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A day in the life with an automated vehicle: Empirical analysis of data from an interactive stated activity-travel survey

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ABSTRACT

Fully Automated Vehicles (AVs) have been widely expected to revolutionise the future travel experience. Recent studies have shown that their impact may also reach beyond the travel episode, and lead their users to alter other activities performed during the day – their daily lifestyles. This study is among the first to empirically investigate the changes that travellers expect in their daily activities with AVs. To this aim, we created an interactive stated activity-travel survey, in which respondents designed their current daily schedule and, following that, redesigned it while imagining that their most frequently used travel mode is replaced with an AV. We administered the survey to 509 commuters in the Netherlands and analysed (changes in) on-board and stationary activity patterns using the multiple discrete-continuous extreme value (MDCEV) model. Results show a clear increase in the prevalence of various on-board activities in the AV compared to current modes, and even stronger increase for the high income and higher educated groups. Changes in stationary activities are less pronounced: no changes in the aggregate, but some changes within particular socio-demographic groups. Specific changes in stationary activities were associated with specific changes in on-board activities for the higher educated respondents: switching to AVs, they were more likely than others to add on-board work, meals, and leisure to their trips and more likely to add a getting ready activity to their stationary schedules. This study contributes to the growing body of literature that recognises and models on-board activities as an integral part of daily schedules.

1. Introduction

Automated Vehicles (AVs) are expected to be among the strongest shaping forces of transport systems, urban environments and lifestyles. For transport systems, AVs promise improved traffic safety and efficiency (Fagnant and Kockelman, 2015; Stern et al., 2018), as well as altered (and conceivably enhanced) travel experiences with resulting impacts on travel behaviour (Mokhtarian, 2018; Harb et al., 2018). For urban environments, they promise city centres freed from extensive parking areas and great improvements in accessibility and liveability (Duarte and Ratti, 2018). Together, these transformations point towards major changes in lifestyles (e.g., Pudāne et al., 2019; Kim et al., 2020).

When considering any specific changes in lifestyles – or, in the days in the life with AVs – studies have often narrowed them down to

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impacts on travel episodes. Clearly, many impacts may originate there: taking away the driving task from travelling[1] could result in higher satisfaction with travel and reduced stress (Singleton, 2019) as well as new or better on-board activities (Kyriakidis et al., 2015; Wadud and Huda, 2019), facilitated also by ever-improving online connectivity (Pawlak, 2020). Many studies have shown that the latter possibility to engage in activities during travel is cherished by public transport users (e.g., Lyons et al., 2007; Russell et al., 2011; Frei et al., 2015; Tang et al., 2018; Malokin et al., 2019; Molin et al., 2020), fuelling expectations of similar reactions from the current car users if their car would be replaced by an AV.[2] Coupled with the conventional approach in most transport models of treating travel as a resistance factor, these improvements in travel experience have been predicted to lead to more accessibility, more per-person travel, and, as a result, to higher congestion levels – see, for example, Childress et al. (2015), Milakis et al. (2018), Taiebat et al. (2019), as well as Soteropoulos et al. (2019) for a review of modelling studies.

At the same time and especially in the last years, other studies have recognised that lifestyle changes with AVs may be more complex than only increasing person-kilometres travelled, and have proposed what we coin the 'saved-time effect' of on-board activities (Pudāne et al., 2018; Mokhtarian, 2018). This effect arises when an activity is transferred from a stationary location (such as home or work place) to the travel episode, thereby freeing time for other or extended activities during the day and potentially triggering a chain of schedule re-arrangements. This saved-time effect conveys the idea that the role of on-board activities may increase in the future with AVs. This seems to be a reasonable prospect, given that many activities may be facilitated in future AVs, and perhaps even better so than in current public transport (due to privacy, storage possibilities, continuity of travel; see Pudāne et al., 2019). And indeed, several studies have found evidence that travellers expect an increased role for their on-board activities. Kim et al. (2020) surveyed residents of the US state of Georgia about their expected schedule changes in a future with AVs. Cluster analysis of their data revealed that young, tech-savvy respondents (13% of the sample) highly rated the 'Time flexibility' statements such as 'Go to work/school at a different time to avoid traffic jams, since I can sleep/work in the car'. Xiao et al. (2020) found that travellers with complex schedules – who may also value the flexibility afforded by AVs – were more interested in using AVs. Krueger et al. (2019) asked public transport and ride-hailing service users in the Chicago metropolitan area, whether the activities they perform during travel would free up time later in the day. An affirmative response (by 40% of respondents) was associated with living with a partner, travelling alone and the trip lasting for 20 minutes or longer. Correia et al. (2019) confronted Dutch respondents with a choice between engaging in leisure or work activities in future AVs. In case of the latter, respondents could indicate whether the new work time would add to or substitute the usual work hours at the workplace. Most of their respondents preferred the substitution option. Similarly, work during travel as a substitute was a common theme in a Dutch focus group study by Pudāne et al. (2019). Some respondents desired this opportunity as an efficiency improvement for their days, but indicated that this would not necessarily lead to a willingness to travel more on a daily basis. Others expressed caution about the possibility to work or otherwise be productive during travel, mentioning that this would elevate the already high social pressure to spend all the time efficiently. The latter finding is in line with results reported in Shaw et al. (2019).

While the afore-mentioned studies offer valuable generic insights into the potential daily schedule changes with AVs, they do not fully answer the question of which concrete changes, if any, various segments of travellers expect in various activity-travel contexts. For example, if some travellers can 'transfer' their morning work tasks to the commute trip, how much (if at all) would that reduce the work time they spend in the office? Having shorter working hours, would they prolong their evening activities or select entirely new activities during the day? Clearly, on-board and stationary activities (i.e., those performed at home, work, or other locations) may interact in countless ways, resulting in a multitude of specific schedule adjustments with AVs. It would be infeasible to explore such a multitude with more generic approaches such as used by Kim et al. (2020), Krueger et al. (2019), or Correia et al. (2019), or to discuss them using qualitative methods as in Pudāne et al. (2019). However, knowledge regarding these specific schedule changes is crucial for long-term transport and urban planning decisions. For instance, several recent modelling studies show that specific interactions between on-board and stationary activities can lead to changed activity-travel demand (Pawlak et al., 2015, 2017; Pudāne et al., 2018) and increased congestion whose shape depends on this interaction (Yu et al., 2019; Pudāne, 2020).

This study aims to take a step towards filling this knowledge gap by analysing activity-travel patterns that were observed using a novel, tailor-made stated activity-travel survey. In this survey, we asked the participants to design their daily schedules with help of a graphical user interface. They first had to report the schedule of a recent workday and then imagine the same day in a future with an AV. We administered the survey to 509 respondents in the Netherlands. Using these data, we model participants' stationary and on-board time-use. In line with the multiple discrete (activity selection) continuous (activity duration) nature of the schedules, we analyse our data with an MDCEV model (Bhat, 2005, 2008). In doing so, we contribute to the wide literature using MDCEV models for modelling daily time-use (e.g., Pinjari and Bhat, 2010a; Bhat et al., 2013; Calastri et al., 2017), as well as to the more recent literature analysing time-use during travel (Enam et al., 2019; Varghese and Jana, 2019; Varghese et al., 2020; Calastri et al., 2021).

The rest of the paper is organised as follows. Section 2 presents the interactive stated activity-travel survey and summarises the statistics of the sample. Section 3 presents the MDCEV model and the specifications for our study. Section 4 reports the modelling results for on-board and stationary activities in the pre- and post-AV schedules. Section 5 discusses potential links between on-board

[1] This paper considers primarily the fully automated or, following SAE International (2016), level 5 automated vehicles, where driving task is completely 'taken away'.

[2] Though, it should be mentioned that in these still early stages of AV development, many travellers also doubt that they will want to do anything else but 'watch the road' during car travel (Cyganski et al., 2015; Schoettle & Sivak, 2019; Wadud and Huda, 2019). Also, challenges remain to design vehicles and infrastructure that would allow these activities, since travellers can experience more motion sickness in car than public transport, and the movements of the vehicle can otherwise disturb the activities (Diels and Bos, 2016; Le Vine et al., 2015).

and stationary activity changes, as well as limitations of the study and avenues for further research. Section 6 concludes and discusses modelling implications.

2. Data collection

2.1. Interactive stated activity-travel survey

To investigate the expected changes in on-board and stationary activities with AVs, we designed an interactive stated activity-travel survey.[3] This survey consists of three parts. In the first part, respondents could read that the survey concerns automated vehicles, which are able to drive themselves at all times (thus, level 5 automation according to SAE International, 2016). The survey mentioned that, when using these vehicles, travellers would be able to perform other activities during travel, such as sleeping, working or spending time on a hobby. Next, we asked a few introductory questions to screen the sample and to customise the main part of the survey. Respondents who mostly work from home or who can reach their work place in less than 10 minutes were screened out from the survey. This ensures that our sample consists of commuters, who may more realistically consider replacing their current commute mode with an AV (in addition, we used the employment status to target the sample; see section 2.2). The introduction part concluded with a video explaining how to create and alter the activity schedules in the graphical user interface. The video and the final screen before proceeding with the main part of the survey emphasised that activities and travel episodes could be 'stacked' (see Fig. 1), which would indicate activities performed during travel.

In the second and main part of the survey, respondents were asked to design two schedules: to first approximate a schedule of a recent workday (in which they used predominantly a single mode), and then to imagine the same day in an AV future. Fig. 1 shows a screenshot of the survey used to elicit the current daily schedule. Respondents could select the activities from the green list and the trips to the activities from the orange list. If none of the activities was seen as appropriate, then the respondents could indicate activity 'Other' and type in its description (9% of the respondents used this option). The activity and trip bars could be moved to earlier and later times in the schedule, and the length of the activity bars was adjustable. The icons on the right-hand side of the green boxes indicate that some activities may only be performed at specified locations, such as shopping (at a shopping centre). A trip to such a location should precede the activity, except for home activities at the start of the day. Other activities could be performed at any location. When proceeding with the second (AV) schedule, respondents could click a button to copy the first schedule into the second one, and modify it from that starting point.

We customised this main survey task to the respondents' daily schedule in three ways. First, we used the indicated main transport mode (car as a driver, car as a passenger, public transport, bicycle, or walking) as the available travel mode for the current activity schedule. Second, the respondents' one-way commute duration (10–30 min; 30–60 min; >60 min) assigned them to one of the three travel time groups. Third, the whole hour of the indicated waking time determined the start of the day in the schedule display. For the future AV schedule, respondents were randomly assigned to one of two AV descriptions: an AV that partially facilitates on-board activities, and an AV that fully facilitates such activities. The partial facilitation scenario was introduced as follows: 'Various activities are possible in an automated vehicle, such as sleeping, working, spending time on hobbies. The movements of the automated vehicle are the same as those of a normal car; they can limit certain activities and/or cause motion sickness, if you are prone to it. You do not need to pay attention to the road, because you do not have any control over the car anyway. Imagine that the vehicle has all the facilities that you would need, as long as they would fit inside a car of a minibus size. You can think, for example, of a table, single bed, coffee machine.' In the ideal facilitation scenario, the second sentence was replaced with the following one: 'Imagine that a solution has been found, such that the movements of the car do not hinder the activities, and the passengers do not get motion sick.'

Overall, this survey tool provides a, relatively speaking, realistic and detailed environment for respondents to report and re-imagine their schedules for the AV future. Nevertheless, it also has two limitations considering how closely the schedules could be approximated. First, in order to ease the understanding of the tool and later modelling efforts, only a single travel mode was allowed in any schedule. In the first schedule, it was the current most commonly used one, and in the second schedule – an AV. Second, the travel times to locations were fixed in each travel time group: these were determined by the commute duration indicated by the respondent. This ensured that all participants considered the activities in a similar way and that there was no self-selection effect, whereby, for example, someone who likes to shop would have chosen to live near a shopping area. However, this resulted in some situations in which the schedule options were deemed unrealistic for the respondent: for example, in the example of Fig. 1, which would have been presented to respondents in the 'long commute' group, travel to shop (from home) would take 15 minutes, but travel back home would take 75 minutes. This issue was less noticeable in the 'short commute' and 'medium commute' groups. In response to the very last question of the survey, which provided space for respondents' suggestions and comments, complaints about this feature appeared 20 times.

In the third and final part of the survey, respondents answered questions about car ownership, expected travel distance changes with AVs, expected frequency of using an AV and inclination towards buying one, proneness to motion sickness, interest in technology, participants' time pressure, and the perceived possibility to work inside an AV. An offline version of the survey tool (in Dutch) is available in Pudāne et al. (2021).[4]

[3] Survey tool, the collected data, and analysis files can be found in Pudāne et al. (2021), https://doi.org/10.4121/14125880.

[4] Survey tool was designed by Game Tailors (https://gametailors.com/).

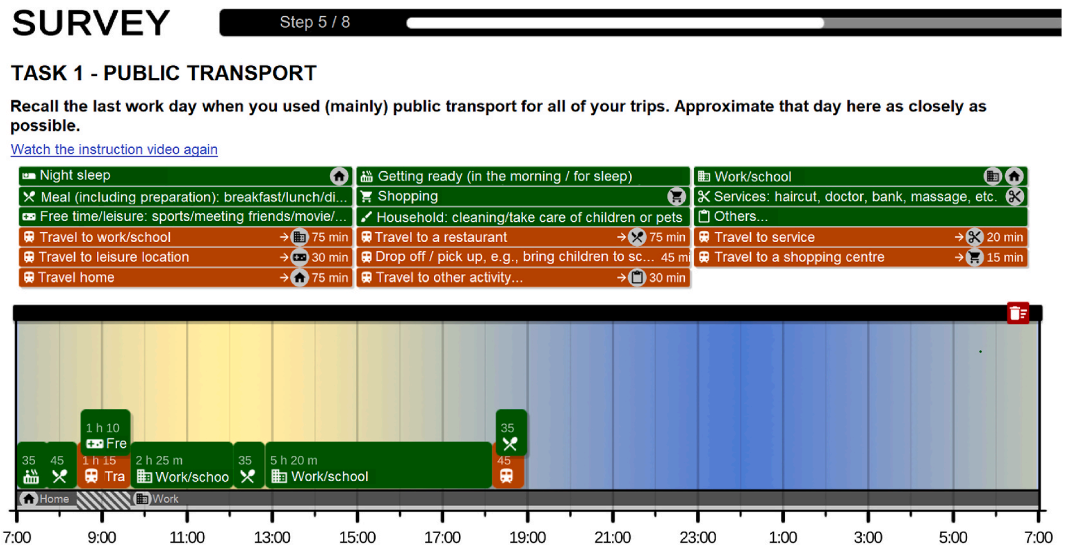

Fig. 1. Survey screen – example of building a current schedule with public transport.

2.2. Survey administration

The survey was administered to workers and students in the Netherlands through a survey agency, which sampled the respondents randomly from their database.[5] Participants received a small incentive of 2.50 euros to complete the survey. From the 802 respondents who started the survey and passed the screening stage, some stopped the survey after watching the instruction video (82), completing the first of the two schedules (175), or at a later point (36). Of the 509 complete responses, 13 were excluded because they did not indicate any sleep or work activity, or because the first (last) trip did not start (end) at home in one or both schedules. The final sample size is 496.

Table 1 reports the socio-demographic statistics of the sample. As compared to the Dutch working and studying population, we observe an overrepresentation of men, highly educated and higher income groups, as well as respondents from adults-only households. The near absence of age group 65+ relates to the sampling of only working and studying population. The shares of the main travel mode in the sample are roughly comparable with the commute modal split in the Netherlands, except for the underrepresented cycling group. However, the share of car owners is much higher than the Dutch average.[6] Travellers who do not regularly commute to work or who have a very short commute (less than 10 minutes) were screened out from the survey. Note that we did not intend to acquire a representative sample from the Dutch working and studying population, because our aim was to gain first insights into how AVs may affect time-use patterns, but not to generalise these insights towards the entire Dutch population. Moreover, sufficient variation exists in terms of relevant socio-demographic characteristics, to ensure that scholars who are interested in deriving forecasts for the Dutch population are able to use appropriate weighting schemes.

2.3. Descriptive statistics

This section reports some statistics of the activity schedules designed in our survey. First, we present statistics of selection and durations of on-board and stationary activities (Fig. 2 and Fig. 3). Afterwards, we turn to correlations between AV-induced changes in activity durations (Fig. 4), which will contribute to the later discussion of MDCEV results.

Figs. 2 and 3 visualise the descriptive statistics related to on-board and stationary activities (i.e., activities not during travel), respectively. The bars represent selection frequency: the share of the corresponding mode users who selected the activity at any point in their schedule. The dots with whiskers display mean activity durations calculated from only the non-zero values, with one standard deviation below and above it. The less frequent activities are grouped into activity 'Other' here, as well as in the analysis later on. Those activities are shop, service, household tasks, and other, as well as activity 'sleep' if it is performed on board.[7] Given that only few respondents represented some transport modes (see Table 1), 'car as a passenger' is joined with 'car as a driver' in the category 'car', and 'walking' is joined with 'bicycle' in the category 'active modes'.

[5] Survey agency: Kantar Media (www.kantar.com).

[6] Commute modal split in the Netherlands: https://www.statista.com/statistics/673009/commute-to-work-in-the-netherlands-by-mode-of-transport/; car ownership in the Netherlands: https://longreads.cbs.nl/european-scale-2019/car-ownership/.

[7] The sleep activity was called 'Night sleep' in the Dutch survey version, while 'Take a nap' was an example in the 'Leisure' activity list. This explains the low selection of sleep during travel.

Table 1
Socio-demographic characteristics of the sample.

Socio-demographic characteristic	Value	Count	Percentage
Gender	Male	312	63%
	Female	184	37%
Age	18–24	42	8%
	25–34	107	22%
	35–44	103	21%
	45–54	152	31%
	55–64	91	18%
	65+	1	0%
Education	No/elementary	13	3%
	Secondary	233	47%
	Higher – bachelor	149	30%
	Higher – master +	101	20%
Household type	Single	92	19%
	Adult household	245	49%
	Household with children, youngest≤12 years old (y.o.)	110	22%
	Household with children, youngest 13–17 y.o.	49	10%
Income	Minimum (<€ 14.100 Euro)	10	2%
	Below average (€ 14.100 - < € 29.500)	38	8%
	Average (€ 29.500 - < € 43.500)	91	18%
	1–2x Average (€ 43.500 - < € 73.000)	188	38%
	2x Average (€ 73.000 - < € 87.100)	52	10%
	More than 2x average (≥ € 87.100)	117	24%
Working/student	Working	452	91%
	Student	44	9%
Main travel mode	Car as a driver	323	65%
	Car as a passenger	4	1%
	Public transport	72	15%
	Bicycle	95	19%
	Walking	2	0%
Commute time group	Short (10–30 min)	249	50%
	Medium (30–60 min)	197	40%
	Long (>60 min)	50	10%
Car ownership	Owns a car	425	86%
	Does not own a car	71	14%

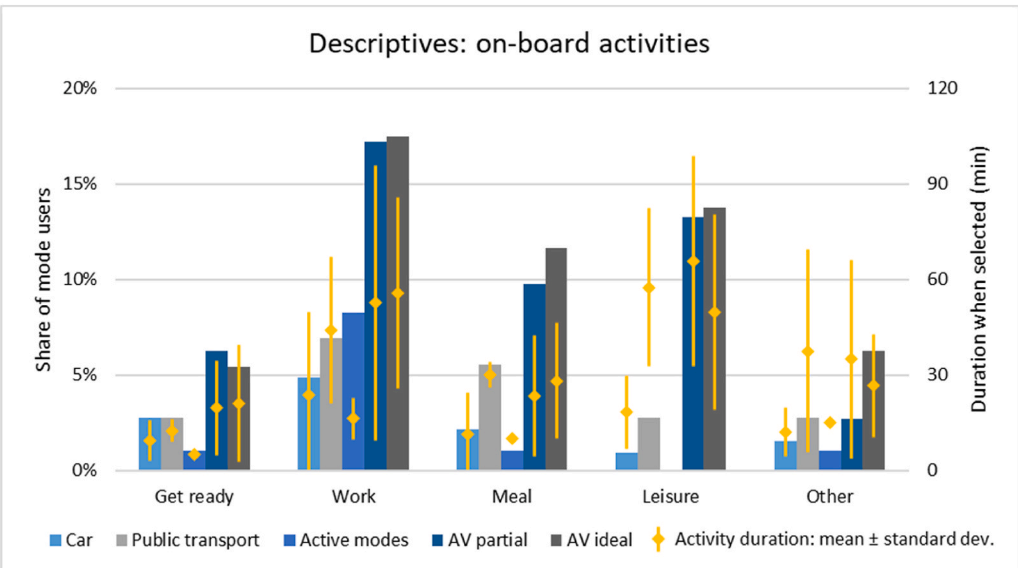

Fig. 2. Descriptive statistics of on-board activities: selection and durations by travel mode.

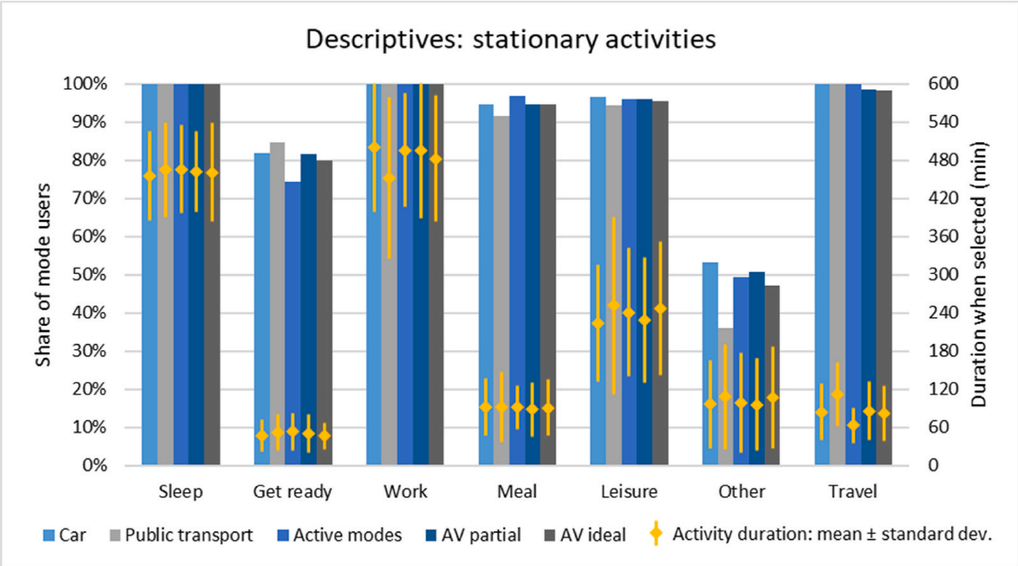

Fig. 3. Descriptive statistics of stationary activities: selection and durations by travel mode.

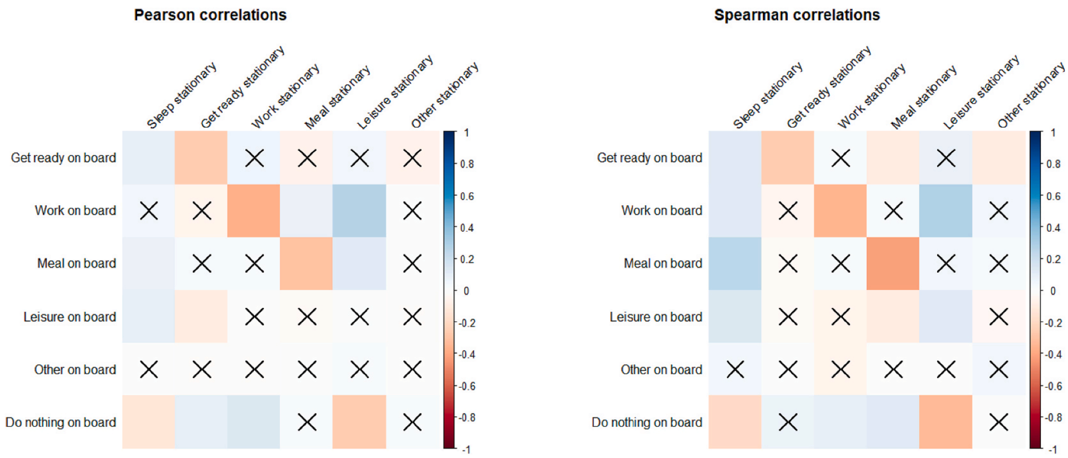

Fig. 4. Pearson and Spearman rank correlations between on-board and stationary activity changes with AVs.

Considering first the on-board activities (Fig. 2), these were in general seldom chosen in all modes, but more often in AVs. In other words, the most common 'activity' during travel, according to the schedules, is to do nothing at all. However, note that we included watching scenery, thinking and listening to music in the 'do nothing' category. Participants were instructed to not specify such background on-board activities in the schedule. Considering this classification, our results align with other surveys of on-board activity engagement in AVs (e.g., Kyriakidis et al., 2015; Wadud and Huda, 2019). However, the engagement in activities in public transport seems lower than observed in other studies (e.g., Lyons et al., 2007; Frei et al., 2015). This may be due to attention bias: the introduction of the survey emphasised the possibility to conduct activities in AVs, but did not emphasise this possibility for the current modes. The AV description – partial or full facilitation during travel – did not affect the results, indicating that participants did not consider motion sickness as an important determinant for their anticipated behaviours in the AV.

Considering specific on-board activities, work, leisure, and meals were most often selected, with work and leisure also being the longest once selected. These results align with the literature. Studies have shown that work during travel is common in public transport in the Netherlands (Ettema and Verschuren, 2007; Molin et al., 2020) and Great Britain (Susilo et al., 2012). In contrast, work is less common in public transport in the US (Enam et al., 2019), crowded trains in Japan (Varghese et al., 2020) and in various modes in India (Varghese and Jana, 2019). Our results show a great increase in the anticipated work activities with AVs by car and public transport users, which aligns with the German results by Pfleging et al. (2016). It would have been interesting to compare only car passengers with AV users – since this may be the closest present-day approximation to the AVs (see also Harb et al., 2018) – but there were too few car passengers in our survey. This travel option is however common in Bangladesh (as many travellers use chauffeur services there), and Wadud and Huda (2019) reported that the passengers often perform work tasks during travel and expect to continue doing so in the AV era. Our results on leisure activities and meals also align with the literature. Studies show that leisure activities are among the most common ones during travel (e.g., Keseru et al., 2015; Krueger et al., 2019; Enam et al., 2019) with meals high in the list in some studies as well (e.g., Pfleging et al., 2016; Susilo et al., 2012). Finally, some cyclists indicated on-board activities as well (as part of the 'active mode' users). Most unexpectedly, eight cyclists (8% of all cyclists) reported that they work during their commute at present. It is hard to imagine specific work tasks that they may be performing (perhaps answering phone calls using a hands-free set or checking their emails at a traffic light). It can be noted that the network of bicycle lanes is very extensive in the Netherlands, and that these are often physically separated from car traffic (e.g., with a traffic island or a canal).

Of the stationary activities (Fig. 3), work and sleep are part of schedules by design (a couple of data points that did not contain these activities were excluded). The next most frequently selected stationary activities were meal, leisure, and get ready. Work and sleep were also on average the longest activities, followed by leisure. The activity durations are similar for different travel mode users, but highly dispersed within groups. Only public transport users seem to work shorter hours and travel longer than users of other travel modes. Here, we would like to highlight another two aspects about the activity 'travel'. First and unsurprisingly, it was almost always selected. This is because travel was 'tied' to some stationary activities: the first survey steps screened out respondents who currently work from home, and travel activity was imposed by the survey tool prior to stationary shop and service activities (see Fig. 1). (For this reason, travel is not modelled as an independent activity in the later MDCEV analysis.) Second, travel durations with AVs are very similar to those of the present modes. Part of this consistency can be explained by the survey design: destinations of activities were 'given' in terms of the travel time (see section 2.1 for more explanation). Hence, respondents could only increase or decrease their daily travel time by selecting more or fewer activities that require travel. Nonetheless, it is noteworthy that our data do not support the hypothesis of increasing daily (person-) travel with AVs, which is a common expectation in the literature, and especially – a common assumption in modelling studies (e.g., see the review of Soteropoulos et al., 2019).

Since this paper concerns the schedule changes with AVs, it is useful to present also the correlations between changes in on-board and stationary activities. Fig. 4 presents Pearson and Spearman rank correlations between the two activity categories. Since on-board activities mostly increased with AVs (see Fig. 2), the correlations mostly represent the sign of the stationary activity change. For example, it shows that increases in on-board activities 'get ready', 'work', and 'meal' are associated with decrease in the stationary counterparts of these activities. Furthermore, the travellers who expected to work (longer) during their travel in AVs, increased their leisure time outside of travel – an intuitive effect. Finally, there is a negative association between stationary leisure and doing nothing during travel. That is, travellers expected to engage in more activities during their AV trips than they do now – in other words, to shorten the 'do nothing' activity during travel. Spending their travel time more actively, they expected to increase their leisure time outside of travel. The remaining correlations are weaker, and the insignificant effects (at a 5% significance level) are marked with $\times$. Spearman correlations are slightly stronger than Pearson correlations, which indicates a weak non-linear relation.

These discussed correlations align well with intuition as well as with the discussion (in the Introduction) about the potential of on-board activities to 'save time' in a day. However, note that this correlation analysis does not show the magnitude of the on-board and stationary activity changes. Even very small increases or decreases in stationary activity durations can result in significant correlation coefficients. It is evident from Fig. 3 (in comparison with Fig. 2) that at least the relative changes in stationary time use are much smaller than those in on-board time use.

Finally, although the sample was not intended to be representative of the Dutch population, the statistics of the schedule change types can be mentioned. Of the 496 respondents, 274 (55%) did not change their activity selection or durations when moving from the current to the future AVs schedule. A further 80 (16%) changed only stationary activities, 43 (9%) changed only their on-board activities, and 99 (20%) changed both stationary and on-board activity selection and/or durations. Furthermore, it may be noted that a vast majority of the respondents (470 or 95% of the sample) did not change their travel amount, 8 (2%) increased it and 16 (4%) decreased it. (However, note the special treatment of travel times in the survey, described in 2.1.) These results align with Kim et al. (2020), who found that close to a half of respondents did not expect any changes in their activity schedules with AVs.

3. MDCEV model

To investigate the AV-induced changes in daily activities, we specify two MDCEV models (Bhat 2005, 2008): one for on-board and the other for stationary activities. As an alternative to this two-model approach, the stationary and on-board activity time-use could be estimated simultaneously, similarly as done by Wang and Li (2011). They analysed participation in physical and virtual activities in a joint nested structure, where the decision about the activities and locations (physical or virtual space) is made at different levels. In the current context, however, this structure would still not fully capture the relationship between stationary and on-board activities. A full joint treatment would require that the time budget for on-board activities is discretely determined by the selection of stationary activities that require travel (Pudāne et al., 2018). Furthermore, estimating two models allows us to analyse the durations of all activities in either of the models, without having to designate any as an outside good.

In our MDCEV models, individuals are assumed to maximise utility function

$$\max_{t_k} \frac{1}{\alpha_1}\psi_1 t_1^{\alpha_1} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha_k}\psi_k\left(\left(\frac{t_k}{\gamma_k}+1\right)^{\alpha_k}-1\right) \tag{1}$$

subject to:

Table 2
Models for on-board activities: estimates (t-values).

Constants-only model	Constant	Full model					
		Constant	Female	Age 18-24	Age 55+	Young child	Student
BASELINE β_k: base							
Get ready	−3.26 (−18.75)	−5.03 (−10.53)	0.84 (2.55)		−1.11 (−1.81)		−1.17 (−1.55)
Work	−2.18 (−17.59)	−3.74 (−13.19)				0.54 (2.39)	
Meal	−2.78 (−18.95)	−5.01 (−11.88)	0.92 (3.38)				
Leisure	−2.71 (−19.02)	−5.46 (−9.09)	0.54 (2.12)				
Other	−3.59 (−18.12)	−3.66 (−18.11)					
Nothing	0.00 (fixed)	0.00 (fixed)					
BASELINE β_k: change with AVs							
Get ready		1.21 (3.39)					
Work		0.26 (0.71)					
Meal		0.89 (1.89)					
Leisure		2.56 (4.01)					
SATIATION δ_k: base							
Get ready	0.22 (4.01)	0.13 (2.28)					
Work	0.71 (5.48)	0.29 (3.22)					
Meal	0.33 (4.94)	0.10 (1.56)					
Leisure	1.55 (3.67)	0.40 (1.19)					
Other	0.38 (3.26)	0.39 (3.21)					
Nothing	4.76 (2.65)	3.54 (2.92)					
SATIATION δ_k: change with AVs							
Get ready		0.13 (1.30)					
Work		0.26 (1.47)					
Meal		0.10 (1.14)					
Leisure		1.28 (1.39)		−1.16 (−1.30)	−1.29 (−1.38)		
Alpha	−9.08 (−0.55)	−8.89 (−0.66)					
Sigma	1.00 (fixed)	1.00 (fixed)					
No. of parameters	12	51					
No. of responses	984	984					
Log-likelihood	−1275.74	−1114.75					
AIC	2575.49	2331.5					
BIC	2634.19	2580.97					
LR test vs constants only		$321.98 > 54.57 = \chi^2_{0.05;39}$					

$$\sum_{k=1}^{K} t_k = T. \tag{2}$$

The decision variables in this problem are the durations t_k of each activity type k. Parameter ψ_k captures the baseline utility: utility of including activity k in the schedule. Parameters γ_k and α_k capture the satiation effect with increasing activity durations: larger γ_k or α_k mean that the activity reaches the satiation later, leading to longer time being allocated to these activities. Only one of the parameter sets – γ_k or α_k – can be estimated independently, leading to the so-called γ- and α-profiles. Constraint (2) ensures that the duration of all activities sums up to the total time T. The estimation of the parameters in (1)-(2) is based on maximum likelihood, where the probability that an individual selects first M of the K activities with durations $t_1^*, \ldots, t_M^*$ is given by

$$P\left(t_1^*, \ldots, t_M^*, 0, \ldots, 0\right) = \frac{1}{\sigma^{M-1}} \left(\prod_{m=1}^{M} f_m\right) \left(\sum_{m=1}^{M} \frac{1}{f_m}\right) \left(\frac{\prod_{m=1}^{M} e^{\frac{V_m}{\sigma}}}{\left(\sum_{k=1}^{K} e^{\frac{V_k}{\sigma}}\right)^M}\right) (M-1)!, \tag{3}$$

where σ is a scale parameter, $f_m = \frac{1-\alpha_m}{t_m^* + \gamma_m}$, and V_m is a function of the selected duration of activity k and its baseline and satiation parameters, which may be further parameterised (see Bhat, 2008). Equation (1) describes the utility of a model with an outside good: such good that is always consumed ($t_1 > 0$) and is not of the primary interest to the study. If there is no outside good, then equation (1) excludes the first term (and the summation in the second term starts from 1).

In our model for on-board activities (section 4.1), we use the structure without an outside good, since there were no on-board activities that were always selected. We use only those schedules that include travel time, which constitutes the time budget of the model. This leads to exclusion of four responses. Furthermore, the seldom-selected on-board activities (i.e., 10 or fewer times in the 996 observed schedules), which are sleep, shop, service, household, other, are grouped into a composite 'other' activity. The remaining time is defined as activity 'do nothing'. As a result, we model the time-use during travel in the following categories: get ready, work, meal, leisure, other, and do nothing.

In our model for stationary activities (section 4.2), we adopt the structure with an outside good. The outside good is a composite good of shop, service, household, other activities, travel time, and gaps in the schedule. These components changed little between current mode and AV schedules, and, except for the travel time, were seldom selected. As a result, we model stationary time-use for the following activities: sleep, get ready, work, meal, and leisure. Because, as shown in 2.3, travel time was not selected in few schedules,

Full model						
Entrepreneur	Higher education	High income	PT user	Active mode user	Medium commute	Long commute
BASELINE β_k: base						
					1.10 (2.77)	1.89 (3.94)
				1.01 (2.25)		1.53 (5.09)
1.30 (1.60)					0.63 (2.07)	1.13 (2.87)
			1.35 (1.46)			
BASELINE β_k: change with AVs						
	1.30 (4.52)	0.50 (1.95)		−0.96 (−1.74)	0.83 (2.99)	
−1.38 (−1.41)	1.37 (3.66)	0.43 (1.43)				
	0.49 (1.75)		−1.89 (−1.86)		0.75 (2.54)	0.97 (2.08)
SATIATION δ_k: base						
			0.30 (1.45)		0.17 (1.35)	
					1.59 (1.49)	
SATIATION δ_k: change with AVs						
		0.67 (1.59)				
−8.89 (−0.66)						
1.00 (fixed)						
51						
984						
−1114.75						
2331.5						
2580.97						
$321.98 > 54.57 = \chi^2_{0.05;39}$						

sometimes leading to the composite good not being selected, we added a small correction term (duration of 0.01 minutes) to all schedules to make the model estimable. In addition, we fixed the baseline utility of sleep and work activities (which were always selected) to 1. The time budget equals 24 hours (plus 0.01 minute).

For all models, the γ-profile of MDCEV is used (Bhat, 2008). This was implemented by estimating activity-specific γ parameters and a single generic α parameter for all activities k. For the models with stationary activities, the α is unrestricted (i.e., $\alpha_k = \alpha$ for $\forall k$). For the on-board activities, it had to be restricted between 0 and 1 to avoid high correlations; this is done with the function $\alpha_k = 1/(1 + \exp(-\alpha))$. The scale parameter σ is fixed to 1. Although Bhat (2018) mentions that the γ-profile theoretically permits the estimation of σ, estimates in our data resulted in high correlations between α_{base}, σ and several γ parameters. The panel nature of the data (two observations per respondent) is captured in the model.

The baseline and satiation parameters ψ_k and γ_k of all on-board and stationary activities are functions of the socio-demographics of the individuals and trip characteristics: commute time group and current mode. The AV usage is specified as a direct predictor (i.e., constant) and as an interaction with socio-demographic and trip characteristics. The baseline parameters ψ_k contain the predictors in an exponential function, which ensures that the utility of selecting activity is always positive. Thus, the baseline parameter for activity k is parametrised as follows:

$$\psi_k = \exp\left(\beta_k + \beta_k^{AV} I_{AV} + \left(\beta_k^{Female} + \beta_k^{Female;AV} I_{AV}\right) I_{Female} + \ldots + \varepsilon_k\right), \tag{4}$$

where I_{AV}, I_{Female} are indicator functions – equal to 1, if the observation is from an AV schedule/if the participant is a female, and 0 otherwise; β_k is the constant component of the baseline parameter; β_k^{AV}, β_k^{Female}, $\beta_k^{Female;AV}$ are the differences in baseline parameter due to AV use, for female participants, and both; ε_k is independently and identically Gumbel distributed error term. This parametrisation allows us to discover, for example, if women may include leisure activities in their schedules more or less often than men ($\beta_{Leisure}^{Female}$), if leisure selection may have changed in the AV schedules for the entire sample ($\beta_{Leisure}^{AV}$) and also if this change was different for women ($\beta_{Leisure}^{Female;AV}$). Unlike the baseline parameters, the satiation parameters γ_k can be negative: $\gamma_k = \sum_i \delta_{ki} z_{ki} + \varepsilon_k$, where δ_{ki} are the parameter estimates and z_{ki} are the predictors. We tested specifications where the activity-effects of AVs with partial and ideal activity facilitation are separated, but did not find any significant differences. Hence, these AV types are joined in the analysis.

Table 3
Models for stationary activities: estimates (t-values).

Constants-only model	Constant	Full model						
		Constant	Female	Age 18-24	Age 35+	Age 45-54	Age 55+	Young child
BASELINE β_k: base								
Sleep; Work	1.00 (fixed)	1.00 (fixed)						
Get ready	−0.41 (−7.06)	0.10 (1.02)	0.21 (2.23)				−0.49 (−3.76)	
Meal	0.75 (9.3)	1.23 (9.86)	0.25 (1.72)					1.15 (4.44)
Leisure	0.64 (7.35)	2.11 (14.49)	−0.50 (−5.60)					−0.77 (−5.84)
BASELINE β_k: change with AVs								
Get ready		0.00 (0.03)						
Meal		−0.11 (−0.78)		0.34 (1.68)			0.45 (2.99)	
Leisure		−0.16 (−0.99)				0.34 (2.63)	0.32 (1.94)	
SATIATION δ_k: base								
Sleep	4.68 (30.54)	8.28 (27.73)						−0.63 (−3.67)
Get ready	0.90 (21.13)	1.09 (12.85)					0.29 (2.19)	
Work	4.87 (29.95)	8.83 (23.03)	−0.35 (−2.03)		0.39 (2.28)			−0.56 (−3.14)
Meal	0.90 (18.61)	1.28 (15.83)	−0.15 (−2.30)					−0.65 (−6.76)
Leisure	2.51 (16.79)	2.57 (11.29)		1.23 (3.50)				
SATIATION δ_k: change with AVs								
Sleep		0.14 (0.83)						
Get ready		−0.04 (−0.48)						
Work		0.06 (0.34)						
Meal		0.02 (0.31)						
Leisure		0.03 (0.10)						0.45 (1.16)
Alpha	−1.62 (−38.65)	−2.06 (−40.51)						
Sigma	1.00 (fixed)	1.00 (fixed)						
No. of parameters	9	59						
No. of responses	992	992						
Log-likelihood	−9025	−8596.22						
AIC	18067.99	17310.44						
BIC	18112.09	17599.52						
LR test vs constants only		$857.56 > 67.50 = \chi^2_{0.05;50}$						

The estimations were performed using the Apollo software (Hess & Palma, 2019, 2020), model codes and data are available at Pudāne et al. (2021). The predictors that are weakly significant, with t-values above 1.2 (corresponding to roughly 20% significance level) were retained. In addition, a few parameters with lower t-values were kept in the model for discussion purposes – that is, to demonstrate that a parameter that may have been expected to be important turned out to be not statistically different from zero.

4. MDCEV model results

4.1. On-board activities

Table 2 shows the MDCEV results for on-board activities. The first column shows the results for a constants-only model. Here, only aggregate baseline and satiation parameters are estimated, with no differentiation among socio-demographic groups of travellers. The results mirror the activity selection and durations during travel, which were presented in Fig. 2. The most frequent and longest 'activity' during travel (indicated by the largest baseline and satiation parameters, respectively) was to do nothing at all. Among travellers who do something, work was most often selected, followed by leisure and meal. Yet, even if work was most often selected, leisure would typically be performed for a longer time, when selected – its satiation parameter is highest among the specified activities (excluding activity 'Nothing'). Interestingly, Enam et al. (2019) observed almost the opposite: work in public transport in the US having the lowest baseline but the highest satiation parameter.

The right-hand side of Table 2 shows the full MDCEV model, in which (disaggregate) socio-demographic and trip characteristics (in columns) are added to the utility specifications. These effects are indicated for the conventional modes as base (top rows in the sections for baseline and satiation parameters) and as additive changes when using an AV (bottom rows in the baseline and satiation sections). See equation (4) for the parametrisation. All of these predictors were estimated only for the specified activities (get ready, work, meal, and leisure); activities 'Other' and 'Nothing' still contain only the aggregate estimates. The likelihood-ratio statistic as well as the AIC and BIC[8] show that the full model explains the data significantly better than the constants-only model.

We now present and where needed discuss the results of the full model in detail, starting from the top of Table 2. The constants

[8] Akaike information criterion (AIC) is defined as follows: $AIC = 2k - 2\ln(L)$. Bayesian information criterion (BIC) is defined as follows: $BIC = k\ln(n) - 2\ln(L)$. Here, $ln(L)$ is the log-likelihood of the model, k is the number of parameters, and n is the number of observations. AIC and BIC are used to select the best among competing models; smaller values are preferred.

Full model							
Single	Student	Entrepreneur	Higher education	High income	Active modeuser	Medium commute	Long commute
BASELINE β_k: base							
0.38 (3.51)						−1.42 (−15.15)	−2.29 (−11.54)
					0.24 (2.32)	−1.59 (−17.04)	−2.78 (−18.79)
				−0.65 (−3.95)		−1.58 (−17.00)	−2.98 (−19.78)
BASELINE β_k: change with AVs							
			0.15 (1.13)				
0.23 (1.56)							
					0.39 (1.13)	−4.47 (−15.55)	−5.95 (−20.64)
	0.42 (2.63)		−0.14 (−1.86)				−0.29 (−2.68)
		−0.94 (−2.95)				−4.90 (−13.33)	−6.60 (−19.52)
−0.13 (−1.74)							
			−0.48 (−3.62)	1.03 (3.30)			
SATIATION δ_k: change with AVs							
−2.06 (−40.51)							
1.00 (fixed)							
59							
992							
−8596.22							
17310.44							
17599.52							
$857.56 > 67.50 = \chi^2_{0.05;50}$							

describe on-board activity selection and satiation for the reference socio-demographic group (being male, aged 25 to 54, without young children living at home, working for someone (thus, not being entrepreneurs or students), not having obtained higher education and not having high income, being a car driver or passenger, and having short commute time) in their non-AV schedule. For this group, the most common on-board activities were the composite activity 'Other' and work. Women were more likely than men to engage in all activities during travel, except for work – as indicated by the positive and significant baseline change parameters. This contrasts with the results of Enam et al. (2019) and Varghese and Jana (2019), where men were found to multitask during travel more. However, Keseru and Macharis (2018) summarise that different on-board activities are preferred by both genders. The oldest respondents (above 55 y.o.) were less likely to get ready during travel. Respondents coming from households with young children were more likely to indicate work during travel – a result also of Enam et al. (2019). Possibly young children give time pressure to these individuals, resulting in a need to transfer some work activities to travel time. The results on stationary activities (section 4.2) support this interpretation: adults from households with young children spend less time at their work places. Considering the current trip characteristics, public transport users were more likely to engage in leisure activities, and active mode users (specifically, cyclists) were more likely to work during travel. Perhaps some cyclists are able to answer phone calls or check their emails at a traffic light. Next, an intuitive result is that longer commutes and hence total daily travel times lead to more and/or longer on-board activities. The reference short commute time here is 10–30 min, medium commute being defined as 30–60 min, and long commute as 60 min or more one way. Clearly, respondents planned for 15-minute trips differently than for travel of 60 minutes.

Traveling in the AV had a strong effect on the selection of all activities. The largest increase was in the popularity of the leisure and get ready activities. Combined with the values for the baseline parameters, this indicates that leisure was the most common activity in AV (except for activity 'Nothing') for this reference socio-demographic group. However, the effect is different for other groups: the highly educated segment selected work during travel most often. They also more often than the reference group indicated that they would eat meals and enjoy leisure during travel. This could reflect their time pressure and the suitability of some activities (such as work) for being performed during travel. Also high income (at least two times the Dutch average) was associated with more work activity and eating meals during travel. That higher education and income is associated with more work tasks during commute trips, is a result also of Molin et al. (2020) and Varghese et al. (2020). Finally, longer travel times made respondents adopt work and leisure activities in AVs, even if they do not perform them in current modes (corresponding to the insignificant base components of the baseline parameters).

Considering the on-board activity popularity in different modes, the stark difference between AVs and public transport stands out. This effect may be partly due to attention bias, because the possibility to perform on-board activities in the AV were emphasised in the introduction of the survey. Public transport and active mode users also have negative coefficients for leisure and work activities in AVs,

Table 4
Internal validity of model in 4.1: on-board activities.

Activity	Selection (%)		Duration when selected (min)	
	Sample	Predicted	Sample	Predicted
Get ready	4	4	17	26
Work	12	11	47	49
Meal	7	6	25	32
Leisure	7	7	56	57
Other	3	3	26	31
Nothing	93	91	76	77

Table 5
Internal validity of model in 4.2: stationary activities.

Activity	Selection (%)		Duration (min)	
	Sample	Predicted	Sample	Predicted
Sleep	100	98	460	472
Get ready	81	78	40	42
Work	100	98	491	490
Meal	95	95	86	89
Leisure	96	96	225	225
Outside	100	100	139	122

Table 6
Summary of on-board and stationary activity changes with AVs.

	On-board changes with AVs	Stationary changes with AVs
All respondents	All activities more frequent and longer	–
High income	More frequent work and meal, longer work	–
Higher education	More frequent work, meal and leisure	More frequent getting ready activity
Age groups 18–24 and 55+	–	More frequent meals
Age group 45+ and singles	–	More frequent leisure
Parents of young children	–	Longer leisure

respectively. These however roughly offset the positive parameters for these activities in their current modes, which means that these travellers had an overall similar preference as other mode users for these on-board activities in AVs. The same holds also for entrepreneurs, who, more than other socio-demographic groups, reported having meals during travel at present, but did not maintain this preference in AVs. We tested the AV-effect also while differentiating between partial and ideal activity facilitation (the two AV types that were randomly allocated to the participants). The obtained parameters were not significantly different. This indicates that the respondents did not respond strongly to the possibility of experiencing motion sickness and having their activities interrupted due to the movements of the AV.

Considering the satiation of on-board activities in current modes, no socio-demographic characteristics play a role there. Public transport users engaged in longer meals than users of other modes, and a medium commute time was associated with longer on-board meal and leisure durations. The effect of long commute times turned out to be insignificant (but positive), partly due to this being the smallest group in the sample (10%). Use of AVs led not only to more frequent selection of on-board activities (as discussed above) but also to overall longer activities. Only the youngest and oldest segments did not desire longer leisure during travel – the interactions with these age groups roughly offset the increase in the constant satiation parameter with AVs. Finally, high income relates to work activity being performed for a longer time. Possibly the respondents in this group expected to use the entire or large share of their travel time for work due to the time pressure or the nature of the job tasks (e.g., managerial tasks that can be performed remotely) associated with high income.

4.2. Stationary activities

Table 3 shows the MDCEV results for stationary activities. Similarly as in the previous section, the first column displays results of an aggregate effects model. Also this model mirrors the descriptive statistics of the data well (see Fig. 3). The activity selection frequencies are reflected in decreasing baseline parameters: from the most frequent sleep and work activities (fixed and always chosen), via meal and leisure (not significantly different) to the least frequently chosen getting ready activity. The satiation parameters mirror the activity durations observed in the data. Work and sleep were the longest stationary activities, followed by leisure, meals, and getting ready.

The remaining columns of Table 3 show a model with socio-demographic and trip-based segmentations (in columns) in addition to the effects associated with traveling in the AV (in rows). More characteristics turned out to be significant predictors for the stationary activities as compared to the on-board ones: there is more explainable variation in the stationary schedules. The likelihood-ratio test as well as the BIC and AIC values indicate that the full model significantly better describes the data than the constants-only model.

We now list and where needed discuss the various socio-demographic and trip characteristics that influence stationary activities. It is convenient to discuss these while considering the baseline and satiation results in conjunction, and we proceed with the non-AV results (i.e., the top rows in the baseline and satiation sections) from the left side of Table 3. Women were more likely to engage in activity 'Get ready', and work for shorter hours. They were more likely to indicate meals during the day, but also reported spending less time on them. Women were also less likely to engage in leisure activities. Similarly, Allard and Janes (2008) found that married women spend less hours on work and leisure compared to married men. The youngest of survey respondents (18–24 years old) spent significantly more time on leisure. This result is in line with Calastri et al. (2017), who found that young adults below 26 years of age spend more time in social activities (which were classified as leisure in our survey). Age above 35 is associated with longer work hours in our data, indicating possibly the most intensive work age. The oldest of the respondents (55 years +) were less likely to indicate getting ready activities (just as they were less likely to indicate these activities during travel) albeit spent more time on them, when indicated. Parents of young children below 12 years of age (or, more accurately, respondents from households with children in this age) indicated sleeping significantly less and spending less hours at work. Also Calastri et al. (2017) found that having underage children in the household is associated with shorter hours spent working or studying by the adults. Our data show that these adults were more likely to have meals during the day, but spent less time on them, and also were less likely to engage in leisure. Similarly, Bernardo et al. (2015) found that individuals from households with children were less likely to invest time in social, recreational activities and meals. Those that live in single-adult households (as opposed to with a partner, housemate, or a family) spent less time on meals, but were more likely to devote time for getting ready. Entrepreneurs spent less time working than those who are employed by someone (in private or government sector). Students spent more time on getting ready activities, while this effect is opposite for those who have obtained higher education. The higher educated also spent less time in leisure, but this reduction was more than offset if they also have high income (at least two times the average income in the Netherlands). Those in this income group were however less likely to mention leisure activities to start with – a finding in line with Bhat et al. (2013).

Among the trip related segmentations, active mode users were more likely to indicate meals during the day and also slept slightly longer – possibly as part of or because of the more active lifestyle. Next and unsurprisingly, individuals with medium and long commute times allocated less time to all stationary activities. This may also reflect scaling effects due to the experimental setup: the respondents of the three groups used different fixed travel times to design their schedules, and hence may have had more or less flexibility in the task.

Finally, whereas the AV effects on on-board activities were pronounced (as shown in the previous section), their impacts on stationary activities were all insignificant (see the bottom rows in the baseline and satiation sections). The highest t-value of the overall effects of AVs on stationary activities is 1.06 (the effects are included in the table to demonstrate this point). Hence, based on the data from our experiment we conclude that there is no general effect of AV usage on stationary activity selection and durations. There are effects for some socio-demographic groups however. The youngest and oldest respondents more often mentioned stationary meals in their AV schedules. This however does not change the meal selection by much – about 95% of all mode users indicated meals in their schedules (see Fig. 3). Respondents aged 45+ as well as those living in single-adult households were more likely to devote time to leisure once having an AV. Parents of young children (or, more specifically, adults from households with young children) indicated longer leisure activities in the AV schedule. Perhaps AVs let them extend the leisure time with their children thanks to having saved energy from driving. Finally, the higher educated respondents were more likely to allocate time to the get ready activity in their AV schedules.

4.3. Internal model validity

We now provide a first internal validity check for the full models presented in previous sections. To do so, we use the obtained estimates to predict activity selection and durations, and compare those with the corresponding sample statistics. The prediction algorithm by Pinjari and Bhat (2010b), which is implemented in the Apollo software (Hess & Palma, 2019, 2020), is used for this purpose. The predictions for the on-board and stationary activities are in Table 4 and Table 5, respectively. The duration predictions for the on-board activities in Table 4 are computed for the cases when each activity was selected. Otherwise, the low selection probabilities of on-board activities are associated with very low mean on-board activity durations in the entire sample.

Predictions for on-board and stationary activities match the summary statistics of the sample well. The selection shares are very well recovered. The predicted and sample on-board activity durations are similar, and the match is better for the more frequent on-board activities. For the stationary activities, the differences between the predicted and sample durations are acceptable proportionally, with the largest being 12% underestimation for the composite outside activity.

5. Discussion

5.1. AV-related changes in on-board and stationary activities

The introduction of this paper outlined how the possibility to perform on-board activities in the AV may trigger changes in stationary activities. It reviewed recent literature that has started to investigate such changes empirically (Kim et al., 2020; Krueger et al., 2019; Correia et al., 2019) and to include them in theoretical frameworks (Pawlak et al., 2015, 2017; Yu et al., 2019; Pudāne et al., 2018; Pudāne, 2020). In this work, we looked for more specific evidence for or against such associations between on-board and stationary activity changes due to the advent of an AV. Table 6 summarises the signs of our results from previous sections.

The table affirms that the on-board time-use changes are significant for the entire sample and for all of the analysed activities, whereas no stationary changes were found to be significant for the entire sample. Note that this may seem to contrast the correlation analysis in Fig. 4. The figure indicated several significant (and intuitive) correlations between on-board and stationary activity duration changes. However, the MDCEV results here show that the magnitude of stationary changes is small and hence, turns out to be not significantly different from zero. This contrast indicates that a larger sample may well have led to some significant changes in stationary activity durations.

Besides the (lack of) aggregate effects, Table 6 shows several significant activity changes within some socio-demographic groups. A connection between on-board and stationary changes is revealed for the higher educated sample segment. That is, they indicated more work, meal and leisure activities during travel (compared to the rest of the sample), and they also more often added a getting ready activity outside of travel to their AV schedules. Examining the schedules in more detail (a visual representation of all schedules is available in Pudāne et al., 2021), it could be noticed that the getting ready activity was often performed in the morning: between sleep and travel to work. Furthermore, especially the morning commute was often used for work and other activities (also literature reports that morning commutes are more often used for work than the afternoon return trips: Keseru and Macharis, 2018). This co-occurrence suggests that the higher educated respondents may have started to work while being on the way to work, or had their breakfast in this time, which would have let them be more relaxed and take their time with the morning activities, such as dressing and grooming at home. This causal interpretation is tentative however, since our data do not allow us to exclude the possibility of reverse causality (i.e., expected changes in stationary schedules could have triggered a change in on-board activities), or the presence of a third effect that generates a spurious correlation between the selected on-board and stationary activities.

5.2. Limitations and future work

The previous sections have highlighted that while traveling in the AV clearly led to performing more and longer on-board activities, this is only modestly associated with changes in stationary activities. Nevertheless, an important limitation should be highlighted for this finding: our models show the mean changes per socio-demographic groups, which could obfuscate rearrangements occurring on an individual level. For example, if some respondents prolonged their stationary work hours with AVs, while others in the same socio-demographic group shortened them, these changes would cancel each other out at the group level. An indirect support for this possibility is provided by Fig. 3: whereas the average stationary activity durations are similar in the current and future AV scenarios, the dispersion in the activity durations is large. This leads us to suggest that future work should explore the co-occurrence of on-board and stationary activity changes at an individual level. A mixed MDCEV (Bhat and Sen, 2006) or a latent segmentation based MDCEV (Sobhani et al., 2013) could address some of this heterogeneity. Of course, societal relevance should be kept in mind here: for some purposes, knowing the aggregate level results is more important, while for others, disaggregate insights are needed.

Furthermore, even if the selection and duration of stationary activities did not change substantially, there would still be room for schedule re-arrangements in terms of activity sequence and timing. For example, the entire workday may be shifted to a later time, if work is possible during travel. Such scenarios would have implications for aggregate travel behaviour and congestion (Yu et al., 2019; Pudāne, 2020). Hence, another suggestion for further research would be to explore activity timing and sequence changes when moving towards AVs.

In addition, we note a few suggestions to extend our survey tool to allow the respondents to design even more realistic current and future activity schedules. First, future studies could use a tool that allows various locations for activities: further locations may be more attractive for some activities, and this choice may be relevant in the AV context. Alternatively, the respondents could be allowed to specify the travel time to their known destinations. Second, future work could extend the tool, such that different travel modes may be used for different trips in the day. Third, the survey tool could allow the respondents to use the AV as a 'personal robot': for example, to let it perform some pick-up or drop-off independently – an option reported popular in the naturalistic AV experiment by Harb et al. (2018). Fourth, further work could explore ways of communicating in the survey tool temporary and limited multitasking opportunities, which would be characteristic of lower automated levels. Especially level 4 AVs would still allow hands-off/eyes-off episodes during travel, and hence multitasking opportunities, but some level of alertness on behalf of the driver would be necessary to react on the take-over requests of the vehicle.

Also, there are plenty of opportunities to further analyse the heterogeneity of travellers. For example, the effects of various occupations could be tested – professions that involve primarily work on a computer versus work with people versus work with (large) equipment. Perhaps also the built environment could play a role in the travellers' willingness to engage in some activities during travel – arguably, travel in rural areas offers more privacy and smoother travel experience than congested traffic in a city centre. The presence of travel companions, and certainly travelling with strangers as in a pooled AV service, would also impact the types of on-board activities.

Finally, note that all of the above recommendations presume that people are able to imagine a future with fully automated vehicles, and that they can anticipate their travel and activity behaviour in this future. Clearly, that is not an easy task, especially if the wide-scale uptake of fully automated vehicles may occur only in few decades. Hence, any data analysis about travel behaviour with AVs is bound to have a degree of hypothetical bias. Furthermore, studies of daily activities in particular suffer from the inevitable assumption (by respondents and analysts) that future activities will resemble the activities of the present. Recalling how the rapid uptake of smartphones in the last two decades have shaped our daily activities, we must acknowledge that daily activities can change significantly in such a time span.

6. Conclusions

This paper set out to find how automated vehicles (AVs) might change daily activities of their users –activities performed stationary and during travel. To this end, we designed a novel interactive stated activity-travel survey, where respondents constructed a recent workday and, following that, redesigned it while imagining that they would use an AV for all their trips. Multitasking during travel was allowed for present modes as well as AVs. We analysed the results of this survey using the multiple discrete-continuous extreme value (MDCEV) framework, including the influence of AV usage (as a binary variable) on selection and duration parameters of on-board and stationary activities. Results show that the AV impact on on-board activities is strong and positive: participants expect to perform more and longer activities during travel in AVs. We also found some intuitive differences across specific socio-demographic groups: the higher educated and high-income respondents, as well as those with longer commute times increased their work, meal and leisure activities in AVs more than other groups. In contrast, the impact of traveling in the AV on stationary activities was weak: there were no clear common ways in which participants adjusted their schedules in response to AVs. The absence of more and stronger stationary activity changes could be seen as an indication of the challenge to elicit behaviour for the future with level 5 AVs. Nevertheless, some significant effects were found for specific socio-demographic groups: the youngest and oldest respondents indicated more meals in their AV schedules; respondents aged 45+ or those from single-adult households were more likely to add leisure time to their days with AVs; adults living with young children spent more time in leisure. Finally, the higher educated respondents indicated specific changes in both their on-board and stationary activity schedules: when switching to AVs, they were more likely than others to spend time on work, meals and leisure during travel and more likely to allocate time to stationary getting ready activities. Moreover, correlation analysis reveals intuitive links between on-board and stationary activity changes with AVs. Hence, in future work a larger sample may yield significant MDCEV parameters as well.

The relatively few changes in stationary activities at the level of socio-demographic groups, as found in this study, should however not be interpreted as an absence of individual-level stationary schedule adjustments. Future work should explore unobserved heterogeneity among travellers to identify, for example, latent classes of travellers with similar expected changes in stationary and on-board schedules (e.g., by using latent segmentation based MDCEV, developed by Sobhani et al., 2013). Such endeavour could be worthwhile, since latent classes have been shown to describe multitasking propensity well in general (Kim et al., 2020; Choi and Mokhtarian, 2020). Nevertheless, our analysis already indicates that the impact of AVs on daily schedules may be more complex than often anticipated: some changes in stationary activity schedules were observed, which were generally not accompanied by changes in travel time (95% of respondents did not change their total travel amount). Therefore, we suggest that future studies, which seek to model the activity-travel impacts of AVs, look beyond the most frequently modelled AV impact: its assumed capacity to reduce the dislike of travel, which inevitably leads to more travel.

Zooming out further, it may happen that the research field of travel-based multitasking may now be treading a path parallel to the initial explorations of ICT impact on travel behaviour. Pawlak et al. (2020) explains how with the revolution of ICT opportunities for remote activity participation, the research on travel-ICT relations progressed from initial expectations of activity substitution (i.e., tele-activities) and complementarity towards a more complex integration of the new opportunities in daily lifestyles. Similarly, the expected increase in on-board activity opportunities may necessitate future work that accommodates complex interactions between activities performed during travel and outside of it. We hope that our study helps to make some necessary steps in this path.

Author statement

Baiba Pudāne: Conceptualisation, Methodology, Software, Investigation, Data curation, Writing – Original Draft, Writing – Review & Editing, Project administration

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