Network Effects of Activity-based Departure Time Choice with Automated Vehicles

A Case Study in the Netherlands

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ABSTRACT

In transportation literature on Automated Vehicles (AV), the commonly adopted approach to capture the effect of increased on-board productivity on individual and aggregate travel patterns, is to reduce the 'penalty' associated with travel time in a travel simulator. However, different types of on-board activities can also directly affect the departure time preferences and thus can have varied impacts on the congestion pattern. This paper incorporates such a direct impact of on-board activities and investigates the network effects of what we call activity-based departure time choice with AVs. To do so, we use a novel form of scheduling preferences in a dynamic traffic assignment (DTA) model. This model is applied to simulate travel with AVs in the Netherlands. Results show that AV users engaging in home, work or both home/work activities respectively increase congestion more at the beginning, end or middle of the morning peak. In addition the new scheduling preferences led to changes in route choice. A shift in vehicle-kilometres is observed from the main to the underlying road network – a change that would likely worsen traffic safety, noise and air pollution. Lastly, it is observed that with mixed traffic situations, Non-AV users move their departure times to less congested periods. AV users are less affected by longer travel times and prioritised their preferred arrival times. A sensitivity analysis indicates that the assumptions about the scheduling parameters have a considerable impact on the magnitudes of the model outputs, but do not influence the general insights and directions of the effects.

INTRODUCTION

Automated vehicles (AV) are expected to cause substantial changes to the way transportation is organised [1]. They might bring many positive effects such as better road/vehicle safety, reduced environmental costs, and also lead to increased on-board productivity. In transportation literature, the commonly adopted approach to capture the effect of increased on-board productivity, is to reduce the 'penalty' associated with travel time. This implies that people are less averse to longer travel times (i.e., congestion), prioritise arriving close to the preferred arrival time and thus, increase peak congestion. Much research has been conducted to assess these effects in a network based on a travel time penalty (TTP) and a varying road capacity [2,3,4]. With AVs the travel time weigh for travelers in deciding their activity and travel choices decreases. Therefore demand is likely to increase, which is widely believed to increase congestion in turn. AVs could however increase road capacities by having shorter headways and/or fewer traffic disruptions as a result of cooperative driving. Despite this increased capacity, congestion might still increase due to impact of AVs on behavioral choices as a result of the the lower travel time weigh associated with on-board productivity [5].

However, we argue that a distinction should be made between the type of performed on-board activity, since this could directly affect the departure time preferences and thus can have an impact on the congestion pattern. Previous theoretical work has shown that travellers with fully automated vehicles in which home activities could better be performed, would depart earlier, and conversely travellers with automated vehicles in which work activities could better be performed, would depart later [6,7]. In addition, the results suggested that automated vehicles could likely increase severe congestion in the future since travellers which use AVs are less averse to peak congestion. However, these insights have been obtained in a theoretical single link (bottleneck) setting. Up to this point differentiation between the substance of activities has not yet been investigated for real-life road networks: settings with multiple origins and destinations, where travellers also choose their routes and have different preferences for the timing of their trips.

This research fills this gaps. We investigate network effects of activity-based departure time choice with fully automated vehicles in the Haaglanden' Region of the Netherlands. The objective is to provide insight in the way departure time preferences affect network congestion in the AV era. To this end we use the scheduling preferences defined in [6], which are based on the well-known α-β-γ model, [8,9], integrate them in a macroscopic dynamic traffic assignment (DTA) model, and assessing various scenarios with varied model parameters.

Impacts on VTT

When discussing the disutility of travel in relation to on-board activities, most research has been focused on determining the reduction of the value of travel time VTT [10,11,12,13]. However, many research conducted in this field has been based on the conventional use of a single travel time penalty, in which it is assumed that the time spent during travel has a lower utility when on board activities can be performed [14]. This penalty is time independent. However, these models neglect the fact that the possibility of performing on board activities, will affect a traveller's daily program [15]. In addition, this penalty embodies the assumption that no differentiation needs to be made between the type of on-board activities [1]. Although, some work has found varying changes in the VTT (or penalty) depending on various on-board activities [10], the impacts of these various activities would likely stretch beyond the impacts that would be predicted while only considering their contribution to the VTT.

Moreover, [11] conducted a stated choice experiment especially designed for measuring the VTT and analysed the data with discrete choice models [11]. They distinguished between AVs with office interior, leisure interior and a conventional car. It was found that the VTT with office interior turned out to be lower with a conventional car. However, the VTT of the leisure interior car stayed constant or even increased in different models. The theoretical underpinnings of the reduced VTT have been revised and it was found that, in both work and home activity facilitating vehicles the VTT depends on the facilitation level [12].

In addition, we should be critical towards adopting a reduction in VTT associated with AVs and especially its source. As stated by [16], many on board activities may nowadays be more about dealing with the "burden" of commuting travel than spending travel time in a productive way. In [17] it is stated that "people might also experience disadvantages based on the fact that travel based multitasking may not uniformly increase trip utility". This could imply a smaller reduction in VTT than anticipated.

Impacts on travel behaviour

The ability of performing on-board activities might reduce the disutility of travel time, which in turn can lead to a change in travel behaviour. The extent to which, for example mode choice, is subject to the level of productivity while travelling has been studied in [18]. They looked into these changes with the use of revealed preferences and concluded that greater perceived multitask ability of a mode increases that mode's utility. Other research also focussed on the (short term) effects on mode choice [19]. They investigated impacts on activity patterns and the impacts on changes in behaviour with a focus group of residents in Georgia. It was found that some of the expected medium-term effects (i.e. change in activity pattern) influenced the long-term changes

However, with limited availability of empirical data, models and simulations are widely used to make assessments on the potential effects of on-board activities. A comprehensive review of several modelling studies is provided in [20]. They identified the main effects from two perspectives: impact on travel behaviour and impact on land use. Regarding travel behaviour, the results indicate that AVs will bring an increase in vehicle kilometers travelled (VKT), and shift in mode share from public transport and slow mode shares to AVs, which is associated with an assumed high reduction of VTT.

An attempt has been made to assess if these effects could also be observed in a semi-realistic field experiment. A situation was mimed in which people experienced possessing a privately owned AV by providing a free chauffeur service [21]. This study provided key insights in the behavioural aspects and although it does not show the (net) effects of vehicle automation on a system, it resembles, as much as possible, the situation in which households do privately own self-driving cars. This experiment showed again an increase in VKT and number of trips (with a substantial portion of empty trips). Similar trends were observed in another research [22]. They presented a literature review which explored, among other things, the potential change of these travel choices. Research showed that AVs could lead to "an increase of travel demand between 3% and 27%, due to longer trips and more trips and a modal shift from public transport and walking to car."

Several studies were also conducted to assess the shift in behaviour regarding route choice. Although it is difficult to say how strong the effects are, it was found that AVs may bring less aversion to longer routes since individuals have the ability to be productive during the trip. A related increase in VKT has therefore been observed in multiple modelling studies [1,23,24,25,26,27]. Many of these studies used DTA models to investigate network effects.

However, they were based on a single, time independent VTT reduction which does not account for the various on-board activities and resulting travel behaviour effects (i.e. departure time choice).

Impacts on congestion

The changes of travel behaviour indicate a reduction in aversion to long trips, i.e. people experience less disutility of travel time. This implies that individuals with self-driving cars might be less affected to (peak) congestion. As a consequence they adjust their departure times to arrive closer to their preferred arrival time - associated with longer travel times - resulting in increased congestion. However, the effects are highly dependent on exact penetration rates of AVs and the level of automation which is considered, and the substance of the on-board activity. For instance, if commuters engage in working activities during their morning trip, they might prefer to depart later since they can be productive, to some extent, during their trip. Others may choose to sleep during their morning trip and therefore prefer to depart earlier. With the use of a single time-independent penalty for travel time, these changes in departure time preferences and their impact on congestion cannot be predicted.

Therefore, another approach was used in which the utility during trip has been differentiated by means of the α-β-γ preferences within the bottleneck model [28]. They assumed that any on-board activity contributes to a decreasing travel penalty and found that congestion is likely to be more severe with AVs than with conventional vehicles. However, they did not differentiate between the type of activity. Therefore, other studies propose to differentiate among on board activities in the α-β-γ scheduling preferences and to study the congestion patterns that emerge from this set-up [7,8,29]. These α-β-γ preferences have also been used to analyse congestion patterns with AVs. They distinguished vehicles in which home/leisure and work activities were more easily performed, similar to [29] who identified three types of AVs: Home, Work and Universal AVs. Home AVs are vehicles in which home activities can better be performed, Work AVs are vehicles in which work activities can better be performed and Universal AVs are vehicles which are suited for both types of activities. Both theoretical studies used a single link setting, which led to the following conclusions:

- If home activities can better be performed in (home) AVs, modelling shows that travellers may shift to the begin of the congestion peak, i.e. depart earlier. Vice versa, if travellers are able to better perform work activities, theoretical results show they might prefer to depart later.
- These results also indicate congestion could increase with the introduction of automated vehicles. Because travellers experience less aversion to longer travel times, due to on-board activities, they will prioritse arriving at or near the preferred arrival time over longer travel times, which increase congestion.
- Lastly, if home, work and universal (home/work) AVs are available, work AVs would increase congestion the least, at least given a single link setting.

METHOD

To investigate network effects of activity-based departure time choice with fully automated vehicles we integrate the extended α-β-γ scheduling preferences [29] in a dynamic traffic assignment (DTA) model. The modeling framework is presented in Figure 1. This modelling framework is used to simulate traffic with AVs in the region Haaglanden in the Netherlands (city of The Hague and its surroundings). In several scenarios, we vary the type(s) of AV, penetration rates and scheduling model parameters (α, β, γ).

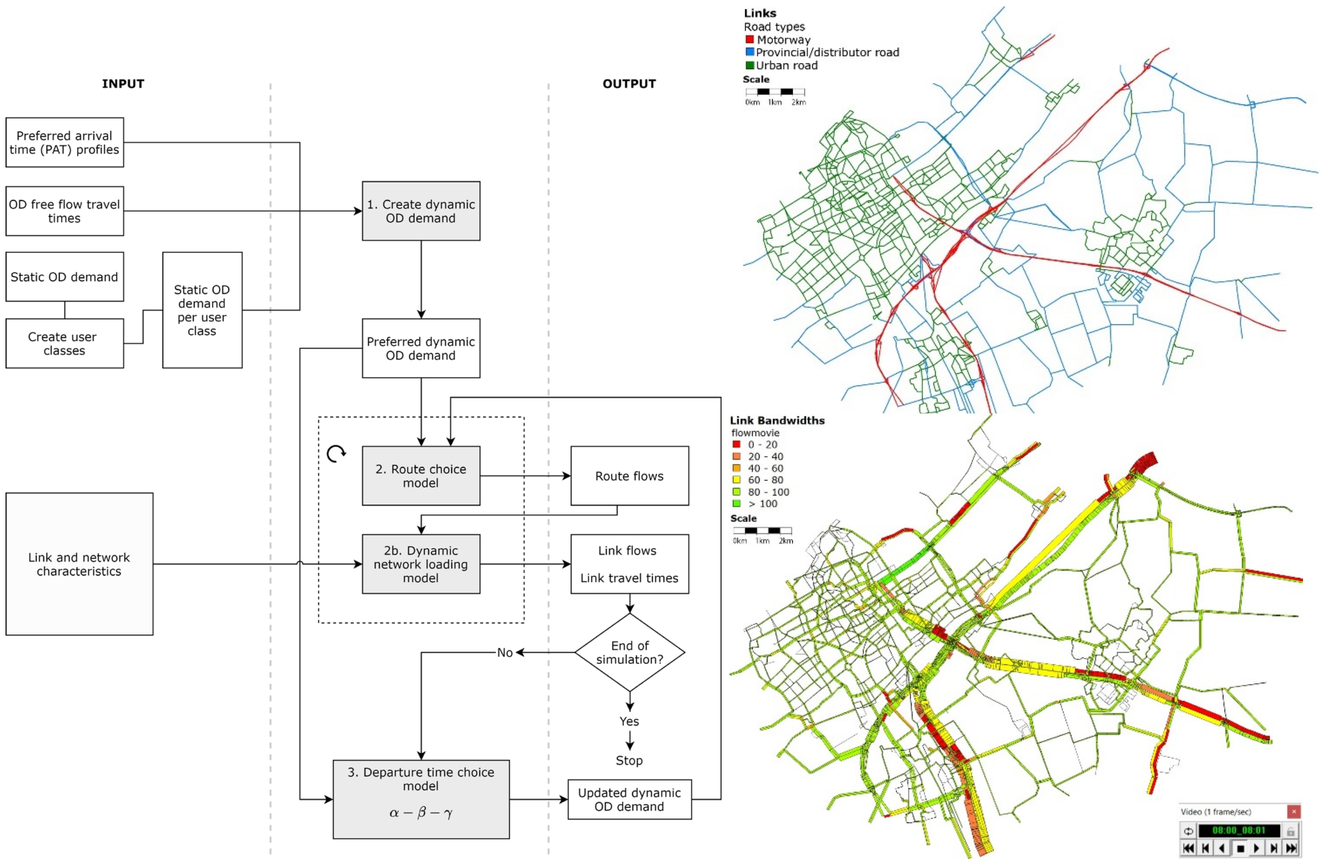

FIGURE 1 Overview of Modelling Framework and Haaglanden region network

Within the overall framework, three sub models can be distinguished. First, the initial dynamic OD demand is created, which is referred to as the Preferred Departure Time (PDT) profiles. These are constructed with the use of the Preferred Arrival Time (PAT) profiles, assuming that travel is a necessity to reach a certain destination at the PAT. I.e. the PAT minus the free flow travel times (FFTT) equals the PDT per OD pair. The PDT and PAT profiles are fixed for all scenarios. The FFTT are calculated at the beginning of each run, as the shortest path length divided by the sum of free flow speed associated with each link within this path. The obtained initial PDT profiles, dynamic OD demand, is used in the second sub model, the DTA model, to determine initial travel times. Since all vehicles are now 'departing' at their PDT, the associated travel times will, during peak moments, be higher than in free flow travel conditions. The DTA model solves the so-called dynamic user equilibrium problem.

The link travel times that follow from the DTA model are then used as input for third sub model, the departure time choice model which is a logit model. Based on the travel times, this model determines fractions of departing vehicles in each time period. This results in a new Dynamic OD Demand, or the 'Actual departures' associated with that outer loop iteration. This new distribution of departures is then used for the next iteration in the DTA to arrive at updated travel times and so on until a stopping criterion is met. This completes the simulation and the model has reached an 'equilibrium' departure time choice and route choice. The complete model ends providing the link flows and travel times from the last DTA model run. Note that because of computation time limits we introduced additional stopping criteria in terms of maximum number of iterations which does not assure complete convergence of the model. Furthermore, note that this research focuses on departure time choice and route choice. Total demand is assumed to be fixed, which means that no feed back loop is considered to model the impact on mode or trip choice and also the possible impact of AVs on link capacities is not considered.

Modeling the departure time choice

The α-β-γ model, states that our departure time choice is based on our value of being at home or at work [8]. A person will try to schedule his/her departure at such a moment that he/she loses the least utility of being at these places. We use the extended α-β-γ scheduling preferences [29] which include the utility associated with on-board activities and differentiates between home and work activities in their departure time choice impacts. This study adopts this model and the definition of three AVs that differ by their facilitation level of home and work activities: Home AV, Universal AV and Work AV. These vehicles are best suited to engage in home, both home/work and work related activities, respectively. Figure 2 graphically presents the step-wise utility formulation of the α-β-γ scheduling preferences for a Universal AV. The 'universal' nature of this AV is reflected in the fact that it is optimal to engage in home activity during travel at any time prior to the preferred arrival time t^*, and it is optimal to engage in work activity during travel after that time.

Specifically, the definitions of the three vehicles in the α-β-γ set up (in which e_h and e_w are efficiency factors for home and work respectively indicating the 'productivity' of these activities while traveling) are the following:

$$\alpha e_h > (\alpha + \gamma) e_w \qquad \text{Home AV} \tag{1}$$

$$\alpha e_h < (\alpha - \beta) e_w \qquad \text{Work AV} \tag{2}$$

$$(\alpha - \beta) e_w < \alpha e_h < (\alpha + \gamma) e_w \qquad \text{Universal AV} \tag{3}$$

Equation (1) and (2) show that, irrespective of departure time t^*, it is optimal for the individual to engage in home or work activities in Home and Work AVs respectively, during the entire trip. For the Universal AV, Equation (3) ensures that it would be optimal to engage in home activities before t^* but switch to work activities after t^* till the end of the trip. This way, the effects of having different types of on-board activities can be investigated.

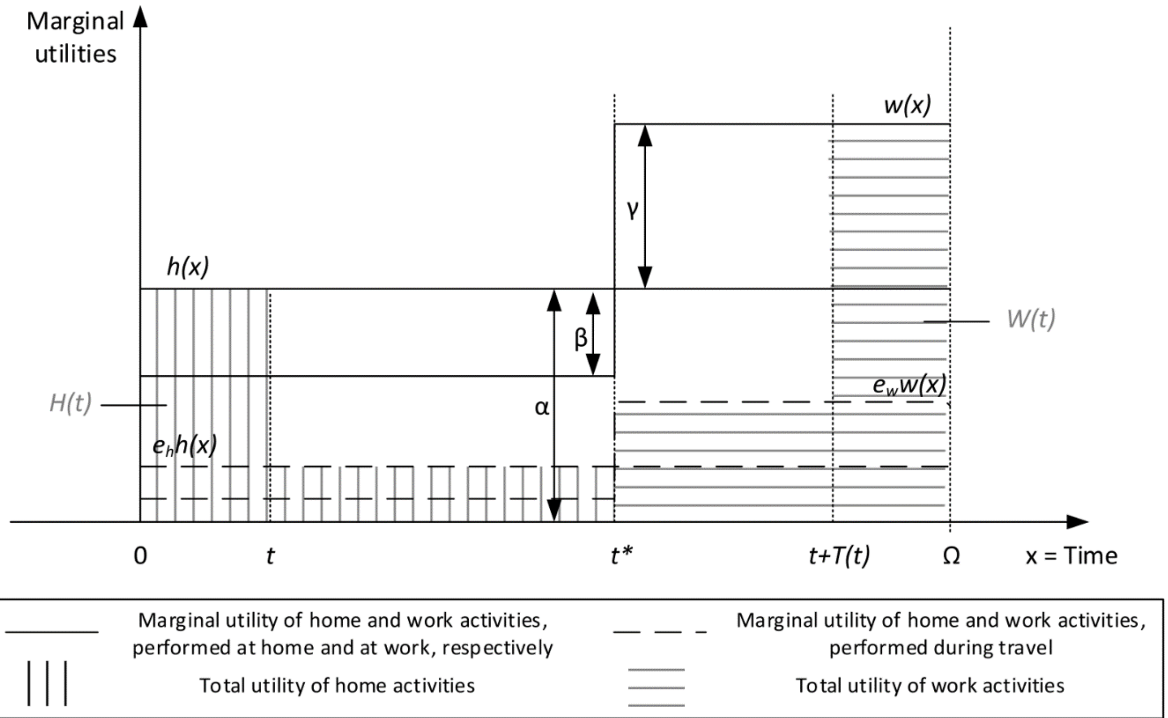

FIGURE 2 α-β-γ scheduling preferences including the utility obtained from home and work activities on board: Universal AV, retrieved from Pudāne (2020).

For each AV type (Home/Universal/Work) the total disutility can be derived by taking the integral of the utility (such as displayed in Figure 2) over time in the morning period $[0, \Omega]$. These disutility functions describe the total utility loss due to travel, while accounting for the on-board productivity. The functions depend on the individual's departure time t, thereby defining three departure time intervals: before the on-time departure time $\tilde{t}$ (defined as the departure time that leads to arrival at exactly t^*), after $\tilde{t}$ but before t^*, or after t^*.

Non-AV

$$\mathrm{U(t)} = \alpha T(t) + \beta(t^* - (t + T(t))) \qquad \text{if } t + T(t) < t^* \qquad (4)$$

$$\mathrm{U(t)} = \alpha T(t) + \gamma((t + T(t)) - t^*) \qquad \text{if } t < t^*, t + T(t) > t^* \qquad (5)$$

$$\mathrm{U(t)} = \alpha T(t) + \gamma((t + T(t)) - t^*) \qquad \text{if } t > t^* \qquad (6)$$

Home AV

$$\mathrm{U(t)} = \alpha(1 - e_h)T(t) + \beta(t^* - (t + T(t))) \qquad \text{if } t + T(t) < t^* \qquad (7)$$

$$\mathrm{U(t)} = \alpha(1 - e_h)T(t) + \gamma((t + T(t)) - t^*) \qquad \text{if } t < t^*, t + T(t) > t^* \qquad (8)$$

$$\mathrm{U(t)} = \alpha(1 - e_h)T(t) + \gamma((t + T(t)) - t^*) \qquad \text{if } t > t^* \qquad (9)$$

Universal AV

$$\mathrm{U(t)} = \alpha(1 - e_h)T(t) + \beta(t^* - (t + T(t))) \qquad \text{if } t + T(t) < t^* \qquad (10)$$

$$\mathrm{U(t)} = \alpha T(t) + \gamma((t + T(t)) - t^*) - e_h\alpha(t^* - t) - e_w(\alpha + \gamma)((t + T(t)) - t^*) \qquad \text{if } t < t^*, t + T(t) > t^* \qquad (11)$$

$$\mathrm{U(t)} = \alpha T(t) + \gamma((t + T(t)) - t^*) - e_w(\alpha + \gamma)T(t) \qquad \text{if } t > t^* \qquad (12)$$

Work AV

$$\mathrm{U(t)} = \alpha(t^* - t) - e_w(\alpha - \beta)T(t) - (\alpha - \beta)(t^* - (t + T(t))) \quad \text{if } t + T(t) < t^* \quad (13)$$

$$\mathrm{U(t)} = \alpha T(t) + \gamma((t + T(t)) - t^*) - e_w(\alpha - \beta)(t^* - t) - e_w(\alpha + \gamma)((t + T(t)) - t^*) \quad \text{if } t < t^*, t + T(t) > t^* \quad (14)$$

$$\mathrm{U(t)} = \alpha T(t) + \gamma((t + T(t)) - t^*) - e_w(\alpha + \gamma)T(t) \quad \text{if } t > t^* \quad (15)$$

The above activity-based scheduling preferences are implemented in a traffic simulation model using a Multinomial Logit model (MNL). After each DTA run providing the travel times for every departure time interval, the disutility of all choice options (i.e. disutility of departure in interval j, given PDT interval i) can be determined. Note that PDT interval i is directly related with a PAT. The MNL, using 0.5 for the scaling parameter, provides the probabilities per departure time interval and is averaged using the well known Method of Successive Averages (MSA).

Macroscopic DTA model

The DTA model is used within the OmniTRANS software package. It must be noted that this model does not include blocking back since the version is not compatible with multiple user classes in combination with blocking back. This leads to less accurate modelling of traffic jams and the fact that not all travel times will be correct. In addition, intersection delay is not included. This affects primarily provincial/distributor roads and urban roads in the way that travel times are underestimated.

Case study

The case study comprises the road network of the 'Haaglanden' region in the Netherlands (see Figure 1). This network includes 168 zones and we use a traffic demand of 473,868 vehicles during the morning period (6:00 – 11:00 AM). The settings for the α-β-γ model were derived from literature, which also provides us upper and lower bounds to investigate the sensivity [7,9,28,29,31,32]. For the base scenarios we use the the following set: α, β, γ = 2, 1, 4 [29]. Note that, given the utility functions (4)-(15), onlythe ratio between these parameters matters – multiplying all with a constant would effectively change the MNL scale parameter.

Furthermore the efficiency factors need to be determined. As this is something which has not yet been investigated extensively, we use the values $eh = ew = 0.3$ as proposed by Pudāne [29].

To investigate the network effects as a result of different on-board activities including its relation to Non-AV, the case study is used to run

- 4 base scenarios (i.e. 100% Non-AV, 100% Home AV, 100% Universal AV and 100% Work AV)
- scenarios in which the penetration rate of Universal AV varied with steps of 25% in which the other vehicles were assumed to be Non-AV (i.e. 0%, 25%, 50%, 75%, 100%)
- sensitivity analyses of parameter settings using the base scenario 100% Universal AV
    - Based on literature additionally 2 scenarios were assessed for the α, β, γ settings, i.e. α-β-γ 1 (2; 0.75; 1) and α-β-γ 2 (1; 0.8; 1.2). These parameters indicate a relatively lower penalty for late arrivals.
    - The efficiency factors were varied resulting in 2 additional scenarios (i.e. 0.5 and 0.8 both assumed to be the same for home and work).

Analysis

To analyse the simulation results, the following three groups of KPIs are evaluated:

- Behavioural effects: shifts in departure time and route choices. Departure time choice provides insight in peoples preferences to departure time and the change in behaviour to depart earlier or later is captured, which is measured as the number of departing vehicles within a 10-minute time interval. Route choice is investigated on road type level. It is hypothised that AV users will experience less aversion to congested routes whereas Non-AV users will prefer the less popular uncongested routes. Based on the VKT per road type, this choice and the observed differences with a reference scenario are assessed.
- Network effects: travel times/delays. Travel times are used to explore the difference between total network travel times for Non-AV and AV users. Delays are investigated as these give a better understanding as well as a more nuanced result of congestion increase.
- External effects: traffic safety and emissions are analysing considering the VKT changes per road type. [33,34].

Assessment of these indicators requires a distinction between the type of road and the proportion of AV/Non-AV users on them. I.e. congestion patterns (travel times) on certain road types might differ for AVs compared to non-AVs, because they depart at different intervals. Similarly, traffic safety differs for Non-AV and AV users, and it depens also on the road type.

RESULTS

Base scenarios

Figure 3 presents the departure time profiles for the entire Haaglanden network of the base scenarios. The x-axis corresponds to the time during the morning peak period. The y-axis corresponds to the number of departing vehicles. Results show that travellers which use AVs to engage in home activities (Home AVs), increase congestion more to the beginning of the morning peak. Vice versa, travellers which use AVs to engage in work activities (Work AVs) move congestion more to the end of the morning peak. Travellers which use AVs for both home and work activities (Universal AVs) concentrate the congestion at the middle and end of the morning period. The departure time profiles are presented for scenarios in which a 100% of the travellers use the same AV types for the entire network (Figure 3). Analysis of specific OD-relations show similar results as the overall changes in departure time profiles.

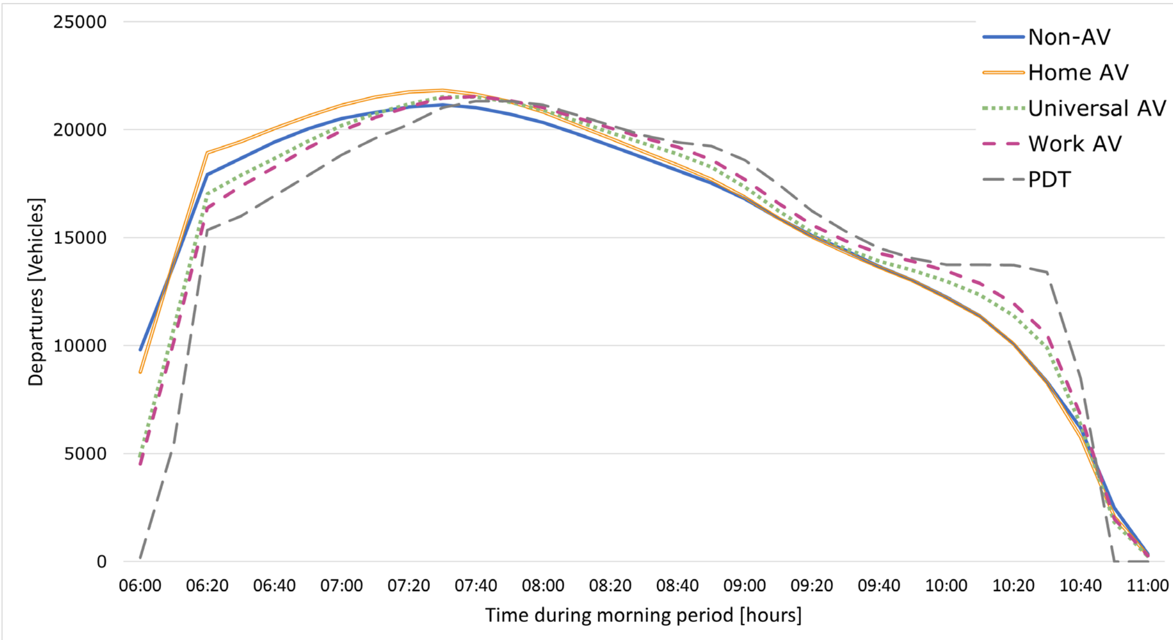

FIGURE 3 Departure time profiles per hour for Non-, Home, Universal and Work AV

It can be noted that Non-AVs (blue) and Home AVs (yellow) show a more similar departure time profile. Likewise, similarities could be observed regarding Universal (green) and Work AVs (purple). This can be explained by the fact that the utility of on-board activities increases during travel (at time t*) for Universal and Work AVs, but it stays constant for Home AVs. Then, since the utility is increasing, late departures are in general less inconvenient with Universal and Work AVs.This leads to the belief that in mixed traffic situations, Home AVs would compete the most with Non-AVs.

The profiles show that AV users tend to shift their departure times towards peak moments (the rise and decline of the graphs is steeper at the beginning and end of the morning interval) which in turn lead to longer travel times and an increase of delays (i.e. congestion). This was true for each scenario with an AV type compared to the Non-AV scenario. The biggest increase was observed for Universal AV, which can be explained by the fact that this type skewes departures towards the middle and end of the morning period, i.e. the period associated with the longest travel times and delays.

Considering route choice, Table 1 shows a shift in VKT from the main road network to the underlying road network. Although no differentiation was made between AV' versus Non-AV users in their preferences for certain routes (motorways vs urban roads, etc.), the fact that AV users are less averse to longer travel times results in route choice changes, primarily for the underlying road network, i.e. provincial/distributor and urban roads. The increase in VKT on these roads is often associated with a negative impact on traffic safety, noise and air pollution in urban areas, although the fact that the increase comes from AVs, means that the deterioration in safety and environment could be less severe (since future AVs may be safer than conventional vehicles and adopt a more eco-friendly way of driving).

TABLE 1 VKT per road type for different AVs including relative changes to Non-AV

	Non-AV	Home AV		Universal AV		Work AV	
Motorway [km]	2.642.545	2.636.128	*-0.24%*	2.637.689	*-0.18%*	2.637.351	*-0.20%*
Prov./dist. road [km]	1.259.488	1.263.714	*0.34%*	1.263.291	*0.30%*	1.263.629	*0.33%*
Urban road [km]	1.236.918	1.239.154	*0.18%*	1.237.602	*0.06%*	1.237.293	*0.03%*
Total [km]	5.138.951	5.140.172	*0.02%*	5.139.582	*0.01%*	5.138.273	*-0.01%*

The observed increase in overall VKT (Table 1) can be directly related to a negative impact on traffic safety. Even though the changes in total VKT seem small and might even be considered insignificant, the direction with differentiation to road types gives a decrease of VKT on motorways and an increase mostly on provincial/distributor roads. The latter is considered the least safe type of road, i.e. the one with the highest associated risk factor [34]. However, one might argue that AVs are expected to be safer, although this might not be true in mixed traffic conditions with Non-AV. Regarding emissions, the primary increase on provincial/distributor roads is regarded as beneficial. Since these roads are often associated with relatively lower emission levels of CO_2 due to more eco friendly driving (speeds). On the other hand, when we assess the air (NO_x, PM10) and especially noise pollution, increase of VKT on the underlying roads, meaning more cut-through traffic, is a negative impact. The changing traffic flows did not severely influence the congestion levels and locations of congestion, although the average travel time slightly increased, which could indicate an increase in emissions. However, regarding the fact that more and more future cars will be electrical, the emissions of substances are expected to be lower in general. Finally, even if on average the travel times increase, AVs could help to avoid road accidents and thereby reduce the chance of non-recurrent congestion.

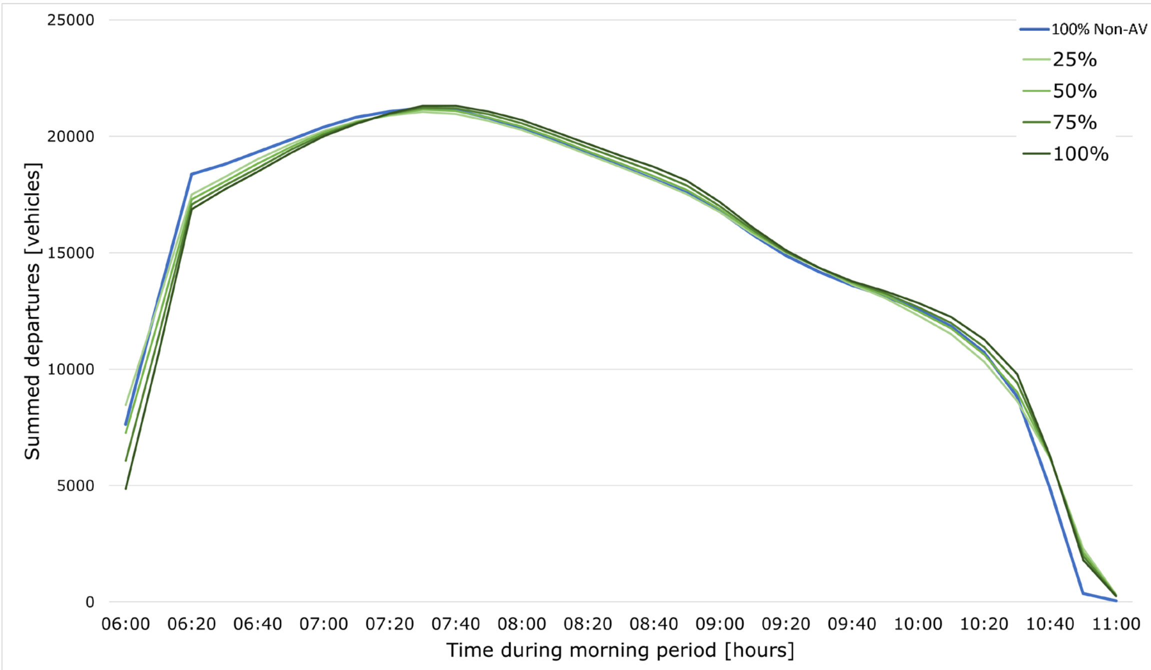

FIGURE 4 Departure time profiles depending on the penetration rate of Universal AVs

Penetration rates

For the Universal AVs the penetration rate was varied to investigate the impact on departure times. Figure 4 shows the departure time profiles for each penetration rate. It can be observed that with increasing Universal AV penetration rates, the overall departure times shift to follow the profile of the scenario with 100% Universal AVs. What stands out is the differences between the variant with 0% Universal AV and the other variants. This is significantly larger than the differences between variants with a percentage of AVs. This might be explained by the expulsion effect, meaning that 25% Universal AV does already take a significant dominance in the congestion peak periods and the 75% non-AV is not able to compensate enough to counter this effect. The following rates show saller changes since the major shift has already taken place at or before the 25% penetration rate.

Table 2 shows the relative change in departures per hour for the non-AV users. The percentages show the relative change in number of departing non-AVs per hour compared to the reference scenario (100% non-AV). It can be observed that with increasing penetration rate, the first two hours correspond to an increase in number of departing non-AVs. The later hours of the morning period are associated with a decreasing number of departing non-AVs when a higher share of Universal AV is present. Thus, as a result of (Universal) AV, non-AV users have to depart earlier to reach their destination in time, because non-AV users are more sensitive for delay compared to AV users. This coincides with the hypothesis that AVs show less aversion to longer travel times, will increase congestion and thus have an adverse effect on non AV users.

TABLE 2 Relative change in departures per hour for non-AV

Time period	25% Universal AV	50% Universal AV	75% Universal AV
6:00 - 7:00 AM	11.1%	11.2%	11.3%
7:00 - 8:00 AM	0.1%	0.4%	1.2%
8:00 - 9:00 AM	-2.2%	-2.4%	-2.7%
9:00 - 10:00 AM	-0.9%	-1.1%	-1.3%
10:00 - 11:00 AM	-20.3%	-20.3%	-20.3%

Analysing the travel times, we observed that the mean travel times decrease for Non-AV users with an increasing share of Universal AVs. However, Non-AV users are also shifting towards the beginning of the peak. They trade off the on-time arrival for shorter travel times. The opposite happens for Universal AVs: they trade off shorter travel times for closer to on-time arrival. This is understandable, since they are able to spend their longer travel time more productively. Although this section analysed only Universal AVs, a similar dynamic would hold also for the other AV types presented earlier.

Sensitivity analysis parameters model

Using the scenario of 100% Universal AV as a base, the influence of the parameter settings was investigated to find out how sensitive the results are with respect to a number of parameter assumptions. We varied, first, the α,β,-γ parameters, and after – the efficiency factors of on-board activities. Figure 5 shows the resulting departure time profiles.

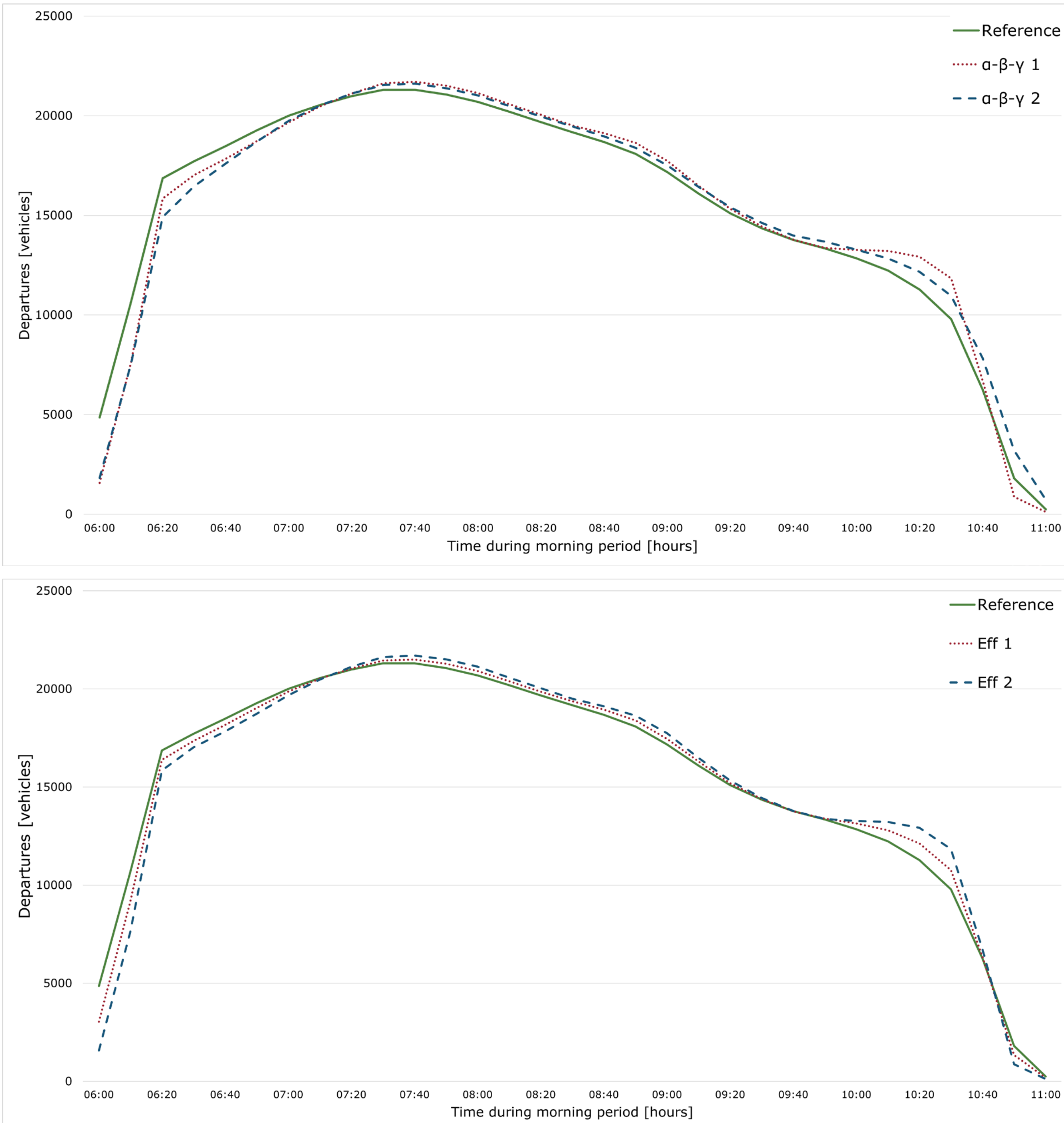

FIGURE 5 Departure time profiles depending of parameter settings

Figure 5 shows that the departure time profiles are significantly dependent on the selected ratios of the parameters. With an increase in β/α and γ/α, AV users shift toward the congested part of the departure time profiles. In other words, a higher 'penalty' associated with deviation from arriving at the PAT means that people accept longer travel times to minimise this deviation which results in more congestion (increase in delays). Furthermore it can be seen that the departure time profile associated with a high β/α and γ/α (α β γ 2), i.e. high penalty for arriving early or late, shift towards the right in direction of the PAT. Vice versa, the departure time profile associated with a lower β/α and γ/α (α β γ 1) widens the profile which corresponds to prioritising low travel times over the PAT. Lastly, the green 'Reference' profile shows the variant with the highest penalty of arriving too late (γ = 4) compared to a relatively low penalty of arriving early (β = 1). This explains why this graph is depicted more to the left (earlier departures), where one could initially have thought it should be positioned in the middle, based solely on the comparison of β/α and γ/α.

Similar to the results associated with $\alpha - \beta - \gamma$ sensitivity analysis, the departure time profiles, with increasing efficiency factors (figure 5), move more towards the right, in direction of the PAT. This can be explained since a lower valuation of travel time, by increased productivity, is associated with less aversion to longer travel times and therefore a relatively stronger preference to arrive at or near the PAT.

Given the results of the sensitivity analysis, the parameter values do show a clear impact on the outcome. However, the direction of the impacts found assessing the base scenarios and depending of penetration rates are likely to be similar, only the extent of impacts will differ. As a result the main insights provided hold.

CONCLUSTIONS AND FURTHER RESEARCH

This study has taken a first step in researching future effects of introducing AVs in real-life road networks. It shows how peak congestion is affected due to shifts in departure times with AVs, caused by the possibility to perform various activities during travel. The results are in line with intuition and theoretical insights [6, 29]: AV users which are able to perform home-type activities during travel better than work-type activities prefer to shift their departure times earlier, while AV users which can perform work type activities better prefer to travel later. Furthermore, this study suggests that congestion might increase with the introduction of AVs, at least under the assumption that the road capacity does not increase due to AVs.

In addition, we find a shift of VKT from the main road network to the underlying road network. Such shift would likey be disadvantageous to traffic safety, especially if this means that AVs will be driving in a mixed traffic situations, which may also include vulnerable road users. Since it is expected that there is still a long way to go before all, or even a significant part of, the vehicles on the road will be fully automated AVs, the routing software in AVs should factor in the safety risks that they would impose with an otherwise optimal route choice. The shift of VKT towards the underlying road network could also worsen emissions (including CO_2, NO_x and PM10) and noise pollution, although the magnitude of this impact is unclear. The increase in all of these due to shift to urban and provincial roads could be mitigated in case AVs adopt eco-driving style. Future work should quantify the net change in pollution and noise levels due to more AVs on the underlying road network.

Finally, the current work should be extended to consider the impact of AVs on capacity of transport networks, and mode and destination choices. The capacity impact of AVs is as of yet unclear – in particular, it could depend on whether AVs will also have the ability of cooperative driving and on the penetration rates of automated and cooperative driving. Considering mode and destination choices, these could also be impacted by the ability of travelers to engage in various activities during travel. Lastly, an extension of this study could consider that AVs of lower automation levels would need to consider their operational design domains in route choice. This extension would likely lead to quite different congestion patterns of AV and Non-AV users.

REFERENCES

1. Pudāne, B., Rataj, M., Molin, E. J., Mouter, N., van Cranenburgh, S., & Chorus, C. G. (2019). How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands. Transportation Research Part D: Transport and Environment, 71(December 2018), 222–235.
2. Childress, S., Nichols, B., Charlton, B., & Coe, S. (2015). Using an activity-based model to explore the potential impacts of automated vehicles. *Transportation Research Record*, *2493*(2493),99–106.doi: 10.3141/249311
3. Snelder, M., Wilmink, I., van der Gun, J., Bergveld, H. J., Hoseini, P., & van Arem, B. (2019). Mobility impactsof automated driving and shared mobility: explorative model and case study of the province of North Holland. *European Journal of Transport and Infrastructure Research*, *19*(4).
4. Madadi, B., van Nes, R., Snelder, M., & van Arem, B. (2020). A bi-level model to optimize road networks for amixture of manual and automated driving: An evolutionary local search algorithm. *Computer-Aided Civil and Infrastructure Engineering*, *35*(1), 80-96.
5. Smit, R., van Mourik, H., Verroen, E., Pieters, M., Bakker, D., & Snelder, M. (2019). Will self-driving cars impact the long-term investment strategy for the Dutch national trunk road system? In *Autonomous Vehiclesand Future Mobility* (pp. 57-67). Elsevier.
6. Pudāne, B. (2020). Departure Time Choice and Bottleneck Congestion with Automated Vehicles: Role of On-board Activities. European Journal Of Transport And Infrastructure Research, 20(4), 306-334. doi:10.18757/ejtir.2020.20.4.4801
7. Yu, X., van den Berg, V. A., & Verhoef, E. (2019). Autonomous Cars and Dynamic Bottleneck Congestion Revisited: How In-Vehicle Activities Determine Aggregate Travel Patterns. SSRN Electronic Journal.
8. Vickrey, W. S. (1969). Congestion theory and transport investment. The American Economic Review, 59(2), 251-260.
9. Small, K. A. (1982). American Economic Association The Scheduling of Consumer Activities: Work Trips. The American Economic Review, 72(3), 467–479.
10. Molin, E., Adjenughwure, K., de Bruyn, M., Cats, O., & Warffemius, P. (2020). Does conducting activities while traveling reduce the value of time? Evidence from a within-subjects choice experiment. Transportation Research Part A: Policy and Practice, 132(October 2019), 18–29.
11. Correia, G. H. d. A., Looff, E., van Cranenburgh, S., Snelder, M., & van Arem, B. (2019). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. Transportation Research Part A: Policy and Practice, 119(December 2018), 359–382.
12. Pudāne, B., & Correia, G. (2020). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey – A comment. Transportation Research Part A: Policy and Practice, 132(November 2019), 324–328.

13. Fosgerau, M. (2019). Automation and the Value of Time in Passenger Transport. International Transport Forum Discussion, OECD Publishing, Paris
14. Steck, F., Kolarova, V., Bahamonde-Birk, F., Trommer, S., & Lenz, B. (2018). How Autonomous Driving May Affect the Value of Travel Time Savings for Commuting. Transportation Research Record, 2672(46), 11–20.
15. Pudāne, B., Molin, E. J., Arentze, T. A., Maknoon, Y., & Chorus, C. G. (2018). A Time-use Model for the Automated Vehicle-era. Transportation Research Part C: Emerging Technologies, 93(March), 102–114.
16. Singleton, P. A. (2019). Discussing the "positive utilities" of autonomous vehicles: will travellers really use their time productively? Transport Reviews, 39(1), 50–65.
17. Shaw, F. A., Malokin, A., Mokhtarian, P. L., & Circella, G. (2019). It's not all fun and games: An investigation of the reported benefits and disadvantages of conducting activities while commuting. Travel Behaviour and Society, 17(March 2020), 8–25.
18. Malokin, A., Circella, G., & Mokhtarian, P. L. (2019). How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios. Transportation Research Part A: Policy and Practice, 124(August 2016), 82–114.
19. Kim, H. S., Mokhtarian, P. L., & Circella, G. (2020). Will autonomous vehicles change residential location and vehicle ownership? Glimpses from Georgia. Transportation Research Part D, 82(March), 102291.
20. Soteropoulos, A., Berger, M., & Ciari, F. (2019). Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies. Transport Reviews, 39(1), 29–49.
21. Harb, M., Xiao, Y., Circella, G., Mokhtarian, P. L., & Walker, J. L. (2018). Projecting travelers into a world of self-driving vehicles: estimating travel behavior implications via a naturalistic experiment. Transportation, 45(6), 1671–1685.
22. Milakis, D., Van Arem, B., & Van Wee, B. (2017). Policy and society related implications of automated driving: A review of literature and directions for future research. Journal of Intelligent Transportation Systems: Technology, Planning, and Operations, 21(4), 324–348.
23. Correia, G. H. d. A., & van Arem, B. (2016). Solving the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility. Transportation Research Part B: Methodological, 87, 64–88. doi: 10.1016/j.trb.2016.03.002
24. Thakur, P., Kinghorn, R., & Grace, R. (2016). Urban form and function in the autonomous era. ATRF 2016 - Australasian Transport Research Forum 2016, Proceedings(November), 1–15.
25. Chen, T. D., Kockelman, K. M., & Hanna, J. P. (2016). Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions.
26. Auld, J., Sokolov, V., & Stephens, T. S. (2017). Analysis of the Effects of Connected – Automated Vehicle Technologies on Travel Demand. Transportation Research Record,

2625(1), 1–8.Transportation Research Part A: Policy and Practice, 94, 243–254. Retrieved from http://dx.doi.org/10.1016/ j.tra.2016.08.020 doi: 10.1016/j.tra.2016.08.020

27. Emberger, G., & Pfaffenbichler, P. (2020). A quantitative analysis of potential impacts of automated vehicles in Austria using a dynamic integrated land use and transport interaction model. Transport Policy, 98(June), 57–67. Retrieved from https://doi.org/10.1016/j.tranpol.2020.06.014 doi: 10.1016/j.tranpol.2020.06.014
28. van den Berg, V. A., & Verhoef, E. T. (2016). Autonomous cars and dynamic bottleneck congestion: The effects on capacity, value of time and preference heterogeneity. Transportation Research Part B: Methodological, 94, 43–60.
29. Pudāne, B. (2020). Departure Time Choice and Bottleneck Congestion with Automated Vehicles: Role of On-board Activities. European Journal of Transport and Infrastructure Research, 20(4), 306-334. https://doi.org/10.18757/ejtir.2020.20.4.4801
30. Zantema, K. (2007). Pay-as-You-Drive Strategies: Case Study of Safety and Accessibility Effects (Unpublished doctoral dissertation). TU Delft.
31. Hjorth, K., Börjesson, M., Engelson, L., & Fosgerau, M. (2013). Estimating exponential scheduling preferences. Transportation Research Part B: Methodological, 81, 230–251.
32. Börjesson, M., Eliasson, J., & Franklin, J. P. (2012). Valuations of travel time variability in scheduling versus mean-variance models. Transportation Research Part B: Methodological, 46(7), 855–873. doi: 10.1016/j.trb.2012.02.004
33. Poppe, F. (1996). Risico's onderscheiden naar wegtype (Tech. Rep.). Leidschendam: SWOV.
34. Janssen, S. (2005). De Verkeersveiligheidsverkenner gebruikt in de regio (Tech. Rep.). Leidschendam: SWOV.