MODELLING THE IMPACT OF AUTOMATED DRIVING – PRIVATE AUTONOMOUS VEHICLE SCENARIOS FOR GERMANY AND THE US

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1. INTRODUCTION

Vehicle automation technology advances and the market entry of autonomous vehicles (AV) is expected within the next years (cf. Fagnant/Kockelman 2015). There is an uncertainty of the impacts of the introduction of AVs on travel demand and road traffic volume. Due to a diversity of assumptions of different studies, a variety of results have been published with negative as well as positive impact on road traffic volume. Most studies are spatially limited, e.g. to certain agglomerations (cf. Childress et al. 2015, Gucwa 2014). Some studies include autonomous sharing systems or are limited to them (cf. Martinez/Crist 2015, Fagnant/Kockelman 2014), other studies are limited to private owned vehicles (cf. Gucwa 2014). Modelled effects are e.g. the adjustment of values-of-travel-time-savings (cf. Childress et al. 2015, Gucwa 2014), the mobilization of new user groups (cf. Harper et al. 2015) and an impact on road capacities (cf. Childress et al. 2015, Gucwa 2014).

This paper presents results from modelling travel behaviour impact of introducing AVs into the private car fleet in Germany and the US. Five levels of automation technology have been defined (cf. SAE n. d.). In this study we limit our analysis of AVs to level four (partially autonomous vehicles) and level five (fully autonomous vehicles) vehicles. This limitation was selected as in the defined situations (i.e., all situations for level five) no human driver is responsible for fallback performance.
Substantial impact on travel choice is expected if drivers do not need to attend to the driving task for most of a trip anymore ("brain off"). By this, a reduction of value-of-travel-time-savings and following from this, impact on destination and mode choice is assumed. As it is not allowed to move without a driver yet, empty trips and consequently autonomous car- and ride-sharing systems are not possible at this time.
In order to model 2035 scenarios, we combine a vehicle technology diffusion model and an aspatial travel demand model. Two scenarios of different AV diffusion rates are modelled for each country, a moderate trend scenario and an extreme scenario with optimistic assumptions in terms of diffusion rates.
The aspatial travel demand model consisting of trip generation, distance choice and mode choice is used to forecast travel by different traveller groups and by car availability (no car, conventional car, AV). When modelling the impact of driving AVs instead of conventional cars on travel behaviour, a reduction of access/egress times due to quicker parking and reduced value-of-travel-time-savings for travellers with AVs are assumed, but no effects on road capacity.

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The paper is organised as follows: Section 2 describes the modelling approaches for the vehicle technology diffusion model and the aspatial travel demand model. Section 3 introduces the scenarios' assumptions of the trend and extreme scenario and the adaptions of the modelling system to model the travel demand with the existence of private AVs. Section 4 presents the diffusion rates of AVs into the private car fleet and resulting impact on travel demand. Section 5 discusses the influence of assumptions on results. Strengths and weaknesses of the modelling approaches are addressed. Further research to depict further developments of autonomous driving is raised. Section 6 concludes the study by naming the main methodical and contentwise findings.

2. MODEL

Two models are developed to quantify the impact of the introduction of AVs into the private car fleet. The first one – a vehicle technology diffusion model – addresses the calculation of diffusion rates of AVs into the private car fleet. The second one is a travel demand model to analyse mode and distance choice in a future context. The results from the diffusion model are used as input for the travel demand model.

2.1 Vehicle technology diffusion model

The diffusion of AV technologies is modelled by an s-shaped market-take-up. It is differentiated for car segments, considering the national car market. Four segments are distinguished for each country. In Germany the segmentation differs between small vehicles, compact class, medium sized vehicles and large vehicles. In the US small vehicles, pick-up-class, medium-sized vehicles and large vehicles are differentiated. The pick-up-class is handled separately because of the large share despite the diversity of vehicles in the pick-up class. The German segmentation is an adapted version of the KBA classification (KBA n. d.). The US classification is an adapted version of the vehicle type definition used in the NHTS (USDOT 2011: A-8).

Differences of the diffusion rates of different car segments arise from different years of introduction, initial diffusion rates and parameters for the increase of the curve. The number of newly registered AVs P_t in year t is calculated as follows

$$P_t = P_\infty * a^{b^t} \qquad (1)$$

With:

P_∞ : maximal number of newly registered AVs (with the assumption of a maximum 95% rate of AVs);

a : quotient of the initial rate of newly registered AVs in the year of introduction;

b : factor of growth;

t : number of years since introduction.

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The differences between the transport modes are set considering historical developments of vehicle technologies for example for driving assistance. The forecast of years of introduction follows published road maps e.g. of suppliers of automation technologies from European Road Transport Research Advisory Council (cf. ERTRAC 2015).

The vehicle technology diffusion model distinguishes between level four and level five automation technologies. Level five can be seen as fully-autonomous vehicles (cf. SAE n. d.). There is no overlapping of level four and level five diffusion. An integrated curve with a change from level four to level five diffusion is used for simplification. The diffusion of automation technologies follows a top down approach. Automation technologies will be introduced first in the luxury segment and later in the smaller vehicle segments. The delay as well as the initial diffusion rate and market growth within the different segments is adapted from the observed market take up automated cruise control (ACC) systems. Since there is no publicly available data, internet automotive classifieds such as cars.com (for the US car market) and mobile.de (for the German market) have been analysed for the share of vehicles equipped with ACC systems for each vehicle segment and model year within the last 15 years. It could be observed that the share of vehicles equipped with ACC systems in the US is significantly lower than in Germany mainly due to the lower share of luxury segment vehicles and longer vehicle lifetime resulting in a slower diffusion of such systems.

2.2 Aspatial travel demand model

The travel demand model approach presented here is a highly-aggregated macroscopic one. Macroscopic models are differentiated from microscopic as well as mesoscopic transport models, depending on the level of detail of representing transportation performance and flow representation (cf. Abdulhai et al. 2011:1.29). Interactions between vehicles, interaction between flows and capacity restraint functions are ignored in the model. Following the classification of Tarko/Anastasopoulos (2011: 4.2), the model is a transportation demand model for demand generation, based on a sequential four-step process, trip generation, trip distribution, modal split and trip assignment. The aspatial travel demand model only consists of the first three steps. With respect to trip distribution a distance choice model is used, combined with a mode choice model. There is no final traffic assignment.

2.2.1 Input data

Socio-demographic forecasts, travel survey data and travel cost data are the main exogenous data inputs for the travel demand model.

Socio-demographic forecasts for the scenario year 2035 are used with population data differentiated by age, gender and spatial area. The national population projections for Germany (Destatis 2009) and for the US (USCB 2014) for the next decades are used. Moreover forecasts of driver license holding rates by age cohorts have to be used. In Germany and particularly in

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the US the rates – reported in the National household travel survey data set – are saturated and the future effects are foreseeable.

National household travel surveys are used for trip generation and calibration of the distance choice and mode choice in the travel demand model. National household travel surveys are conducted in many countries in a comparative but partly dissimilar way to get an idea of how and why people travel (cf. Kunert et al. 2002). To compare impacts in Germany and the US, data sets of the MiD 2008 (BMVI n. d.) for Germany and the NHTS 2009 (USDOT n. d.) for the US are used. The German and the US survey are mostly comparable. Both data sets consist of different data, namely a household data set, a person data set, a trip data set and a vehicle data set. Weights are given for each data point.
Due to different minimum age limits in MiD and NHTS (zero years in MiD 2008, five years in NHTS 2009) and due to the fact that the minimum age of using an AV in the scenarios is at least ten years, partial data sets of persons of ten years and older are used.
For the US data, the reported proxy variable "being a driver" is used instead of holding a driver license due to a lack of information.
Main users of vehicles are reported in the vehicle data set and determined if missing. If respective main users are not completely known, main users are identified based on actual behaviour of the household members.
Some missing values in the data set need a reduction of data. This concerns persons without a stated age value. The final step of data preparation is the calibration of the data set weights to meet benchmark values. We assume that an additional weight for correctly assigned person and trip data is better than the consideration of randomly aged persons. In other cases of missing data in a larger extent, strategies of data imputation have to be used (e.g. for non-reported vehicle mileage).

Besides assumptions of out-of-pocket costs such as fuel costs and fares, the use of generalised costs for mode and distance choice modelling require a monetised valuation-of-travel-time-savings. Beside the comparability of the travel survey data, the comparability of the values-of-travel-time-savings is necessary. Due to country-specific external effects such as GDP the values differ.
For Germany the time-valuation study of Axhausen et al. (2014) is used, which describes a logarithmic curve of values-of-travel-time-savings over distance. The USDOT Departmental Guidance on Valuation of Travel Time (USDOT 2015) is used for US values, with an adjustment to a logarithmic curve.

2.2.2 Model approach

The aspatial travel demand model consists of a trip generation and a combined mode and distance choice. Besides the reweighting for trip generation, the assumptions of the distribution of activity locations in space and the idea of generalised costs as input for the logit mode choice model are central elements of the developed aspatial travel demand model.

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The model distinguishes two trip purposes, namely education- and work-trips on the one hand (mandatory trips) and all other trips on the other hand (non-mandatory trips). Trip purpose differentiation is important for valuation-of-travel-time-savings and the heterogeneity of trip length distribution.

The reweighting of the person and trip data aims at fulfilling the benchmark values by groups of persons (differentiated by age, gender, spatial area and driver license holding). Reweighting in this context means that the weights of reported trips made by a growing group of persons, with respect to share of total population (e.g. older people), increase and by other groups of persons decrease. Clustering the trips by trip purpose and car availability category leads to a trip table of the summarised trip weights. The total sum of the person weights is the total number of persons in person data. The total number of trips is the total number of trips per day based on the travel survey. The day has to be seen as an average day as all trip data from the survey is considered. A differentiation of weekday and weekend travel would imply the need of an adjusted reweighting after splitting the data set.

Reweighting with regard to driver license rate forecasting follows the shares of groups differentiated by gender and five-year-groups. Current shares are forecasted into the future by adding the age difference. The most important shift results from the increasing ownership of driver license among older women in Germany. Driver license information is essential to classify car availability, as we assume availability if the person holds a driver license and the affiliated household owns at least one vehicle.

Generalised costs involve variable monetary costs of a trip such as fuel costs, fares and monetised travel time costs. Constant fuel costs per kilometre, based on average consumption per 100 kilometres and a price per litre, and almost constant public transport ticket costs per kilometre are set. Estimated fares for very short public transport trips are higher using an asymptotic function.
The generalised costs as explanatory variable are difficult to handle for car passenger mode choice decisions. The fuel price elasticity is positive for the car passenger mode in contrast to the car driver mode (cf. Litman 2004: 50). In the model, the share of car passengers is fixed for all distance bands for each of the trip purpose-car availability-categories. Therefore a smoothed function is used, because the share for many distance bands would be zero or one due to the discontinuity of values.

Due to the lack of reported travel mode alternatives and related data, in particular travel time, mode choice is calibrated by an assumed choice set of alternatives consisting of the attributes of the reported alternative and generated attributes of the other alternatives. Travel modes are walk, bike, car driver and public transport; the car passenger mode is handled with fixed shares per distance band per trip purpose-car availability-category as described above. Travel times consist of an access/egress constant and a calculated travel time resulting from speed functions. The reported value for the chosen alternative comprises already both values, this is true for MiD and NHTS data.

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Speed functions for the different travel modes have to be developed for both countries to calculate travel times for generated mode alternatives. These speed curves are logarithmic over distance but not differentiated for trip purposes. The speed curves are derived from used travel survey data sets. The missing differentiation between access/egress times and vehicle-use-times (in-vehicle-travel-times) in the MiD and NHTS complicates to estimate the speed curves. A differentiation of travel speeds considering the travel distance for generated mode alternatives can improve a mode choice model (cf. Agarwal/Kickhöfer 2015: 10f.) and is regarded as necessary for analysing the data.

The total travel times $tt_{total,i}$ of the alternatives i are calculated by:

$$tt_{total,i} = \begin{cases} tt_{reported,i} & \text{,if } i \text{ is the reported mode alternative} \\ tt_{access|egress,i} + \dfrac{d}{v(d,i)} & \text{, if } i \text{ is not the reported mode alternative} \end{cases} \quad (2)$$

With:

$tt_{access|egress,i}$: mode specific constant access/egress time values;
$tt_{reported,i}$: reported travel time in the travel survey for the chosen mode alternative;
d : travel distance which is constant for all travel modes;
$v(d,i)$: distance- and mode-dependent travel speed.

The mode specific constant access/egress time value is determined by an incremental regression analysis of the total travel times. The access/egress time values used in the model are set for Germany and the US as followed (see Table 1):

Table 1: Overview of access/egress times of different modes used in the model for Germany and the US

	Germany	US
$tt_{access\|egress,walk}$ [min]	5	
$tt_{access\|egress,bike}$ [min]	5	
$tt_{access\|egress,car(driver)}$ [min]	5	4
$tt_{access\|egress,public\ transport}$ [min]	15	

A problem of estimating general speed functions for different travel modes based on reported mode choice alternatives is the lack of non-reported mode alternatives with worse characteristics. Considering the minimum public transport modal share in the US and the qualitative differences in public transport supply between big cities and the countryside, the 0.4-decile has been taken as average speed. Different maximum distances between the German and the US model result from the intranational trip lengths distributions modelled here. The maximum value in the German model is set to 512 km, the maximum value in the US model is set to 1024 km.

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A multinomial logit-based mode choice is used. The probability p_i of choosing a mode alternative i from a set of alternatives J = {*walk; bike; car (driver); public transport*} is calculated by:

$$p_i = \frac{e^{U_i}}{\sum_{j=1,\ldots,4} e^{U_j}} \tag{3}$$

With:
U_i : utility of a mode alternative i.

The utility U_i is calculated as:

$$U_i = \beta_i + \beta_{gc} * gc_i \tag{4}$$

With:
β_i : mode specific constant;
gc_i : mode-specific generalised costs.

Table 2 gives an overview of the mode specific constants. The mode-specific generalised costs are a sum of travel costs as out-of-pocket costs for car and public transport trips only and the monetised travel time which depends of access/egress times, distances, speeds and the value-of-travel-time-savings.

Table 2: Model parameters of the mode choice model

		trip purpose work/education		other trip purposes	
		no car availability	car availability	no car availability	car availability
Germany	mode specific constants				
	β_{walk} (reference mode)	0	0	0	0
	β_{bike}	-1.117	-0.894	-1.263	-1.686
	$\beta_{car\ (driver)}$	-4.469	+0.246	-3.318	-0.155
	β_{PT}	+0.423	-0.319	-1.327	-2.470
	β_{gc}	-0.705	-0.589	-0.284	-0.346
US	mode specific constants				
	β_{walk} (reference mode)	0	0	0	0
	β_{bike}	-3.280	-3.143	-2.436	-3.755
	$\beta_{car\ (driver)}$	-5.926	+0.835	-3.593	+0.222
	β_{PT}	-0.424	-2.232	-1.757	-4.053
	β_{gc}	-0.587	-0.386	-0.339	-0.522

The model step of trip distribution is replaced by a distance choice approach concerning different heterogeneities of activity locations of different trip purposes. Distance bands of one kilometre are distinguished. Analysing travel survey data, the trip length distribution of different trip purposes differ resulting also in different average trip lengths. Among others the density of activity locations and the heterogeneity of activity locations for different trip purposes are influencing factors for this. To give an example, for shopping a

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supermarket in a certain distance does probably not significantly differ from others in a closer distance, but a workplace may be much more specialised than the others in a closer distance.
Choosing trip length and travel mode for a trip depends on costs and benefits. To estimate a distance-based benefit, parameters for activity location density and heterogeneity are chosen for each trip purpose-car availability-category to calculate a benefit value for each distance band. Combined with generalised travel costs (weighted by modal shares) a distance band probability can be calculated. Mode choice for each distance band is independent from the benefit.

The output from the combined mode-and-distance-choice model is a table with probabilities of choosing a travel mode and a distance band for a trip classified by trip purpose and car availability. Multiplying the probabilities by the appropriate trip sum from the trip table leads to modal shares over all trips. Multiplying the numbers by distances leads to vehicle and person kilometres of car mode and the alternatives.
The total modal share P_i for travel mode i for all trips is

$$P_i = \sum_{tpccat} \left(n_{tpccat} * \sum_{dist} p_{dist,i,tpccat} \right) \tag{5}$$

With:
$tpccat$: trip purpose-car availability-category;
n_{tpccat} : total number of trips from trip table for each $tpccat$;
$p_{dist,i,tpccat}$: probability of choosing travel mode i and a distance band $dist$ dependent on $tpccat$.

The total trip lengths L_i for travel mode i over all trips is thus

$$L_i = \sum_{tpccat} \left(n_{tpccat} * \sum_{dist} \left(p_{dist,i,tpccat} * dist \right) \right). \tag{6}$$

The resulting table from the combined mode-and-distance-choice model characterise different travel behaviour of persons in different car availability-categories. An expected value of kilometres per person per mode can be calculated in that way the total trip length is calculated.

3. APPLICATION AV

The models previously described are used to estimate the impact of introducing AVs into the private car fleet on travel demand. Therefore both models complement each other. The output of the vehicle technology diffusion model is used for reweighting the data sets and setting up different scenarios in the travel demand model. The travel demand model is adapted to model the impact of autonomous driving. Figure 1 gives an overview of the combined model scheme.

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In the following, at first the scenarios are described, then the adjustments of the aspatial travel demand model to model the impact of introducing AVs into the private car fleet on travel demand are named.

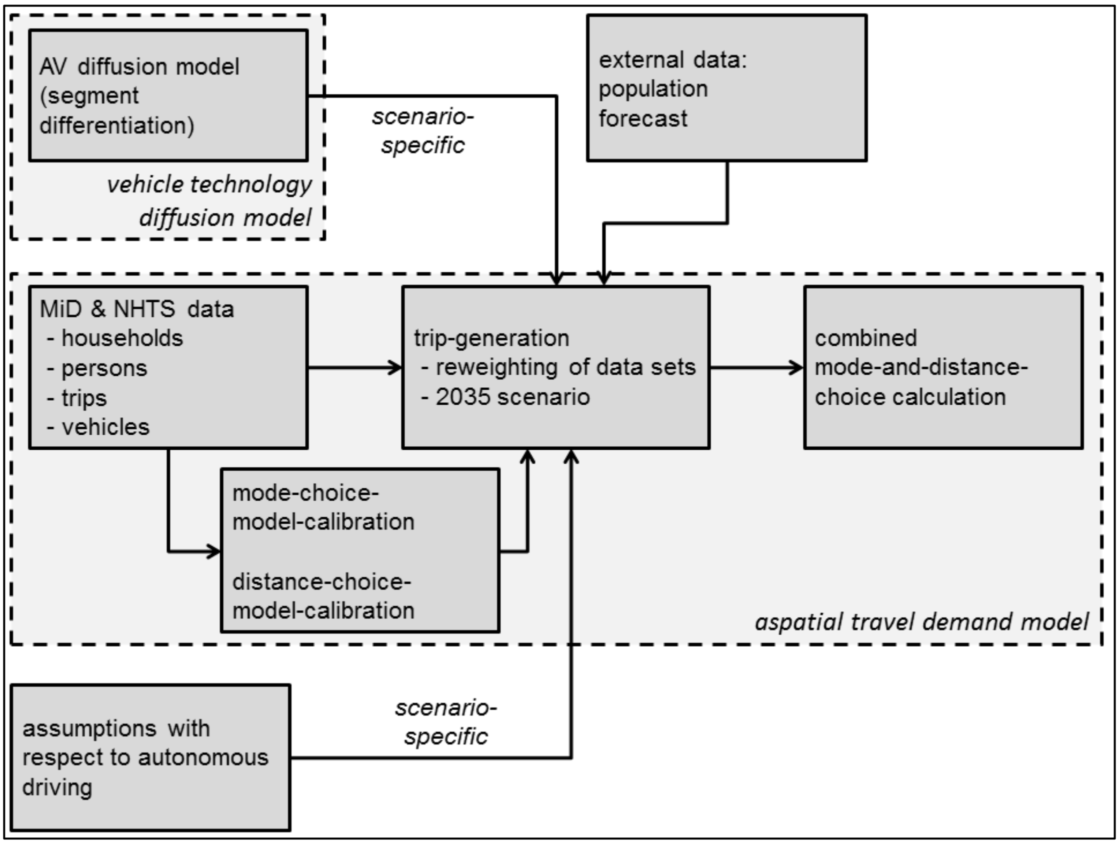

Figure 1: Model scheme of the combined model approach for AV application

3.1 Scenario description

Estimating and describing the impact of introducing AVs into the private car fleet and comparing the results for the US and Germany is realised in two scenarios: a "trend scenario" and an "extreme scenario".

The main difference between the two scenarios is the variance of diffusion rates of AVs by adjusting the parameters in the vehicle technology diffusion model. The differences result from earlier years of introduction (level four vehicles are rolled out from 2022 on instead of 2025, level five vehicles are rolled out from 2025 on instead of 2030). Additionally, the initial diffusion rates are varied, and the legal age of using an AV available in the household is lowered from 14 years in the trend scenario to 10 years in the extreme scenario.

Beyond that, assumptions are equal for both scenarios. The reduction of the value-of-travel-time-savings for driving an AV is set to 25% compared to the value-of-travel-time-savings of driving a conventional car. However, this applies only to travel time longer than ten minutes due to an assumed make-ready time.

A reduction of access/egress times to AVs is assumed. This reduction has to be understood as a self-ride-preparation on private ground. It has to be mentioned that the assumptions do not strictly adopt the differentiation of

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automation level. On the one hand it is said that a person has still to be present in the AVs while driving, on the other hand among others blind people and people without driver license can sit in the vehicle on their own. The attendance in a vehicle does not require the ability to intervene in driving.
Mobility impaired people are considered in both scenarios prioritised in such a way that a levels of car availability comparable to non-mobility impaired persons in the same age-gender-groups are reached. The high share of mobility impaired elder people enforce the additional mobilization of elder people which is stronger than that of other groups by implication. For elder people, no additional extra mobilization is considered in the scenarios. The cohort effects of additional mobilization due to a higher driver license holding rate especially for women is true for all three scenarios.
The scenario assumptions for both AV scenarios are listed in Table 3.

Table 3: Overview of scenario assumptions

	trend scenario 2035	extreme scenario 2035
Market introduction of AVs (differentiated by car segments)		
level four	2025-2030	2022-2025
level five	2030-2034	2025-2028
reduction of value-of-travel-time-savings	reduction of 25% from eleventh minute of driving on	
reduction of access and egress times to and from AVs	reduction of access and egress time from five minutes (GER) resp. four minutes (U.S.) to three minutes	
car availability of teenagers	minors from 14 years on can use a household-owned AV	minors from 10 years on can use a household-owned AV

Several considerations lead to the assumption of a reduction of value-of-travel-time-savings of about 25%. The reduction applies to all trips of persons with AV availability, although not all individuals are willing to use the time otherwise (cf. Cyganski et al. 2015).
Gucwa (2014) varies the reduction of value-of-travel-time-savings in one scenario in comparison to that one using high-quality-trains. A comparison of car and public transport values-of-travel-time-savings used in this study leads to a reduction of about 25% (not constant for all distance bands).
A comparison of amortization costs of hardware and software leads to annual costs of about 600 € (total costs 3,000 €[1], depreciation over five years). Considering an average annual driving time of about 300 hours, the benefit per driving hour should be in the range of 2 €. The value-of-travel-time-savings depends on distance but the proportion is in that range.
Childress et al. (2015) use a perceived travel time reduction of 35% driving in an AV which has in consequence the same generalised costs as less negative valued travel time. Litman (2013: 10) states a relative difference of value-of-

[1] 3,000 € is about the value most respondents (who did not named a value of 0 €) of a study answered when asked about their willingness to pay for fully-autonomous-vehicle-technologies (cf. Kyriakidis et al. 2015: 134). It has to be mentioned that this questionnaire has been taken in 40 countries with different GDPs. But an analysis of prices of today's driving assistance systems on the German market leads to a comparable value.

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travel-time-savings of 30% when comparing a car driver and a car passenger on the one hand and a standing and sitting public transport user on the other hand. Both cases are considered to be transferable to the comparison of driving a conventional car and being driven in a fully-autonomous car.
The reduction applied in this study is 25%.

3.2 Model adjustments of the aspatial travel demand model

The vehicle technology diffusion model and the aspatial travel demand model are linked by allocating AVs in the travel demand model according to the extent calculated in the vehicle technology diffusion model.
AVs are assigned to households being ranked by annual mileage. The vehicles are ranked in twelve groups of vehicle segment and vehicle age differentiation. Vehicle age groups are 0-4 years, 5-8 years and >8 years. The shares result from the vehicle technology diffusion model. The car segment groups are those from the diffusion model and differ between Germany and the US. A similar vehicle age distribution of vehicles compared to present age values in the vehicle data set is assumed. Therefore the vehicle age in the vehicle data set in the base year is the determining age for classification. Reweighting factors result from person and household reweighting.

In the aspatial travel demand model, different assumptions of modelling autonomous driving are made. The resulting changes in travel demand are resulting from that combination of assumptions.
One of these assumptions is the activation of new user groups, in particular the mobility impaired people and teenagers. The rate of car availability of mobility impaired people is raised to the level of non-impaired people by reweighting person and trip data weights. The higher mobility impairment rates of older people enforce the stronger mobilization due to the introduction of AVs of older people compared to younger people by implication. For older people, no additional mobilization is assumed. The cohort effects of additional mobilization due to a higher driver license holding rate especially for women is true for the base case and both AV scenarios.
While the respective main user of an autonomous car within a household can use it for all of his/her trips, for any other household member usage is limited to non-mandatory trips only. The macroscopic model presented here does not facilitate the use of car diaries, this would be necessary to consider real trip-based car availability. To avoid an overuse of the AVs and due to the lack of intra-household-empty rides this constraint is set.

The value-of-travel-time-savings is reduced in both scenarios by 25% from the eleventh minute of driving on. The relative reduction applies to all car trips made by persons with availability of an AV for that trip. As car diaries are not available for the macroscopic simulation, actual, real-time car availability is unknown. The estimated parameters are based on this assumption. There is a differentiation between the main user of a vehicle and other household members: Main users can access the AVs at any time, any other household member can use them for non-work and non-education trips only. By this, all identified main users have the AV availability for all trips.

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With respect to of access/egress times to AVs, a reduction is assumed. In Germany the access/egress time is reduced from five to three minutes, in the US from four to three minutes. In Germany the initial value is higher due to infrastructure conditions, e.g. reduced parking areas.
Adjustments of both access/egress times and valuation-of-travel-time-savings are considered by adapting the mode choice data.

The diffusion model differentiates between level four and level five automation levels. To model the impacts on travel demand only level five vehicles with fully-autonomous driving technology are considered, by passing only the level five diffusion rates.

4. RESULTS

In the following, modelling results are presented. First the results of the vehicle technology diffusion model are described, which are inputs for the travel demand model. Second the impact on travel behaviour is named.

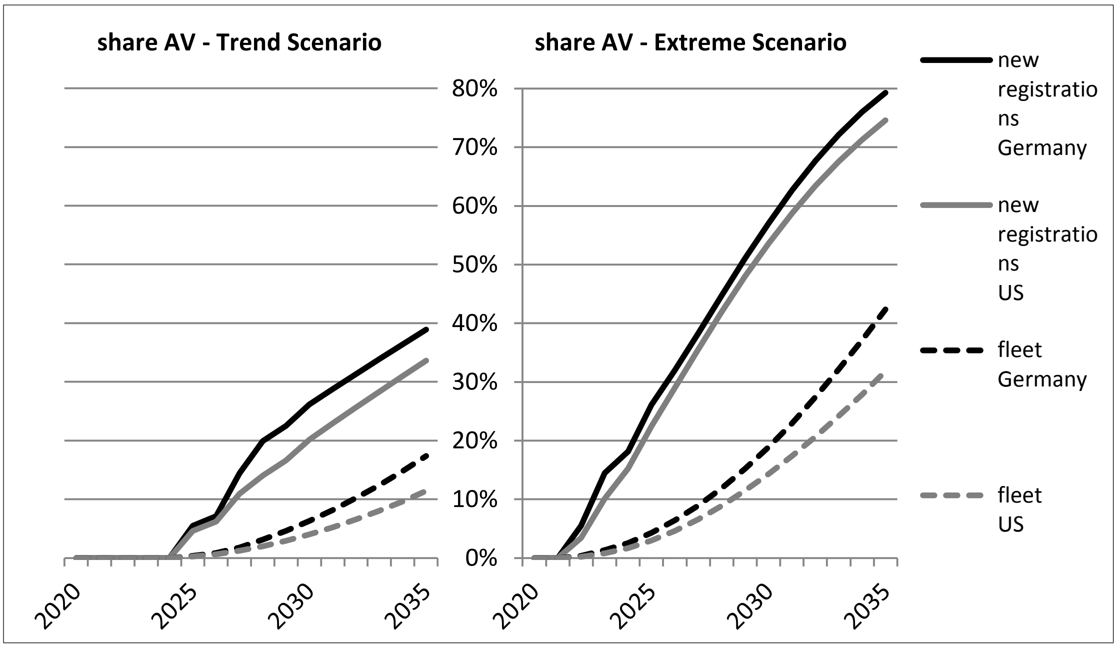

Figure 2: Shares of AVs in the fleet in Germany and the US according to trend and extreme scenario (share as sum of level four and level five vehicles of all vehicles of all segments) (own scenario calculation)

An s-shaped curve of the share of AVs in the car fleet can be observed (see Figure 2). The point of inflection of the car fleet curve will not be reached until 2035, not even in the extreme scenario. New registrations, however reach a rate of almost 80% in Germany and 75% in the US in the scenario year 2035. The fleet curve results from the function of new registrations and the lifetime of vehicles and the resulting rate of abolition of vehicles. The curve of new registration has discontinuities because of the different years of introduction of the vehicle technology of different car segments with a given initial diffusion rate. The influence on the fleet curve from this is extremely small.

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Diffusion rates in Germany are higher than in the US because of the higher share of luxury vehicles in the new car market as well as the longer vehicle lifetime resulting in a slower fleet renewal (see Chapter 2.1). The years of introduction do not differ between the two countries. The differences between the scenarios show an earlier growth of the curves in the extreme scenario and hence a higher growth rate in the scenario year 2035.

Table 4 gives an overview of the share of AVs in the fleet, differentiated for level four and level five and the sum over all vehicles. Resulting from the function, higher values can be observed for Germany and for the extreme scenario. The share of level four vehicles is smaller in the extreme scenario due to the earlier year of introduction of level five vehicles. The total share of AVs in the vehicle fleet reaches a value of 11.4% (US) and 17.4% (Germany) in the trend scenario and 31.8% resp. 42.4% in the extreme scenario. The shares of level five vehicles on all AVs with 92% (US) and 89% (Germany) in the extreme scenario is much higher than in the trend scenario with 66% and 58% respectively.

Table 4: Overview of share of AVs in 2035 in the different scenarios (Table based on own assumptions and calculations)

	trend scenario 2035		extreme scenario 2035	
	US	Germany	US	Germany
year of introduction level four (by segments)	2025-2030		2022-2025	
year of introduction level five (by segments)	2030-2034		2025-2028	
share of AVs in vehicle fleet over all segments				
level four	3.9%	7.3%	2.5%	4.8%
level five	7.5%	10.1%	29.3%	37.6%
sum	11.4%	17.4%	31.8%	42.4%

The values shown in Table 4 are further used for calculating the impact on travel demand.
The introduction of private AVs leads to a moderate increase of vehicle kilometres, resulting from changes in mode and destination choice and because of new mobility options for a part of the population. Table 5 summarises the impacts on total vehicle mileage and on modal shares. The scenarios described above are compared to a base case scenario ("no automation 2035") without AVs but with the same socio-demographic effects for 2035 depicted by reweighting.
Vehicle mileage increases in the trend scenario by 2.4% in Germany and by 3.4% in the US and in the extreme scenario by 8.6% in Germany and 8.6% in the US. Vehicle mileage is the sum of trip length of trips as car driver using conventional cars or AVs. The relative increase of the number of trips as car driver is almost equal with these values in Germany with 2.1% resp. 8.2% but a bit lower in the US with 2.0% resp. 5.7%. A higher relative increase of the vehicle mileage than of the trip number would be expected due to the additional effect of the distance effect. This is more pronounced in the US. An explanation for the small extent of this effect notably in Germany can be the

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shift of trip purpose shares. Commute trips are longer in average, but in the present model the use of AVs by other household members than the main user is allowed only for non-work and non-education trips. The stronger distance effect in the US can be a result from longer trip distances in average and the higher value-of-travel-time- savings compared to Germany used in the model. The lower number of shifted trips in the US is resulting from the lower diffusion rate of AVs than in Germany. Public transport demand is reduced in both countries.

Table 5: Overview of the impacts of private AVs on vehicle mileage and modal share in the trend and extreme scenario for the US and Germany (Table based on own calculations)

	US			Germany		
scenario	reference scenario (no automation) 2035	trend scenario 2035	extreme scenario 2035	reference scenario (no automation) 2035	trend scenario 2035	extreme scenario 2035
total vehicle mileage [1,000 Mio km per year]	4,481	4,635	4,865	594	608	645
relative increase compared to reference scenario		+3.4%	+8.6%		+2.4%	+8.6%
modal share (based on number of trips) car driver	65.6%	66.9%	69.4%	45.1%	46.1%	48.8%
increase compared to reference scenario						
absolute		+1.3%	+3.8%		+0.9%	+3.7%
relative		+2.0%	+5.7%		+2.1%	+8.2%
modal share (based on number of trips) public transport	2.6%	2.4%	2.2%	8.6%	8.3%	7.7%
increase compared to reference scenario						
absolute		-0.2%	-0.4%		-0.2%	-0.9%
relative		-6.3%	-17.6%		-2.8%	-10.6%

The considered assumptions of advantages of driving an AV compared to a conventional car evoke two effects with respect to distance differentiation. On the one hand benefits for medium- and long-distance-trips due to the reduction of costs of travel time savings and on the other hand profits for very short distances due to the reduction of access and egress times result.

On long-distance trips the competition among transport modes concerns mainly car and public transport. On short distance trips, the non-motorised modes have to be regarded, too.

A comparison of modal shifts shows impacts on all transport modes. The relative increase of number of trips for car driver mode and relative decrease for public transport mode differentiated for distance bands is shown in Figure 3. The most negative developments for public transport can be seen for very long and very short distances with a relative decrease of up to 32% resp. 28% for distances of more than 64 kilometres and 13% resp. 21% for distances under two kilometres for Germany and the US in the extreme scenario. The

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same but inverse trend can be observed for trips as car driver. The distance effect for trips as car driver is stronger in the US with a higher gap of increase rates between very-short- and very-long trips on the one-hand and trips of medium distances (four to sixteen kilometres) on the other hand. The highest relative increase rates of car driver trips reach up to 9-11%.

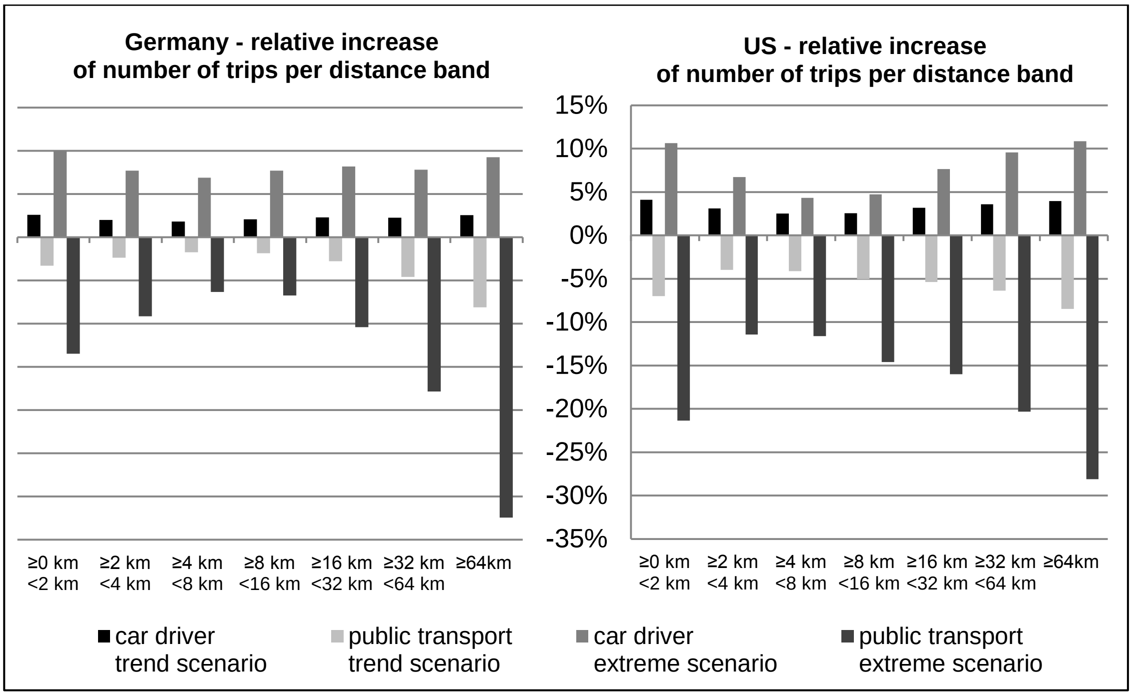

Figure 3: Increase of number of car driver and public transport trips differentiated for distance bands (Figure based on own calculations)

Our results show a not negligible decrease of the mode shares of non-motorised transport modes. Due to the small absolute mode shares of non-motorised transport modes in longer distance bands the comparison of all mode shares is shown in Table 6 only for trips with a trip length below 4 kilometres. The relative car shares increase by 1-2% resp. 2-6% in the trend and in the extreme scenario faces a relative public transport share decrease of 3-7% resp.8-19%, a relative walk share decrease of 1-2% resp. 3-7% and a relative bike share decrease of 2-6% resp. 5-18%. In spite of the small US values of the non-car transport modes in the initial state the relative reduction is bigger than in Germany. On the other side, the relative car-mode-share increase on short distances is higher in Germany.

Sensitivity analyses are calculated for the value-of-travel-time-savings and a possible increase of system velocity, the results are shown in Table7.

There is an uncertainty of the extent of the reduction of the value-of-travel-time-savings. The modelled reduction of 25% is compared to a 0%- and a 50%-reduction case for both scenarios, the assumptions of access/egress times and the make-ready-time remain the same. If the reduction would be 0%, the relative increase would be reduced but not to zero. Doubling reduction to 50% would result in a growth of the impact of 50-100%. Maximum impacts of 12.7% (Germany) respectively 15.7% (US) are observed in the extreme scenario. The actual reduction will be valued individually and may be influenced by external factors like being allowed to work or relax while driving

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an AV. Such alternative activities are likely to be perceived as additional driving comfort.

Table 6: Modal share and changes for trips of less than 4 kilometres (Table based on own calculations)

	US			Germany		
scenario	reference scenario (no automation) 2035	trend scenario 2035	extreme scenario 2035	reference scenario (no automation) 2035	trend scenario 2035	extreme scenario 2035
modal share car (driver & passenger)	72.2%	73.0%	74.5%	41.2%	42.0%	44.5%
increase compared to reference scenario						
absolute		+0.8%	+2.3%		+0.8%	+2.5%
relative		+1.1%	+3.2%		+1.9%	+6.0%
modal share public transport	2.3%	2.2%	1.9%	7.7%	7.5%	6.9%
increase compared to reference scenario						
absolute		-0.2%	-0.4%		-0.2%	-0.6%
relative		-7.0%	-19.1%		-2.8%	-8.1%
modal share walk	24.1%	23.6%	22.4%	39.0%	38.6%	37.4%
increase compared to reference scenario						
absolute		-0.5%	-1.6%		-0.4%	-1.2%
relative		-2.2%	-6.8%		-1.0%	-3.1%
modal share bike	1.4%	1.3%	1.2%	12.1%	11.9%	11.2%
increase compared to reference scenario						
absolute		-0.1%	-0.3%		-0.2%	-0.6%
relative		-5.9%	-17.9%		-1.7%	-5.3%

The influence of autonomous driving on road capacities and in connection with this the change of velocities is an often discussed topic (cf. Friedrich 2015). The current modelling approach does not allow for any capacity restraint effects. A sensitivity analysis reveals impacts of possible relative increases of speed of 2%, 5% and 10% for all trips. It should be mentioned that an overall increase of travel speeds (the system velocity) provide benefits for all infrastructure users, in particular the non-autonomous drivers and those driving only short distances. The maximum values at an increase of the system velocity of 10% in the extreme scenario are 12.5% (Germany) respectively 10.8% (US), thus the speed effect is stronger in Germany.
The increase of system velocity depends on the diffusion rate of AVs, and on the interactions of autonomous and non-autonomous vehicles (cf. Parkin et al. 2016) and is influenced by driving behaviour in accordance to road traffic regulations. The actual future development depends on transportation system designs and hardware and software developments.

Comparing both analyses it can be said that the effects of a reduction of the value-of-travel-time-savings are stronger in the extreme scenario and the effects of system velocity could be already strong in the trend scenario, but real speed effects are expected only for higher diffusion rates. It can be

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mentioned that speed effects may be realised already for high diffusion rates of partially autonomous vehicles with good driving-assistance-systems although effects of the value-of-travel-time-savings can be questioned.

Table 7: Sensitivity analysis for the value-of-travel-time-savings (VoTTS) and for the differentiation of system velocity (Table based on own calculations)

	US		Germany	
scenario	trend scenario 2035	extreme scenario 2035	trend scenario 2035	extreme scenario 2035
relative increase compared to reference scenario (differentiation of the value-of-travel-time-savings)				
VoTTS -0%	+2.0%	+2.6%	+1.4%	+4.9%
VoTTS -25% (original scenario value)	+3.4%	+8.6%	+2.4%	+8.6%
VoTTS -50%	+5.1%	+15.7%	+3.5%	+12.7%
relative increase compared to reference scenario (differentiation of the system velocity)				
velocity +0% (original scenario value)	+3.4%	+8.6%	+2.4%	+8.6%
velocity +2%	+4.2%	+9.3%	+3.3%	+9.5%
velocity +5%	+5.4%	+10.4%	+4.6%	+10.7%
velocity +10%	+7.2%	+10.8%	+6.6%	+12.5%

5. DISCUSSION AND OUTLOOK

The aim of the present paper includes two aspects: (a) the development of a model consisting of an aspatial travel demand model and a preceding technology diffusion model of AVs into the private car fleet (b) the application of the developed tools to describe the impact of introducing AVs into the private car fleet for different scenarios.
The model system is used to compare scenarios of different diffusion rates of AVs for Germany and the US, to draw conclusions and to find similarities and differences between the countries.

Policy implications
Some policy implications can be drawn from the results presented here. A moderate increase of vehicle mileage can be expected for a private-autonomous-vehicle scenario without allowance of empty rides. The extent depends among other things on the setting of a legal age of using private AVs. The increase may be higher if empty-vehicle-trips will be allowed.
Mode share losses of public transport are likely for long-distance trips because of the changing time-use opportunities driving an AV. Mode-share losses are likely on very-short-distance trips for public transport and non-motorised modes, too. The attractiveness of car usage for short distance increases because of the easier access and egress. Parking policies should consider this. This point is most important in urban areas.
Increasing traffic capacities and system velocities in consequence of the introduction of AVs may be realised, but the actual interactions cannot be

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foreseen with certainty. If so, an additional increase of vehicle mileage and car-modal-share is probable. This is more important for urban and suburban areas.
Other policy implications as influences on traffic safety and reverse influences from traffic safety on travel demand could not be modelled and no suggestions can be drawn.

Comparing the results with values from literature

A multitude of studies has been published estimating effects of autonomous driving on travel demand. The assumptions differ a lot. As empty-vehicle-trips and shared systems are excluded in this study, only some of the studies are more or less comparable.
Gucwa (2014) calculates vehicle mileage increase for different scenarios for the San Francisco Bay Area, differentiated by a reduction of value-of-travel-time-saving and an increase of road capacity in different extents. For scenarios of reductions of value-of-travel-time-saving of up to 50% the vehicle mileage increase is in the range of 4-8%.
Childress et al. (2015) calculate different scenarios for the Seattle region. A scenario with a fully-automation of all vehicles, a road capacity increase of 30%, a reduction of the value-of-travel-time-saving of 35% and halved parking costs leads to a vehicle mileage increase of almost 20%, a scenario with a lower diffusion rate and reduced assumptions leads to a vehicle mileage increase of about 5%.
Harper et al. (2015) calculate for the US a potential increase of vehicle miles travelled of about 12% for a use of AVs of all non-drivers, elderly populations and people with travel-restrictive medical conditions. No diffusion model and diffusion rates are considered, shared AV systems are not mentioned. Car trips of comparable groups of driving persons are projected to the considered groups of persons using new mobility options. No mode choice is modelled and aspects of valuation-of-travel-time-savings are not considered. The result is described as an upper bound of the potential for these user groups.
Fagnant/Kockelman (2015: 172) state an increase of vehicle miles travelled per AV of 20% at a 10% market penetration and of 10% at a 90% market penetration.
Our values of vehicle mileage increase are comparable but rather below average compared to the studies above. Restrictively the assumption of road capacity increase is ignored so far.

The AV application

Calculations of the impacts of autonomous driving have been done considering only level five vehicles due to an uncertainty of the individual kind of automation technology (e.g. use in cities or on highways), due to an uncertainty of the highway share of the trip lengths in that kind of travel survey data and other spatial allocations and due to an uncertainty of the extent of gains of value-of-travel-time-savings of driving partially-autonomous-vehicles. The share of level four vehicles in the extreme scenario is quite small (less than 12% in both countries) but higher in the trend scenario (at a range of 40% in both countries). Thus the uncertainty of the values of the trend scenario is higher and the possible underestimations of the impacts are more evident.

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AVs are assumed to improve road safety as in most cases of traffic accidents human error can be observed (cf. Haghi et al. 2014). Impacts on travel demand resulting from this are not modelled. For consideration the mode-specific constant should be raised. But the estimating of the extent is difficult and depends on the diffusion rate. At higher diffusion rates an adaption of the other modes (including conventional cars and non-motorised modes) would be necessary to be correct.
Induced travel demand is named in the context of AVs due to reduced generalised travel costs and less congestion because of a more efficient traffic situation (cf. Fagnant/Kockelman 2015: 172). Safety impacts and other factors could increase the demand, too. The cost component could be implied, but induced travel demand is largely ignored here, with the exception of the group of the mobility impaired people which is reweighted because of the distribution of AVs to mobility impaired people. This leads to an increase of the total trip number of 1.1% in the US and 0.2% in Germany.
Data inconsistencies between the German and the US data are most obviously considering the characteristics of mobility impairment and routinely driving. Causes can be missing data e.g. because of different shares of questionnaires answered on someone’s behalf and the different definitions of being a driver and having a driver license. Some inaccuracies result inevitably from this. Comparing the results in Table 5, it can be seen that the proportion of the modal shifts in both scenarios differ between the countries in some sense. The mobilization of mobility impaired people seems to be slightly overestimated by the US values which results in a stronger shift from public transport to car. The additional increase in the extreme scenario is not touched by this due to the prioritised mobilization equal in both scenarios.

Future Research:
Future research should be directed to shared AV systems due to the potentials of those systems on vehicle mileage decrease and increase. Shared AVs combine the advantages of car rental systems and AVs (cf. Fagnant et al. 2015). The main advantages are the short access and egress times, long average use times of the vehicles per day because of autonomous repositioning, few costs for staff, and possibilities of ride-sharing without a defined “main driver”. Modelling these systems should be focused on mode choice with an expanded spatial differentiation to depict the more heterogeneous market.
Relevant improvements of autonomous car and ride-sharing systems can be realised when driverless cars enable very short access times compared to today’s car free-floating car-sharing systems. (cf. Litman 2015: 14). Vehicle mileage increase to an additional mobilization of new user groups and empty rides are possible and decreases due to a higher party size in ride-sharing systems are possible.

The model approach
Considering the aspatial travel demand model, some points have to be mentioned. The aim of developing an aspatial travel demand model, simplified compared to macroscopic demand models of whole states based on traffic-analysis-zones and a physical network, is the comparison of general

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developments/influences in transportation in different states/regions and/or for different time snapshots.
Collecting or identifying individual travel time values for the mode alternatives and different travel distances necessitate either detailed knowledge of the respondents about the alternatives or geocoded data of all activity locations. In the latter case, moreover a calculation of the travel times in the chosen level of detail is required. The procedure used in this model is a simplification and could be enhanced by using more explanatory variables.
Dependent on the extent of impacts due to the modelled influences, changes of traffic volume for different spatial areas (mainly the concentrated urban areas) should be considered and if necessary the model has to be extended to take into account generalised fundamental diagrams, which have been described at an aggregated city-wide level so far (cf. Daganzo/Geroliminis 2008, Geroliminis/Daganzo 2008, Mahmassani et al. 2013). This point may often concern an avoidance of overestimating the potential of new mobility options but can also concern the less congested status-quo. Estimating a capacity restraint function from travel speeds reported in travel surveys evokes the difficulty of handling with trip distance influences. The average trip distance is not constant over a day, but the travel speed is correlated to trip distance (cf. Mahmassani et al. 2013).
By now we do not have implemented any travel behaviour changes based on mobility trends as increasingly online shopping due to uncertainties about the extent. In general it is possible to consider similar developments by identifying persons with changing mobility behaviour resulting from this.
A problem, which is more important concerning US than German data is the heterogeneity between different public transport modes for very long distances. This is complicated by the general sparsity of long-distance travel data (cf. Monzón/Rodríguez-Dapena 2006). A differentiation of public transport modes for long-distance data could be helpful. Another possibility is to separate a long-distance and a short-distance travel demand model as applied for many national and regional transport models.

6. CONCLUSIONS

This paper introduces a vehicle technology diffusion model, an aspatial travel demand model and the application to estimate the impacts of autonomous driving and presents results of a trend and extreme scenario comparing the US and Germany.

The travel demand model approach is a possibility to get an idea of the impact of general transport issues as introducing AVs on travel demand. Because of the aggregated model approach a fast comparison of different countries, spatial areas, groups of persons or future time snapshots is possible with limited but comparable data. Different model steps can be combined as shown with the preceded diffusion model of private AVs into the private car fleet.

The model results show a moderate impact of introducing a private AV fleet on travel demand. The total vehicle miles travelled increase depending on the diffusion rate. This additional traffic is a combination of distance choice (resp.

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destination choice) and mode choice effects and moreover the occurrence of new user groups using cars as drivers. The relative mode change effects are more significant for very short and very long distances. The results in the present paper are based on the assumption of no allowance of empty rides. Next, the model presented here will be adapted to consider the influence of sharing systems as autonomous car- and ride-sharing.

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