default mode, i.e. $ASC_{car\ driver} = 0$. The default mode for the *no-car group* was *public transport*, i.e. $ASC_{public\ transport} = 0$. The estimated parameters can be seen in Table 2. McFadden's pseudo-rho square ρ^2 was 0.321 for the car group and 0.249 for trips made by the no-car group, which indicates that the models have an acceptable fitness (McFadden, 1979). Full details on the estimation are available in Supplementary note 7.

We also investigated the robustness of the preference parameters using likelihood profiling by re-estimating the $ASC_{i,n}$ parameters for selected values of β_n. β_n. was varied between 0 and −0.05, as seen in Fig. 3.

The likelihood profile indicates that the log-likelihood-sum is rather insensitive to variation in the preference parameter β_n. The reason for performing the likelihood profiling is that in the scenario simulations (Section 4), we want to understand the robustness of the simulations to different, yet plausible, parameterisations of the choice function.

To limit the number of simulations in the sensitivity analysis in Section 4.3, we use two specific alternative parameterisations of the choice function: i) $\beta_n = 0$ and ii) values of β_n that give the same normalised log-likelihood as obtained with $\beta_n = 0$ (i.e., the parameterisation of High cost-sensitivity is as likely as the parameterisation of No cost sensitivity). $\beta_n = 0$ can be interpreted as a reference case where the mode choice is only determined mode specific preferences ($ASC_{i,n}$) and not at all impacted by the GTC. The High cost-sensitivity case is just the symmetrical counterpart to $\beta_n = 0$, obtained by choosing β_n to minimise $LL(\beta_n)\text{-}LL(\beta_n{=}0)$. The associated values of $ASC_{i,n}$ are shown in Table 3. The maximised log-likelihood sum is larger for the car group as this group has 23 412 observations whereas the no-car group only has 7 736 observations.

4. Scenario analysis

4.1. Scenario assumptions

When creating scenarios for the future transport system, technological development is a key component. This section describes the main assumptions regarding the introduction of autonomous buses and cars, and e-bikes in the vehicle fleet, as well as the expected impact on TTC and travel speed. All costs in the scenarios are estimated in 2019 value (the start year of the scenarios).

4.1.1. Autonomous buses

We assume that partly autonomous buses are introduced in

[3] 1 SEK ≈ 0.11 EUR in 2014.

Table 2
Estimated MNL-model parameters for two user groups. The table shows parameter estimates with the robust standard error in parentheses.

		ASC				
Group *n*	β_{GTC} (kr^{-1})	Car driver	Car passenger	Bike	Public transport	Walking
Car group	−0.0092 (0.000576)	0	−2.08 (0.026)	−2.88 (0.037)	−1.44 (0.024)	−1.11 (0.039)
No-car group	−0.014 (0.0010)	−2.97 (0.068)	−1.26 (0.053)	−2.54 (0.057)	0	−0.356 (0.0041)

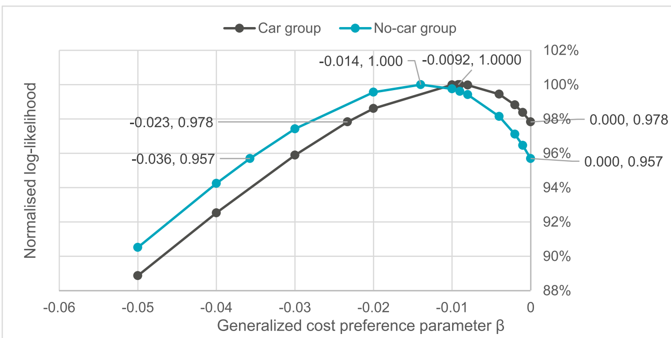

Fig. 3. The normalised log-likelihood LL(β) for two user groups when varying the generalised cost preference parameter β. Maximum LL(β) occurs at $\beta_{car} = -0.0092$ for the car group, and at $\beta_{no\text{-}car} = -0.014$ for the no-car group. For the sensitivity analysis, $\beta_n = 0$ is chosen as well as β_n values with the corresponding $LL(\beta_n)$ for each group. ASC_i are reoptimized for every value of β when evaluating LL(β).

metropolitan areas in the early 2020 s. We also assume that fully autonomous buses will not be introduced on a large scale before 2050, since there are both potential issues with passenger trust in driverless vehicles (Kassens-Noor et al., 2020) and urban buses operate in complex traffic and passenger environments.

The diffusion of technology in public transport buses is assumed to follow a Gompertz distribution. Based on the assumption that the first partly autonomous bus is introduced in 2023 (full size commercial buses were piloted in Europe in 2022 (Nikel, 2022)), full market penetration will be reached in 2041. Previous experience shows that new technology could be adapted rather quickly by public transport, although the adoption rates depend on a number of factors such as public transport market structure and technology cost (Costa and Fernandes, 2012).

Fleet diffusion is calculated with a fleet turnover-model where a bus is assumed to have a lifespan of 12 years. The lifespan is based on a review of bus LCA studies, where the assumed lifetime was one of the parameters considered (Ager-Wick Ellingsen et al., 2022). 12 years is also the assumed lifespan by the Swedish Public Transport Industry Association, due to age requirements in public procurement contracts for buses (Atterhall, 2024). Age requirements are common in such contracts in Sweden (Lidestam et al., 2018). Both market and fleet penetration rates can be seen in Fig. 4. More details (regarding vehicle lifetime distribution, annual market share etc.) of the fleet turnover-model can be found in Supplementary note 6.

With a bus driver still present, we assume there is no change in passengers' willingness to use public transport, i.e., the parametrisation of the choice parameters stays the same. However, the TTC is assumed to be affected as partly automated buses could bring some benefits to passengers. A smooth ride is an important part of the perceived comfort and the driving style could affect the comfort (dell'Olio et al., 2011). Bus manufacturers also claim that automated high precision mooring at bus stops could speed up boarding and alighting, resulting in shorter stop times and less travel time variability (MAN Truck and Bus, 2022).

There are only a few estimates of the impact of TTC on autonomous buses. A scenario analysis of autonomous buses in the Stockholm area assumes a 30 % reduction for both fully and partly autonomous buses (Almlöf et al., 2022a). This is fairly high. Studies on how the TTC for car drivers may be affected by autonomy end up with a number on the same level (e.g., Steck, et al (Steck et al., 2018).). It seems unlikely that the relative impact of autonomy on TTC for bus passengers would be as large as for car drivers (as the driver would no longer need to steer the car, while bus passengers are "only" affected by improved comfort). To stay internally consistent with the assumptions for autonomous cars (described in the next subsection), we assume a more cautious TTC reduction of 5 % for bus riders. This also takes into consideration that some public transport trips are made by tram, metro, and train, which will remain unaffected by the introduction of autonomous buses. As a sensitivity analysis, we also run the model with a 10 % reduction in TTC for public transport.

For bus operators, the largest benefits are connected with driverless buses as this could potentially reduce operating costs substantially (Abe, 2019). As we assume that buses are only partly automated and that there is still a need for an on-board driver, there are no changes to operational costs, the bus network, or the level of service that would impact public

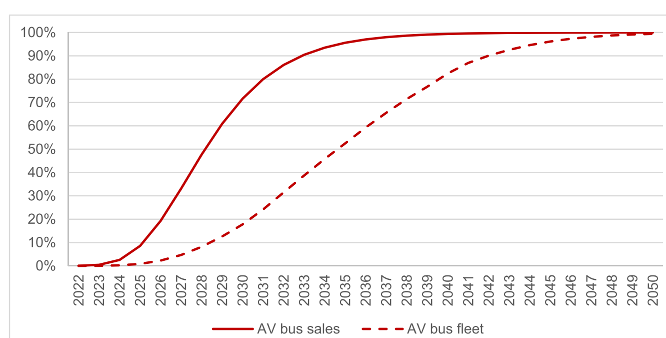

Fig. 4. Market and fleet penetration rates for partly autonomous buses assumed in this paper.

Table 3
Parameter values β_n and $ASC_{i,n}$ used in sensitivity analysis with no cost sensitivity and a corresponding increase in cost sensitivity (i.e. $\beta_n^{'}$ chosen so that $LL(\beta_{n,}^{'}) = LL(0)$), and the relative log-likelihood sum for each set of parameter values.

				$ASC_{i,n}$				
User group	Case	RelativeLL (β_n)	β_n (kr^{-1})	Car driver	Car passenger	Bike	Public transport	Walking
Car group	Maximum LL(β)	100 %	−0.0092	0	−2.08	−2.88	−1.44	−1.11
	No cost sensitivity	97.8 %	0	0	−1.87	−2.97	−1.63	−1.86
	Increased cost sensitivity	97.8 %	−0.023	0	−2.43	−2.79	−1.15	−0.52
No-car group	Maximum LL(β)	100 %	−0.014	−2.97	−1.26	−2.54	0	−0.36
	No cost sensitivity	95.7 %	0	−2.68	−0.67	−2.34	0	−1.00
	Increased cost sensitivity	95.7 %	−0.036	−3.43	−2.23	−2.90	0	0.02

transport fares.

4.1.2. Autonomous cars

The technology diffusion pace for AVs is highly uncertain. Estimates range from 10 to 100 % of car sales in 2050 (Shabanpour et al., 2018; Talebian and Mishra, 2018). As the aim of this paper is to investigate the dynamics between modes rather than AV diffusion, we simply assume a Gompertz growth. The first partly autonomous cars are introduced in 2022 and a saturated market penetration rate of 95 % for partly and fully autonomous cars is reached in 2050. Sales of cars with full autonomy in metropolitan areas will start in 2030. As the market share of fully autonomous cars grows, market shares decrease for both cars without any automation and eventually also for partly autonomous cars. Fleet diffusion is calculated with a fleet turn-over model based on the existing vehicle fleet composition in 2020 and a mean lifespan of 17 years. The lifespan is based on the age of cars scrapped in Sweden between 2014 and 2018 (Morfeldt et al., 2021). The market and fleet diffusion of partly and fully autonomous cars can be seen in Fig. 5. Details on lifetime distributions and the 2020 fleet can be found in Supplementary note 6.

Autonomous cars can affect the GTC in different ways. In this study, we assume a change in TTC for both car drivers and passengers when using partly or fully autonomous cars, and a minor change in the access-egress time for car drivers when using fully autonomous cars. We assume no change to the in-vehicle speed or the driving cost. Even though an AV might be more expensive to buy, we already assume that the car driver does not take the levelised cost into account when choosing the mode of travel. We also assume no change in the parking cost for autonomous cars.

The TTC reduction is assumed to be smaller for partly autonomous cars than for fully autonomous cars. Drivers of fully autonomous cars face a reduced TTC of 30 % in this paper. This is similar to Steck, et al (Steck et al., 2018). and Abe (Abe, 2019), and it is in the mid-range of other literature estimates as well (Wadud et al., 2016; Taiebat et al., 2019). As a sensitivity analysis, we also run the model without any change in TTC and a doubled change (i.e., a 60 % reduction).

Drivers of partly automated cars have a 10 % reduction in TTC. The reduction mainly comes from decreased driver stress. A lower TTC is expected to result in increased vehicle kilometres travelled (VKT). Our trips are all short (<100 km), whereas the observed increase in VKT (15.5–19 %) in previous studies of partly automated cars arose mainly from longer trips (Hardman et al., 2022). Even though the increased VKT cannot directly be interpreted as a change in TTC, it does indicate a TTC reduction. Car passengers in both partly and fully autonomous cars are assumed to have the same TTC reduction as bus passengers (5 %), as the main benefit is increased comfort rather than decreased driving stress.

In AV studies, access time is often assumed to be zero for non-shared AVs and non-zero for shared AVs (e.g., Tian, et al (Tian et al., 2021).) even though some also account for access time for cars (e.g., 3 min

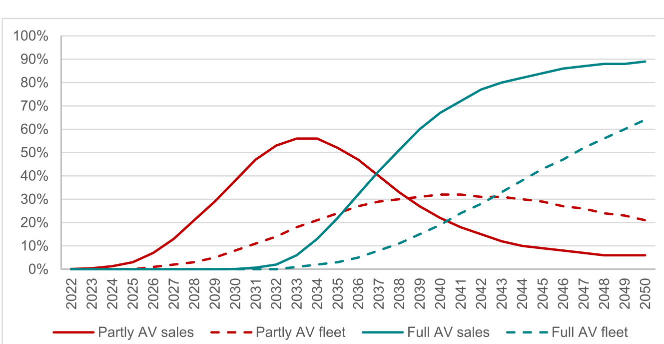

Fig. 5. Market and fleet penetration rates for partly and fully autonomous cars assumed in this paper.

assumed by Compostella, et al (Compostella et al., 2021).). As this study is limited to non-shared AVs, we assume no change in access-egress time for partly automated cars, and a fixed access-egress time of 2 min for fully autonomous cars for car drivers. This is a 10 % decrease from the observed access-egress time in the NTS data (average of 2.2 min). We assume no change for car passengers, which on average has a slightly longer access-egress time (2.6 min).

The diffusion of electric cars is not explicitly modelled in the vehicle turnover model. Instead, we assume an increasing share of electric cars in the vehicle stock as time progresses, resulting in a lower driving cost, and that cars with and without automation have similar market shares of electric cars (i.e,. an increasing number of new cars are electric, but there are also autonomous cars sold with a combustion engine). The share of electric driving is based on the Swedish EPA forecast (Naturvårdsverket, 2022). Details on the driving costs, including the electric driving share, can be found in Supplementary note 3. The overall driving share with electric vehicles can be seen in Fig. 6. As a result, the fuel cost changes from 1.22 SEK/km in 2019 to 0.40 SEK/km in 2050.

4.1.3. E-bikes

Even though the NTS does not contain information on the type of bike used, it can be assumed most trips were made using a conventional bike. Between 2011 and 2016, a total of 126 000 e-bikes were sold in Sweden,[4] while the total bike stock is estimated to be around 7.5 million (Chen et al., 2022). E-bikes sales before 2011 were low.

Since 2016, e-bike market share has risen to about 20 % of annual sales (Cykling, 2020, 2018; Cykelbranchen, 2022, 2021, 2019). In a future scenario, we assume that the market share of e-bikes continues to increase until reaching a saturation level of 40 %. In comparison, the market share of e-bikes in the Netherlands in 2020 was about 50 % (Toll, 2021).

Fitting a Gompertz curve of e-bike growth to the existing sales between 2011–2021 results in a growth curve reaching the saturation level of 40 % in 2042, and the 90 %level (i.e., 36 %) in 2030. The growth rate (12 years from 1–50 % of saturation level) is a little slower than argued by e.g., Grubler, et al (Grubler et al., 2016)., who suggest a growth rate of 8 years for an S-curve diffusion of e-bikes.

The total share of e-bikes in the Swedish bike stock is calculated using a fleet turnover-model. All bikes are assumed to be personal bikes and not shared bikes. The assumed lifespan of 15 years is longer than the economic lifespan of five or six years commonly used for bikes (e.g (Montgomery, 2010).), but similar to the lifespan used in other bike-fleet studies (Chen et al., 2022). Fig. 7 shows historical sales data, the fitted Gompertz curve of sales, and the resulting share of e-bikes in the bike stock for 2010–2050.

The second issue is to forecast future bike speed based on the share of e-bikes. E-bikes generally travel at a higher speed than conventional bikes (Kazemzadeh and Bansal, 2021). However, cycling speed also varies by trip length as previously seen in this study as well as by age of the cyclist, gender, trip purpose, and infrastructure type (Schleinitz et al., 2017; Flügel et al., 2017).

Average bike speed derived from the NTS (14.9 km/h) is in the lower span of the literature, ranging from 9.9 km/h (Montgomery, 2010) and 24.8 km/h (Khan and Raksuntorn, 2001). This suggests that factors like bike path gradients, shared infrastructure with pedestrians, or multiple stops at traffic lights impact bike travel in metropolitan areas. We assume that e-bikes have a 15 % higher speed than conventional bikes for each trip length bin. This assumption is similar to the overall difference of 14 % between bikes and e-bikes reported by Schleinitz, et al (Schleinitz et al., 2017)., but lower than the difference between bikes and e-bikes going uphill in the same study (27 %). On the other hand, it is slightly higher than the difference between conventional bike and e-bike speeds of 5–16 % in a study of male and female commuting and

[4] Personal communication, e-mail Cykelbranchen 2017–02-21.

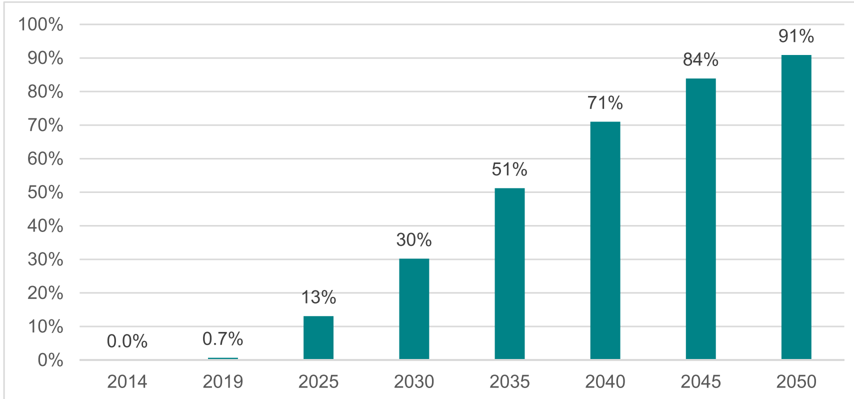

Fig. 6. Share of vehicle kilometres travelled with electric cars at the midpoint of the travel survey (2014), the model base year (2019) and according to a forecast by the Swedish EPA (Naturvårdsverket, 2022).

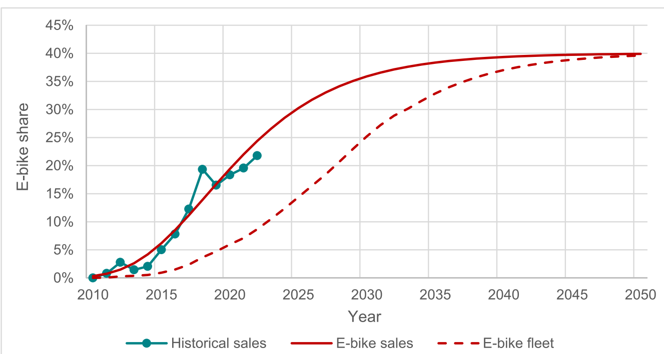

Fig. 7. A Gompertz curve of future e-bike sales together with actual e-bike sales for 2010–2022 (Cykling, 2020, 2018; Cykelbranchen, 2022, 2021, 2019; Cykling, 2017).

leisure trips in Oslo (Flügel et al., 2017).

We've found no estimates of TTC differences between bikes and e-bikes. Instead, we follow the example by Rich, et al (Rich et al., 2021). and assume no difference in TTC between bikes and e-bikes. However, it is possible that riding an e-bike could have a lower TTC due to higher comfort. As a sensitivity analysis, we also make a model run where TTC is 30 % lower for e-bikes.

4.2. Mode choice results

For the scenario results, we focus on mode shares for the base year 2019, and for 2030, 2040, and 2050. Mode shares are calculated as both the share of trips and the share of transport (pkm). First, the results are described for a future scenario where TTC is decreased when using AVs and travel speed is increased for e-bikes. Secondly, the mode shares for this base scenario are compared with three cases where there is only technology development for cars, buses, and bikes, respectively.

Overall, the impact of technology and cost development on mode choice in metropolitan areas is limited in the context of the total number of trips and transport distance. The main impact is a decrease in walking, biking, and use of public transport and an increase in car driving. The resulting trip shares are shown in Table 4 and the resulting transport shares in Table 5. Between 2019 and 2050, the share of trips made by public transport decrease from 26.3% to 24.1%, and the share of car driving increase from 52.4% to 57.3%. Most of this change occurs after 2030 due to the slow diffusion of new technology in the car fleet. In addition, the share of TTC in GTC increases over time (and consequently its impact on the utility of traveling with a specific mode), which contributes more and more over time to a shift towards modes with high speeds and relatively low TTC, i.e., automated cars. Even with the more rapid increase in sales of autonomous buses (72% of buses sold in 2030 are partly autonomous), there is still a delay in fleet automation, which, together with the small decrease in TTC for autonomous buses, is not enough to compete with increasingly automated cars.

Table 4
Mode share of trips in Swedish metropolitan areas for the base year 2019 and scenario results for 2030, 2040 and 2050.

Mode	2019	2030	2040	2050
Car driver	52.4%	53.4%	55.2%	57.3%
Car passenger	15.1%	15.2%	15.0%	14.7%
Public transport	26.3%	26.0%	25.3%	24.1%
Bike	2.6%	2.4%	2.2%	1.9%
Walking	3.6%	2.9%	2.4%	1.9%

Table 5
Mode shares of transport (passenger kilometres) for trips made in Swedish metropolitan areas for the base year 2019 and scenario results for 2030, 2040 and 2050.

Mode	2019	2030	2040	2050
Car driver	55.3%	56.5%	58.7%	61.3%
Car passenger	16.4%	16.3%	15.7%	15.2%
Public transport	25.5%	24.8%	23.6%	22.0%
Bike	1.9%	1.7%	1.4%	1.1%
Walking	0.9%	0.7%	0.5%	0.4%

When looking at transport shares the shifts are slightly larger than for trip shares. The share of public transport kilometres decreases from 25.5% in 2019 to 22% in 2050, and the share of car driven kilometres increases from 55.2% to 61.3%. The shares of walking and biking kilometres are already low but decrease from 1.9% to 1.1% for bikes and from 0.9% to 0.4% for walking. One explanation is the annual increase in TTC, the only component of the GTC for walking and biking, making these modes less competitive.

The trip shares for 2050 are presented again in Table 6. together with four different cases of technological development. In the "no technology" case, all modes remain as in 2019 meaning there is no automation and the same share of e-bikes as in 2019. In the car/bus/bike only cases, the respective mode develops accordingly to the base case, whereas the others remain the same as in 2019.

As expected, the mode with the highest level of technological development increases its mode share. But in all cases, the differences are small. The largest relative difference is for the maybe most realistic case, where the share of e-bikes is increasing, but there is no vehicle automation. This results in a relative increase of bike trips by 8%, although the absolute increase is only 0.15% percentage points.

Table 6
Mode share of trips 2050 for different cases of technological development of modes.

Mode	All modes	No technology	Car only	Bus only	Bike only
Car driver	57.35%	55.57%	57.62%	55.34%	55.52%
Car passenger	14.75%	15.46%	14.99%	15.22%	15.44%
Public transport	24.10%	25.01%	23.66%	25.50%	24.98%
Bike	1.88%	1.93%	1.80%	1.92%	2.03%
Walking	1.93%	2.04%	1.94%	2.03%	2.03%

Table 7
Mode share of transport (pkm) 2050 for different cases of technological development of modes.

Mode	All modes	No technology	Car only	Bus only	Bike only
Car driver	61.35%	59.24%	61.69%	58.92%	59.19%
Car passenger	15.21%	16.19%	15.51%	15.89%	16.17%
Public transport	21.96%	23.04%	21.39%	23.67%	23.02%
Bike	1.13%	1.15%	1.06%	1.14%	1.24%
Walking	0.35%	0.38%	0.35%	0.38%	0.38%

4.3. Sensitivity analysis with respect to model parameterisation

We check for the sensitivity of the model result to changes in TTC and β. Table 8 shows the resulting mode shares in 2050 for the cases with changed β, and Table 9 the results with changed TTC assumptions. The assumptions behind the choice of β are described in Section 3.3.3, and the assumptions regarding TTC are described in Section 4.1.

Similarly to the base case, the overall changes to the modal split were limited. The largest differences occurred when β almost tripled. In this case, the model fit had a lower fitness than the best fit (Fig. 3), but not by much (normalised log-likelihood was 0.98 for the car group and 0.96 for the no-car group). With this change, the trip share of car driving increased to 62.8% in 2050 compared to 57.3% in the base case (67.2% of pkm compared to 61.3%). The share of biking decreased by more than 50% for both trips and transports in the case of a high β.

A 30% reduction in TTC for e-bikes had a limited impact on the overall results, which is not surprising considering that the TTC was still larger for biking than using a car or public transport. However, in relative terms for biking, it had a larger impact, increasing the biking trip share from 1.9% to 2.2%, and the transport share from 1.1% to 1.4%. The ASC for biking was also large compared to other mode constants, indicating that factors not included in the model have a strong influence on the choice to bike.

We also conducted a sensitivity analysis where the GTC (not only the TTC) was varied, with an assumption of GTC being 50% higher or lower than the base case for car and bus respectively. This was done to test the overall model sensitivity to costs. The changes in mode shares were larger than when we just varied TTC (as the overall change in cost were larger), but the impact on mode shares was still moderate. As an example, the GTC for car drivers decreased by 22% by 2050 compared to 2019 for a 3.25 km long trip in the base case. This was due to a 64% reduction in driving costs, and a 22% increase in TTC. In the sensitivity analysis, a 50% increase in the GTC compared to the base case instead meant that the GTC increased by 17% between 2019 and 2050 for car drivers. In the base case, the share of trips increased from 52.7% in 2019 to 57.4% in 2050 (Table 4, and in the sensitivity analysis when the GTC varied with 50% compared to the base case, the share of trips by car drivers varied between 53.9% (with a 50% decrease in bus costs) to 60.0% (a 50% GTC increase in bus costs). Detailed results for 2050 in the GTC sensitivity analysis can be seen in Supplementary Note 9, Table 22.

5. Discussion

5.1. Automation impact on urban transport systems

This paper has modelled future mode shares with and without AVs. Although the introduction of partly and fully autonomous cars results in increased car travel, the impact in this paper is moderate. This is in contrast with some previous studies which argue that automation can lead to large increases in VKT due to reduced GTC through reduced TTC and/or increased accessibility for new groups (Almlöf et al., 2022b; Zhao and Kockelman, 2018). However, existing research provides ambiguous answers to how automation will change the (urban) transport system (Wadud et al., 2016; Soteropoulos et al., 2018). Some instead picture an efficient transport system in which cars and rides will be shared leading to a sizeable reduction in VKT and/or vehicle fleet size (ITF, 2015; Lorig et al., 2023).

The moderate impact is this paper compared to other studies can be explained by two main methodological choices. Firstly, studies showing large reductions in VKT or fleet size typically assume extensive substitution between private car trips and trips made by shared robot-taxis, where shared rides lead to increased average occupancy rates. We do not consider robot-taxis or shared mobility in our study but assume that the transport system is organised largely as it is today, with private cars and bikes, and buses in regular service rather than new on-demand services. Secondly, studies indicating large increases in VKT by car often assume one or both of the following: i) endogenous land use pattern, where changes in GTC impact where people and workplace choose to locate, and frequency and/or distance of traveling increases, or ii) relatively simple relationships between cost of traveling and traveling distance, where a decrease in GTC results in increased car travel, taking less consideration for other preferences. Our study is restrictive in the sense that we take as a starting point that the frequency and distance of the journeys remain fixed. Instead, we focus on the competition between modes in a situation where multiple modes undergo technical changes that increase their attractiveness. Overall, this

Table 8
Mode shares for trips and transport (pkm) in 2019 and 2050 with a model sensitivity analysis. The base scenario is included for comparison. The cost parameter β is varied between 0 (no cost sensitivity) and increased values of β corresponding to the same log-likelihood.

	Year	2019			2050		
	Case	Base case	β = 0	$\beta = -0.023\ /\ -0.036$	Base case	β = 0	$\beta = -0.023\ /\ -0.036$
Trip share	Car driver	52.4%	49.0%	52.7%	57.3%	49.0%	62.8%
	Car passenger	15.1%	13.7%	15.0%	14.7%	13.7%	13.3%
	Bus	26.3%	21.7%	28.4%	24.1%	21.7%	22.0%
	Bike	2.6%	3.7%	1.7%	1.9%	3.7%	0.9%
	Other/ walking	3.6%	12.0%	2.2%	1.9%	12.0%	1.0%
Transport share (pkm)	Car driver	55.3%	50.8%	54.0%	61.3%	50.8%	67.3%
	Car passenger	16.4%	13.2%	18.2%	15.2%	13.2%	14.5%
	Bus	25.5%	20.6%	26.6%	22.0%	20.6%	17.8%
	Bike	1.9%	3.6%	0.9%	1.1%	3.6%	0.4%
	Other/ walking	0.9%	11.7%	0.3%	0.4%	11.7%	0.1%

Table 9
Mode shares for trips and transport (pkm) in 2050 with sensitivity analysis of TTC assumptions. The base scenario for 2019 and 2050 is included for comparison.

	Year	2019	2050					
	Case	Base case	Base case	No annual TTC increase	3% annual TTC increase	No TTC change for AVs	Double TTC reduction for AVs	-30% TTC for e-bikes
Trip share	Car driver	52.4%	57.3%	55.4%	59.5%	56.5%	58.2%	57.2%
	Car passenger	15.1%	14.7%	14.0%	15.6%	15.2%	14.3%	14.7%
	Bus	26.3%	24.1%	24.8%	22.5%	24.4%	23.8%	24.0%
	Bike	2.6%	1.9%	2.5%	1.3%	2.0%	1.8%	2.2%
	Other/ walking	3.6%	1.9%	3.4%	1.1%	2.0%	1.9%	1.9%
Transport share (pkm)	Car driver	55.3%	61.3%	59.5%	63.6%	60.1%	62.5%	61.2%
	Car passenger	16.4%	15.2%	14.6%	16.0%	15.9%	14.5%	15.2%
	Bus	25.5%	22.0%	23.3%	19.7%	22.4%	21.5%	21.9%
	Bike	1.9%	1.1%	1.8%	0.6%	1.2%	1.1%	1.4%
	Other/ walking	0.9%	0.4%	0.9%	0.1%	0.4%	0.3%	0.4%

restriction means that the own price elasticity of demand is not considered in this study. This omission is likely to lead to an underestimation of the increase in car travel, as the overall demand might increase as the GTC decreases.

The reason for finding relatively limited changes in mode choice in this paper is that the fitted MNL model indicates that the travel patterns are only to a relatively limited extent determined by the variable cost of the mode and largely determined by other factors (as determined by the mode alternative specific constants in the MNL model). Although it can be seen as a weakness of the model, it also shows that taking non-economic preferences into account is vital in other modelling studies.

The different types of model approaches all have their relevance. On the one hand, the "optimistic" studies where VKT is reduced due to automation tend to focus on how efficiently the transport system can be given certain accessibility requirements. The studies indicating large increases in VKT tend to be designed based on the question of how large the consequence of automation can be if the integrated land use and transport system develops without restrictions. On the other hand, if the goal is to explore probable future pathways, the inclusion of near-term technologies like partly automated vehicles and e-bikes is relevant.

5.2. Model assumptions and sensitivity

The model presented in this paper is intentionally simple and aggregated. The simple form makes the model transparent, which has been an identified shortcoming of e.g., agent-based models (An et al., 2020). Nevertheless, model simplifications have trade-offs between transparency and accuracy. The first simplification concerns mode availability and population homogeneity. In practice, all modes are not available for all trips for different reasons. This is not considered in the model, besides using different model parameters for the car and no-car groups. Further model development could be the inclusion of bike ownership as a condition for bike trips, or to extend the model to bike sharing services, as these are available in all regions of this study. A trip chain-approach, rather than aggregate trip patterns, would also enrich the analysis, e.g., by considering vehicle availability for each trip conditioned by the location of the vehicle and decision maker simultaneously. None of these factors are covered in the model, making the mode competition mechanisms transparent (a function of GTC) but also hiding the influence of heterogeneity.

The second simplification concerns the fleet models, and in particular the bike fleet model. Bike fleet and ownership models are generally an unexplored field. It is assumed in this study that an increased share of e-bikes equals a corresponding increase in access to e-bikes among the metropolitan population. Another possibility is that e-bike diffusion is unevenly distributed between regions, but the lack of regional bike data makes further disaggregation impossible. The possibility of uneven diffusion is also true for AVs and EVs. Another aspect is that an increased sale of e-bikes (or AVs) might not correspond to the same increase in access in the population, but rather that existing owners increase the number of owned vehicles, e.g. by owning multiple types of bikes such as e-bikes, cargo bikes and mountain bikes. In addition, we have assumed the same lifespan for conventional bikes and e-bikes, and autonomous/electric cars and conventional ones, which might not be the case. The average lifespan in this study is based on statistics and previous studies. It is possible that the average lifespan or the lifespan distribution will change with the introduction of autonomous and electric vehicles. A shorter lifespan will, in general, speed up fleet turnover and a longer lifespan will result in a slower turnover. For buses, it seems more likely that the introduction of electric buses might relax the age requirements in current contracts and result in a longer lifespan (as the age requirements are partly related to concern for exhaust emissions). For cars, it is more difficult to assess the impact of automation and electrification on lifespan. A higher annual mileage (if AVs drive more) will likely result in a shorter lifespan, but there are arguments for both longer and shorter lifespans for electric cars compared to fossil-fuelled cars (Held et al., 2021; Morfeldt and Johansson, 2022).

A third simplification is the assumption of unchanged urban infrastructure for AVs. Measures such as intelligent traffic management or dedicated lanes for AVs would likely increase the competitiveness of AVs, either by reducing the travel time or by reducing the GTC for AVs more than we have assumed in this analysis (as travel would be perceived as even more comfortable with these measures). This could result in a larger increase in car travel, compared to our results. We also do not make any explicit assumptions on charging infrastructure for electric vehicles, but the expansion of charging is assumed to be in line with the increase of electric vehicles.

Finally, even though this study does not include any representation of the public transport network and service levels, we do think that most of the trips are made from destination where there is a good supply of public transport services. Analysis of the NTS data shows that public transport ridership does vary during the different hours of the day but that the mode share remains relatively stable between day and night. The most obvious simplification in this aggregated model is the lack of detailed origin/destination (O/D) data and travel time ratios between public transport and car, as there are commonly some O/D relations where travel time is much longer for public transport (typically travel along the periphery of a metropolitan area). This level of detail is not available in the NTS data and would require other data sources, like GPS or mobile phone traces to set up a dataset with detailed O/D data.

This paper has explored the sensitivity to two important parameters in AV research: the TTC and the cost preference parameter β. The exact values of assumed TTC reductions for different levels of automation are not known since the technology is not yet available. This study simply assumes a fixed reduction per technology, where a more likely outcome is that TTC savings will differ with sociodemographic groups or trip purposes (Börjesson and Eliasson, 2014). Our sensitivity analysis shows that the model is relatively insensitive to changes in TTC. Assuming no change in TTC for AVs decreases the car driver trip share by 0.8 percentages, while doubling the TTC reduction results in an increased car driver trip share by 0.9 percentages. One explanation is that the competitiveness of being a car or bus passenger increases, as TTC is reduced for these modes as well, but the changes in biking and walking are also moderate. Another explanation is the size of the cost parameter β compared to the ASCs. 70% of the trips in our dataset have a GTC in the range of 0–100 SEK per trip, and 90% a GTC within the range of 0–200 SEK per trip. This means that $\beta * GTC$ mostly ranges between −2 and −1 while the ASCs range from −2.9 to −1.1 (both ranges are for the car group, which is the largest group in this study). One way of understanding model sensitivity to changes in GTC is to compare the ratio ASC/β with other studies. The absolute value of ASC/β *(for* $ASC \neq 0$), ranges from 3.1 (ASC_{bike} for the no-car group) to 31 (ASC_{bike} for the car-group) in our study (after rescaling β to US dollars instead of SEK and normalising the ASC for car driving to 0). The lower end of the range is similar to other studies, while the higher end is a little higher. Our results can be compared to the ratio ASC/β in Harb et al (Harb et al., 2022)., who also included autonomous cars, public transport, biking, and walking in their estimated model. The absolute values of ASC/β, estimated by Harb et al. but with the *ASCs* normalised to 0 for cars by the authors of this paper, range from 5.3 (public transport) to 22.5 (walking). Wicki et al. do not include car driving as an option but only autonomous buses, biking and walking, and ASC/β absolute values range from 6.5 to 13 (Wicki et al., 2019). The latter is estimated on a stated preference survey while Harb et al. uses revealed preference data.

Finally, the GTC consists of both time and other costs. A 30% reduction of the TTC, affecting the time cost, which makes up about 50–80% of the GTC for our studied trips, would result in a smaller reduction in the GTC. The impact of electrification on GTC in this study is about as large as that of automation, since the marginal driving cost per km is reduced by 50% with an electric car.

We studied the sensitivity to changes in the cost parameter β by assuming no sensitivity to costs ($\beta = 0$), and a symmetrical increase in cost sensitivity (maintaining the same log-likehood with a larger β as for $\beta = 0$). The case of $\beta = 0$ cannot be seen as realistic but is still a relevant benchmark case in which new technologies do not affect travel patterns. The resulting modal shares changed by less than 10 percentages in all cases of sensitivity analysis, although the relative change in, e.g., biking was substantial. For example, with a larger β the mode share of car driving increased from 52.7% in 2050 to 62.8%, and the share of bike trips decreased from 1.7% to 0.9%. Overall, it is important to keep in mind that the estimated β is obtained from the maximisation of a likelihood function that can have varying degrees of steepness - or flatness. A sensitivity analysis such as the one performed, which considers model sensitivity, in addition to the more commonly investigated parameter assumption sensitivity, can provide further insight into how to interpret scenario studies. This is of importance for both researchers and practitioners when presenting scenario studies. Researchers and practitioners should also keep the importance of other factors than GTC in mind in transport system scenario studies.

6. Conclusion and contribution

We have investigated how travel in metropolitan areas could be affected by the introduction of new technologies: autonomous cars and buses, and e-bikes. Rather than looking at a transformed transport system with shared or on-demand mobility services, we have studied the impact of technology where the ownership and transport system structure of cars and public transport remains mainly the same as today (private cars and bikes, and regular service buses).

With a MNL choice model with parameters based on a statistical analysis of the Swedish NTS, the impact of new technology on mode choice is moderate. The model results indicate an increase in car travel and a decrease in public transport, biking, and walking. This is overall in line with previous studies (Almlöf et al., 2022b; Harb et al., 2022; Kröger et al., 2019) although the impact of AVs is heavily dependent on model assumptions, which vary between studies.

Onereason for the moderate change is that our statistical model indicates that other factors than generalised travel cost are also important in determining utility. Furthermore, the impact of lower driving costs with electric cars might have an equal-sized impact on generalised travel costs as a lower travel time cost with autonomous cars. The model and estimates of travel costs in this paper are simple, but the order of magnitude of estimated parameters is in the same range as other literature estimates. This means that even TTC reductions by 30–60% for car drivers using fully autonomous cars will have some but limited impact on mode choice in the model. This study is limited to privately owned autonomous cars, and car travel will likely increase more if shared or on-demand services are available also for those who currently do not own a car.

A valuable insight is, however, that even though car travel will likely increase with higher levels of automation, the effects are partly counteracted by the technological development of e-bikes and autonomous buses.

CRediT authorship contribution statement

Cecilia Hult: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Daniel J.A. Johansson:** Writing – review & editing, Methodology, Funding acquisition, Data curation. **Frances Sprei:** Writing – review & editing, Methodology, Funding acquisition.

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.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ets.2024.100010.

Data availability

The authors do not have permission to share data.

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