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Assessing travel time savings and user benefits of automated driving – A case study for a commuting relation

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ABSTRACT

Combining cooperative vehicle driving behavior of Connected and Automated Vehicles with supporting information infrastructure, is expected to increase the capacity of roadway infrastructure, which in turn results in travel time savings and user benefits. Automated driving also relieves the driver from steering the car, allowing to conduct other activities during the trip, which is likely to generate further user benefits. In order to assess the magnitude of automated driving on travel time-related user benefits, a typical commuting relation is analyzed, considering three route options as well as level 4 and 5 vehicle automation. The impacts on travel times are estimated by microscopic traffic flow simulations. The simulations reveal that around 27% of the travel time can be saved on a commuting relation due to road automation according to level 5. For level 4 vehicles the travel time savings amount to up to 20%. User benefits that accrue from time savings and the passenger's option of using travelling time for activities other than conducting the car, are expected at a relevant magnitude. Even under consideration of higher operating costs of an automated car, significant user benefits accrue: 1,310–2,240 € p.a. for level 4 and 2,770–3,440 € p.a. for level 5 vehicles during a passenger car's typical depreciation period. Thus, automated driving will decrease the commuters' generalized user costs for individual motorized mobility, which is likely to enhance the urban hinterland's attractiveness as residential area. This pattern and inherent second-order effects pose challenges for transport, land use and urban planners. Furthermore, it represents a challenge for transport research: to elaborate appropriate concepts that allow for exploiting the benefits of use of automated vehicles while countervailing undesirable socio-economic effects, as well as strains on the transport system and land use.

1. Introduction

Automation of road transport lies traditionally far behind the automation of other transport modes such as rail, air or marine transport. The introduction of Connected and Automated Vehicles (CAVs) aims to organize road transport more systematically. Especially the combination of cooperative vehicle driving behavior of CAVs and supporting information infrastructure could lead to increased capacity of roadway infrastructure. Assuming that appropriate policies (e.g., pricing schemes of CAV operation) will avoid induced traffic demand, the roadway capacity increase could alleviate congestion, reduce energy use and emissions and improve safety.

The Operational Design Domain (ODD) defines how and where the CAV is supposed to function and operate. The ODD is based, among others, on the roadway type, the condition of the road and the availability of necessary supporting infrastructure features. Due to limited access and more homogenous traffic flow, the ODD is expected to be limited to freeways at first. Nevertheless, highly automated, self-driving, or driverless vehicles are going to operate in complex urban traffic in a rather near or distant future as well, especially once the supportive infrastructure could compensate for perception system limitations of CAVs.

Based on the assumptions by Krause et al. (2017), CAVs could increase the capacity of German freeways on average by 30% beyond 2050. Thus, automated driving may prevent congestion, decrease trip durations and allow time savings. Furthermore, autonomous driving allows the passenger to conduct further activities during the trip such as working, texting or sleeping. Pfleging et al. (2016) investigated the user needs for non-driving-related activities during automated driving. As a

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Nomenclature

BPR	US Bureau of Public Roads
CAV	Connected and Automated Vehicle
HBS	German Highway Capacity Manual
ODD	Operational Design Domain
PPF	Parking Pressure Factor
VC	Volume to Capacity
VoT	Value of Time

result, CAVs are expected to provide a broad range of applications to satisfy the needs of CAV passengers to conduct further activities during the trip. More interestingly, also those CAV in-vehicle applications are assessed desirable, which allow conducting activities that can be continued even during driving at a lower automation level. Other surveys confirm that the passengers of autonomous cars are willing to pay for being able to conduct other activities during a car trip (Fraunhofer IAO und Horváth & Partners 2016; McKinsey & Company, 2016). Thus, the outcomes of surveys demonstrate that autonomous driving will generate user benefits beyond travel time savings and the reduction of monetary costs. On the other side, user costs are affected by impacts such as decrease in insurance fees due to enhanced safety, decrease in fuel consumption because of improved driving efficiency or higher vehicle costs for automation (see, e.g., Ticoll, 2015; Wadud, 2017; Bösch et al., 2018).

In this context, the current paper addresses the following research questions: how does infrastructure capacity enhancements due to the operation of automated vehicles translate into travel time savings? How large is the magnitude of user benefits that accrue from travel time savings and from the user's possibility to conduct further activities during the trip? Which magnitude have travel time-related user benefits on generalized user costs? These research questions are raised for a commuting relation in Germany, under consideration of two different automation levels and three different route options, thus addressing different Operational Design Domains of road automation.

The paper is structured as follows: first, the case study is presented and the ODD of each level of automation is defined. The next section gives an estimation of CAVs' impacts on travel time, presenting in detail the methodology and the assumptions made. Based on the computed travel time savings, the next section deals with the estimation of travel time-related user benefits. Subsequently, generalized user costs are calculated to put the scope of travel time-related user benefits in the context of overall changes in generalized user costs. Lastly, the obtained results are discussed and conclusions are drawn.

2. Description of the case study

In Germany, there are about 18.4 million daily commuters with 68% of them using a passenger car for their commuting trips (Statistisches Bundesamt, 2016). This high level of automobile dependency leads to pronounced demand peaks during the day, especially in the morning and afternoon commuter traffic. Therefore, a typical commuting relation during a morning peak hour was chosen to estimate the impacts of CAVs on travel time and to estimate travel time-related user benefits that accrue from a partial or complete automation of a passenger car commuter trip.

The selected origin-destination relation between the municipality of Graben-Neudorf and a central neighborhood of the City of Karlsruhe represents a typical German commuting relation. The route can be driven by three routes with similar generalized costs in terms of distance and travel time. These three routes are labelled as freeway, arterial and collector routes, according to the prevailing roadway type along the route (see Fig. 1).

Fig. 1 also depicts the ODD of level 4 and 5 vehicles, respectively. The automation levels are assumed to be in line with the SAE standard J3016 (SAE International, 2014). The criteria applied for assigning a roadway to the ODD of level 4 or 5 vehicles are based on discussions with experts. Since the Operational Design Domain of level 5 vehicles covers per definition all driving environments, irrespective of the complexity of the urban road environment, all three routes as well as the parking process allow fully automated driving and are therefore marked green in Fig. 1 (b). The assumed criteria for assigning a roadway to ODD of level 4 vehicles are roadways with restricted access for pedestrian/bicycles, grade-separated intersections as well as dedicated place for vehicle handover. Therefore, at-grade intersections including pedestrian/bicycle movement represent in this case study the system boundaries of level 4 ODD (see Fig 1 (a)). Finally, automated cruising for parking is

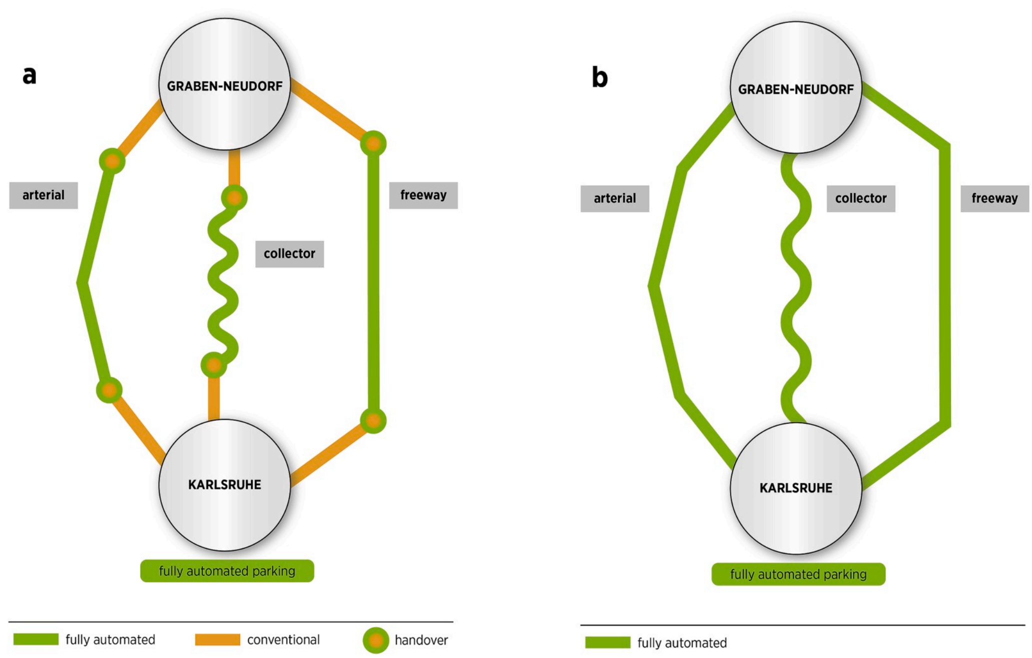

Fig. 1. Shows the routing alternatives between Graben-Neudorf and Karlsruhe.

Table 1
Operational Design Domain of level 4 and 5 vehicles in the case study.

Network element	Level 4 ODD	Level 5 ODD
Road with at-grade intersections (ped/bike crossing)	No	Yes
Road with at-grade intersections (no ped/bike)	Yes	Yes
Road with multi-grade intersections	Yes	Yes
Neighborhood (cruising for parking)	Yes	Yes
Handover delay	Yes	No

expected to be included into ODD of both level 4 and 5 vehicles. For clarity, we give a summary of the operational design domain for both level 4 and 5 vehicles in the case study in Table 1.

3. Estimation of CAV impacts on travel time

3.1. Methodology

The routes indicated in Fig. 1 consist of a sequence of roadway segments and intersections, typically represented in a traffic flow model by component links and nodes. First, we estimate travel time and mean vehicle delays for representative component links and nodes analytically based on standardized delay-flow relations in the German Highway Capacity Manual (HBS) (FGSV, 2015). In the next step, we estimate travel time and vehicle delay for a scenario using 100% penetration of CAVs by updating the delay-flow relationship with new capacities resulting from the automated vehicle operation. The new capacity values are obtained from a microscopic traffic flow simulation of representative road types in Germany. Furthermore, each route ends within the Karlsruhe-Oststadt district, known for its high parking pressure and lengthy cruising for parking. To estimate travel time savings resulting from automated parking systems, we developed a microscopic traffic flow model of the Karlsruhe-Oststadt district. Finally, we assume that level 4 vehicles are handed over to the driver at the ODD borders. To model this handover, we add a little delay penalty to the overall travel time for level 4 vehicles. This penalty suggests that the vehicle handover is conducted at lower speeds to assure safe vehicle handover under any dynamic driving task. To summarize, the estimation of travel time and mean delays on the selected commuter trip is a combination of analytical and simulation approach where standardized delay-flow relations are enhanced by a microscopic traffic flow simulation of representative network elements.

In this work, we use microscopic traffic flow simulation to estimate impacts of vehicle automation on travel time indirectly by investigating the impact of CAVs on capacity and then subsequently translating the capacity change into travel time savings approximating existing vehicle-delay functions. For signalized intersections, we estimate the mean vehicle delays in intersections based on the computation methods given in chapter S4 of HBS 2015 (FGSV, 2015). For freeway segments, we estimate the mean travel time savings based on capacity-restraint functions from the Bureau of Public Roads (BPR) (1964) implemented in the macroscopic traffic assignment model of the German road network Validate (PTV Group, 2016). In both cases, we assume a 100% penetration rate of connected and automated vehicles.

In traffic flow simulators, different car-following, lane changing and gap acceptance models represent human driving behavior. Empirical distributions of acceleration and deceleration of human drivers underpin these models. To model automated driving, the imperfect human driving behavior incorporated within the existing behavioral models such as “Intelligent Driver Modell” (Treiber et al., 2000) or the psycho-social model from Wiedemann (1974) is replaced with a sensor-driven behavior of automated vehicles. In our approach, we adapt Wiedemann’s model of driving behavior in VISSIM and investigate the impacts on the traffic flow resulting from altered driving behavior. For a detailed description of the Wiedemann model, we refer to the literature (Aghabayk Eagely et al. 2014; Wiedemann, 1974). ATKINS (2016), Haberl et al. (2017) and Krause et al. (2017) have taken similar research efforts.

Table 2
Summary of car following parameters.

Car following behavior	CC0 [m]	CC1 [s]	CC2 [m]	CC4 & 5 [m/s]
Human driver	1.2	1.4	4	−0.35/0.35
Cautious AV	0.5	0.9	0	0/0
Assertive AV	0.5	0.5	0	0/0

It is recognized, that level 4 and 5 vehicles differ according to their ODD rather than according to the driving behavior. Instead, we differentiate between cautious and assertive driving behavior of AVs. The analysis is conducted for three types of driving behavior representing a human driver, a cautious autonomous vehicle and an assertive autonomous vehicle. We first assume that driving behavior of CAVs will become more homogenous, thus, we limit the variation and oscillation within the car following (CF). We next assume that CAVs will not enable any increase of desired acceleration. In contrary, we refer to other research indicating that CAVs might have to limit the desired longitudinal and especially lateral acceleration to the magnitudes used in high-speed trains to enable engagement in the choice of leisurely or economically productive (non-driving) tasks (Le Vine, Zolfaghari and Polak, 2015).

In the Wiedemann 99 model, the standstill distance (CC0) and the time distribution of speed-dependent part of desired safety distance (CC1) are the primary parameters determining the desired safety distance. In our approach, we adjust the oscillation of the car following given the more precise determination of the predecessor’s speed and acceleration by vehicle sensors. This is achieved by limiting the longitudinal oscillation (CC2 – ‘following’ variation, CC4 – negative ‘following’ threshold and CC5 – positive ‘following’ threshold), thus increasing the sensitivity of the car follower to the changes of the distance. Hence, the traffic stream moves more compact, which allows smaller time gaps to be utilized. Table 2 shows the key car following parameters of the adjusted car following model.

3.2. Signalized intersection

It is recognized, that intersections represent bottlenecks in the urban roadway network. Hence, in this work, we selected a signalized three-leg intersection as a representative network element to estimate capacity increase and travel time savings for level 4 and 5 vehicle automation and to compare it with the mean vehicle delays by conventionally controlled traffic. In the HBS, the capacity of an intersection approach is defined as the portion of the saturation flow proportional to the green time allotted (FGSV, 2015, p. 4–14), that is, the amount of traffic that can pass the stop line during the green time. Empirical analyses of departure headways incorporated in the HBS methodology assume that the departure headways converge to so-called mean time requirement of 1.8 s (FGSV, 2015, p. 4–11). The reciprocal value of the mean time requirement expressed for one hour yields saturation flow of 2,000 vehicles per hour (vph).

To investigate the impact of the vehicle automation on the saturation flow, we measured the mean time requirement under altered driving behavior differentiated by vehicle automation level. This approach considers changes in the car following behavior only, since the mean time requirement is derived based on longitudinal movement within a single lane. Table 3 summarizes the results from a calibrated microscopic traffic flow simulation of a signalized three-leg intersection in Karlsruhe. The table also gives mean travel time savings for CAVs, as a result of a difference between the vehicle delay of conventional and automated vehicle. The results show that different automated driving behavior, represented by cautious and assertive driving behavior, does not yield significant differences in travel time savings. This is an expected result, since the impacts of assertive driving behavior on travel

Table 3
Time requirement, capacity and travel time saving on example intersection.

Car following behavior	Mean time requirement [s]	Saturation flow [vph]	Discharge flow [vph]	Capacity increase [%]	Mean travel time savings at capacity [min]
Human driver	1.88	1,915	681	–	–
Cautious AV	1.24	2,900	1,031	51	0.9
Assertive AV	1.03	3,495	1,245	83	1.0

times are mitigated at high traffic flow rates.

Next, we modified the capacity within the HBS calculation by the modeled capacity increase and estimated new mean vehicle delays for automated vehicles. We assigned the cautious and assertive driving behavior to level 4 and 5 vehicles, respectively. Finally, we assumed that the conventional signal control would still be used due to the presence of other, non-connected traffic users, such as pedestrians or bicyclists. In our approach we therefore only consider the queue spillback component of the vehicle delay to be mitigated by automated vehicles; the uniform delay component of the vehicle delay is kept. As a result, travel time savings on intersections remain relatively low.

3.3. Freeway basic road segment

From a macroscopic perspective, reducing the longitudinal gap between two vehicles leads to increased road capacity. In literature, researchers indicated capacity increase between 30% and unprecedented 80% (Friedrich, 2015; Krause et al., 2017; ATKINS, 2016), depending on the road type, CAV penetration, vehicle following setup, and other parameters. In our approach, we tie the analysis of travel time impacts to the results of a microscopic traffic flow simulation indicating 30% average capacity increase on German freeways (Krause et al., 2017) for 100% CAV penetration. To obtain the travel time impacts for the freeway portion of the commuter trip, we translate the capacity increase investigated by Krause et al. into travel time savings by incorporating the new nominal capacity within the volume-delay function, used generally to model vehicle delays macroscopically. It remains unclear, whether standard BPR capacity-restraint functions hold also for CAVs. Nevertheless, due to lack of alternatives, we use the underlying BPR function of the Validate model. Fig. 2 shows the relationship between nominal capacity increase resulting from road automation and traffic load, represented by a range of volume-to-capacity (VC). The relationship is expressed by the amount of travel time savings in min/km. The diagram reveals that an average 30% capacity increase on freeways results in travel time savings between 0–0.9 min/km depending on the current traffic load.

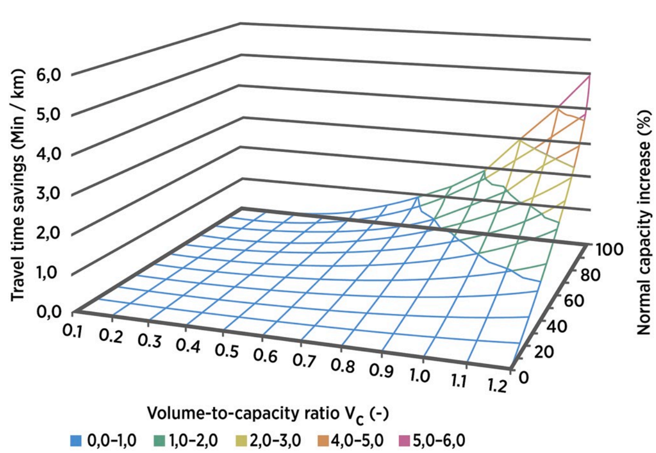

Fig. 2. Shows the sensitivity of travel time savings to volume-to-capacity ratio and nominal capacity increase.

3.4. Neighborhood

To investigate the potential travel time savings by avoiding cruising for parking, we developed a microscopic traffic flow model of the neighborhood's road network in the Karlsruhe-Oststadt district. There are estimated 2,000 curb parking places within the neighborhood distributed over 25 streets. Within the model, human drivers are randomly assigned a desired destination street; in case there is no vacant parking place within the desired street, the drivers are rerouted to the nearest parking option, without the knowledge about its availability. We therefore model cruising for parking as searching for parking around the blocks. Should a parking place approached by an automated vehicle be occupied, the CAVs is redirected to the nearest vacant parking place. This behavior therefore simulates the presence of vehicle-to-infrastructure communication. For simplicity and comparability of the results, we assume that CAVs do not have previous information about the original parking place occupancy. Finally, due to the residential character and morning peak hour, we only consider passenger car traffic within the neighborhood.

First, a comprehensible definition of cruising for parking is required. The definition by Reinhold (1999) describes cruising for parking as "the entire vehicle mileage and travel time intended for looking for parking starts with the point, where the road user approached the destination of the trip to that extent, that the next vacant parking place can be accepted". The empirical evidence from Reinhold (1999) reveals 26–44% share of cruising for parking within the circulating traffic; in extreme case, up to 80% "avoidable" traffic resulting from "externally caused pressure" can be observed. Following the definition above, on average one third of the vehicle mileage in a dense urban area can be labelled as undesired cruising for parking.

The results of our simulations show that already by 75% average parking occupancy the mean cruising time for parking by human driver is 1.5 min. To add a within-day dynamic to the model, we adjust the number of vacant parking places relative to the parking demand, represented by the so-called Parking Pressure Factor (PPF). The simulation results show, that the cruising time for parking under regular PPF and parking occupancy between 75% and 100% takes on average 2 min. As expected, increasing the PPF correlates positively with the mean cruising time. It is recognized, that in case of a high parking pressure and unsuccessful parking search, and drivers either leave the neighborhood seeking alternative options or park illegally. Hence, the estimated travel times for cruising for parking under higher PPF are considered to represent overestimations; nevertheless, they show a theoretical scale of the problem. To conclude, we assume 2 min as an average cruising for parking by a human driver in the investigated scenario and set this value as the travel time saving of CAVs that are able to navigate to the neighborhood's parking garage autonomously.

4. Results

To provide estimates of total travel times for each scenario, we sum the impacts of CAVs on travel time for each of the analyzed network element. All travel time estimates are given for a mean VC ratio of 0.7, i. e. a degree of infrastructure capacity utilization of 70%, which reflects a high level of road infrastructure usage during the daily commuting peaks. Table 4 gives the estimated total travel times for the described commuter routes. We show travel times for the current conditions,

Table 4
Estimated mean travel times within the case study.

Automation Level	Route	Travel time for VC 0.7 [min]	Cruising for parking [min]	Vehicle handover [min]	Total travel time [min]
0	Freeway	28	2.0	–	30
	Arterial	29.5	2.0	–	31.5
	Collector	30	2.0	–	32

Table 5
Estimated mean travel time savings within the case study.

Automation Level	Route	Intersections [min]	Links [min]	Cruising for parking [min]	Vehicle handover [min]	Total travel time savings [min]
4	Freeway	0.5	4.0	2.0	−0.5	6.0
	Arterial	1.0	1.5	2.0	−0.5	4.0
	Collector	0.5	1.5	2.0	−0.5	3.5
5	Freeway	2.0	4.0	2.0	–	8.0
	Arterial	1.5	2.0	2.0	–	5.5
	Collector	2.5	3.5	2.0	–	8.0

labelled as automation level 0, as a mean value of observed travel time from Google Traffic and estimated mean time during cruising for parking.

Table 5 displays travel time savings for three commuter routes differentiated by component network element and automation level. The results confirm that travel time savings increase with higher automation level, due to the longer driving time in automated mode. This especially improves the travel time on the collector route, where the ODD of level 4 vehicles is expected to limit automated driving only to a minor extent. Generally, the results point towards approximately 11–27% travel time savings in comparison to today's travel times depending on the automation level and commuter route chosen. In the next section of this paper, we translate the travel time savings and the possibility to use the travel time for alternative purposes into monetary user benefits.

5. Travel-time related user benefits

The estimation of travel time-related user benefits by CAV operation on the exemplary commuting relation focuses on impacts related to changes in travel time as well as benefits caused by the re-purposing of travel time. Second order effects, such as an increase in road traffic as a consequence of enhanced comfort on door-to-door relations by passenger cars, are not considered in our estimations.

The impacts on travel time by the use of CAVs are due to enhanced infrastructure capacity and higher fluidity of traffic flows, as demonstrated through traffic simulations in the previous section, and because searching for parking space does not need to be carried out by the driver. For the monetization of these time savings, the Value of Time (VoT) used for the evaluation of transport infrastructure projects in the context of the German Transport Masterplan 2030 is applied (PTV, TCI Röhling, and Mann, 2016; TNS Infratest/IVT, 2013). Thus, for the estimation of the monetary value for time savings the rate of 6.90 €/hour is used, which represents the VoT of a work commuter by car mode for the distance range of 20–30 km (TNS Infratest/IVT, 2013).

Monetizing the benefits caused by a re-purposing of travel time, i.e. allowing the car driver to conduct other activities during the trip, lacks from ample research on how the individuals' perceptions of travel time is affected by the use of automated cars (e.g., Batley et al., 2018). Following the VoT concepts by De Serpa (1971), Evans (1972), McFadden (1981) and Jara-Díaz (2000), the value of travel time is the difference between "the opportunity value of the time" and "the value of the utility that is created during the travel time" (Kouwenhouven and de Jong, 2018). Thus, if travel time can be spent for useful or productive tasks, the utility generated during travelling may increase, which results in a decrease in VoT.

Therefore, it is recognized, that using a CAV instead of a conventional car will decrease the passenger's VoT, as it enhances the usefulness of travel time by allowing to carry out other activities than driving (e.g., van den Berg and Verhoef, 2016; Wadud et al., 2016; Stephens et al., 2016). Lyons, Jain and Holley (2007) reveal a "positive utility of travel time" of rail passengers, since rail passengers conduct further activities during travelling which the passengers consider useful. Wadud and Huda (2019) studied the activities of passengers of chauffeur-driven cars, and identified working or studying onboard to be the "second most popular activity during outbound business and commute trips" (Wadud and Huda, 2019, p. 13), which indicates a productive travel time use in an automated vehicle. Analyzing the results of a stated preference (SP) study conducted in the Netherlands, Kouwenhoven and de Jong (2018) found that train users who are able to spend their travel time in a useful manner, have a 20% lower VoT than other respondents. The results of an online survey conducted by Kolarova et al. (2019) reveal the use of autonomous cars for commuting to be perceived less negatively than driving a conventional car. The literature review by NZ Transport Agency (2014) on how the VoT of car drivers compares to that of car passengers reveals ambiguous results, ranging from a lower VoT for passengers compared to drivers to a higher VoT for car drivers. These differences are also caused by the pattern that the perception of VoT is determined by user type and mode effects, whereas, however, "most studies fail to disentangle the user type and mode valued effects" (Wardman, 2004) and thus produce ambiguous results. The SP survey conducted by Yap et al. (2016) reveals that passengers using automated vehicles as last mile public transport of multimodal train trips do not expect benefits from being able to carry out other activities during the trip, since they value in-vehicle time in a CAV more negatively than in-vehicle time in conventionally driven cars. The survey by Nazari et al. (2018) shows that the respondents' disposition to ownership and usage of automated vehicles decreases with growing travel demand (measured in vehicle mileage), thus also putting in question the occurrence of in-vehicle time benefits.

On the other side, Daziano et al. (2017) derived from a discrete choice experiment on vehicle-purchase in the US that a household's average willingness-to-pay for automation amounts to around $3,500 for partial automation and $4,900 for full automation, without analyzing however the determinants of these willingness-to-pay values. Market studies suggest that CAV passengers are willing to pay for being able to conduct other activities during a car trip (Fraunhofer IAO and Horváth & Partners 2016; McKinsey Company 2016). The willingness-to-pay reaches its highest values for activities which facilitate time savings (McKinsey Company 2016), and increases with trip duration (Fraunhofer IAO and Horváth & Partners 2016). Thus, the outcomes of these surveys demonstrate that autonomous driving will generate user benefits beyond travel time savings and the reduction of monetary costs.

For an approximate monetization of benefits generated by a re-purposing of travel time the following considerations are made: the average willingness-to-pay values for using additional services in an automated car derived by Fraunhofer IAO and Horváth & Partners (2016) can be interpreted as the monetary equivalent of a passenger's benefit for using these additional services during the car trip.

The average willingness-to-pay value for using additional services in a fully automated car amounts to 27 € per month for a trip whose duration is up to 30 min. As the average willingness-to-pay increases with the duration of a journey in an automated car, the assumption is made that it rises linearly in the interval [0, 30 min]. Furthermore, it needs to be considered that the provided willingness-to-pay value refers to all car trips made within one month, and not only to the commuting trips regarded in our case study. Under the assumption of 220 working days per year, resulting to around 9,700 km yearly travelled commuting distance on the considered commuting relation, and an annual mileage of a German commuter of 14,923 km (Chlond et al., 2014), a share of 65% of the monthly willingness-to-pay value is assigned to the regarded commuting relation, i.e. 17.55 € per month. If the duration of the fully automated part of the commuting trip is below 30 min, this amount is reduced according to the assumption that the derived willingness-to-pay value increases linearly in the travel time interval [0, 30 min].

With these assumptions, and comparing the use of CAV according to level 4 and level 5 with the reference case, in which the use of conventionally driven cars is assumed, user benefits due to time savings (Table 6), due to re-purposing of travel time (Table 7) and the total travel time-related user benefits (Table 8) are estimated.

Proportionally with the scope of time savings, the user benefits due to travel time savings are higher for the level 5 than for the level 4 scenario. While in the level 4 scenario the highest user benefits are expected on the freeway route, the users of the freeway and the collector route can realize the highest benefits of automation in the level 5 scenario. Also the user benefits due to the re-purposing of travel time are considerably higher for the level 5 than the level 4 scenario. For the level 4 scenario, the freeway option reveals the longest time period in which automated driving is possible, thus resulting in the highest benefit value. For level 5, the duration of automated driving coincidence with the duration of the commuting trip. Since the travel time is expected to reach its maximum value for the arterial route, the user benefits due to the re-purposing of travel time on this route alternative are higher than for the other routes.

The total user benefits reveal that benefits for level 5 are around 50–160% higher than for level 4. The order of magnitude of total user benefits within the same scenario however differs: while for the level 4 scenario the highest user benefit can be expected for the freeway route, in the level 5 scenario the collector route option is expected to generate the highest user benefits.

The user benefits obtained from the calculations show a relevant magnitude of up to 374 € p.a. (level 4) and 573 € p.a. (level 5), respectively. Extrapolating these values over a passenger car's depreciation period of six years, benefits of around 1,310–2,240 € (level 4) and 2,770–3,440 € (level 5) can be expected during the economic lifetime of a passenger car (without discounting), which represents a considerable asset.

Table 6
User benefits due to travel time savings.

Automation Level	Route	Travel time savings [min/day]	User benefit due to travel time savings [€/day]	User benefit due to travel time savings [€/year]
4	Freeway	12	1.38	304
	Arterial	8	0.92	202
	Collector	7	0.81	177
5	Freeway	16	1.84	405
	Arterial	11	1.27	278
	Collector	16	1.84	405

Table 7
User benefits due to re-purposing of travel time.

Automation Level	Route	Autonomous driving time (w/o parking) [min/trip]	User benefits due to re-purposing of travel time [€/day]	User benefits due to re-purposing of travel time [€/year]
4	Freeway	10	0.32	70
	Arterial	7	0.22	49
	Collector	6	0.19	42
5	Freeway	22	0.70	154
	Arterial	26	0.83	183
	Collector	24	0.77	168

Table 8
Total travel time-related user benefits.

Automation Level	Route	Total travel time-related user benefits [€/day]	Total travel time-related user benefits [€/year]
4	Freeway	1.70	374
	Arterial	1.14	252
	Collector	1.00	219
5	Freeway	2.54	559
	Arterial	2.09	461
	Collector	2.61	573

6. Impacts on generalized costs

Comparing the computed travel time-related user benefits with the overall generalized costs of passenger car use, allows a better understanding of the overall impact of the calculated user benefit changes. The generalized cost function embraces "all the main attributes related to the disutility of a journey" (Ortúzar and Willumsen, 2011), such as travel time, monetary costs, terminal costs (parking) or modal penalty. It can be measured in monetary or time units.

For this estimation, the generalized user costs of a journey in a passenger car, C_{gen} , are determined by summing up operating costs C_o and travel time-related costs C_t:

$$C_{gen} = C_o + C_t$$

Bösch et al. (2018) examined the operating costs of conventional and automated private passenger cars, taking into account the following cost components: depreciation, interest, fuel, parking and tolling, maintenance and wear, insurance, taxes and cleaning. The total operating costs amount to 0.485 Swiss Francs (CHF)* per passenger-kilometer for a

Table 9
Generalized costs (conventional passenger car).

Route	Distance [km/day]	Operating costs [€/day]	Time costs [€/day]	Generalized costs [€/day]	Generalized costs [€/year]
Freeway	52.8	23.98	6.90	30.88	6,793
Arterial	40.6	18.44	7.25	25.68	5,650
Collector	41.2	18.71	7.36	26.07	5,735

* The conversion rate applied to convert Swiss Francs (CHF) into Euro (€) is 1.07 CHF/€.

Table 10
User benefits of automated driving.

Automation Level	Route	Operating costs [€/day]	User benefits due to changes in operating costs [€/year]	User benefits due to changes in travel time-related costs [€/year]	Total user benefits [€/year]	Cost reduction by changes in travel time-related user benefits [%]
4	Freeway	24.92	−207	374	167	5.5
	Arterial	19.16	−159	252	93	4.5
	Collector	19.44	−161	219	58	3.8
5	Freeway	24.92	−207	559	353	8.2
	Arterial	19.16	−159	461	302	8.2
	Collector	19.44	−161	573	412	10.0

conventional passenger car, and to 0.504 CHF for an AV operating at level 5. The AV reveals lower operating costs for fuel and insurance, which however are outbalanced by the automated car's higher purchasing cost (resulting in higher depreciation and interest costs). Applying the operating cost factor to the three route options and adding the respective time costs, the generalized cost values for conventional cars are estimated as displayed in Table 9.

Making the assumption that the estimated operating cost factors for private automated cars applies both to level 4 and level 5 vehicles, the operating costs are calculated for each route option, as well as the user benefits due to changes in operating costs, i.e. the difference in operating costs of an automated and a conventional passenger car. Adding the user benefits due to changes in travel time-related costs (section 4), the total user benefits are derived (see Table 10). The last column of Table 10 entails the percentage cost reduction of automated driving due to travel time-related user benefits.

The obtained results reveal that the use of automated passenger cars is expected to generate relevant user benefits, even if their operating costs are moderately higher than for conventional cars. Travel time-related user benefits result in a decrease in generalized costs by 3.8–5.5% for automation according to level 4, and by 8.2–10.0% for level 5 vehicles (depending on the route chosen). The total annual user benefits, under consideration of operating costs and travel time-related benefits, amount to 58–167 € for level 4, and to 302–412 € for level 5 vehicles.

Autonomous driving offers a sound pre-requisite for new mobility services, such as ridesharing or pooled services. Therefore, the estimation of impacts on generalized costs is complemented by a sensitivity analysis regarding ridesharing. Assuming that different commuters use the same vehicle for the trip between their places of living and places of work, the operating costs per passenger-kilometer decrease because of the higher vehicle occupancy rate. Following Bösch et al. (2018), the total operating cost of an automated pooled trip in a conventional passenger car amounts to 0.21 CHF per passenger-kilometer for operation in a regional/non-urban area and to 0.29 CHF for driving in an urban area. Applying a weighted average (80% operation in a regional area, 20% in an urban area) results in operating costs for automated pooled trips of 0.226 CHF (compared to 0.504 CHF for a privately owned AV without pooling).

The results (see Table 11) show considerable user benefits due to changes in operating costs, generating total user benefits in the range of 2,417–3,191 € p. a. for level 4, and in 2,627–3,376 € p.a. for level 5 automation. The share of travel time-related user benefits in total user benefits amounts to around 9–12% for level 4, and to 17–21% for level 5 AV's. The sensitivity analysis however, does neither take into account that higher vehicle occupancy rates may reduce the individual comfort level nor that ridesharing services may increase the individuals' travel times because of altered vehicle routing. Nevertheless, the sensitivity analysis reveals that ridesharing solutions, for which vehicle automation provides a sound basis, have a tremendous potential to decrease generalized user costs.

7. Discussion and conclusions

In this paper, user benefits due to travel time savings and the passengers' possibilities of re-using travel time for other activities are estimated for level 4 and 5 CAVs at the example of a commuter relation in Germany. These travel time-related user benefits are put into relation with overall changes in generalized user costs due to the use of automated passenger cars.

The impacts on travel times are estimated by microscopic traffic flow simulations taking congestion effects into account. The simulations reveal—under the assumption of a volume-to-capacity ratio of 70% on all road links—that about 27% of the travel time can be saved on a commuting relation due to road automation in case of 100% penetration rate of level 5 vehicles. For level 4 vehicles the travel time savings amount to up to 20%. For both level 4 and 5 vehicles, the highest percentage time savings are expected for the freeway route option.

User benefits that accrue from these time savings and the passenger's option of using travelling time for activities other than conducting the car, are expected at a relevant magnitude: 219–374 € p.a. for level 4, and 461–573 € p.a. for level 5 vehicles (depending on the route chosen). The calculated benefits represent only the benefits that accrue from a certain share of the generated annual trips (i.e. commuting trips). The estimated travel time-related user benefits are in a similar magnitude of order as the willingness-to-pay values for the purchase of automated vehicles identified by Daziano et al. (2017) averaging around $3,500 for partial, and $4,900 for full automation. Even under consideration of higher operating costs of an automated car, significant user benefits are expected to accrue at around 1,310–2,240 € p.a. for level 4 and 2,770–3, 440 € p.a. for level 5 passenger cars over a depreciation period of six years. The results also underline that potential user benefits by ridesharing concepts that are enabled by autonomous vehicles, will significantly exceed the scope of travel time-related benefits.

The outcomes of this research are dependent on several assumptions: among the key assumptions are the underlying volume-to-capacity ratio of 70% for all road links which are used by the commuting relation in each option. As demonstrated by the sensitivity analysis, any changes in

Table 11
Sensitivity analysis–potential user benefits of pooled automated driving.

Automation level	Route	Operating costs [€/day]	User benefits due to changes in operating costs [€/year]	User benefits due to changes in travel time-related costs [€/year]	Total user benefits [€/year]	Share of travel time-related user benefits in total user benefits [%]
4	Freeway	11.17	2,817	374	3,191	11.7
	Arterial	8.59	2,166	252	2,418	10.4
	Collector	8.72	2,198	219	2,417	9.1
5	Freeway	11.17	2,817	559	3,376	16.6
	Arterial	8.59	2,166	461	2,627	17.5
	Collector	8.72	2,198	573	2,771	20.7

this underlying assumption has significant impacts on infrastructure capacity increase and travel time savings. The market penetration of automated cars which for the simulation has been assumed to be 100% on all considered network links and intersections, represents an optimistic hypothesis according to more conservative adoption forecasts for example by Talebian and Mishra (2018). Moreover, all lanes of multilane road sections have been assumed to be used by automated vehicles, rather than applying separated lanes dedicated for automated and conventional vehicles as examined by Chen et al. (2019). Furthermore, the approach applied to estimate time savings does not take into account any further effects of automated driving, i.e. possible increase in road transport demand due to modal shift from public transport or cycling/walking to private passenger cars, facilitating private car transport to new user groups, or changes in land-use pattern (see e. g., Harper et al., 2016; Sivak and Schoettle, 2015; Fagnant and Kockelman, 2014; Szimba and Orschiedt, 2017). A certain share of the estimated benefits is likely to be outweighed by induced demand due to enhanced attractiveness and accessibility of passenger car usage. Finally, the paper does not address imminent conflicts between private interests of users of automated cars and the requirements of other, non-automated road users such as pedestrians or cyclists: for instance, dedicated infrastructure for automated driving may cause barrier effects, which increase the time costs for non-automated users of the transport system.

Nevertheless, the analyses reveal that automated driving has the potential to decrease significantly the generalized user costs of individual motorized mobility for commuting. In combination with excessive residential rents in many metropolitan areas world-wide, the possibilities for commuters facilitated by an automated mobility system will considerably increase the urban hinterland's attractiveness as residential area. Thus automated driving is likely to have detrimental impacts on land-use and urban sprawl, and—through second-order effects—on induced transport demand and related indicators such as energy consumption or infrastructure capacity. Furthermore, providing a comfortable door-to-door transport facility with lower user costs than conventional cars, automated vehicles will become serious competitors to public transport modes.

The findings of this paper pose challenges for both research and policy: further research efforts are required to estimate the magnitude of automated driving on travel behavior and, particularly, on land-use patterns, as well as to study related impact mechanisms. For transport policy, land use and urban planners as well as public transport operators, it is crucial to develop strategies to avoid unfavorable impacts of automated driving to occur. Furthermore, policy-makers and planners need to find a sound balance between the beneficiaries of users of automated vehicles on the one side, and both public interests and non-automated traffic users on the other. This in turn implies a further matter of research: to elaborate appropriate concepts that allow for exploiting the benefits of automated vehicles while countervailing undesirable socio-economic effects as well as strains on the transport system and land use.

CRediT authorship contribution statement

Eckhard Szimba: Writing - original draft, Conceptualization, Formal analysis. **Martin Hartmann:** Writing - original draft, Conceptualization, Formal analysis.

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References

Bureau of Public Roads, 1964. Traffic Assignment Manual. Washington D.C.
McKinsey & Company, 2016. Monetizing Car Data – New Service Business Opportunities to Create New Customer Benefits.
PTV Group, 2016. PTV VISUM 16: User Manual.
Aghabayk, K., Sarvi, M., Forouzideh, N., Young, W., 2014. Modelling heavy vehicle car-following behaviour in congested traffic conditions. J. Adv. Transport. 48, 1017–1029. https://doi.org/10.1002/atr.1242.
ATKINS, 2016. Research on the Impacts of Connected and Autonomous Vehicles (CAVs) on Traffic Flow. Stage 2: Traffic Modelling and Analysis. Technical Report.
Batley, R., Dekker, T., Stead, I., 2018. Worthwhile Use of Travel Time and Implications for Modelling, Appraisal and Policy Planning – the United Kingdom Experience. ITF Roundtable Zero Value of Time, Paris, pp. 25–26. September 2018.
Bösch, P., Becker, F., Becker, H., Axhausen, K., 2018. Cost-based Analysis of Autonomous Mobility Services. Transport Policy, vol. 64, pp. 76–91. https://doi.org/10.1016/j.tranpol.2017.09.005.
Chen, S., Wang, H., Meng, Q., 2019. Designing autonomous vehicle incentive program with uncertain vehicle purchase price. Transport. Res. C Emerg. Technol. 103, 226–245. https://doi.org/10.1016/j.trc.2019.04.013.
Chlond, B., Weiss, C., Heilig, M., Vortisch, P., 2014. Hybrid modeling approach of car uses in Germany on basis of empirical data with different granularities. Transportation research record. J. Transport. Res. Board 67–74. https://doi.org/10.3141/2412-08, 2412.2.
Daziano, R., Sarrias, M., Leard, B., 2017. Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. Transportation Research Part C. Emerg. Tech. 78, 150–164. https://doi.org/10.1016/j.trc.2017.03.003.
De Serpa, A.C., 1971. A theory of the economics of time. Econ. J. 81 (324), 828–846. https://doi.org/10.2307/2230320.
Evans, A., 1972. On the theory of the valuation and allocation of time. Scot. J. Polit. Econ. 19 (1), 1–17. https://doi.org/10.1111/j.1467-9485.1972.tb00504.x.
Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transport. Res. C Emerg. Technol. 40, 1–13.
FGSV, 2015. Handbuch für die Bemessung von Straßenverkehrsanlagen.
Fraunhofer, I.A.O., Horváth & Partners, 2016. The Value of Time. Nutzerbezogene Service-Potenziale durch autonomes Fahren.
Friedrich, B., 2015. Verkehrliche Wirkung autonomer Fahrzeuge. In: Maurer, M., Gerdes, J., Lenz, B., Winner, H. (Eds.), Autonomes Fahren: Technische, rechtliche und gesellschaftliche Aspekte. Springer, Berlin Heidelberg, pp. 331–350.
Haberl, M., Neuhold, R., Fellendorf, M., Rudiger, M., Kerschbaumer, A., Eichberger, A., Rogic, B., 2017. Simulation Assisted Impact Analyses of Automated Driving on Motorways for Different Levels of Automation and Penetration, International Conference on Intelligent Transport Systems in Theory and Practice, mobil.TUM, Munich, Germany.
Harper, C.D., Hendrickson, C.T., Mangones, S., Samaras, C., 2016. Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. Transport. Res. C Emerg. Technol. 72, 1–9. https://doi.org/10.1016/j.trc.2016.09.003.
Jara-Díaz, S., 2000. Allocation and valuation of travel-time savings. In: Hensher, D.A., Button, K.J. (Eds.), Handbook of Transport Modeling. Pergamon, Amsterdam, pp. 303–319.
Kolarova, V., Steck, F., Bahamonde-Birke, F., 2019. Assessing the effect of autonomous driving on value of travel time savings: a comparison between current and future preferences. Transport. Res. Part A Policy and Practice 129, 155–169. https://doi.org/10.1016/j.tra.2019.08.011.
Kouwenhoven, M., de Jong, G., 2018. Value of travel time as a function of comfort. J. Choice Model. 28, 97–107. https://doi.org/10.1016/j.jocm.2018.04.002.
Krause, S., Motamedidehkordi, N., Hoffmann, S., Busch, F., Hartmann, M., Vortisch, P., 2017. Auswirkungen des teil- und hochautomatisierten Fahrens auf die Kapazität der Fernstraßeninfrastruktur. Forschungsvereinigung Automobiltechnik e.V, Schriftenreihe 296. https://doi.org/10.13140/RG.2.2.20460.56968.
Le Vine, S., Zolfaghari, A., Polak, J., 2015. Autonomous cars. The tension between occupant experience and intersection capacity. Transport. Res. C Emerg. Technol. 52, 1–14. https://doi.org/10.1016/j.trc.2015.01.002.
Lyons, G., Jain, J., Holley, D., 2007. The use of travel time by rail passengers in Great Britain. Transport. Res. Pol. Pract. 41 (1), 107–120. https://doi.org/10.1016/j.tra.2006.05.012.
PTV, TCI Röhling, Mann, 2016. H.-U.: Methodenhandbuch zum Bundesverkehrswegeplan 2030.
McFadden, D., 1981. Econometric models of probabilistic choice. In: Manski, C., McFadden, D. (Eds.), Structural Analysis of Discrete Data with Econometric Applications. MIT Press, Cambridge, pp. 198–272.
Nazari, F., Noruzoliaee, M., Mohammadian, A., 2018. Shared versus private mobility: modeling public interest in autonomous vehicles accounting for latent attitudes. Transport. Res. C Emerg. Technol. 97, 456–477. https://doi.org/10.1016/j.trc.2018.11.005.
NZ Transport Agency, 2014. Research Report 551. Car Passenger Valuations of Quantity and Quality of Time Savings. Ian Wallis Associates Ltd.
Ortúzar, J. d. D., Willumsen, L.G., 2011. Modelling Transport, 4th edition. John Wiley & Sons Ltd, Chichester.
Pfleging, B., Rang, M., Broy, N., 2016. Investigating user needs for non-driving-related activities during automated driving. In: Proceedings of the 15th international conference on mobile and ubiquitous multimedia, 91–99. https://doi.org/10.1145/3012709.3012735.

Reinhold, T., 1999. Die Bedeutung des Parksuchverkehrs: eine quantitative Abschätzung am Beispiel von zwei Stadtgebieten in München. Int. Verkehrswes. 51 (6), 250–255.
SAE International, 2014. Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems. Standard J3016_201401.
Sivak, M., Schoettle, B., 2015. Influence of Current Nondrivers on the Amount of Travel and Trip Patterns with Self-Driving Vehicles. Transportation Research Institute, The University of Michigan, Ann Arbor.
Statistisches Bundesamt, 2016. Pendeln in Deutschland: 68 % nutzen das Auto für den Arbeitsweg. Retrieved on February 2, 2018 from. https://www.destatis.de/DE/ZahlenFakten/GesamtwirtschaftUmwelt/Arbeitsmarkt/Erwerbstaetigkeit/TabellenPendler/Pendler1.html.
Stephens, T., Gonder, J., Chen, Y., Lin, Z., Liu, C., Gohlke, D., 2016. Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles. National Renewable Energy Laboratory. https://doi.org/10.2172/1334242. Technical Report.
Szimba, E., Orschiedt, Y., 2017. How beneficial is fully automated driving in urban areas from a socio-economic point of view?. In: Proceedings of the Conference "Future City 2017: Urban Sustainable Development and Mobility. University of Transport and Communications, Hanoi, Vietnam.
Talebian, A., Mishra, S., 2018. Predicting the adoption of connected autonomous vehicles: a new approach based on the theory of diffusion of innovations. Transport. Res. C Emerg. Technol. 95, 363–380. https://doi.org/10.1016/j.trc.2018.06.005.
Ticoll, D., 2015. Driving Changes: Automated Vehicles in Toronto. Munk School of Global Affairs, University of Toronto.
TNS Infratest/IVT, Dec. 2013. Ermittlung von Bewertungsansätzen für Reisezeiten und Zuverlässigkeit auf der Basis eines Modells für modale Verlagerungen im nicht-gewerblichen und gewerblichen Personenverkehr für die Bundesverkehrswegeplanung. https://doi.org/10.3929/ethz-b-000089615.
Treiber, M., Hennecke, A., Helbing, D., 2000. Congested traffic states in empirical observations and microscopic simulations. Phys. Rev. 62 (2), 1805–1824. https://doi.org/10.1103/PhysRevE.62.1805.
van den Berg, V., Verhoef, E., 2016. Autonomous cars and dynamic bottleneck congestion: the effects on capacity, value of time and preference heterogeneity. Transp. Res. Part B Methodol. 94, 43–60. https://doi.org/10.1016/j.trb.2016.08.018.
Wadud, Z., 2017. Fully automated vehicles: a cost of ownership analysis to inform early adoption. Transport. Res. Part A: Policy and Practice 101 163–176. https://doi.org/10.1016/j.tra.2017.05.005.
Wadud, Z., Huda, F.Y., 2019. Fully automated vehicles: the use of travel time and its association with intention to use. Proc. Inst. Civil Eng. - Transport. https://doi.org/10.1680/jtran.18.00134.
Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transport. Res. Pol. Pract. 86, 1–18. https://doi.org/10.1016/j.tra.2015.12.001.
Wardman, M., 2004. Public transport values of time. Transport Pol. 11 (4), 363–377. https://doi.org/10.1016/j.tranpol.2004.05.001.
Wiedemann, R., 1974. Simulation des Straßenverkehrsflusses, vol. 8. Institute for Transportation Science, University of Karlsruhe, Schriftenreihe.
Yap, M., Correia, G., van Arem, B., 2016. Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. Transport. Res. Pol. Pract. 94, 1–16. https://doi.org/10.1016/j.tra.2016.09.003.