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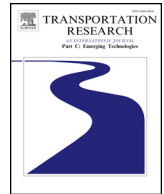
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A Time-use Model for the Automated Vehicle-era[☆]

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ABSTRACT

Automated Vehicles (AVs) offer their users a possibility to perform new non-driving activities while being on the way. The effects of this opportunity on travel choices and travel demand have mostly been conceptualised and modelled via a reduced penalty associated with (in-vehicle) travel time. This approach invariably leads to a prediction of more car-travel. However, we argue that reductions in the size of the travel time penalty are only a crude proxy for the variety of changes in time-use and travel patterns that are likely to occur at the advent of AVs. For example, performing activities in an AV can save time and in this way enable the execution of other activities within a day. Activities in an AV may also eliminate or generate a need for some other activities and travel. This may lead to an increase, or decrease in travel time, depending on the traveller's preferences, schedule, and local accessibility. Neglecting these dynamics is likely to bias forecasts of travel demand and travel behaviour in the AV-era. In this paper, we present an optimisation model which rigorously captures the time-use effects of travellers' ability to perform on-board activities. Using a series of worked out examples, we test the face validity of the model and demonstrate how it can be used to predict travel choices in the AV-era.

1. Introduction

Today, many public transport passengers conduct activities while travelling (Keseru and Macharis, 2017, Frei et al., 2015, Lyons et al., 2007, Ettema et al., 2012, Malokin et al., 2016). Many scholars, policy makers and automotive industry practitioners anticipate that future Automated Vehicles¹ (AVs) will allow their users to engage in an even wider range of on-board activities. The ability to perform new on-board activities in the AV is generally expected to increase productivity and well-being (Kyriakidis et al., 2015, Bansal et al., 2016). Nevertheless, the increased attractiveness of travelling is also feared to cause more car travel in the AV-era and in due time even relocation of home and work locations to places further apart (Milakis et al., 2017; Fagnant and Kockelman, 2015; Heinrichs, 2016; Sadat Lavasani Bozorg, 2016). In order to anticipate these changes in travel and location choices, the AV-effect is usually conceptualised using the idea of a reduced travel time penalty, or similarly, a lower value of travel time savings (Gucwa, 2014, Childress et al., 2015). However, this approach has important limitations, which we illustrate with an imaginary narrative of a future traveller.

Before purchasing her AV, Anne used to commute to work with a conventional car. In the mornings, she used to wake up at 7:00 to get ready (dress, eat breakfast), depart at 8:00, and reach work at 9:00. She often contemplated visiting a swimming pool in the

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¹ We refer throughout the article to so-called level 5 automated vehicles, according to SAE International (2016) standards.

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morning, but ultimately did not want to get up earlier to do so. In the evening of a typical working day, she used to leave her work at 18:00, headed home for a 30-min nap, and then drove to meet her friends for dinner at 20:00. She often felt like working longer, but did not want to miss out on her evening activities.

Recently, Anne’s company has adopted a new policy allowing employees to perform their morning work tasks in their fully automated vehicles, and arrive at the office at 9:30. Now, Anne has switched to an AV. She leaves home at 8:30 and arrives at the office at 9:30. About 30 min of her journey she spends preparing and eating breakfast; the remaining 30 min she spends replying to work emails. She uses the gained one hour in the morning to visit a swimming pool, which she reaches with her AV. In the evening, Anne stays an extra hour and a half at work, and takes a nap in her AV, while it drives her straight to the meeting with friends (saving her a detour to home).

This example exposes two key aspects of travel behaviour in the AV-era, which are overlooked when applying the travel time penalty approach:

1. On-board activities can create time savings. If an activity is transferred from another time of the day to the AV, then time is saved, because the activity and travel are simultaneous. In the example, Anne gains time in the morning, as well as in the evening. If the analyst does not account for such possibilities (which is the case when AV-implications are conceptualised using the travel time penalty approach), then he/she implicitly assumes that all activities that are executed in the AV are *added* to the existing daily activity schedule of the traveller, rather than being *transferred*. Note that the share of work activities transferred to the business travel time is explicitly modelled in Hensher’s equation (used to obtain the value of business travel time savings, Hensher, 1977), and empirical evidence for such transfer of work activities is available (e.g., Gustafson, 2012).
2. Changes in on-board time-use can lead to more travel, as is commonly argued. However, it can also lead to less travel, given a certain activity wish-list (or daily activity plan) of the traveller. The narrative illustrates both possibilities: more travel (in the morning) and less travel (in the evening). When only reductions in the travel time penalty are considered as in many previous studies, the possibility of a decrease in travel is implicitly ruled out. Note that conceptually this idea is not new: already 20 years ago, Kitamura et al. (1997) wrote that ‘the key question to be addressed when dealing with induced or suppressed trips is how people use time’.

The above aspects summarise the main problem of solely using (reduced) travel time penalties to model the impact of on-board activities in the AV. This travel time penalty-approach disregards the duration of on-board activities and their interactions with other activities. Therefore, more subtle effects, such as the difference between adding and transferring activities, are likely to be missed. In other words, by solely using the travel time penalty as a proxy for the effect of productive time use in the AV, the researcher or policy analyst implicitly assumes that activity-travel patterns - beyond the added activities during travel and extended or generated trips - will remain unchanged in the AV-era. This assumption leads to an incomplete understanding of travel behaviour and potentially mistaken forecasts of travel demand in the AV-era, which carries important and obvious risks for transport policy making.

We aim to address this problem by modelling on-board activities in the AV explicitly, rather than implicitly assuming that their only effect is a reduced penalty associated with travel time. Specifically, we propose a formal model that accounts for changes in time-use, when some of a traveller’s activities can be performed on board the AV. The model is based on, and extends, classical time-allocation frameworks (Becker, 1965; DeSerpa, 1971; Evans, 1972). Our model is also in line with previous studies that have made important steps towards using the time-allocation framework to model on-board activities and ICT use (Pawlak et al., 2015, 2017; Banerjee and Kanafani, 2008). Pawlak et al. (2015, 2017) build upon Winston’s (1982) extension of the classical time-allocation framework and represent the effect of AVs with higher intensity of on-board activities. They study a multi-dimensional choice, including the choice of on-board activities, in a two activity, single-trip setting. This implies an interaction between on-board activities (and their productivity) and the scheduling of the directly neighbouring activities (pre- and post- travel). Banerjee and Kanafani (2008) adapt the time-allocation framework to study effects of working in the train (using wireless internet) on travel choices. They model a choice to transfer the work activity from a fixed office location to train.

Our work contributes to this literature in several important aspects. First, whereas previous work exogenously specified which activities are to be performed in stationary locations or on board, we allow for endogenous selection of activities and their locations. Second, by considering longer activity lists than in previous studies and by allowing activity transfers to the AV, our model captures a wider range of possible changes in daily travel and time-use, which can be expected in the AV-era.

The remaining sections are structured as follows. Section 2 builds the time-use model. Section 3 illustrates the model’s working using minimalistic examples. Section 4 applies the model to an extended example. Section 5 reflects on the role and scope of our model and provides suggestions for calibrating, applying and extending our model. Section 6 concludes and discusses policy implications.

2. Time-use model considering on-board activities

We base our model on the core ideas behind the classical time-allocation frameworks derived by Becker (1965), DeSerpa (1971) and Evans (1972). These microeconomic frameworks postulate that people choose the activities that provide most utility for them, while staying within total available time and monetary budget constraints. In other words, they suggest that an optimisation task is solved to obtain the optimal daily activity plan.

However, the original formulations of the model, for understandable reasons, do not allow for overlapping activities, such as the

execution of non-driving on-board activities during travel. Moreover, they do not explicitly model travel to activity destinations. Yet, these elements are crucial for modelling the interaction between on-board and other activities. In our model, we capture these elements, and specifically, we model the interplay among stationary activities, travel, and on-board activities. The interplay results from the complementarity and substitution relationships in this triplet, which is contained in three statements:

1. Stationary activities generate a need for travel.
2. Travel enables on-board activities.
3. On-board activities may (partially or completely) replace stationary activities.

The main contribution of our model is that it explicitly models on-board activities. However, and beyond this main contribution, our model in fact captures all three components of travel utility, as classified by Mokhtarian and Salomon (2001): the intrinsic utility of travel, utility of on-board activities, and the utility of reaching potentially better destinations. Note that our model could be extended to allow an overlap not only between travel time and on-board activities, but between any two or more activities. Such a generic model was proposed by Sanchis (2016). However, our model in another way extends the model of Sanchis (2016) by introducing the above-mentioned complementarity and substitution relationships between activities. On the other end, complementarity and substitution, but not an overlap (in the use of time or goods), has been modelled in the context of multiple discrete-continuous models by Bhat et al. (2015).

Following is the introduction of the model. We consider a set of activities $i \in I$, a set of stationary locations where activities may be performed $l \in L$, and a set of travel modes $m \in M$. The utility of performing activity i is U_i^l , if it is performed stationary at location l , and U_i^m , if it is performed on board travel mode m . For example, an individual may perform shopping activity in several shopping malls or online while travelling in AV, taxi, or public transport.

Similar to the utilities, the necessary time for activity $i \in I$ is denoted by parameters T_i^l and T_i^m , which correspond to the total time necessary to perform the entire activity at a stationary location l and on board mode m , respectively. The reason for specifying different parameters for stationary and on-board activities is the intuitive idea that activities may be better or worse facilitated at different (stationary and on-board) locations.

The parameters describing the travel to stationary location l to perform activity $i \in I$ are V_i^m for travel (dis)utility and H_i^m for travel time, both assuming that the entire trip is performed with mode m . The travel (dis)utility V_i^m refers to the intrinsic (dis)utility of travelling in mode m , which is unaffected by on-board activities and includes mode-specific costs such as travel effort, inconvenience, monetary costs, as well as motivations of curiosity, status, and independence (Ory and Mokhtarian, 2005). Travel times H_i^m and (dis)utilities V_i^m are assumed to be known and not dependent on other selected activities, nor their sequence.² In case any stationary location is suitable for an activity (e.g., read a book in the library or in a park), then travel time H_i^m to this stationary activity is zero.³

All the selected activities and the associated travel to reach them need to fit within the total time constraint T . In order to maximise the utility, the person makes three choices, represented by decision variables. First, the choice to perform activity i is denoted by binary decision variable $x_i \in \{0, 1\}$. Second, the choice of location(s) for activity i is represented with continuous decision variables $y_i^l, y_{ij}^m \in [0, 1]$. These variables represent the shares of activity i performed at each stationary location l (y_i^l) and on board each mode m during each trip (y_{ij}^m), respectively. A trip is identified by its destination l and activity j at that destination. To indicate that activity i is performed on board during a trip to activity j , we use two indices i and j that belong to the same set I . Thus, the product $y_i^l T_i^l$ represents the time spent on activity i at location l , and $y_{ij}^m T_i^m$ represents the time spent on activity i while on board mode m on the way to activity j at location l . Third, the choice of travel mode(s) to reach the stationary location l of activity i is denoted by continuous decision variables $z_{il}^m \in [0, 1]$ that indicate the share of mode-specific total trip time (i.e., the share of H_{il}^m). The product $z_{il}^m H_{il}^m$ represents the time spent in mode m while travelling to perform activity i at the location l .

The decision variables y_i^l, y_{ij}^m and z_{il}^m are defined as continuous to represent the idea that activities may be split between several locations and, similarly, travel may be split among several travel modes. Time and utility of split activities is composed proportionally. For example, one may have a choice of reading a newspaper in a cafeteria, which could take 30 min and give a utility of size 2, or on the way home in mode m , which could take 60 min and give a utility of size 1 (perhaps due to lower comfort levels in that mode). Faced with a time constraint, this person may choose to read 80% of the newspaper in the cafeteria, and 20% of it on the way in mode m . In such a case, the utility obtained from reading the newspaper equals $0.8 \times 2 + 0.2 \times 1 = 1.8$. The time spent reading the newspaper equals $0.8 \times 30 + 0.2 \times 60 = 36$ minutes.⁴ However, splitting an activity among several locations may be inconvenient (e.g., 'flow' may be interrupted, or equipment may need to be set up each time). Therefore, an activity-specific weight ψ_i (expected to be negative or zero) is used to penalise each additional fragment of activity i (at stationary locations l and/or on-board locations m).⁵

The time-use model that maximises utility from selected activities, including on-board activities, is as follows:

² If our model is implemented in comprehensive simulation frameworks, then the travel times and (dis)utilities would need to be updated by a subsequent optimisation of activity sequence. Note that separation of activity selection and sequencing steps is a common practice in activity-based modelling (Arentze et al., 2010, p. 72).

³ Travel times would also be zero, if the traveller happens to be in the stationary location for the preceding activity. Our model is not sensitive to such situations (see the previous footnote).

⁴ Note the difference between reading 80% of the newspaper in the cafeteria and spending 80% of the newspaper reading time in the cafeteria. The decision variable refers to the former.

⁵ In a similar way, mode changes within a trip could also be penalised in an extended version of the model.

$$\max \sum_{i \in I} \left(\sum_{l \in L} \left[y_i^l U_i^l + \sum_{m \in M} \left(z_{il}^m V_{il}^m + \sum_{j \in I} y_{ijl}^m U_i^m \right) + \psi_i \left(r_i^l + \sum_{m \in M} \sum_{j \in I} s_{ijl}^m \right) \right] - \psi_i x_i \right), \tag{1}$$

subject to:

$$\sum_{i \in I} \sum_{l \in L} \left(y_i^l T_i^l + \sum_{m \in M} z_{il}^m H_{il}^m \right) \leq T, \tag{2}$$

$$\sum_{i \in I} y_{ijl}^m T_i^m \leq z_{ijl}^m H_{ijl}^m \quad \forall j \in I, \forall l \in L, \forall m \in M, \tag{3}$$

$$\sum_{l \in L} \left(y_i^l + \sum_{m \in M} \sum_{j \in I} y_{ijl}^m \right) = x_i \quad \forall i \in I, \tag{4}$$

$$y_i^l \leq r_i^l \quad \forall i \in I, \forall l \in L, \tag{5}$$

$$r_i^l \leq G y_i^l \quad \forall i \in I, \forall l \in L, \tag{6}$$

$$y_{ijl}^m \leq s_{ijl}^m \quad \forall i \in I, \forall j \in I, \forall l \in L, \forall m \in M, \tag{7}$$

$$s_{ijl}^m \leq G y_{ijl}^m \quad \forall i \in I, \forall j \in I, \forall l \in L, \forall m \in M, \tag{8}$$

$$\sum_{m \in M} z_{il}^m = r_i^l \quad \forall i \in I, \forall l \in L, \tag{9}$$

$$x_i, r_i^l, s_{ijl}^m \in \{0, 1\} \quad \forall i \in I, \forall j \in I, \forall l \in L, \forall m \in M, \tag{10}$$

$$y_i^l, y_{ijl}^m, z_{il}^m \in [0, 1] \quad \forall i \in I, \forall j \in I, \forall l \in L, \forall m \in M. \tag{11}$$

In the model, the objective function (1) maximises the utility from the selected activities, including the (dis)utility of the travel to them and penalties for fragmentation (variables r_i^l and s_{ijl}^m are explained below). Constraint (2) limits the total time of all selected activities to T . It includes the time spent in stationary activities and the time spent travelling. On-board activities are conducted simultaneously with the travel; therefore they are not part of the total time constraint. This constraint is a key to the potential preference for on-board activities, even if their utility and/or time parameters are worse than the parameters of stationary activities. Constraints (3) limit the time for the on-board activities in each trip: the time allocated to the on-board activities while travelling with mode m to location l to perform activity j must be less than or equal to the travel time to that location with the respective mode. Constraints (4) ensure that each activity is either performed completely (shares of activity at different locations add up to one) or not performed at all (all share variables are zero). Activity would not be started, if there is not enough time to complete it stationary (due to constraints (2)) and/ or on board (due to constraints (3)). Constraints (5) and (6) define a binary flag r_i^l that indicates whether activity i is at least partly performed stationary at location l . Similarly, constraints (7) and (8) define a binary flag s_{ijl}^m that indicates whether activity i is at least partly performed while travelling with mode m to location l to perform activity j . These binary flags are defined using G as a large positive constant. It can be checked that by substituting y_i^l (in case of constraints (5) and (6)) with values from $[0, 1]$, constraints (5) and (6) replicate the following logic: if $y_i^l > 0$, then $r_i^l = 1$; otherwise $r_i^l = 0$. The sum of binary flags r_i^l and s_{ijl}^m over j, l, m indicate the number of fragments of each activity i , which is penalised in the objective function (1). Constraints (9) make sure that each necessary travel is completed, whenever an activity is at least partly performed stationary (indicated by flag r_i^l). Finally, constraints (10) and (11) define the domain of variables. The resulting system (1) and (11) is a mixed-integer linear model, which can be solved by commercial integer linear programming solvers.

Besides extending the time-allocation framework to include on-board activities, our model differs from more recent commonly used representations of the classical time-allocation framework (such as Jara-Díaz et al., 2008) in several other aspects.

1. We exclude the utility of consuming obtained goods from the objective function. In doing so, we follow Evans (1972), who stated: ‘utility is not derived from the properties or characteristics of the goods but from the activities for which the goods are used.’ (p. 14)
2. We exclude the monetary budget constraint for model expediency. We assume that the AV users will generally belong to the high-income market, where the budget constraint would typically be ineffective (Evans, 1972) in the context of daily travel and activity choices. Nevertheless, budget constraint might be re-introduced in an extended version of the model. Budget constraint should also be included when modelling vehicle purchase decision.
3. We shift the emphasis away from activity duration choices to activity selection by assuming that the considered activities have a fixed duration. This shift suggests that many activities are rather stable in their duration (certain work tasks, sleep time, meal time). This assumption could be relaxed, for example, by defining groups of activities, where each group contains alternative durations for a single activity, and one option is chosen from each group. In such a way, flexible relationships between activity duration and utility could be modelled.

Table 1
Anne’s activity wish-list.

Activity	Activity stationary		Travel to the stationary activity		Activity on board	
	Utility (per activity)	Time (h)	Utility (per h)	Time (h)	Utility (per activity)	Time (h)
Morning activities:						
Swim	9	0.7	−10	0.3	−10 ⁴	1
Get ready	20	1	0	0	−10 ⁴ / 15	1
Work emails	20	0.5	0	0	−10 ⁴ / 20	0.5
Work in office	20	0.5	−10	1	−10 ⁴	0.5
Evening activities:						
Work in office	8	1.5	0	0	−10 ⁴	1.5
Take a nap	20	0.5	−10	1	−10 ⁴ / 10	0.5
Dinner with friends	20	1	−10	0.5	−10 ⁴	1

Total time constraints: 3 h for the morning activities and 3 h for the evening activities.

- We do not distinguish work activity from other activities. We implicitly assume that on most days the utility generated by, for example, 8 h of work, far exceeds utility of 8 h of leisure. The income and commitment to work is part of the work utility. If the utility of leisure exceeds the utility of work for a particular day, then the decision maker would take a ‘day-off’. Alternatively, one may model work (and other appointment-like activities such as theatre shows, job interviews) as an inflexible activity that defines the time boundary T of the model. We adopt the latter approach as we illustrate the model in the next section.
- We adopt a linear utility function, instead of the multiplicative Cobb-Douglas form. This is done for model tractability reasons, and has no implications for the general validity of results discussed further.

3. Illustration of the model

In this section, we illustrate the model using the fictive example of Anne from the introduction. We translate her morning and evening activities⁶ into an activity wish-list and add hypothetical utilities and time requirements for all activities (see Table 1). All activities of Anne’s wish-list can be performed stationary (see column ‘Activity stationary’), and some would require travel when performed stationary (see column ‘Travel to the stationary activity’). Some activities can also be performed on board, once Anne has switched to an AV (see column ‘Activity on board’). Note that if an activity cannot be performed on board, then assigning a large negative utility ensures that the activity is not selected to be performed on board.^{7, 8} Cells with two utility values specify both the utility in a conventional car (i.e., a large negative utility) and in an AV (positive). Some activities, when performed in the AV, have a reduced utility: getting ready in the morning, taking a nap in the evening may be less comfortable in the AV.

Using these settings as an input for the model,^{9,10} we obtain the optimal activity schedule for Anne both before and after she switches to an AV, see Fig. 1. The results correspond to the description in the introduction.

A clear pattern can be seen in Fig. 1: AVs enable Anne to perform more activities within the time available to her (attend a swimming pool in the morning, work longer in the evening). Note that Anne’s examples assume time pressure – given the time constraint, she cannot perform all the activities of her wish-list at stationary locations. She needs to choose between the activities, or between full or partial benefit of the activities, since some activities are imperfectly facilitated in the AV, as assumed earlier. In other cases (not modelled here), activities could be better facilitated in an AV compared to a stationary location: for example, some travellers may prefer being isolated for activities that require high concentration, such as work. Such travellers would transfer activities to the AV also in absence of time pressure, and there would be more changes in the time-use patterns, compared to the current example.

Furthermore, notice how the switch to an AV changes Anne’s total utility and total travel time differently in the morning and evening activity plans. The total utility is always increased by adopting an AV, but in the morning this increase is smaller than in the evening. The total travel time is increased in the morning (from 1 h to 1.3 h), but decreased in the evening (from 1 h to 0.5 h).

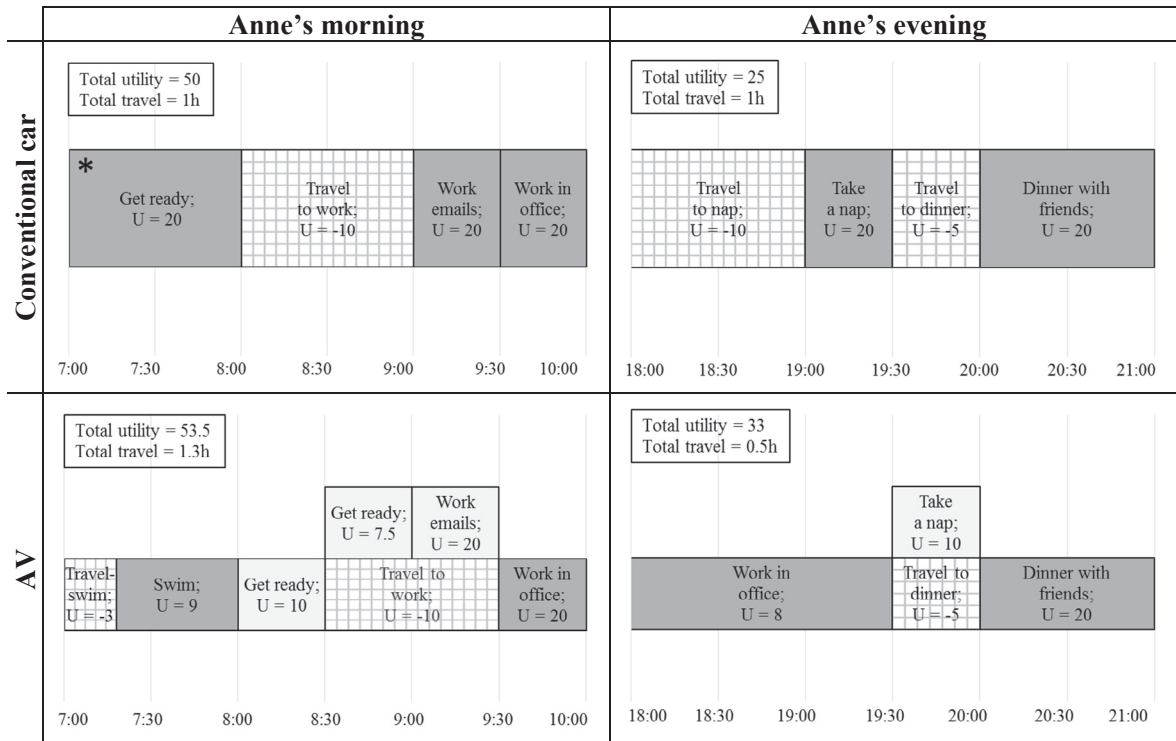
⁶ The mid-day activity is assumed to be work, which is not modelled here (see the example in Section 1).

⁷ In addition to this, one could set the time necessary for an impossible activity-location pair to a positive infinity (large positive number). Still, it is important that the utility of the impossible pair is a large negative number. Otherwise, the optimal solution may assign a small portion of the activity to an impossible location in order to complete the activity (due to constraints (4)).

⁸ Future AVs may also offer novel entertainment options, which could be impossible or unattractive in any other location (similarly as the way in which Pokemon Go recently attracted much pedestrian traffic). Such options can be modelled by assigning a positive utility for the activity on board, but large negative utility for the same activity performed stationary. We thank a reviewer for this remark.

⁹ Note that a restricted version of the model is sufficient to represent Anne’s situation. First, each activity in Anne’s wish-list has a single possible stationary location l . Second, Anne has access to only one travel mode m at a time. Third, she does not mind fragmentation of activities. We therefore use a restricted model to compute results in Anne’s example. In the reduced model, the fragmentation penalty ψ_i is set to 0 for all activities. Fragments of each activity do not need to be counted; therefore constraints (7) and (8) are excluded, and variable y_{ijl}^m is replaced with y_i^m . Then, constraints (3) can and should no longer differentiate between trips, but should only restrict total on-board time as less than total travel time: $\sum_{i \in I} y_i^m T_i^m \leq \sum_{i \in I} z_i^m H_i^m$.

¹⁰ All results are obtained using internal solver ‘intlinprog’ in MATLAB. Computation for our examples takes less than a second.



* The various shading patterns represent different activity types. The dark shading is for stationary, non-transferable activities. The light shading is for transferable activities (in AV scenario). The checked fill is for travel.

Fig. 1. Model predictions for the illustrative example.

This illustration confirms the intuition that changes in time-use patterns may lead not only to an increase in total travel time (as conventionally assumed), but also to a decrease. This depends on traveller’s activity wish-list, time constraints, and possibilities offered by different locations, including on board travel modes. As shown using this simple example, our model is able to capture such effects.

4. Model predictions in an extended example

So far, a single activity wish-list of Anne was used to illustrate our model. Conclusions about individual travel demand were based on the selection of stationary activities with fixed travel times. However, in reality activity locations (with different travel times) can often be chosen and in that way influence travel demand. Possibly, the facilitation level of on-board activities could also be chosen, if, for example, different AVs are available for rental. This would as well influence the selection of on-board and stationary activities, and therefore travel demand.

Therefore, this section builds an extended activity wish-list, which includes several scenarios of different activity distances and facilitation levels of on-board activities. We discuss a wider range of possible adjustments in the activity schedules than before, and we demonstrate how larger and more realistic applications of our model may be built.

In order to create the extended activity wish-list, we first classify activities in types based on their travel requirements and transferability to AVs (Section 4.1). Subsequently, we specify the traveller’s activity wish-list as a combination of the activity types (Section 4.2). Finally, we report and discuss the results of the extended example (Section 4.3).

4.1. Activity types

When considering time-use changes in the AV-era and their effects on travel demand, two characteristics of each activity in the wish-list are important:

1. Can the activity be performed on-board?
2. Does the activity require a designated location (and thereby travel), if no AV is available?

According to these two characteristics, we systematise all possible activity types in four quadrants, see Fig. 2. This classification relates to the insightful analysis of multitasking behaviour by Circella et al. (2012), who created a library of examples for primary and

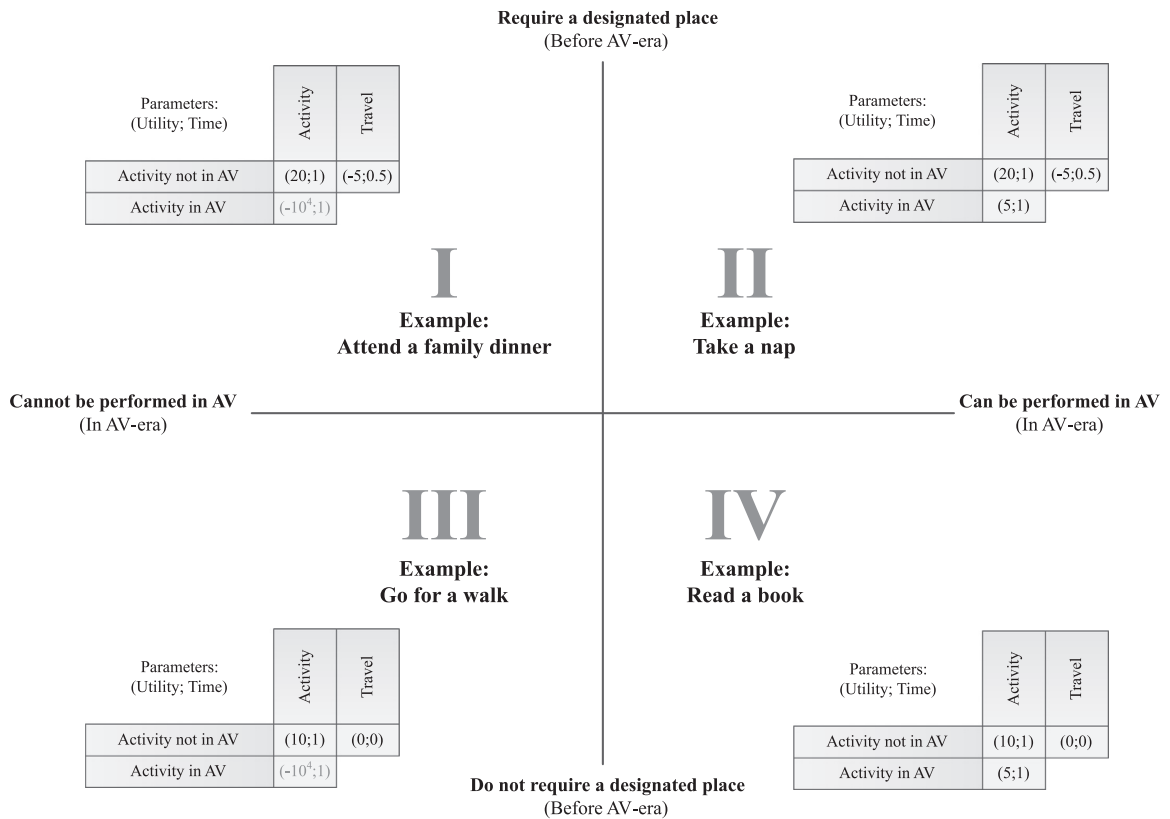


Fig. 2. Activity types.

secondary activities. They noted that work, leisure, shopping and personal care secondary activities are easily combined with travel as a primary activity (as in quadrants II and IV in Fig. 2), whereas travel activities (or activities that involve travel, as in quadrants I and III) can hardly be secondary. In Fig. 2, we illustrate the classification and provide an activity example for each quadrant, as well as a possible representation of it in model parameters.

Considering the rows, the activities in quadrants I and II can be performed only in designated locations. Using a conventional car, these activities would require travel, unless the preceding activity is performed at the same location. The activities in quadrants III and IV do not require a designated location nor travel. Considering the columns, activities in quadrants II and IV can be performed in the AV, because of its enhanced facilitation for specific activities. To some extent, these activities may also be performed in other modes (e.g., one can take a nap in a taxi or train), but likely with more difficulty. Activities in quadrants I and III cannot be performed in AV (nor in other travel modes).

Intuitively, if the traveller transfers type IV activities to the AV, it would save him or her time at other parts of the day. The redeemed time can be used to prolong activities, for additional activities and/or for more travel. In these cases, the total travel time would stay unchanged or increase. However, if the traveller transfers type II activities to the AV, it may save him or her not only time, but also trips. Theoretically, this may reduce the total travel time. Therefore, prevalence of each activity type matters.

4.2. Extended example

We proceed by constructing an activity wish-list (i.e., list of activities desired for a specified time period), considering the activity classification presented above. In order to do that, we need to assume relative frequency for each activity type in the activity wish-list. In Table 2, we indicate the assumptions along with their underlying rationale and their implications. The word ‘quadrant’ is abbreviated with the letter ‘Q’, and the frequency of activities in each quadrant is denoted with the norm sign (e.g., |QI| stands for the number of activities in quadrant I).

The first two assumptions are intuitive, if one adopts a conservative view on the changes in on-board activities that would result from the introduction of AVs. That is, activities of quadrant II are ‘complex’, in the sense that they require a designated place at present. However, they are transferrable to the AV. By specifying only few activities of this type, we conservatively assume that the increase of complex on-board activities will be moderate.

In contrast to the first two assumptions, the last two are driven by pragmatism. Different specifications could have been equally realistic. However, constraining the activities in the given way allows us to most effectively demonstrate the effects of AVs using a small example and a minimum of computation requirements.

Table 2
Assumptions used to create the extended example.

Assumption	Rationale and implications
$ QI > QII $	Rationale: Activities that require a designated place now and continue to require a designated place in the AV-era (QI) will likely outnumber the activities that will cease to require a designated place (will be transferable to AVs, QII). Implications: If more activities of QII were included, it would lead to more activity re-arrangements than in the current example.
$ QIV > QII $	Rationale: Activities that do not require a designated place now nor in the AV-era (QIV) will likely outnumber the activities that require a designated place now but not in the AV-era (QII). Implications: If more activities of QII were included, it would lead to more activity re-arrangements than in the current example.
$ QI > QIV $	Rationale: Activities that involve travel are assumed to be more frequent than activities that do not require travel. However, the opposite is possible, too. Implications: If fewer activities involving travel were included, then there would be less possible variation in total travel times; the effects of AV on travel demand would be less clear.
$ QIII = 0$	Rationale: Activities in QIII are expected to be much less affected by the advent of AVs, because they do not require travel nor can be performed on-board. (They may however be affected indirectly through changes in duration and location of other activities.) We therefore do not include activities of this type in the example. Implications: Including activities of QIII would not bring major changes to the results.

According to these assumptions, we construct the extended activity wish-list, which displays the relative prevalence of activity types (see Table 3: quadrant I – 3 activities; quadrant II – 1 activity; quadrant III – 0 activities; quadrant IV – 2 activities).

Column ‘Activity stationary’ specifies the utility that traveller obtains from engaging in each specified activity at a stationary location. Column ‘Travel to the stationary activity’ sets the travel time to each of the stationary activities that require travel. For activities 2 and 3 (‘meet a friend’ and ‘repair bicycle’), two stationary locations are specified. One stationary location is nearer (0.25 h), but performing activity there is not as rewarding (utility is 20). The other location allows to better perform the activity (e.g., a nicer location to meet, better bicycle repair store, utility is 30), but is located further. Several scenarios are defined for the distance to the better location – from 0.25 h to 2 h with a step of 0.25 h. We simulate the acceptance of further travel given different facilitation levels for on-board activities in the travel mode. The facilitation levels are defined in column ‘Activity on board’:

- (a) ‘No facilitation’ – execution of all activities on board is impossible (this represents the conventional car scenario). For this case, all utility values are specified as -10^4 , ensuring that on-board location is never selected by the traveller;
- (b) ‘Partial facilitation’ – execution of the type II and IV activities on board the AV is possible, but yields only 70% of the utility and requires 140% of the original time for completion, compared to a stationary location (utility values 14, 7 and time value 1.4 h);
- (c) ‘Perfect facilitation’ – execution of type II and IV activities in the AV yields the same utility and requires the same time as when they are performed stationary.

Finally, it is assumed that the intrinsic disutility of travelling is the same in a conventional car and in an AV. Although higher utility is allocated for the activities of quadrants I and II, this is compensated by the need to travel to those activities (mandatory for type I, optional for type II activities). The travel reduces the total utility as well as increases the total time necessary for performing

Table 3
Extended example.

Quadrant and activities	Activity stationary		Travel to the stationary activity		Activity on board		Fragmentation	
	Utility (per activity)	Time (h)	Utility (per h)	Time (h)	Utility (per activity)	Time (h)	Utility (per fragment)	
I	Family dinner	20	1	-10	0.25	-10^4	1	-10
	Meet a friend	20; 30	1	-10	0.25; 0.25 to 2	-10^4	1	-10
	Repair bicycle	20; 30	1	-10	0.25; 0.25 to 2	-10^4	1	-10
II	Take a nap	20	1	-10	0.25	$-10^{4a}/14^b/20^c$	$1^{a,c}/1.4^b$	-5
IV	Watch a movie	10	1	0	0	$-10^{4a}/7^b/10^c$	$1^{a,c}/1.4^b$	-2
	Read a book	10	1	0	0	$-10^{4a}/7^b/10^c$	$1^{a,c}/1.4^b$	-1

Total time constraint: 5 h.

^a No facilitation.

^b Partial facilitation.

^c Perfect facilitation.

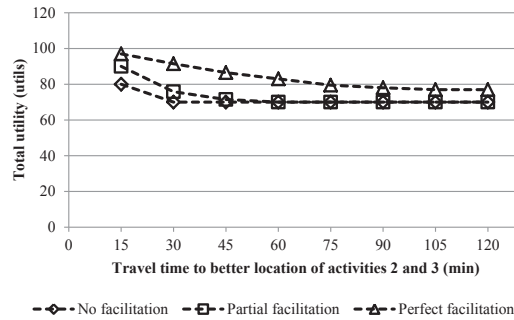


Fig. 3. Total utility depending on travel time to better locations and facilitation scenario.

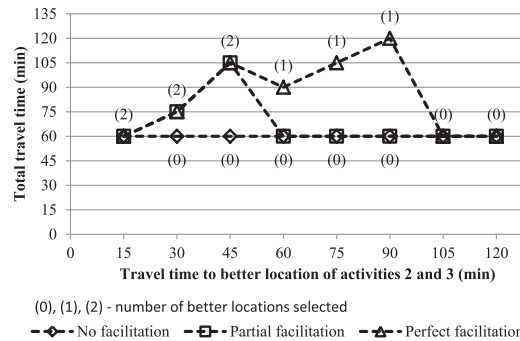


Fig. 4. Total travel time depending on travel time to better locations and facilitation scenario.

the activity. As a result, the total utility per hour of type I and II activities (if type II is performed stationary) is similar to the utility of type II and IV activities (if type II is performed on board).

4.3. Model predictions

We use the constructed activity wish-list to find traveller’s total utility and total travel time¹¹, assuming different travel times needed to reach better locations for activities 2 and 3 and different facilitation levels for on-board activities. The resulting total utilities and total travel times are shown in Figs. 3 and 4, respectively. The travel time scenarios are set on the x-axis. The facilitation level scenarios (no facilitation to perfect facilitation) correspond to different series.

In accordance with intuition, Fig. 3 shows that total utilities increase from the ‘no facilitation’ to ‘perfect facilitation’ scenarios. Furthermore, travellers with longer travel times to the better locations of activities 2 and 3 experience lower total utility, despite the possibility to engage in on-board activities during travel. (The utility is constant, if the better locations are not chosen.) Fig. 4 shows that total travel time tends to increase by acquiring access to an AV, as well as with increasing distance to the better locations (in AV scenarios). Having higher facilitation levels for on-board activities, the further and better location is more likely to be accepted. However, once the travel distance becomes too long, the traveller abandons the better location and the total travel time decreases. This is the case, for example, for the travel times of 45 and 60 min and partial activity facilitation. Fig. 5 shows the selected activities (and their locations) as well as examples of schedules in 45- and 60-min scenarios. The schedule examples demonstrate how it would not be worthwhile to travel to the better location to meet a friend or repair the bicycle, once the travel time to the better location increases from 45 min (top row of Fig. 5, left) to 60 min (top row, right). In order to fit within the 5 h constraint, it would be feasible to extend only one of the trips (e.g., to the repair store). However, if the individual does not extend any trips, then it is possible to schedule the activity ‘nap’ at a stationary location (bottom row in Fig. 5). In this case, the higher utility from the activity ‘nap’, lack of penalties for fragmentation, and shorter total travel time outweighs the benefit of reaching a better location for bicycle repair.

5. Reflections and suggestions for further research

5.1. How our model is positioned in the spectrum between ‘soundness’ and ‘expedience’

Our model can be seen as a move from the state-of-practice (i.e., the travel time penalty approach to model the impact of AVs on

¹¹ We use the full model of Section 2 for computations. The only simplification is the assumption that a single travel mode *m* is available to the traveller in each scenario (however, we vary the characteristics of that mode).

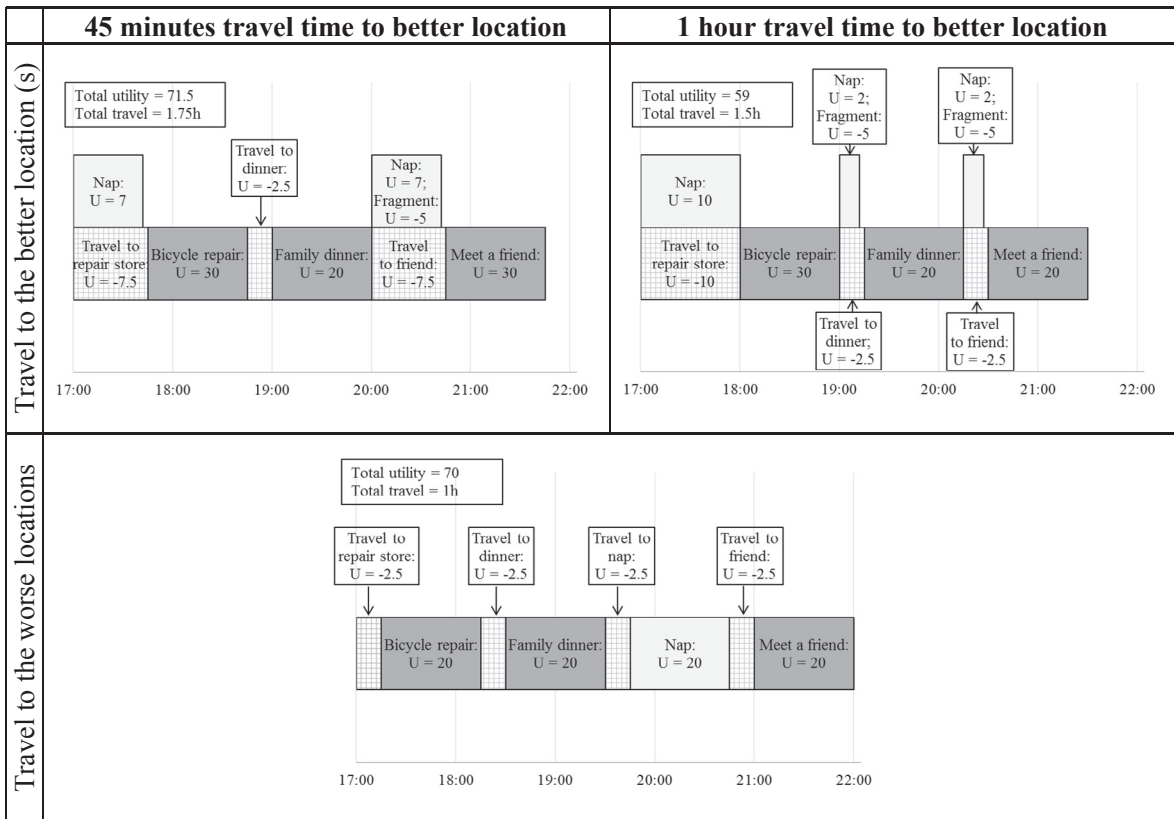


Fig. 5. Schedule examples in partial facilitation scenario. Travel times to the better locations: 45 min and 1 h.

mobility and time-use patterns) towards a more theoretically sound approach of representing travel behaviour in the AV-era. By explicitly modelling on-board activities in a time-use framework, it acknowledges that productive use of on-board time is the result of engaging in activities. Performing on-board activities in future AVs may therefore lead to re-arrangements in activity schedules, many of whom would not be considered or predicted when using the travel time penalty approach.

In more general terms, our contribution can be positioned in the spectrum between what has been called the theoretical soundness and expedience of models (Ortúzar and Willumsen, 2011, p. 26–27). The authors recommend to prioritise soundness over expedience in the choice of models when possible, and to take care that applied models are backed by a theory of travel behaviour.

Although complete theoretical soundness is unachievable, and a balance with expedience is the reality of all travel behaviour models, our view is that the current state-of-practice in modelling on-board activities is leaning too much towards the side of expedience. Possibly even, the travel penalty approach, when used to model on-board activities, might be capturing correlation instead of causation, which is a common shortcoming of models also highlighted by Ortúzar and Willumsen. Specifically, in the current range of available on-board activities, it is possible that more facilitating on-board environments correlate with a reduction in generalised travel costs, which leads to induced travel (this is the basic idea underlying the travel time penalty reduction-approach). However, AVs may offer such a leap in the on-board travel experience that the role of on-board activities (e.g., transferred versus additional on-board activities) becomes an entirely new variable which may substantially alter or even extinguish the correlation between the activity facilitation level and individual travel demand (see the example cited in the Introduction, where the AV in a given context will trigger less, not more, travel).

With our model, we offer a possibility to take a step towards such more theoretically sound approaches while maintaining a reasonable level of tractability ('expedience'). However, we also emphasise that our model is by no means complete in representing all relevant considerations of the traveller in choosing on-board activities and re-arranging schedules accordingly. For example, a choice to transfer an activity from a stationary to an on-board location may also be influenced by activity schedules of family members (e.g., intra-household negotiations and alignments), activity sequence requirements (e.g., ordering effects), and suitable time windows (e.g. closing times of shops); all these aspects are not captured in our model.

Nevertheless, the exclusion of these afore-mentioned considerations in our model is deliberate. Accounting for a full range of relevant attributes would obscure the most important message that we wish to bring across, which is that on-board activities deserve to be explicitly modelled in a time-use framework. This is an important first step towards understanding the impacts of AVs on travel patterns.

5.2. Suggestions for applying our model

Besides the daily activity schedules in the AV-era, which was the context of our discussion so far, our model can (and perhaps should) be used also in other contexts. First, just as our model can predict a preferred activity distance and facilitation level of activities on board the AV (see Section 4.3), it can model the long-term or higher-order choices that influence these variables: residential location and vehicle type choice. Second, our model could be applied to model activity re-arrangements of travellers that (have the option to) switch to public transport or other modes that facilitate complex on-board activities. However, such application may not be as successful and useful as an application to modelling activity schedules in the AV-era; this is explained further below.

Higher-order choices, such as residential (or work) location and vehicle type choice (for purchase or rental), can be modelled using our model. Similar as selecting the best locations for individual activities in Section 4, optimal home (work) locations may be determined (e.g., in a simulation framework that includes a spatial dimension). The most preferred vehicle types may also be obtained, if the facilitation level is known for various activities offered by each vehicle (e.g., there may be AVs with an interior that is adjusted to office or leisure needs). Surely, to capture all subtleties involved in these higher-order choices, it would be necessary to add additional variables, such as costs, neighbourhood, characteristics of the house for the residential location, appearance, energy efficiency, price, and size for the vehicle type choice. Our model can serve as a module in such a more complex simulation framework to predict these higher order choices in the AV-era.

Just as other studies have applied the same tools for modelling the time-use on board AV and public transport (Pawlak et al., 2015, Malokin et al., 2016, Adjenughwure et al., 2018), our model could be applied for studying activity schedules of travellers that (have the option to) switch to public transport (or other modes that allow complex on-board activities). In addition, public transport passengers at present already perform some activities, such as working with a laptop, that are potentially transferred from other parts of the day (Gustafson, 2012, Banerjee and Kanafani, 2008). Therefore, in the current absence of automated vehicles on roads, applying the model to study the time-use of public transport users could help to validate it. However, it should be kept in mind that AVs will likely offer much higher levels of privacy, absence of distractions and presence of high-quality equipment than current travel modes. Furthermore, if the on-board environment in AVs strongly resembles any location of currently stationary activities (e.g., office, bedroom, kitchen), it could trigger more activity transfers (according to the earlier definition) rather than simply add new on-board activities. Therefore, results obtained from applying the model to public transport users (or switchers to public transport) may bear limited resemblance to results of future AV users. In an extreme but not entirely unrealistic case, the activity-transfer effects of public transport users may even not be estimable, or the predictive performance of our model may not improve much on the travel time penalty approach. For this reason, we recommend using a survey, for example, a stated choice experiment, and hypothetical future AV scenarios to calibrate our model. In order to do so, a transition to a stochastic econometric model is necessary. Such transition has previously been performed with conventional and advanced time-use models (Bates, 1987, Pawlak et al., 2015, 2017), which may be used for guidance.

5.3. Suggestions for extending our model

Our model fulfills the core purpose of demonstrating the necessity of explicit consideration of on-board activities to understand travel behaviour in the AV-era. However, we wish to emphasise that the model is not complete (in a sense of capturing all the relevant considerations and constraints). We now list several extensions that would be especially desirable:

1. ‘Classical’ considerations of activity-based models: for example, joint activity planning, ordering effects in activity-sequencing,
2. Possibility to violate constraints (e.g., not complete some activities),
3. Possibility that AVs perform certain tasks without the driver (e.g., pick up groceries, drive to car-wash); this could be included by modelling two time frames – one of the traveller, the other of the AV,
4. Lower levels of automation (i.e., on-board activities allowed only during some parts of the trip),
5. Boundedly rational behaviour in activity and travel choices.

6. Conclusions and policy implications

This paper has presented a modelling framework describing the link between facilitation of on-board activities in AVs and travellers’ time-use and travel behaviour. We argued that the current approaches analysing this link, based mostly on the idea of a reduced travel time penalty, are not sufficient. Most importantly, current approaches struggle to capture the duration of on-board activities and their relationship with activities performed at other parts of the day. As such, current models may lead to biased predictions of travel behaviour in the AV-era, which carries important risks for transport policy making. To address this issue, this paper developed a time-use model which explicitly accounts for possible activity transfers to AVs and the consequences of that transfer (freed time, different travel patterns, etc.). The model was explored using illustrative examples and applied to stylised extended examples. Changes in time-use patterns and their implications on total utility and total travel time were observed and interpreted. The examples demonstrated that the model effectively captures a range of subtle and sometimes unexpected effects (e.g., some activity wish-lists leading to less travel in the AV-era), which have so far been overlooked in literature.

Our model can be used to provide input for answering key AV-related policy questions that are currently high on the agenda of transport policy-makers:

1. what will be the market demand for AVs with different activity-facilitation levels?
2. how will travel demand (kilometres travelled) and travel behaviour (including location-, mode-, route-, and departure time-choices) of AV-users and non-users differ?
3. how should the welfare effects of new transport infrastructure be measured in the AV-era?

Whereas it is fairly easy to see how our model may help policy-makers find answers to the first two of these questions, the third one deserves more detailed discussion. Currently, the notion of Value of Time (VoT) – giving the amount which a representative traveller is willing to pay per unit of travel time savings – is key to the ex-ante evaluation of transport policies (e.g. [Wardman et al., 2016](#)). Such analysis is based on the idea that travellers have innate VoTs, which may differ across, for example, different trip purposes, but are otherwise stable. It is easily seen that this notion is no longer realistic, when one wants to analyse the welfare effects of transport policies (e.g., investments in infrastructure) in the AV-era. Suppose a new highway is built, which significantly lowers the commute time of many travellers. For a traveller who does not use an AV, it is reasonable to use her VoT to monetise the corresponding daily savings in travel time. However, an AV-user might well have been using her travel time very effectively before the transport policy was implemented, for example, by taking a nap to compensate for a very early morning rise. It is a priori unclear how the AV-traveller would value the reduction in daily commute time, as this crucially depends on her optimal time-use pattern before and after the policy is implemented. Perhaps the commute becomes too short for an effective nap after the policy is implemented, triggering an entire re-arrangement of the traveller's daily activity program. In other words, the AV-user's valuation of travel time is influenced by the policy itself (which is a result also of [Kono et al., 2018](#)). Given information about travellers' activity wish-list and activity facilitation level of her AV, our model can provide the difference in utility of AV-user's optimal time-use pattern before and after the policy change. Combined with a parameter measuring the traveller's marginal utility of income (through a proxy, such as a travel cost parameter, which may be obtained from a stated choice experiment), benefits of the policy can then be translated into monetary terms. In sum, while conventional notions such as the VoT will likely struggle to measure welfare effects of transport policies in the AV-era (as they become endogenous to the policy itself), models that explicitly capture time-use on board the AV – such as our model but also the model proposed in [Pawlak et al. \(2015, 2017\)](#) – seem to be better prepared for that task.

In conclusion, this paper has presented a tractable time-use model which enables studying a range of subtle and often overlooked effects on travel behaviour, resulting from the ability to conduct activities on board AV. Calibrating and incorporating the model into larger simulation frameworks will allow the researchers and policy makers to better anticipate long term, wider effects of the introduction of AVs, such as congestion, urban sprawl and environmental impacts.

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