Time Use and Travel Behaviour with Automated Vehicles

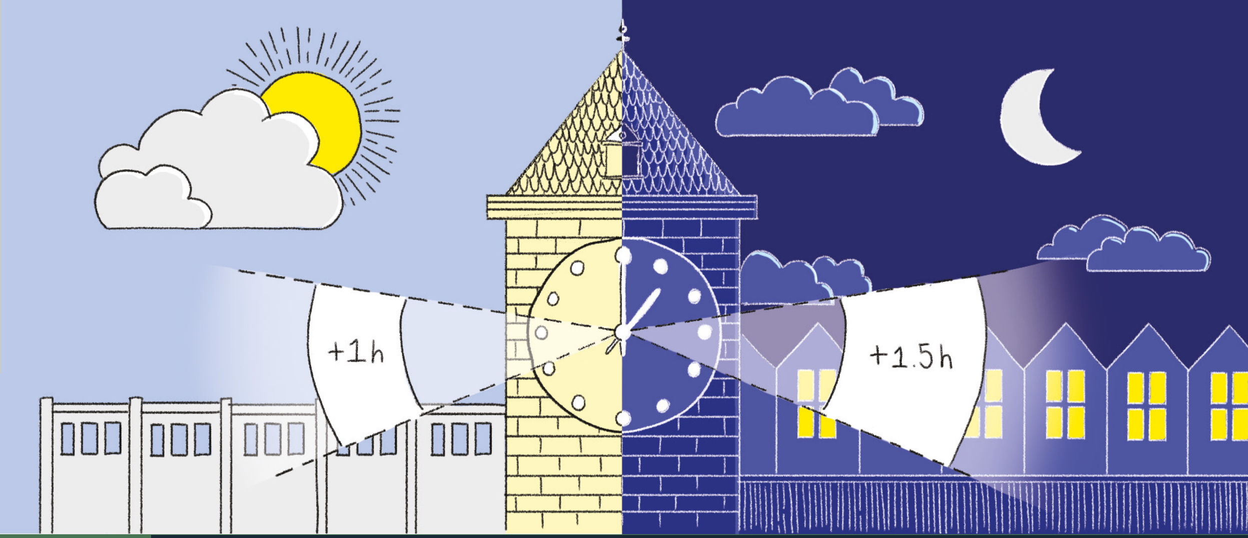
Pudane, B.

DOI
10.4233/uuid:98eb22bf-6d0b-4cfb-8bd2-b3f0d316e316

Publication date
2021

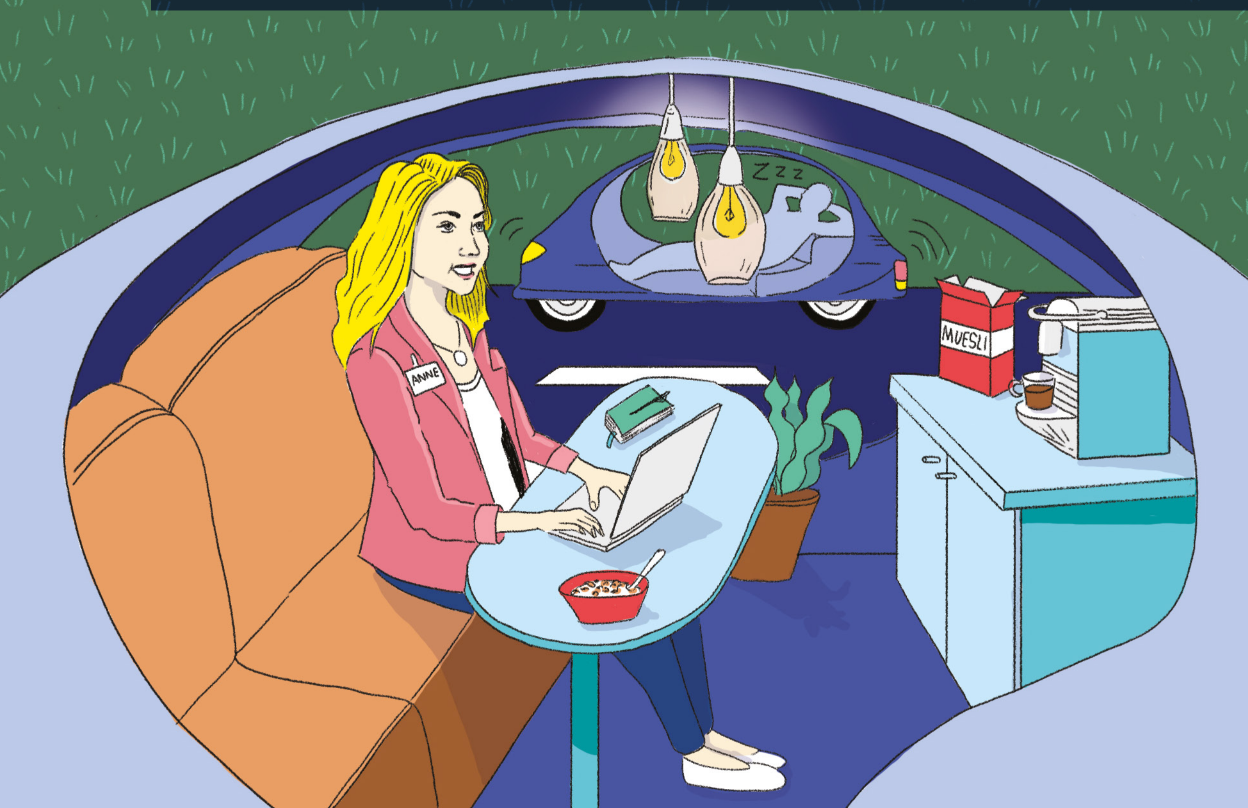
Document Version
Final published version

Citation (APA)
Pudane, B. (2021). *Time Use and Travel Behaviour with Automated Vehicles*. [Dissertation (TU Delft), Delft University of Technology]. TRAIL Research School on Transport, Infrastructure and Logistics. https://doi.org/10.4233/uuid:98eb22bf-6d0b-4cfb-8bd2-b3f0d316e316



Time Use and Travel Behaviour with Automated Vehicles

Baiba Pudāne



Time Use and Travel Behaviour with Automated Vehicles

Baiba Pudāne

Delft University of Technology

This research was funded as part of the project Spatial and Transport impacts of Automated Driving (STAD) by the Netherlands Organization for Scientific Research (NWO) under contract 438-15-161.

NWO

Spatial and Transport Impacts of Automated Driving

Time Use and Travel Behaviour with Automated Vehicles

Proefschrift

ter verkrijging van de graad van doctor
aan de Technische Universiteit Delft,
op gezag van de Rector Magnificus Prof.dr.ir. T.H.J.J. van der Hagen,
voorzitter van het College voor Promoties,
in het openbaar te verdedigen op maandag 12 juli 2021 om 15:00 uur

door

Baiba PUDĀNE
Master of Science in Transport and Logistics,
Technische Universität München, Duitsland
geboren te Ogre, Letland.

Dit proefschrift is goedgekeurd door de:
promotor: Prof.dr.ir. C.G. Chorus
copromotor: Dr.ir. S. van Cranenburgh

Samenstelling van de promotiecommissie:

Rector Magnificus	voorzitter
Prof.dr.ir. C.G. Chorus	Technische Universiteit Delft, promotor
Dr.ir. S. van Cranenburgh	Technische Universiteit Delft, copromotor

Onafhankelijke leden:

Prof.dr. G.P. van Wee	Technische Universiteit Delft
Prof.dr. B. van Arem	Technische Universiteit Delft
Prof.dr. P.L. Mokhtarian	Georgia Institute of Technology, Verenigde Staten
Prof.dr. E.T. Verhoef	Vrije Universiteit Amsterdam
Prof.dr. K.W. Axhausen	Eidgenössische Technische Hochschule Zürich, Zwitserland

TRAIL Thesis Series no. T2021/21, the Netherlands Research School TRAIL

TRAIL
P.O. Box 5017
2600 GA Delft
The Netherlands
E-mail: info@rsTRAIL.nl

ISBN: 978-90-5584-296-4

Cover design by Amy-Jean Hahndiek, hahndiekcreative.nl

Printed in the Netherlands

Preface

This book concludes a very fulfilling four and a half years of doctoral study. For this, I am indebted to many, but first and foremost – to my promotor Caspar Chorus and daily supervisor Sander van Cranenburgh. Caspar – from start to the end, it has been a great privilege to be your student. From your broad scientific knowledge to your creativity and ability to draw parallels between different fields, to your wisdom in managing scholarly life, to your philosophy of research and education – I have learnt a whole heap in all these areas from you. Thank you for believing in my abilities and for your encouragement. And your positive energy and enthusiasm – they are contagious. Sander – I learned so much from you in the choice modelling field. Not only our battling with the wicked problem of estimating whole-day activity-travel models, but also our discussions about the seminal papers helped me to find my way around and grow in this field. Next to that, your very sharp look at every written word, your mentorship in my daily research management, and advice in learning to live in an academic world have been invaluable.

During my first PhD years, I received much valued guidance from Eric Molin and Theo Arentze. Eric – thank you for helping me get started on my PhD journey. The project definitely benefited from your inputs, not least of which the idea to conduct a focus group study – whose results inspired several later chapters of this thesis. Theo – thank you for our discussions in the first years as well. They helped me to appreciate the very complex world of daily activity modelling. I would furthermore like to thank all the teachers of the TUD and TPM Graduate Schools and TRAIL research school for the valuable courses. I am especially grateful to Sören Johnson and Veronica Alfano, who helped me to step up my English writing skills. To Heide Lukosch: thank you very much for your caring mentorship.

Thanks to my committee members who agreed to review my thesis despite not being able to enjoy the travel to the beautiful city of Delft and social events. Thanks to the wide academic community: to all the (anonymous) reviewers and editors, who provided very helpful feedback for the papers published in this thesis, and conference organisers and participants for many inspiring events. Thank you, Mogens Fosgerau, for welcoming me on a short visit in Copenhagen. Thank you to everyone who was involved in the data collection for this thesis: to

participants, including the TU Delft volunteers for the first focus group and TLO and ESS colleagues who tested the activity-travel survey; to Thijs Groen (Bureau Fris) and Martin Schalkwijk (Kantar TNS) for the organisation; to student assistants Dion Munsters and Otis van der Meij for data processing. Special thanks to Bas Dado and Olivier Hokke from Game Tailors for patiently designing and redesigning: not only the survey instrument, but also my research idea took shape in discussions with you. Thank you to my MSc students Michał Rataj, Fatima-Zahra Debbaghi, Floris Hooft and BSc student group – I learnt from your fresh perspectives!

My appreciation goes to NWO, who funded this research through the project STAD. Thank you, Bart van Arem, for setting up and leading this project with great dedication. I enjoyed the stimulating interactions with consortium partners, of whom I would like to mention especially Luc Wismans, Klaas Friso, Kobus Zantema, Paul van Beek (Goudappel Coffeng) and Taede Tillema (KiM). To my fellow STAD researchers Anirudh, Bahman, Francis, Jeroen, Pablo, Reanne: I learnt a lot from your varied expertise on different facets of AVs. And our dinners after consortium meetings and other get-togethers – I will miss those!

To my TLO colleagues – time after time I have been impressed by the expertise, creativity and openness of this group, and am extremely happy to continue my research path with all of you. Thank you, Bert van Wee, for your interest in my work and our discussions, and for being the first to suggest that I apply for the tenure track position, which I thought impossible at the time. Maarten Kroesen and Niek Mouter – I have been inspired by your research and enjoyed our discussions a lot. Yousef Maknoon, thank you for taking your time to guide me in the operations research world. Thank you, Natalia Barbour, for your encourgamanet in my last PhD steps; I look forward to having lots of fun teaching together with you. Thank you, Betty, Ellen, Esther and Conchita, for your friendly responsiveness to any organisational questions and confusions, and for tolerating my attempts to communicate them in Dutch. Conchita, thank you also for your help with the printing process of this book. Amy-Jean, thank you for the wonderful cover design.

Thank you, my fellow PhDs of the corner office – Ahmad, Ignacio, Wenhua, Shahrzad, Bing, Steven, Hong, Lucky (Fuqi), Mehrnaz, Kailan, Patrick, Rick, Sander, Mahsa and others throughout the years – we shared not only many lovely coffee breaks, but also good and bad news, excitements and anxieties. To my fellow book club members, dear readers: Ahmad, Tom, Teodora, Tanzhe, Lucky, Shahrzad, Nicolas, Ignacio, Kartika, Bing, Matthew and Samantha – thank you for your enthusiasm and commitment; our discussions were delightful and enlightening. Special thanks to my walking buddy María José. Our daily walks helped me keep my sanity in tough times, and it is not only thanks to the fresh air! I am very happy to have gained a dear friend during this PhD journey.

To my Latvian family: mam, tēt, omīt (ja Tu šo lasītu), opīt – tikai ar jūsu atbalstu manā izglītības ceļā es spēju nokļūt līdz šai doktorantūras vietai, paldies. Lindiņ un Urzuliņ – mūsu draudzība cauri gadu desmitiem un par spīti attālumam man nozīmē ļoti daudz. To my Malaysian family: thank you for accepting me in the family with open arms and for your support and love in everything. To my darling Dagne, your sweetest smiles helped mama round up the last mile of this work. Some day you will read this, and, who knows, you may want to continue the doctorate line in the family (but know this: we will support you in wherever your talent and interest will lie)! The final words go to my husband Tharsis: thank you for the many hours of formatting, and for all the dinners that you made during my late work evenings, and for critically and patiently listening to many half-baked research ideas regardless of the clock. Thank you for believing in me and cheering me up until the end, and for your enduring support and love.

Baiba Pudāne
Pijnacker, June 2021

Content

1 Introduction

1.1 Background and problem statements

Automated vehicles (AVs) have been a dream for a long time. In the earliest days, the genre of this dream was clearly science fiction. In his ‘Wonder Stories’ (1935) David H. Keller describes ‘The Living Machine’:

> *Old people began to cross the continent in their own cars. Young people found the driverless car admirable for petting. The blind for the first time were safe. Parents found they could more safely send their children to school in the new car than in the old cars with a chauffeur.*
> *(Keller, 1935, as cited in Weber, 2014)*

In the same years, Bel Geddes envisioned automated highways in his Futurama ride at the New York World's Fair (1939), and Saturday Evening Post published the iconic drawing in which a family plays board games while being ‘driven by the electricity’ (1950s). We are approaching a century since these first visions, and the AVs have been filling news’ headlines with announcements of test cases and first on-the-market experiences for the last few years. It is clearly no longer science fiction. However, also the high expectations of full automation seem to be lowered. Until recently, researchers and practitioners believed that full automation will eradicate the number one cause of fatalities in traffic: human error (e.g., Fagnant & Kockelman, 2015). At present, more research and engineering show that the full and faultless AVs are quite far ahead (if not far-fetched). And, tragically, a number of deadly accidents in the recent years revealed that the users of the current partially automated vehicles, possibly influenced by the marketing overstatements of the vehicles’ capabilities, had placed too much trust in the technology (Dixon, 2020).

At the time of writing this thesis, the dream of substantial safety gains with automation still lives. But the literature now also discusses several more down-to-earth, but nevertheless important benefits of AVs. These include productivity and well-being gains because AV users would expend less energy on travel (Cyganski et al., 2015; Zmud et al., 2016; Correia et al., 2019; Singleton, 2019) and would be able to perform non-driving activities during it (Malokin et al., 2019; Wadud & Huda, 2019; Kolarova, 2020). For cities, AVs provide opportunities to re-design central areas by moving parking to the outskirts (Zhang & Guhathakurta, 2017; Duarte & Ratti, 2018; González-González et al., 2020) and to enhance public transport systems by supplementing or replacing it with smaller AV services (Alonso-González et al., 2018; Fielbaum, 2019; Tirachini & Antoniou, 2020). Considering traffic flow, they promise environmental gains thanks to reduced stop-and-go traffic (Talebpour & Mahmassani, 2016; Stern et al., 2018; Wu et al., 2018) and adopted eco-driving as the default mode (Jiang et al., 2017; Ma et al., 2021). Last but not least, AVs can improve accessibility and social inclusion of underserved traveller groups, such as the very young or old, people with low income or disabilities, and those living in remote areas (Harper et al., 2016; Das et al., 2017; Faber & Lierop, 2020; Milakis & van Wee, 2020). Clements and Kockelman (2017) conclude that benefits and losses for 13 industries (such as freight transportation, insurance, land development, electronics and software technology) due to automated vehicles result in net gains for the US economy in the magnitude of 1.2 trillion dollars.

With these numerous benefits, the pursuit of AV technology is clearly worthwhile, and so is the interest of policy makers in it. Several countries have included AV development among their top transport goals, and KPMG has pitched them against each other 'in the race for autonomous vehicles' by issuing a yearly Autonomous Vehicles Readiness Index (KPMG, 2020). The Netherlands was in the high second position in year 2020 (following Singapore, and was leading the ranking two years prior) thanks to the many electric vehicle charging stations and expanding smart road infrastructure. Crucially, the Netherlands (as well as other countries in the top of the KPMG ranking) allow AV testing on public roads. Since 2019, AVs in these tests do not need to carry a driver and may instead be monitored only remotely (Government of the Netherlands, 2019). On the EU level, countries have committed to cooperate in cross-border AV tests and demonstrations (Government of the Netherlands, 2016), and a 2030 vision by the European Commission include a milestone of automated mobility being deployed at large scale (European Commission, 2020).

Along with this strong interest in AVs also comes the need to comprehensively assess the implications of an AV future. This task is inherently difficult, since there are unknowns surrounding the technological development (e.g., balance between automation and connectivity, level of automation, timeline of development) as well as the travel behaviour of future AV users (and non-users). Insights in both of these areas are needed to assess the first-order (e.g., capacity, congestion, vehicle use), second-order (e.g., vehicle design, vehicle ownership, residential location), and eventually the third-order (e.g., energy consumption, safety, economy) impacts of AVs (Milakis et al., 2017). Elaborating further on travel behaviour, letting go of the steering wheel can result in more complex behaviour changes than may be initially expected. First of all, AV users may perform non-driving activities, thus saving time in the day, as well as possibly energy from often tiresome driving tasks – which could let them accomplish more and, in some cases, reorganise their daily schedules (Mokhtarian, 2018). For example, if travellers may perform work tasks during commute, then that could decrease the time they spend at work, and increase time spent – and potentially, trips made – for leisure. In other instances, a traveller may be able to skip a detour to home, if a certain activity (such as getting ready, preparing a simple meal, etc.) is possible during travel. A further major change for current drivers could be the possibility to let AVs park themselves – parking availability may no longer discourage from visiting busy urban destinations and events –, and AVs could also stimulate urban nightlife (Cohen & Hopkins, 2019). In addition, long-distance travel at night may become more attractive, if sleeping is possible in an AV (LaMondia et al., 2016). And people may start using AVs as personal robots for pick-up and delivery tasks, resulting in less trip-chaining (Harb et al., 2018). The list of possible complex behaviour shifts by current car drivers does not end here. Nonetheless, the list may be even longer for those who may become new car users with the introduction of AVs.

Given such complex new opportunities, policy makers need to answer questions about aggregate travel patterns: how could the travel demand and congestion patterns change? How will these cars use the existing transport infrastructure, and is there a need for expansion in specific areas? What will be the demand for public transport services, and will active travel be impacted? How will the travellers' needs and desires for housing change, and what could be the resulting evolution of cities? Or, to put it more urgently (since deterioration of the status quo is usually seen as more painful than even substantial gains): will there be negative side-effects of a wide-scale AV introduction – for example, worsening of congestion or urban sprawl, or negative impacts on public health and well-being?

The links between the individual behaviour and aggregate travel patterns are traditionally the area of travel behaviour models, which are part of (large-scale) transport models. These models have so far been developed, successfully applied and fine-tuned for predicting travel patterns with the current, non-AV travel modes. The question that needs to be answered before applying them for AVs is: can they reliably describe the travel behaviour of AVs? This PhD is, for the largest part, inspired by my conviction that the answer to this question is 'no'. There are aspects of travel experience that will likely be very prominent in AVs, but are marginal to non-existent in the current modes.

In particular, as the name of this thesis gives away, I argue that a crucial missing piece in the travel behaviour models is the time-use dimension, and especially the effects of time-use in AVs on daily time-use. In this regard, the current models most often assume that on-board activities lower the so-called travel time penalty or the value of travel time (depending on whether the model is used for prediction or evaluation).

Within the prediction framework, the lower the travel time penalty, the lower the resistance of travellers to long travel times. Inevitably, these models predict more person-travel with AVs. Comparing this representation with the new opportunities of AVs described few paragraphs above, the reader can see that this reasoning constitutes a dramatic reduction in the dimensionality of on-board activities. By condensing all activities into a single travel time penalty indicator, the analyst is forced to consider only one way in which on-board activities may influence travel behaviour: by making longer travel times less inconvenient. Given that the role and diversity of on-board activities will likely increase in the AV future, this limitation of current transport models can result in not only imprecise, but also biased predictions for the future travel behaviour.

Within the evaluation framework, lower value of travel time in AVs leads to the argument that economic gains from travelling in AV, and not in a conventional vehicle, are proportional to the travel time. However, considering that activities (stationary and on-board ones) often require a certain minimum time window, the benefits may not accrue gradually, but rather step-wise. For the same reason also, the gains from saving travel time may in fact be dependent on the initial travel time and the travellers' activities on board, and certain combinations in these factors may even lead to losses from travel time reduction.

To summarise the above argument, two problem statements can be proposed to illustrate the scientific and policy problem.

- Scientific problem. The current travel behaviour and transport models assume identical time-use implications of varied on-board activities. This could lead to biased travel behaviour predictions and estimates of AV benefits.
- Policy problem. With the current modelling tools being potentially misaligned with future travel behaviour, policy makers are left with unreliable tools for predicting transport system performance and assessing transport investments for the AV era. This

could lead to poor transport policy decisions, wasteful investments, and detrimental impacts to society.

1.2 Research aims

Given the misalignment between travel behaviour and time-use models and the conceivable behaviour of future AV users, the main aims of this thesis are as follows:

- to obtain and analyse data on the travellers' expectations of their future time use and travel behaviour with AVs, and to identify aspects that are not well represented in the current time-use and travel behaviour models;
- to use the insights from the analysis to build and update models describing time use and travel behaviour in the AV era;
- to use the updated models to obtain insights into aggregate travel patterns.

To specify the second aim, three models from the wide assortment of time-use and travel behaviour models are selected in this thesis. First, a new daily time-use model is proposed, which allows overlap between activities and travel. Second, a time-use module is incorporated in a departure time choice model. Third, a model used to theoretically derive the value of travel time is revised to more generally capture the time-use effect of on-board activities. To specify the third aim, the updated departure time choice model is used to predict congestion forming in a basic bottleneck setting.

1.3 Research approach

This thesis adopts several methodological perspectives and contributes to several modelling disciplines. This diversity is quite natural, given that, as explained above, the thesis aims to update several modelling tools and to do so based on empirical insight.

For the empirical works, the thesis contains both a qualitative and a quantitative study, enabling the study of travellers' expectations both in depth, as well as in breadth. In the qualitative study, focus groups were conducted to gain deep insights into travellers' expected changes in their daily schedules in the AV era. In the quantitative study, current and expected activity-travel diaries were collected using an interactive online tool. Both data sets have been published (see the list of publications).

For the theoretical works, the thesis contributes to several disciplines: daily time-use modelling, congestion modelling based on scheduling preferences, and the theoretical analysis of the value of travel time. Common in these studies, as well as in the empirical analysis of the activity-travel diary data is the microeconomic utility-maximisation perspective. That is, all these contributions are based on the idea that individuals are fully rational and, in planning their daily schedules, optimise their activity selection and timing to gain the highest utility. This perspective is a useful starting point, since most models in the travel behaviour research arena and definitely in policy practice are based on this paradigm. As such, it is worthwhile to see how much flexibility and behavioural realism can be gained by including time-use aspects of on-board activities in the models within this framework. Nevertheless, the author believes that future work on travel behaviour and especially time-use with AVs should venture outside of this framework. This conviction is partly based on several prominent insights from the focus group study, where the participants occasionally argued about their choices in ways that clearly go beyond the utility-maximisation framework: mentioning, for example, the role of habit and satisfaction with current daily schedules, and choice-set dependency and social pressure in needing to work in AV, even if they would not want to do so.

1.4 Scope

Before explaining the content contributions of each of the following chapters, it should be mentioned that two content assumptions were made in analysing and modelling the time use and travel behaviour in all chapters.

First, it was assumed that AVs are fully automated – level 5, according to the SAE (2018) standards. This is notwithstanding the fact that, as mentioned in the beginning of this chapter, the dream of full automation has moved away from the spotlight, giving place to more realistic goals of partial (i.e., up to level 3) or high (i.e., level 4) automation. However, considering lower automation levels would pose a question – in what way will the automation be partial? Even within the often used SAE levels of automation, there are many possible configurations. Automated on freeways, but not in the cities? Partial automation, where the driver is still in charge? These variations would impact the available activities during travel, and the time periods when they are available (e.g., maybe the activities would need to be fragmented, if the AV moves in and out of the 'operational design domains' – this would exclude activities such as sleep). Accounting for such conditions would add a thick layer of complexity in the models, and prevent obtaining any closed form results.

In addition, considering any specific AV configuration would mean to commit to one or few variants of AV design, and subject the results to risk of getting outdated, if a more fine-tuned AV image turns out to be false. Therefore, the models in this thesis favoured the simpler and more general assumption of full automation. In the empirical works, likewise, the participants were instructed to imagine fully automated vehicles. The difficulty of picturing schedules with AVs was deemed to be high enough, and it was preferred to avoid the discussion about, for example, divided attention and difficulty of taking over control.

Second, the empirical studies asked the participants to reimagine their current days with an AV, not their future schedules. Similarly as with automation levels, it is unclear how far in the future these automation levels will be reached. And furthermore, imagining ones lives decades later would be a difficult task, filled with uncertainty, even without AV presence.

1.5 Thesis structure and contributions

Figure 1-1 illustrates the structure of the thesis. The sequence of the chapters follows the first two of the three aims as explained before. The third aim is (briefly) addressed in chapter 5 and hence is not reflected in the diagram.

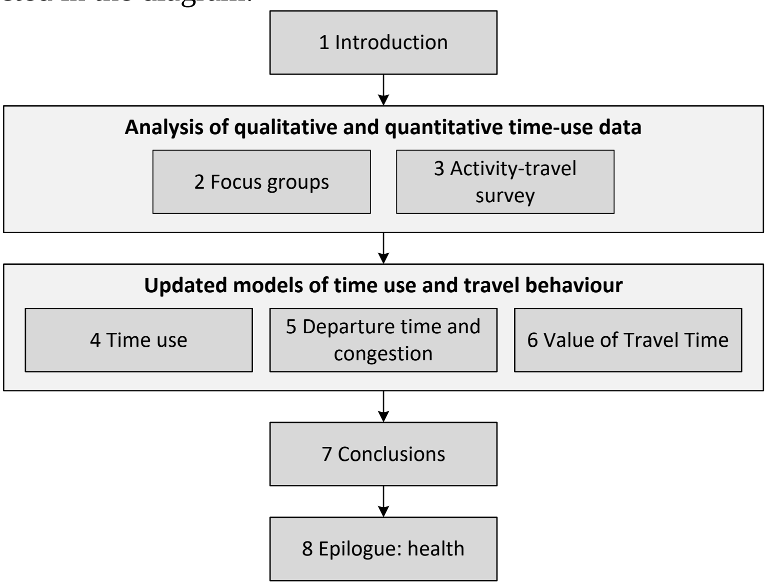


Figure 1-1 Structure of this thesis

Chapter 2: How will automated vehicles shape users′ daily activities? Insights from focus groups with commuters in the Netherlands.

This chapter begins to explore the largely unknown terrain of the travel behaviour and daily activity effects of automated vehicles. It uses qualitative focus group interviews and finds various reactions to the possibility to perform new activities in automated vehicles: some travellers would change their current on-board activities while others would not; some would engage in substantial high-priority activities while others would rather perform optional or background-type activities, such as leisure and relaxing. Consequently, automated vehicles can be expected to have different impacts on travel satisfaction, daily activity schedules, travel amount and daily time pressure for different individuals. These insights pave the way for travel behaviour models developed in the later chapters of this thesis.

Chapter 3: A Day in the Life with an Automated Vehicle: Empirical Analysis of Data from an Interactive Stated Activity-Travel Survey

Like the previous chapter, this study considers the impact of automated vehicles on daily activity schedules. Unlike the previous analysis, however, this chapter is based on quantitative data from a medium-large online sample (n = 509), which allows to generalise some key findings. Respondents were asked to record their current activity schedules using an interactive stated activity-travel diary, and then adjust them or design new schedules, while imagining that automated vehicles are available for their trips. The AV impacts on on-board and stationary activities are analysed using the multiple discrete-continuous extreme value framework. Results show that, while a considerable share of participants did not indicate any changes in their activities, AVs lead to more on-board activities in the aggregate. The overall impacts on stationary activities are negligible, but present in a few socio-demographic groups, which allows a discussion on potential time-saving effects in these groups, in line with the expectations from the previous chapter.

Chapter 4: A Time-use Model for the Automated Vehicle Era

While the previous two chapters described, based on two sets of data, how on-board and, importantly, also stationary activities may change with automated vehicles, this chapter argues that this influence may not be peculiar to these data, but could in fact be expected from economic agents. It develops this argument by formulating a microeconomic time-use model, which considers the possibility of using travel time for other activities. It demonstrates how this possibility can save time for individuals and allow them to perform more activities during a day. It also shows that on-board activities can lead to more or less daily travel in different scenarios. Thereby, this chapter provides an alternative to the pervasive travel time penalty approach, which condenses the effects of any on-board activities into a single indicator and typically predicts only such changes in daily time-use that result from further destinations or more frequent trips becoming more attractive with AVs.

Chapter 5: Departure Time Choice and Bottleneck Congestion with Automated Vehicles: Role of On-board Activities

Comprehensive time-use models, such as the one presented in the previous chapter, are known to be difficult to estimate, and even more difficult to integrate with models of other transport system components, such as traffic congestion. Hence, the modelling practice often treats the travel behaviour choices as relatively isolated from the entire daily activity pattern, for example, by considering only the origin and destination activities of every trip. Nevertheless, this chapter shows that also such models can – and should – account for the time-use effects of on-board activities. Considering congestion forming due to morning commute travel, this chapter demonstrates, first, how on-board activities can influence departure time choice. Performing home-type activities during travel would lead rational individuals to depart to work earlier, while work-type activities would make later departures more attractive. Second, it uses a basic bottleneck setting (i.e., travellers commuting from a single origin to a single destination using a single route and forming a queue, because their number exceeds the capacity at a bottleneck point) to analyse changes in congestion patterns that result from these on-board activities. It becomes clear that the enhanced activities in automated vehicles will lead to more intense congestion. However, the shape of congestion is influenced by the type of on-board activities, of which work activities lead to the least dramatic increase.

Chapter 6: On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey – A comment

Unlike the largest part of this thesis that focuses on travel behaviour prediction, this chapter turns to the evaluation framework and the most important tool used therein – the value of travel time. Since the theoretical foundation of the value of travel time is the classical microeconomic time-use framework, it is possible to modify the framework to account for AV specifics and, consequently, to theoretically derive the value of travel time with AVs. Correia et al. (2019) followed this path and derived the value of travel time in automated vehicles, while assuming that travel time doubles as either work or leisure time. This chapter highlights an implicit assumption in their theoretical conclusions and also offers an extended version of the model. Finally, it concludes the main part of this thesis with a mathematical and intuitive observation: if our current travel experience can be decomposed into, first, an intrinsic liking (or disliking) of travel and, second, the loss of time that could be used for other activities, then automated vehicles can be expected to ‘give back’ the latter to future travellers.

Chapter 7: Conclusions and reflection

This chapter summarises the work that has been done to fulfil the research aims outlined earlier: to empirically investigate the potential gap between the expected travel and time-use behaviour and the models that represent it, to update and build models time-use and travel behaviour models that could help to narrow this gap, and to gain first insights into the aggregate travel patterns that result from the updated models. The chapter further summarises and reflects on the applicability of the current modelling tools – the travel time penalty and the value of travel time. Finally, it suggests some directions for further research and discusses how the insights from this work could be applied in policy settings and how they relate to some current policy considerations regarding the introduction of AVs.

Chapter 8 – Epilogue: Potential health and well-being implications of autonomous vehicles

This chapter discusses health and well-being effects of AVs. My main contribution to this chapter is the discussion on the potential AV effects on travel behaviour (section 3 in the chapter). Two aspects of the behaviour are deemed crucial for the health and well-being discussion: the amount of individual travel and the travel mode choice. With regard to the former, this section discusses various ways how individual travel amount may change, but not necessarily increase. With regard to the latter, it argues that shared and pooled AVs may draw their users from (relatively) sustainable travel modes, such as public transport, active modes, and conventional car sharing. This idea is grounded in literature and in the concept of substitutability among travel options, and is captured in a conceptual map. The consequence of such modal shifts would be more vehicle-travel, even assuming the same amount of person-travel – an outcome that should clearly be a concern in the health and well-being discussion.

References

Alonso-González, M. J., Liu, T., Cats, O., Van Oort, N., & Hoogendoorn, S. (2018). The potential of demand-responsive transport as a complement to public transport: An assessment framework and an empirical evaluation. Transportation Research Record, 2672(8), 879-889. https://doi.org/10.1177/0361198118790842

Bel Geddes, Norman (1939). Futurama. An exhibit at New York World's Fair. Sponsored by General Motors.

Clements, L. M., & Kockelman, K. M. (2017). Economic effects of automated vehicles. Transportation Research Record, 2606(1), 106-114. https://doi.org/10.3141/2606-14

Cohen, S. A., & Hopkins, D. (2019). Autonomous vehicles and the future of urban tourism. Annals of Tourism Research, 74, 33-42. https://doi.org/10.1016/j.annals.2018.10.009

Correia, G., Looff, E., van Cranenburgh, S., Snelder, M., & van Arem, B. (2019). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. Transportation Research Part A: Policy and Practice, 119, 359-382. https://doi.org/10.1016/j.tra.2018.11.016

Cyganski, R., Fraedrich, E., & Lenz, B. (2015). Travel-time valuation for automated driving: A use-case-driven study. In Proceedings of the 94th Annual Meeting of the TRB.

Das, S., Sekar, A., Chen, R., Kim, H. C., Wallington, T. J., & Williams, E. (2017). Impacts of autonomous vehicles on consumers time-use patterns. Challenges, 8(2), 32. https://doi.org/10.3390/challe8020032

Dixon, L. (2020). Autonowashing: the greenwashing of vehicle automation. Transportation research interdisciplinary perspectives, 5, 100113. http://dx.doi.org/10.1016/j.trip.2020.100113

Duarte, F., & Ratti, C. (2018). The impact of autonomous vehicles on cities: A review. Journal of Urban Technology, 25(4), 3-18. https://doi.org/10.1080/10630732.2018.1493883

European Commission (2020, 9 December). A fundamental transport transformation: Commission presents its plan for green, smart and affordable mobility. https://ec.europa.eu/transport/themes/mobilitystrategy_en (accessed on 6th March, 2021)

Faber, K., & van Lierop, D. (2020). How will older adults use automated vehicles? Assessing the role of AVs in overcoming perceived mobility barriers. Transportation research part A: policy and practice, 133, 353-363. https://doi.org/10.1016/j.tra.2020.01.022

Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transportation Research Part A: Policy and Practice, 77, 167-181. https://doi.org/10.1016/j.tra.2015.04.003

Fielbaum, A. (2019). Strategic public transport design using autonomous vehicles and other new technologies. International Journal of Intelligent Transportation Systems Research, 1-9. https://doi.org/10.1007/s13177-019-00190-5

González-González, E., Nogués, S., & Stead, D. (2020). Parking futures: Preparing European cities for the advent of automated vehicles. Land Use Policy, 91, 104010. https://doi.org/10.1016/j.landusepol.2019.05.029

Government of the Netherlands (2016, 29 April). Declaration of Amsterdam "Cooperation in the field of connected and automated driving". https://www.rijksoverheid.nl/documenten/rapporten/2016/04/29/declaration-of-amsterdam-cooperation-in-the-field-of-connected-and-automated-driving (accessed on 6th March, 2021)

Government of the Netherlands (2019, 2 July). Green light for Experimental Law for testing self-driving vehicles on public roads. https://www.government.nl/latest/news/2019/07/02/green-light-for-experimental-law-for-testing-self-driving-vehicles-on-public-roads (accessed on 6th March, 2021)

Harb, M., Xiao, Y., Circella, G., Mokhtarian, P. L., & Walker, J. L. (2018). Projecting travelers into a world of self-driving vehicles: estimating travel behavior implications via a naturalistic experiment. Transportation, 45(6), 1671-1685. https://doi.org/10.1007/s11116-018-9937-9

Harper, C. D., Hendrickson, C. T., Mangones, S., & Samaras, C. (2016). Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. Transportation research part C: emerging technologies, 72, 1-9. https://doi.org/10.1016/j.trc.2016.09.003

Jiang, H., Hu, J., An, S., Wang, M., & Park, B. B. (2017). Eco approaching at an isolated signalized intersection under partially connected and automated vehicles environment. Transportation Research Part C: Emerging Technologies, 79, 290-307. https://doi.org/10.1016/j.trc.2017.04.001

Kolarova, V. (2020). Exploring the elements and determinants of the value of time for manual driving and autonomous driving using a qualitative approach. Transportation research record, 0361198120953770. https://doi.org/10.1177/0361198120953770

KPMG (2020). Autonomous Vehicles Readiness Index (AVRI) . Assessing the preparedness of 30 countries and jurisdictions in the race for autonomous vehicles. https://home.kpmg/xx/en/home/insights/2020/06/autonomous-vehicles-readiness-index.html (accessed on 6th March, 2021)

LaMondia, J. J., Fagnant, D. J., Qu, H., Barrett, J., & Kockelman, K. (2016). Shifts in long-distance travel mode due to automated vehicles: Statewide mode-shift simulation experiment and travel survey analysis. Transportation Research Record, 2566(1), 1-11. https://doi.org/10.3141/2566-01

Ma, F., Yang, Y., Wang, J., Li, X., Wu, G., Zhao, Y., Wu, L., Aksun-Guvenc, B. and Guvenc, L., 2021. Eco-driving-based cooperative adaptive cruise control of connected vehicles platoon at signalized intersections. Transportation Research Part D: Transport and Environment, 92, p.102746. https://doi.org/10.1016/j.trd.2021.102746

Malokin, A., Circella, G., & Mokhtarian, P. L. (2019). How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios. Transportation Research Part A: Policy and Practice, 124, 82-114. https://doi.org/10.1016/j.tra.2018.12.015

Milakis, D., Van Arem, B., & Van Wee, B. (2017). Policy and society related implications of automated driving: A review of literature and directions for future research. Journal of Intelligent Transportation Systems, 21(4), 324-348. https://doi.org/10.1080/15472450.2017.1291351

Milakis, D., & van Wee, B. (2020). Implications of vehicle automation for accessibility and social inclusion of people on low income, people with physical and sensory disabilities, and older people. In Demand for emerging transportation systems (pp. 61-73). Elsevier. https://doi.org/10.1016/B978-0-12-815018-4.00004-8

Mokhtarian, P. L. (2018). The times they are a-changin': what do the expanding uses of travel time portend for policy, planning, and life?. Transportation Research Record, 2672(47), 1-11. https://doi.org/10.1177/0361198118798602

SAE International, 2018. Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. SAE International, Warrendale, PA. https://www.sae.org/standards/content/j3016_201806/

Saturday Evening Post (1950s) Driverless Car of the Future, advertisement for 'America's Electric Light and Power Companies'.

Singleton, P. A. (2019). Discussing the "positive utilities" of autonomous vehicles: will travellers really use their time productively?. Transport reviews, 39(1), 50-65. https://doi.org/10.1080/01441647.2018.1470584

Stern, R. E., Cui, S., Delle Monache, M. L., Bhadani, R., Bunting, M., Churchill, M., ... & Work, D. B. (2018). Dissipation of stop-and-go waves via control of autonomous vehicles: Field experiments. Transportation Research Part C: Emerging Technologies, 89, 205-221. https://doi.org/10.1016/j.trc.2018.02.005

Talebpour, A., & Mahmassani, H. S. (2016). Influence of connected and autonomous vehicles on traffic flow stability and throughput. Transportation Research Part C: Emerging Technologies, 71, 143-163. https://doi.org/10.1016/j.trc.2016.07.007

Tirachini, A., & Antoniou, C. (2020). The economics of automated public transport: Effects on operator cost, travel time, fare and subsidy. Economics of Transportation, 21, 100151. https://doi.org/10.1016/j.ecotra.2019.100151

Wadud, Z., & Huda, F. Y. (2019). Fully automated vehicles: the use of travel time and its association with intention to use. In Proceedings of the Institution of Civil Engineers-Transport (pp. 1-15). Thomas Telford Ltd. https://doi.org/10.1680/jtran.18.00134

Weber, M. (2014): Where to? A history of autonomous vehicles. https://computerhistory.org/blog/where-to-a-history-of-autonomous-vehicles/

Wu, C., Bayen, A. M., & Mehta, A. (2018, May). Stabilizing traffic with autonomous vehicles. In 2018 IEEE International Conference on Robotics and Automation (ICRA) (pp. 6012-6018). IEEE. https://doi.org/10.1109/ICRA.2018.8460567

Zhang, W., & Guhathakurta, S. (2017). Parking spaces in the age of shared autonomous vehicles: How much parking will we need and where?. Transportation Research Record, 2651(1), 80-91. https://doi.org/10.3141/2651-09

Zmud, J., Sener, I. N., & Wagner, J. (2016). Consumer acceptance and travel behavior: impacts of automated vehicles (No. PRC 15-49 F). Texas A&M Transportation Institute.

2 How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands

Pudāne, B., Rataj, M., Molin, E. J., Mouter, N., van Cranenburgh, S., & Chorus, C. G. (2019). How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands. Transportation Research Part D: Transport and Environment, 71, 222-235.

Abstract

Automated Vehicles (AVs) are expected to allow their users to engage in a broad range of non-driving activities while travelling, such as working, sleeping, playing games. The impact of this possibility on the satisfaction with travel and on travel demand has been extensively discussed in the literature. However, it has been hardly recognised that the availability of on-board activities influences the (time-geographic) constraints of daily activities and may alter the selection, location, and sequencing of other activities in the day. This hampers correct representation of travel behaviour in activity-based models aiming to predict the effects of AVs on mobility and environment (e.g., greenhouse gas emissions). To help fill this gap, we gathered and analysed qualitative data from focus groups, in which 27 commuters discussed their expectations concerning on-board activities and daily schedules in the AV-era. Among the core insights are the following three. First, it is useful to separate in modelling the satisfaction with travel and the potential for on-board activities during travel: they have different determinants and different consequences for activity schedules and individual travel demand. Second, on-board activities may be classified in 4 quadrants according to their novelty and priority level: this classification is helpful in understanding the potential re-arrangements of daily activities. Third, performing new activities during travel may lead to complex re-arrangements of daily activity patterns; the re-arrangements may ease or also increase time pressure. These, and other

reported insights may facilitate more realistic representation of activity-travel behaviour in future travel behaviour models.

2.1 Introduction

Fully Automated Vehicles[1] (AVs) are expected to bring many positive effects, such as improved road safety and increased productivity and well-being thanks to more meaningful travel time use and reduced stress from driving. However, due to their increased attractiveness, AVs may also induce car travel and, by doing so, contribute to congestion and negative environmental impacts, which may be fully or partially offset by smoother driving cycles, shorter headways and lighter vehicles. These counteracting effects have been investigated in several recent studies (e.g., Milakis et al., 2017; Wadud et al., 2016; Auld et al., 2017; Chen et al., 2017). To anticipate the up- and downsides of the introduction of AVs, the changes in travel behaviour due to more meaningful travel time-use have been routinely modelled using a lower penalty associated with travel time (e.g., Childress et al., 2015; Gucwa, 2014; Kröger et al., 2018). This is despite the fact that previous studies have called into question this approach when applied to productively used travel time (Lyons et al., 2007; Lyons & Urry, 2005; Gripsrud & Hjorthol, 2012) and indicated that activity patterns in fact influence the travel time penalty (Paleti et al., 2015).

Complementary to these studies, we propose that a simple reduction in the travel time penalty does not fully capture the potential impact of on-board activities on daily activity schedules of travellers. In this regard, it is useful to recall the perspective of time-geography (Hägerstrand, 1970), which suggests that individuals choose their activities, activity locations and times guided by capability, coupling and authority constraints. Capability constraints relate to the physical ability of the individual to reach locations considering that certain time should be spent for biological needs (sleep, meals) at given places. Coupling constraints relate to the necessary access to tools, materials and other individuals to perform some activities. Authority constraints address mainly the legal boundaries for activities (e.g., in-store shopping is possible only within the shopping hours). From here, it can be observed that the possibility of performing new activities on board of the AV may affect all classes of constraints: activities on board are allowed (authority constraint), possible thanks to undivided attention and potentially some equipment available in the AV (coupling constraint), and potentially enable to reach further locations if some of the biological needs (e.g., meals) can be satisfied in the AV. Therefore, on-board activities can be expected to influence daily activity schedules of travellers, for example, make them more efficient and more relaxed, and this influence is due not only to the changes in travel time penalty, but importantly also to changes in the constraints of activities.

To model changes in daily activity schedules, it is possible to adopt not only time-geographic but also activity-based or time-use perspectives (Arentze & Timmermans, 2004; Kitamura, 1988; Becker, 1965). Steps towards developing such a modelling perspective are being taken in several recent studies where the traveller's ability to engage in on-board activities is explicitly modelled (Pawlak et al., 2015, 2017; Banerjee & Kanafani, 2008; Pudāne et al., 2018). We aim to support such modelling efforts by exploring questions, which have so far received little attention, but are important in developing activity-based, time-use, and time-geographic models for the AV-era. Many such questions relate to the (assumed) interactions between on-board and stationary activities: would activities be *transferred* to an AV from another location and time-of-day (or would they rather be *added* to the traveller's activity-list)? What types of re-arrangements in activity schedules could be expected? What type of re-arrangements will occur due to more pleasant travel (if travel in AVs is indeed more pleasant),

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

and what type of re-arrangements will occur due to interactions between on-board activities and other activities?

Given the uncertainty associated with these crucial questions, we believe that the time has come to take a step back, and to explore them using a qualitative research method – specifically, focus groups. Our goal is to derive qualitative insights which can be used 1) to verify and validate existing formal, mathematical models describing activity schedules in AV-contexts and 2) to help design the next generation of such models. The resulting methodological advancement can be pivotal for the evaluation of policies concerning AV-adoption and -usage. Crucially however, the research presented in this paper aims to serve as a building block for formal modelling efforts, not as an alternative to such models. Our data is not suited for quantitative, statistical, or confirmatory analysis, but aims to help in designing such studies.

We gathered data in a focus group setting, where participants discussed how they expect their travel to change in the AV-era, envisioned on-board activities and their impact on their daily routines. Our study is in line with several qualitative studies who have successfully investigated various aspects of travel behaviour in the AV-era: on-board activities and satisfaction with travel (Trommer et al., 2016), intentions to use AVs (Payre et al., 2014; Silberg et al., 2013), and changes in daily activity schedules with an emphasis on travel demand (Zmud et al., 2016). However, we direct our attention specifically into daily activities of future AV-users, which the current literature, to the best of our knowledge, has not yet addressed in depth. In the following sections, we explain the planning and execution of the focus groups (section 2.2), present our findings (section 2.2.4), and discuss the findings in a broader context, as well as suggest directions for modelling (section 2.4).

2.2 Methods

2.2.1 Motivation and limitations of using focus groups

Focus groups, compared to other qualitative research approaches, such as individual interviews, allow participants to learn from, build upon and contrast each other's ideas (Stewart & Shamdasani, 2014). This is desirable for our study, as many participants may not yet have thought about the possible influence of AVs on their daily lives. In addition, focus groups provide a more efficient way of gathering qualitative data compared to individual interviews: less time is needed to complete the interviews. Finally, previous studies show that focus groups can provide valuable insights on new transport technologies; see, for example, Kenyon and Lyons (2003) and Maréchal (2016), including AVs (Trommer et al., 2016; Silberg et al., 2013). Krueger and Casey (2014), Onwuegbuzie et al. (2009), and Morgan (1996) helped to design several aspects of the focus groups, such as an appropriate questioning path and optimal number of participants and groups.

Yet, the focus group approach also has its limitations for studying future phenomena. Since no statements about the future can be made with full certainty, a fully-automated future may still be quite distant, and incentive-alignment is practically unenforceable in a focus group setting, participants occasionally described quite unlikely scenarios, which may have (partially) been intended as entertainment[2]:

> *'I imagine a kitchen inside it (the AV), you can prepare everything, cut vegetables, and when you're home you can eat everything, everything's done.' (Johanna)*

[2] Yet, bold ideas for how to take most advantage of the self-driving mode are abundant and currently seriously explored. (MIT Technology Review, 2018)

2.2.2 Sample description and recruitment

Five focus groups were conducted in the Netherlands between September and November 2017. Each group consisted of 4-7 participants, adding up to 27 participants in total. To ensure that participants have regular daily activity schedules that involve travel, we invited only daily commuters (travelling to work or studies). Furthermore, we recruited mostly current car or public transport users, because those modes are easier to compare with AVs than active modes. Although, in line with the focus group and qualitative studies' methods (Marshall, 1996), the sample was not intended to be representative of the Dutch population in terms of either sociodemographic background nor in terms of travel behaviour, the following are useful statistics to better understand our findings.

Of the 27 participants, slightly more than half (15 participants) were male. Age groups 30-39 (11) and 40-49 (10) were most represented, followed by 20-29 (5) and 60-69 (1). Almost all the participants were employed, except two students and one recent retiree. Most participants were commuters by car (as drivers) or by public transport, but some participants mostly commuted by bike. Those participants who were cycling on a day-to-day basis were in the first group, which consisted of TU Delft students and researchers. However, they were asked to recall past experiences of commuting by car or public transport as a comparison for AV in the discussions. Participants in other groups were selected such that approximately two thirds were car drivers and one third was public transport users. The reported commute travel times ranged from very short (15 minutes) to rather long (1 hour or more one way). Five participants reported making multiple trips a day for work (e.g., visiting clients). Their travel time amounted to several hours every day, and all of them travelled by car.

Of the 27 participants, 21 are cited on an individual basis in this paper. Respecting the privacy of our participants, we replaced their real names with fictive ones. Socio-demographics of participants – their age group, gender, profession, travel mode(s), commuting times – are available in Table 2-3 in the Appendix. Participants of the first group were invited through posters in TU Delft and through personal networks. Participants of focus groups 2 to 5 were recruited through a marketing company and received an incentive of 40 Euro for participation.

2.2.3 Focus group sessions

To allow the participants full creativity in considering their daily activity schedules in a future with AVs, the most facilitating scenario for on-board activities was discussed: AVs are fully automated (i.e., level 5 according to the standards of SAE International, 2016), available for private use (i.e., not shared), fully safe and secure, available (i.e., purchase or rental costs were not considered), and permits a range of on-board activities. A general introduction of AVs and these assumptions were presented to the participants in a short animation movie at the start of each session. The possible on-board activities (e.g., working, watching television, sleeping) and some potential re-arrangements were illustrated with examples in the movie.[3]

All focus group sessions lasted 1.5 hours. After briefly introducing themselves and the introduction movie, participants discussed 10 questions. The discussions were assisted by a moderator, who was not involved with the research until after the focus groups. This helped to minimise any confirmation bias and, we believe, made participants more comfortable expressing their opinions. The questions relate to their activity and travel behaviour currently or as envisioned in the future, when they will have the access to AVs. See Table 2-1 for a list of questions used in one focus group. Based on experience and suggestions of the moderator, the questions for every group were slightly adjusted, combined or split, mostly to improve their clarity.

[3] The animation movie (in Dutch) is available from the corresponding author upon request.

The first questions inquired about the current travel behaviour of participants and their satisfaction with it. Thereafter, participants were asked to broadly reflect on the possibility of travelling in an AV (question 3), in order to become more comfortable with the topic. Questions 4-6 address the core of the study: performing activities in the AV and possible changes in daily routines. Questions 7-9 inquire about potential travel demand changes, including changes in residential location. Finally (question 10), participants could reflect on what they believed were the most crucial points of the discussion.

Table 2-1 Focus group questions - example from the 4th focus group

1. How do you travel normally? - Train/car/…? - How long does the trip take? - What do you do during the travel?
2. Are you satisfied with how you use your travel time or would you like to use it differently? Travel time is for you: - Time to relax - Time to do something - Wasted time - Time to kill
3. Imagine that you travel with an AV. What are pros and cons in comparison to your normal way of travelling?
4. Imagine that you have an AV and can arrange the interior the way you want. What would you like to do when travelling and why?
5. Would you like to perform such activities in the AV which you normally perform in traditional environment like at home or at work? If so, do you think you can save time for other things which you would like to (or have to) do?
6. Would you change anything in your daily routine if you had an AV?
7. Would you travel further or more frequently to perform activities if you had an AV?
8. Would an AV be a good alternative for trips which you usually perform by a bicycle or public transport?
9. Would you like to move if you had an AV? - If yes, where to? - If no, imagine you need to move (e.g., because of a job). Would an AV influence your decision?
10. Would an AV make your life better or worse?

2.2.4 Data analysis

The focus group discussions were audio-recorded and transcribed afterwards.[4] The transcripts were coded and analysed following content analysis principles (Elo & Kyngäs, 2008). The analysis was mostly inductive, but some categories during analysis were derived deductively – i.e., based on own hypotheses and literature. The influence of preconceived ideas could be considered a limitation of our method, especially when viewed from fully-inductive perspectives, such as grounded theory (Charmaz, 2006). However, we believe that it is nearly impossible for any researcher to completely isolate oneself from the ideas in the field's literature.

[4] The complete transcripts are available here: http://doi.org/10.4121/uuid:994f0ab2-0fa2-493f-88ad-fbf4eaaf470e (Pudāne, 2018).

Thus, the following section presents the final storyline, which is a combination of inductive and deductive analyses. We systematise the core outcomes in conceptual maps. The main findings we illustrate with quotes from focus groups as well as contrast them with insights from literature.

2.3 Findings

The focus groups offered rich information on all questions. The findings are presented roughly according to the questioning path (Table 2-1) as follows:

1. Pleasure from travelling and feasibility of activities in an AV (questions 3 and 4) – subsection 2.3.1,
2. Types of activities while travelling (questions 4 and 5) – subsection 2.3.2,
3. (Changes in) daily activity schedules (questions 5 and 6) – subsection 2.3.3,
4. Individual's travel demand (questions 7 and 8) – subsection 2.3.4.

Subsection 2.3.5 presents a synthesis of the core factors and their relationships.

2.3.1 Pleasure from travelling and feasibility of activities in an AV

A major part of all focus group discussions was a reflection on the many aspects of travel that will (likely) be different with fully automated vehicles compared to present travel modes. Participants often imagined how many inconveniences of travel in public transport (e.g., having to make interchanges, lack of privacy) and private cars (having to stay focused on the road, limited comfort) would be reduced making the travel more pleasant (or: increasing the intrinsic utility of travel). Furthermore, participants often reasoned that many aspects of travel in AVs would make new non-driving activities possible. These aspects were not always the same as the characteristics enhancing the pleasure from travel. Although clearly both travel pleasure and possibility to conduct on-board activities influence the overall satisfaction with travel (Ettema et al., 2012; Frei et al., 2015), literature recognises that it is useful to separate the two (Mokhtarian & Salomon, 2001; Singleton, 2018).

Table 2-2 lists all the characteristics of travel in an AV which were mentioned in the focus group discussions, and their perceived influence on both effects. Note that some of the characteristics apply also to conventional cars – for example, travel continuity – yet, their effects (especially on the feasibility of on-board activities) are different due to the cars also being fully automated. Some factors received mixed assessment from the participants, when describing their impact on the pleasure of travel. For example, privacy was seen as desirable, but its flipside, isolation from other travellers, was sometimes perceived as undesirable.

Table 2-2 Influence of characteristics of travel in AV on pleasure from travelling and feasibility of on-board activities

Characteristics of travel in AV	**Influence of the characteristics on …**	
	pleasure from travelling in AV	feasibility of on-board activities
a) Fully automated driving	mixed	positive
b) Availability, little planning needed	positive	neutral
c) Travel continuity	positive	positive
d) Comfort	positive	positive
e) Equipment, storage possibilities	neutral	positive
f) Privacy, isolation	mixed	positive

g) Predictability, reliability of travel time	mixed	positive
h) Longitudinal and lateral movement, position of the traveller	negative	negative

Below we discuss each characteristic and illustrate its impact with quotes.

a) Fully automated driving enables advanced on-board activities. However, automated driving also takes away the driving task from travellers. This was perceived differently by focus group participants (especially current car-drivers):

'Continuously you must pay attention (while driving a car): in case of congestion, traffic jams cars can suddenly come from everywhere. (...) If you can fully rely on the equipment of the car (AV) in terms of safety, then you are very relaxed in the car. Then you can do a lot of other things.'
(Pieter)

'I'm afraid it (the AV) is too slow. If you're in such a thing you're out of control, I'm afraid that I just get stressed.'
(Gabrielle)

The latter sentiment relates to the literature of mode-specific preferences and motivations for travel, such as independence, curiosity and status (Ory & Mokhtarian, 2005; Anable & Gatersleben, 2005; Steg, 2005). Automated driving might alter these affective characteristics of car travel (Haboucha et al., 2017; Nordhoff et al., 2018).

b) Availability at any time and a limited need for planning was appreciated by many participants, especially current public transport users:

'You have the freedom: I get into the AV when it suits me, and that AV is ready for me at the front of my door.'
(Linda)

c) Travel continuity was appreciated both for allowing the traveller to engage in advanced on-board activities and for its own sake:

'What would be nice: now, I often have to wait because I have to transfer, that would be gone.'
(Norbert)

'The fact that I have to switch (to different modes) means that I cannot really do anything, prepare for work or whatever.'
(Linda)

d) In a similar fashion, comfort was also appreciated on its own as well as for facilitating on-board activities (including sleeping):

'(In an AV) You are in your own cocoon which does the work for you, maybe it will take longer (than a plane for a long-distance trip), but you will travel in a very relaxing way to your destination.'
(Pieter)

'If I am able to sleep in the AV, I would do the travel at night. (...) I would arrive at my destination in a much better shape than when I have to sleep on a chair in a bus.'
(Bart)

e) Participants recognised that equipment and storage possibilities enable many more advanced on-board activities:

‘- (You could hold) A kind of work consultation (in an AV). Your colleagues are also on their way home, you can just do it on the way.
- In your AV, Skype.
- (You would need) A good screen and a good sound system.’
(Elisabeth and others)

f) Privacy was appreciated for allowing more on-board activities. At the same time, it was recognised that complete privacy (or complete isolation from other travellers who are not one’s travel companions) would mean foregoing positive experiences that sometimes result from travelling with others. In the latter regard, te Brömmelstroet et al. (2017) lead an interesting discussion into how different travel modes influence the feeling of being connected to places and communities.

‘I will take the AV as a mini office space and do office-work that does not need any interaction with people. It is different (than public transport) because it is a confined environment where I can concentrate.’
(Bart)

‘I am afraid that if we use AVs all the time, we will find ourselves in bubbles. We go from point A to B in an isolated way. So, there may be not much room left for interaction and unpredictable things.’
(Bart)

g) Respondents imagined that travel times with AVs, especially if everyone is using AVs, would be perfectly predictable and reliable. This would allow to arrive at the desired time and to also better plan on-board activities. Also literature widely acknowledges that reliable travel times are desirable (e.g., Bates et al., 2001) and that unpredictability causes stress (Evans et al., 2002).

‘If someone (now) looks at his phone and causes a head tail collision, then the highway is stuck. (...) (With AVs) it takes away a bit of uncertainty, adding a bit of peace. You can say much better, if I have to go to work, it takes me 20 minutes, and there is little variation in that.’
(Maarten)

‘If the car would drive itself and stop at the right points, I could watch Game of Thrones.’
(Felix)

However, a perfect predictability of commute routine (in a broader sense than reliable travel times) was sometimes dreaded for potentially making days too monotonous:

‘If you have to travel by public transport, like me, sometimes you encounter unexpected moments, right? But if you have the same trip every day in that AV, then every day is the same. (...) It becomes monotonous.’
(Norbert)

h) Some participants expressed a concern that they may experience motion sickness in an AV, which would not allow performing activities while travelling. It was also mentioned that movement itself could be an obstacle for some activities while travelling:

'I cannot actually read a book inside the car, because I will get sick.'
(Renate)

'You are playing a game inside the car and then the car suddenly brakes. How does that work?'
(Paulien)

Several studies confirm that longitudinal and lateral movements of AVs, as well as new positions of travellers in the AV (e.g., not facing forward) can cause motion sickness for future AV users (Diels & Bos, 2016; Le Vine et al., 2015). As such, the impact of AV movements may be underestimated in the present study, where participants imagined an on-board environment where many activities are feasible (limited only by the necessary space and equipment).

2.3.2 Types of activities desired for travel in AV

A core part of the focus group discussions related to the envisioned (type of) non-driving activities to be performed during travel in AV. Clearly, not all activities are feasible in AVs:

'Ideally, you could do everything in such a car. Brushing your teeth, putting on your lenses, everything. You cannot take a shower, that's a little over-enthusiastic.'
(Norbert)

Feasibility is therefore a pre-requisite. Nevertheless, even if new activities are feasible in an AV, participants did not always express a desire to make full use of that feasibility. Their current time-use might be optimal, or, in other cases, this might be due to a general resistance to adopting a new travel mode (König & Neumayr, 2017) or response lag (Chen & Chen, 2009). The potential unwillingness of travellers to change their travel time-use is also a core insight of Singleton (2018) and Fraedrich et al. (2016).

'Well, if I compare with public transport or a bus, I would do the same thing (in an AV). I would listen to a podcast or read a book.'
(Dennis)

In addition to the choice to engage in new activities during travel in an AV (versus continuing to pursue current on-board activities), an important dimension is the priority level of selected activities. Some participants imagined performing activities of high priority that need to be performed during the day (e.g., work, sleep, meals, personal care, scheduled appointments and commitments). Other participants thought that AVs would provide a good opportunity for optional, medium to low-priority activities – activities that are performed only if there is extra time available for them (e.g., hobbies without appointments, time to contemplate – if those have medium to low priority for the individual).

Building on these two dimensions (new or current and high-priority or optional activities) we can classify on-board activities into four types, see Figure 2-1: new high-priority activities (I), current high-priority activities (II), current optional activities (III), new optional activities (IV). Note that some activities could be classified in different types by different individuals – for example, writing emails could be a type II activity for current public transport users, but a type I activity for current car drivers.

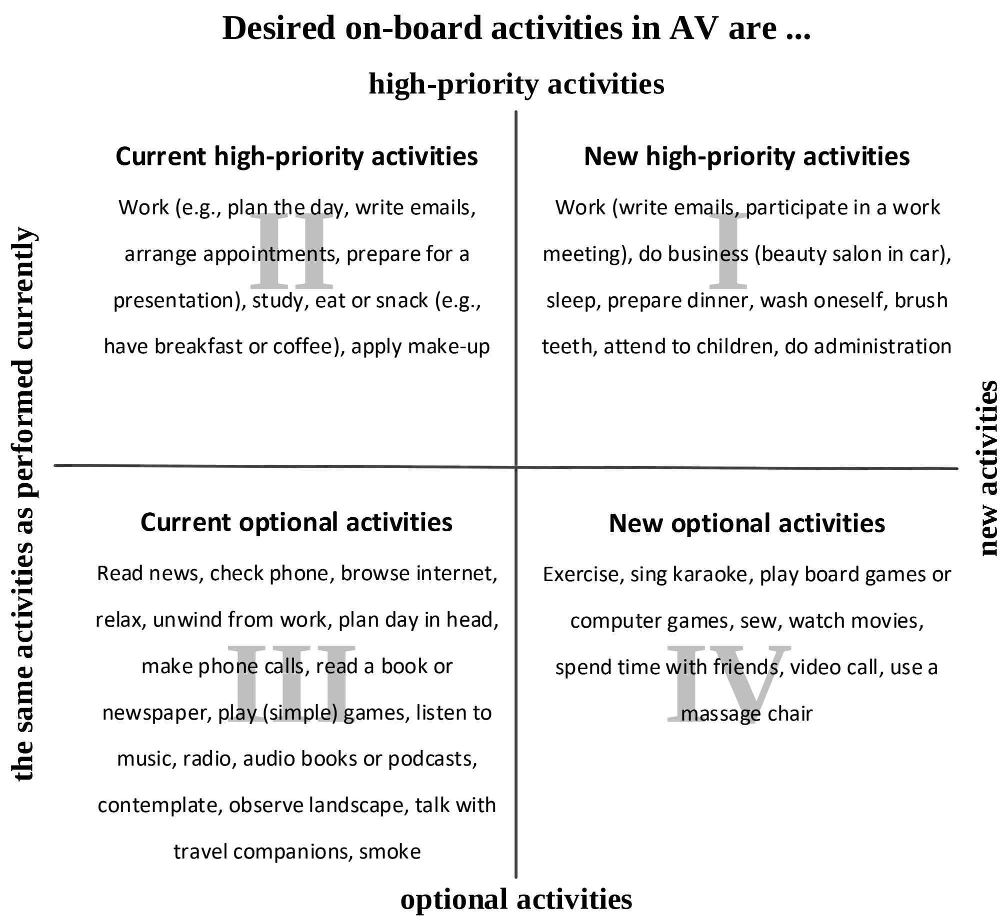


Figure 2-1 Classification of desired activities in AV considering their priority level and difference from current on-board activities

Type I or **Type II** (high-priority) activities were most often desired or already performed during travel by participants who experience time pressure (a result also of Ettema & Verschuren, 2007), which could be either chronic or acute (as defined by Gunthorpe & Lyons, 2004). This is not surprising, since multitasking is a known strategy to reduce time pressure (Kaufman-Scarborough & Lindquist, 1999). Furthermore, some high-priority activities are time-inflexible (e.g., important phone calls), which means that they may need to be performed during travel:

> *'I'm currently experiencing a structural sleep shortage of 1 to 1.5 hours a day. I would really use it (the AV) for that.'*
> *(Eric)*

> *'On my way I make calls, I try to put it on Bluetooth, with calls I usually do. Often my boss sends a WhatsApp to me, that's the only time I have contact with that man. (...) The most immediate effect, if I had such an AV tomorrow, would be less stress, because the work pressure is less.'*
> *(Jelmer)*

> *'Now, someone is driving a car, a mother or a father – you often look backwards at your child who wants something. These are dangerous situations. (...) With AV, you can feed a baby; you don't have to stop (...).'*
> *(Niek)*

Having to perform high-priority activities during travel can create tension between the existing and necessary conditions to perform the activity. The above statements suggest that (some participants believe that) AVs could resolve that tension.

At other times, participants desired to perform high-priority activities during travel in order to free time for *other* activities within the day. They reported having insufficient private time, which is related, but not equivalent to time pressure:

> *'I feel that people do not spend time, which is essential, for casual interaction, not about work. (...) Spending some time to work in the car will liberate, make available some time for this kind of interaction.'*
> *(Bart)*

Type III activities – primarily transition or time-out activities using the words of Jain and Lyons (2008) – were mentioned by participants whose travel is too short for more substantial activities. This accords with several studies, as summarised by Keseru and Macharis (2018), and potentially explains the preference for AVs for long-distance trips (Yap et al., 2016; Fraedrich et al., 2016; LaMondia et al., 2016):

> *'If you have 2 hours then it (possibility to perform activities while travelling) really matters. (...) But, within a short time there is nothing to do.'*
> *(Laurens)*

Passive on-board activities (like transition, time-out) were often also selected seemingly for no reason. But, as described by Holley et al. (2008), such anti-activity may 'assist creativity by providing "incubation" time':

> *'- Sometimes (in public transport) I was just looking at the landscape.*
> *- Just relax?*
> *- Yeah, looking around. (...) Sometimes an idea may come up.'*
> *(Bart)*

Type IV activities were selected by participants who desire leisure (or other optional) activities, which at present do not have a suitable time or place in their schedules:

> *'I think in my AV I would do something that I never have time for. For example, maybe use the car as karaoke salon.'*
> *(Caroline)*

Another interesting reason (offered by participants) for selecting activities of **any type** was their perfect compatibility with the on-board environment (or with the fact of being in motion):

> *'In public transport I used to read quite a lot, more than when I am at home. (...) We are changing places, so we change environment and it gives the will, I think, to see differences, different experiences. Traveling is an experience. Reading is an experience as well. It is a kind of travelling.'*
> *(Bart)*
> *'-I always have to go to the customer with my suitcase (to perform pedicure), that is quite a heavy thing. (...)*
> *-You can make a studio in your (automated) car. (...)*
> *- Yes, just a collapsible treatment chair, and you have everything with you. That would be ideal!*
> *- The car gets a completely different function.*
> *- I do not have to do anything; I do not even have to drive to the next client.*
> *- No, of course, that will save time.*

> *- Meanwhile, I can clean up my things for the next client.'*
> *(Paulien and others)*

The above-mentioned reasons for selecting different types of on-board activities can be summarised as an attempt to re-balance activity needs and wishes with their constraints, once a new location (on board) is available. The new location not only relaxes the constraints for activities, but may also create new activity wishes and needs, which in turn could create new constraints.

Finally, we observed that some participants appreciate the *possibility* to use the travel time for activities, which can be chosen flexibly or even spontaneously, even if they currently do not desire specific activities. In modelling terms, the activities seem to have an option-value (Laird et al., 2009), which may matter for their decision utility, but not necessarily experienced utility (Kahneman et al., 1997; Chorus & De Jong, 2011; De Vos et al., 2016).[5]

> *'For me personally it (activities in the AV) would not matter much (for the daily habits) because I don't have a partner. (...) I have a lot of time, and I occasionally get bored. (...) The nice thing is that you can do something active or something passive (in the AV), that you can make the choice.'*
> *(Petra)*

2.3.3 AVs' impact on travellers' daily activity schedules

After contemplating the activities that participants would like to perform during travel in AVs, they were asked to think about the impact of those activities on their daily activity schedules. With 'impact on travellers' daily activity schedules' we refer to changes in activities performed outside travel time, as well as changes in travel and activity timings. This excludes changes in activities performed during travel, which are discussed in the previous subsection.

From the statements of focus group participants, we infer that AVs may lead to changes in daily activity schedules primarily via what can be named a 'saved time' effect. Time may be saved by transferring new high-priority activities to the travel episode (Type I activities, according to Figure 2-1). This may result in various changes in daily activity schedules: new activities might be scheduled in the freed time, activities or travel might be extended, activities might also be swapped or reshuffled. Participants usually did not know or did not specify the exact form of re-arrangements, but agreed that in general there would be substantial changes in their daily activity schedules – which depend on activity needs, wishes and constraints. Note that this notion is at the basis of time geography (Hägerstrand, 1970):

> *'It can go two ways. On the one hand, I sometimes stay late at my work, but then I am working on something and then I want to finish it. (...) I could catch up on the way home. But, of course, that can also occur when I get up: I have to do things for another hour, so I will be able to prepare some things in advance.'*
> *(Maarten)*

In addition, some participants imagined dispatching an empty AV to perform some activities, if such a possibility would become available (e.g., to pick up groceries from a supermarket, a guest from train station, or to send children to some activity locations).[6] Such 'outsourcing' of activities was popular also in a real-world chauffeur experiment, intended to resemble AVs (Harb et al., 2018). Similarly as transferring high-priority activities to the travel

---

[5] Decision utility refers to the weight of outcomes and attributes in the process of making decisions. Experienced utility is the actual, subjective hedonic experience – 'the pleasure and pain' – resulting from the choice ex post. (Kahneman et al., 1997)

[6] The possibility to dispatch empty AV may be available for fully automated vehicles, but that would also be determined by other factors, such as legislation. In the focus groups, sending an empty AV was assumed to be possible.

episode, the outsourcing creates a ‘saved time’ effect. However, trust is necessary for the travellers to make use of this possibility (especially to allow their children to use the AV alone):

> *‘We have to bring my daughter to her internship two evenings a week. (…) Now, she can get in that car and the car will take her there. And that car comes back to us, so that would save time. So, that would be nice, if I trusted it. But I have to trust that thing first.’*
> *(Nora)*

Furthermore, the ‘saved time’ effect was appreciated by many participants for making their schedules ‘more efficient’ and relieving their time pressure:

> *‘For me, it would be more efficient use of time, your working time starts as soon as you get out of the door. On the other hand, your free time starts again when you step out of the door at work, or that last bit of work you can do on your way home. So, that ultimately gives you more free time, so you can be more relaxed in it.’*
> *(Linda)*

However, and this was an unexpected but prominent insight from the focus groups, some participants noticed a potential downside of the saved time effect. They imagined that the possibility to be productive (work) in the AV would rise the expectations at the work places either formally (their manager would request that) or informally (their co-workers would set the norm). Higher expectations increase the time pressure and stress (see Figure 2-2):

> *‘Immediately you would think: I drive across the country, I have a two hour ride, this means a workload because you have a two hour drive. [..] The expectation pattern is there, you cannot choose anymore.’*
> *(Eric)*

The perception of increased time pressure could also be due to the availability of a wider choice of activities. If more activities are feasible in a day, it may create an illusion that more activities *should* also be performed in the AV-era, which leads to time pressure (Ackerman & Gross, 2003). The effect also resembles the more general impact of ICT, which has been called ‘technostress’ (Ayyagari et al., 2011) – the feeling that the ever higher pace of communication and availability enabled by ICT should be matched by their users. This also relates to blurred boundaries between work and life afforded by ICT, and perhaps also AVs (Wheatley & Bickerton, 2016; Gustafson, 2012).

A middle path of the two options (as illustrated in Figure 2-2) would be a modest increase in amount of activities and also expectations, such that the same level of time pressure is maintained. That would make the perceived time savings disappear, changing little in how individuals experience their days:

> *‘You get used to it (extra time) very fast, so you do not even appreciate having that extra time.’*
> *(Elisabeth)*

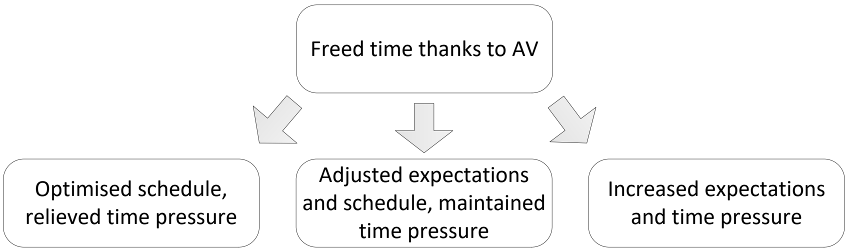


Figure 2-2 Possible adjustments of daily activity schedule and expectations given freed time thanks to AV

Finally, discussion in all focus groups at some point deviated from daily activity schedules to non-daily and holiday activity schedules. Almost unanimously, participants agreed that AVs would offer major gains for these non-regular and often long-distance trips: transferring long activities (such as sleep) to a long journey done with an AV, would let the traveller arrive at the (holiday) destination while barely noticing the trip. This would likely influence activity schedules, because the traveller would not need as much time to rest and recover from the long journey.

> *'-Yes, you are less tired. You do not have to account for a return trip. If I go far away, I want to eat and drink, but that's not possible, because you have to go back in the evening. In this way, you can easily go to Brussels or Paris.*
> *- To have dinner there?*
> *- Yes, nice, right? Eat there and then go back and sleep in your car.'*
> *(Gabrielle)*

2.3.4 AVs' impact on demand for travel

The final insight from the focus groups relates to the expected changes in an individual's demand for travel. Participants had varied opinions about whether their *daily* travel demand would increase, remain unchanged, or even decrease. However, many participants indicated that their *non-daily* travel demand might increase, either by accepting further locations for activities, by performing long trips more often, or by switching their travel mode from plane or train to AV for long-distance trips. The following paragraphs briefly discuss these findings.

Some participants imagined accepting longer travel distances daily because of the higher pleasure from travelling in an AV:

> *'I would meet with my customers more easily outside the office. If I want to meet outside the office now, (…) then I have to sit in a car for an hour and a half there and back. Then I think: I am not going to do that.'*
> *(Paulien)*

However, other participants found that more comfortable travel alone should not make them travel more, because compared to the AV there are still better places to spend their time:

> *'We should not spend more time in the car just because the car is comfortable. My home is also comfortable, so why not spend time there?'*
> *(Caroline)*

Furthermore, several participants noted that they would not like to extend their travel time indefinitely, because they would still be 'locked up':

> *'However, I still think I will get bored at a certain moment, you are still locked up. You get some more degrees of freedom, but you're still trapped.'*
> *(Linda)*

These contrary opinions point at a need for further research into whether the ease or pleasure of travelling could lead to accepting longer travel distances, a suggestion which has been often been made in the literature (e.g., Singleton, 2018). Participants were also rather ambiguous when considering changed travel distances due to changed daily activity schedules (a finding also of Zmud et al., 2016):

> *'My routine, how it will look like, I do not know, but my pattern will really change. (…) I do not think I would travel a lot of extra kilometres or travel more.'*
> *(Linda)*

Some said they would even travel less because of 'outsourcing' some activities – but the resulting change in vehicle-kilometres-travelled is unknown in this case:

> *'I would travel less – I will send the vehicle to pick up children, if I would have, or friends from airports. Or help somebody to deliver something. Usually you ask the person who has a car. (…) I prefer to do something more useful.'*
> *(Daniel)*

Compared to the varied expectations regarding daily travel demand, participants were rather certain about the benefits of AVs for long distance and holiday travels (as discussed also by LaMondia et al., 2016). The first four factors contributing to increased pleasure of travelling (subsection 2.3.1, Table 2-2) were most often mentioned in the context of long distance travels: automated driving (and therefore relieved burden and spared energy for the activities at the destinations), availability and less planning needed (compared to travelling by air or public transport), travel continuity, and comfort. The possibility to engage in long activities, such as sleep, was also recognised as beneficial (see the quote of Gabrielle at the end of subsection 3.3). Thanks to these factors, several participants indicated that they would travel longer or more often both for work, as well as leisure:

> *'(The biggest change in my life with AVs would be that I would) travel more, visit friends and family. My parents live in Brabant, which is quite far. I could go there more often. Now it is doable in public transport, but you have to cycle to the station, to the train. And with an AV, if money is not an issue, I would also go climbing.'*
> *(André)*

Therefore, considering irregular trips, our findings align with the often-feared impact of induced travel (Haboucha et al., 2017; Fagnant & Kockelman, 2015; Harb et al., 2018) or its positive counterpart of increased accessibility (Meyer et al., 2017; Milakis et al., 2018). Some participants also indicated that they may perform long-distance trips with AVs and not with airplanes or trains. However, other participants preserved their preference for air and train travel for long distances.

2.3.5 All factors in a nutshell

The most important findings of the focus groups can be summarised as follows:

- AVs will influence the pleasure of travel as well as feasibility of activities on board. But the causes of both influences differ – subsection 2.3.1;
- Travellers do not always desire to perform the feasible activities on board – the choice of activity type is influenced by activity needs, wishes and constraints, and aspects of

the existing activity schedule. The desired on-board activities may be classified in four types based on their novelty and priority level – subsection 2.3.2;

- Activity needs, wishes and constraints determine travellers' daily activity schedules, but schedules will also be influenced by the selected activities during travel in AV (and vice versa – certain on-board activities may be selected because of their impact on activity schedule). Schedules with new on-board activities may become more relaxed, thanks to newly freed time. However, freed time may also create new activity needs and wishes and increase the (feeling of) time pressure – subsection 2.3.3;
- More pleasant travel in AV may influence daily travel demand directly or via the daily activity schedule. But, opinions differed across participants when considering increased/ decreased/ unchanged daily travel demand. More evidence is found for an expected increase in non-daily travel demand – subsection 2.3.4.

Figure 2-3 visualises a summary of all the influencing links (represented by the arrows). Numbers at the bottom right corners of the boxes refer to the subsections that explain their content.

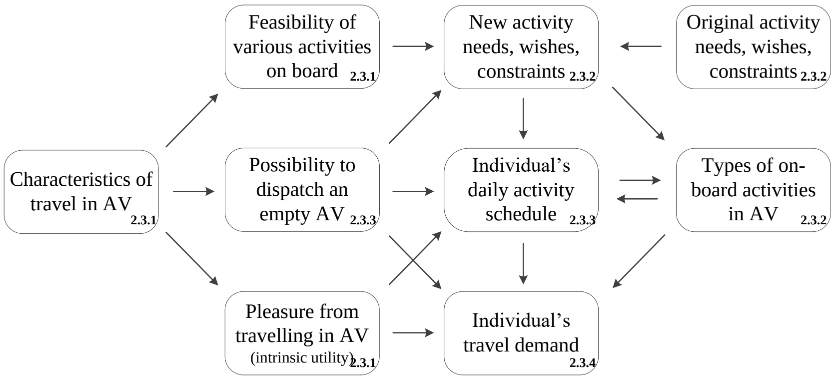


Figure 2-3 Synthesis of the main factors and their relationships

2.4 Conclusions and suggestions for further research

2.4.1 Conclusions

This paper offers qualitative insights, obtained in focus groups, into potential changes in daily activity schedules of future AV users. It aims to facilitate verification and validation of existing models and to help design behaviourally realistic representations of activity-travel behaviour in future models. To this end, our focus group data offer several insights. We find that – in the eyes of focus group participants – the expected adjustments in daily activities in the AV-era result from the AVs offering more pleasant travel and a wider selection of feasible on-board activities than present modes. More pleasant travel has clearest impact on participants' acceptance of more frequent or longer non-daily travels. The feasibility of new on-board activities may cause re-arrangements in daily activity schedules. However, as also pointed out by Singleton (2018), we find that the availability of more activities while travelling does not always lead to those activities being desired – some travellers are most happy to use the travel time for simple activities (which do not require much facilities) such as relaxation or 'transition' activities or are not willing to change their current travel time-use. Notwithstanding this, in some cases – for participants under time pressure, participants whose schedules include inflexible high-priority activities or who have unfulfilled wishes for other activities – the possibility to engage in new on-board activities may lead to activity re-arrangements, such as activity transfers to the AV, ‘outsourcing’ some pick-up or drop-off activities to the fully automated vehicles, and other re-arrangements that make schedules more efficient. The expectation that AVs may substantially influence activity schedules (e.g., make them more efficient), which was grounded in a reflection on the time-geographic constraints of activities and the activity-centric perspective of activity-based models at the start of our work, has been supported for this group of respondents. However, an interesting and somewhat unexpected finding is the mixed attitude towards the prospect of more efficient schedules. Whereas some participants think that clever use of AVs will ease time pressure, others envision that the possibility to be productive during travel would in fact increase time pressure. The relaxation of the time-geographic constraints may make the schedules more relaxed or more intense due to a rebound-like effect for activity demand. Asked directly about possible changes in their daily travel distances and frequency, participants gave mixed answers. This affirms that the travel time penalty approach, which invariably predicts more (daily) travel in the AV-era, should be rethought. Advances in methodology, that is, a more subtle and realistic treatment of time-use effects brought about by the advent of AVs, will impact the assessment of benefits and – primarily environmental (e.g., greenhouse gas emissions) – threats of AVs and will influence policies concerning AV-adoption and -usage.

2.4.2 Suggestions for modelling

Faced with the challenging task of modelling travel adjustments due to the disruptive innovation of AVs, modellers have arguably too often resorted to the convenient (but rough) travel time penalty (or value of time) as the sole predictor for changes in travel patterns in the AV-era. The results from our focus group study in contrast echo at every step that a variety of sometimes contradictory adjustments are possible, resulting from the subtle interplay between activity needs, wishes and constraints. Yet, note again that our findings should be considered as an input for further empirical research and modelling efforts, rather than as stand-alone or final conclusions about activity-travel behaviour in the AV-era. Therefore, we formulate several questions as suggestions for future work:

- What share of travellers would transfer new activities (type I in Figure 2-1) to be performed in the AV?
- What are the psychological reasons behind a preference for different activity types during travel? Is there a deeper ground, perhaps related to timestyles (Cotte et al., 2004), that leads people to desire ‘time savings’ (primarily type I) as opposed to ‘time spending’ (other types)?
- What is the option-value of activities while travelling (in the AV) – the value of being able to engage in new on-board activities, even if this opportunity is not used?
- How does freed time affect daily activity schedules of travellers and the (individual) travel demand?
- How does freed time influence activity needs, wishes and constraints? Who will experience increased time pressure (and in which contexts) due to newly available activities during travel?
- What is the impact of ‘outsourcing’ activities to the AV on the (individual) travel demand?
- To what extent does pleasure of travel and availability of on-board activities influence the acceptance (and desire) of further travel?
- How large is the untapped demand for long-distance and holiday travel that might be served by AVs?
- Under which conditions and in which contexts are AVs a viable alternative for overnight travels (where all passengers sleep while travelling)?

2.4.3 A final remark

The interesting finding of the possibly increasing time pressure due to freed time in AVs deserves a final revisit. It was observed that some participants prefer to use travel time passively (e.g., as a time to transition as in Jain & Lyons, 2008) now, as well as in the AV-era. However, whereas in present modes the passive time-use could be motivated out of necessity – travel time may not be suitable for performing productive activities – in the hypothetical AV scenarios with perfect facilities for a wide range of activities, (the traveller may feel that) being unproductive is no longer justified. This seems to generate a new conflict between maximising productivity and maximising the satisfaction with daily activities schedules (including a proper work-life balance), where the two objectives now need to be traded-off.

In this way, AVs are simultaneously expected to lead to increased levels of productivity and wellbeing, and decreased levels of rest and wellbeing. Although this seems paradoxical, similar contradictions have already been observed in the context of ICT psychological impact on their users. Jarvenpaa and Lang (2005) masterfully recognise eight paradoxes there: mobile technology leads to both empowerment and enslavement, independence and dependence, competence and incompetence, planning and improvisation, illusion and disillusion; it is both engaging and disengaging, public and private, and fulfils needs as well as create them. Will AVs add to these modern-day challenges? That remains to be seen.

Acknowledgment

The work reported in this paper was funded by the Netherlands Organisation for Scientific Research (NWO) as part of the project 'Spatial and Transport impacts of Automated Driving' (STAD), project number 438-15-161. Comments from three reviewers and guest editors have been a valuable input for the paper. Special thanks go to Hadi Asghari for the keen advice during focus group study and Bert van Wee for the insightful comments on an earlier version of this paper.

References

Ackerman, David S.; Gross, Barbara L. (2003): So many choices, so little time: measuring the effects of free choice and enjoyment on perception of free time, time pressure and time deprivation. In ACR North American Advances.

Anable, Jillian; Gatersleben, Birgitta (2005): All work and no play? The role of instrumental and affective factors in work and leisure journeys by different travel modes. In Transportation Research Part A: Policy and Practice 39.2-3, 163-181. https://doi.org/10.1016/j.tra.2004.09.008

Arentze, Theo A.; Timmermans, Harry J. (2004): A learning-based transportation oriented simulation system. In Transportation Research Part B: Methodological, 38(7), 613-633. https://doi.org/10.1016/j.trb.2002.10.001

Auld, Joshua; Sokolov, Vadim; Stephens, Thomas S. (2017): Analysis of the effects of connected–automated vehicle technologies on travel demand. In Transportation Research Record: Journal of the Transportation Research Board 2625: 1-8. http://dx.doi.org/10.3141/2625-01

Ayyagari, Ramakrishna; Grover, Varun; Purvis, Russell (2011): Technostress: technological antecedents and implications. In MIS quarterly 35.4, 831-858. https://doi.org/10.2307/41409963

Banerjee, Ipsita; Kanafani, Adib (2008): The value of wireless Internet connection on trains: Implications for mode-choice models. University of California Transportation Center.

Bates, John; Polak, John; Jones, Peter; Cook, Andrew (2001): The valuation of reliability for personal travel. In Transportation Research Part E: Logistics and Transportation Review, 37(2-3), 191-229. https://doi.org/10.1016/s1366-5545(00)00011-9

Becker, Gary S. (1965): A Theory of the Allocation of Time. In The economic journal, 493-517. https://doi.org/10.2307/2228949

Charmaz, Kathy (2006): Constructing grounded theory: A practical guide through qualitative analysis. SAGE Publications.

Chen, Cynthia; Chen, Jason (2009): What is responsible for the response lag of a significant change in discretionary time use: the built environment, family and social obligations, temporal constraints, or a psychological delay factor?. In Transportation 36.1, 27-46. https://doi.org/10.1007/s11116-008-9184-6

Chen, Yuche; Gonder, Jeffrey; Young, Stanley; Wood, Eric (2017): Quantifying autonomous vehicles national fuel consumption impacts: A data-rich approach. In Transportation Research Part A: Policy and Practice, In Press.

Childress, Suzanne; Nichols, Brice; Charlton, Billy; Coe, Stefan (2015): Using an activity-based model to explore the potential impacts of automated vehicles. In Transportation Research Record: Journal of the Transportation Research Board 2493, 99–106. https://doi.org/10.3141/2493-11

Chorus, Caspar G.; De Jong, Gerard C. (2011): Modeling experienced accessibility for utility-maximizers and regret-minimizers. In Journal of Transport Geography, 19(6), 1155-1162. https://doi.org/10.1016/j.jtrangeo.2011.02.009

Cotte, June; Ratneshwar, S.; Mick, David G. (2004): The times of their lives: Phenomenological and metaphorical characteristics of consumer timestyles. In Journal of consumer research, 31(2), 333-345. https://doi.org/10.1086/422112

De Vos, Jonas; Mokhtarian, Patricia L.; Schwanen, Tim; Van Acker, Veronique; Witlox, Frank (2016): Travel mode choice and travel satisfaction: bridging the gap between decision utility and experienced utility. In Transportation 43(5), 771-796. https://doi.org/10.1007/s11116-015-9619-9

Diels, Cyriel; Bos, Jelte E. (2016): Self-driving carsickness. In Applied Ergonomics, 53, 374–382. https://doi.org/10.1016/j.apergo.2015.09.009

Elo, Satu; Kyngäs, Helvi (2008): The qualitative content analysis process. In Journal of advanced nursing 62(1), 107-115. https://doi.org/10.1111/j.1365-2648.2007.04569.x

Ettema, Dick; Friman, Margareta; Gärling, Tommy; Olsson, Lars E.; Fujii, Satoshi (2012): How in-vehicle activities affect work commuters' satisfaction with public transport. In Journal of Transport Geography 24, 215-222. https://doi.org/10.1016/j.jtrangeo.2012.02.007

Ettema, Dick; Verschuren, Laura (2007): Multitasking and value of travel time savings. In Transportation Research Record: Journal of the Transportation Research Board, 19-25. https://doi.org/10.3141/2010-03

Evans, Gary W.; Wener, Richard E.; Phillips, Donald (2002): The morning rush hour: Predictability and commuter stress. In Environment and Behavior 34.4, 521-530. https://doi.org/10.1177/00116502034004007

Fagnant, Daniel J.; Kockelman, Kara (2015): Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. In Transportation Research Part A: Policy and Practice 77: 167-181. https://doi.org/10.1016/j.tra.2015.04.003

Fraedrich, Eva; Cyganski, Rita; Wolf, Ingo; Lenz, Barbara (2016): User Perspectives on Autonomous Driving: A Use-Case-Driven Study in Germany.

Frei, Charlotte; Mahmassani, Hani S.; Frei, Andreas (2015): Making time count: Traveler activity engagement on urban transit. In Transportation Research Part A: Policy and Practice, 76,58–70. https://doi.org/10.1016/j.tra.2014.12.007

Gripsrud, Mattias; Hjorthol, Randi (2012): Working on the train: from 'dead time' to productive and vital time. In Transportation 39.5, 941-956. https://doi.org/10.1007/s11116-012-9396-7

Gucwa, Michael (2014): Mobility and energy impacts of automated cars. In Proceedings of the Automated Vehicles Symposium.

Gunthorpe, Wendy; Lyons, Kevin (2004): A predictive model of chronic time pressure in the Australian population: Implications for leisure research. In Leisure sciences 26.2, 201-213. https://doi.org/10.1080/01490400490432127

Gustafson, Per (2012): Travel time and working time: What business travellers do when they travel, and why. In Time & Society 21.2, 203-222. https://doi.org/10.1177/0961463x12444057

Haboucha, Chana J.; Ishaq, Robert; Shiftan, Yoram (2017): User preferences regarding autonomous vehicles. In Transportation Research Part C: Emerging Technologies 78, 37-49. https://doi.org/10.1016/j.trc.2017.01.010

Hägerstrand, Torsten (1970): What about people in regional science? Papers of the Regional Science Association. Vol. 24. No. 1. Springer-Verlag. https://doi.org/10.1007/bf01936872

Harb, Mustapha; Xiao, Yu; Circella, Giovanni; Mokhtarian, Patricia L.; Walker, Joan L. (2018): Projecting travelers into a world of self-driving vehicles: estimating travel behavior implications via a naturalistic experiment. In Transportation, 1-15. https://doi.org/10.1007/s11116-018-9937-9

Holley, David; Jain, Juliet; Lyons, Glenn (2008): Understanding business travel time and its place in the working day. In Time & Society 17.1, 27-46. https://doi.org/10.1177/0961463x07086308

Jain, Juliet; Lyons, Glenn (2008): The gift of travel time. In Journal of Transport Geography, 16(2), 81-89. https://doi.org/10.1016/j.jtrangeo.2007.05.001

Jarvenpaa, Sirkka L.; Lang, Karl R. (2005): Managing the paradoxes of mobile technology. In Information systems management 22, no. 4: 7-23. https://doi.org/10.1201/1078.10580530/45520.22.4.20050901/90026.2

Kahneman, Daniel; Wakker, Peter; Sarin, Rakesh (1997): Back to Bentham? Explorations of experienced utility. In The Quarterly Journal of Economics 112 (2), 375–405. https://doi.org/10.1162/003355397555235

Kaufman-Scarborough, Carol; Lindquist, Jay D. (1999): Time management and polychronicity: Comparisons, contrasts, and insights for the workplace. In Journal of Managerial Psychology 14.3/4, 288-312. https://doi.org/10.1108/02683949910263819

Kenyon, Susan; Lyons, Glenn (2003): The value of integrated multimodal traveller information and its potential contribution to modal change. In Transportation Research Part F: Traffic Psychology and Behaviour, 6(1), 1-21. https://doi.org/10.1016/s1369-8478(02)00035-9

Keseru, Imre; Cathy Macharis (2018): Travel-based multitasking: review of the empirical evidence. In Transport Reviews 38.2: 162-183. https://doi.org/10.1080/01441647.2017.1317048

Kitamura, Ryuichi (1988): An evaluation of activity-based travel analysis. In Transportation, 15(1), 9-34. https://doi.org/10.1007/bf00167973

Kröger, Lars; Kuhnimhof, Tobias; Trommer, Stefan (2018): Does context matter? A comparative study modelling autonomous vehicle impact on travel behaviour for Germany and the USA. In Transportation Research Part A: Policy and Practice. https://doi.org/10.1016/j.tra.2018.03.033

König, Michael; Neumayr, Lambert (2017): Users' resistance towards radical innovations: The case of the self-driving car. In Transportation Research Part F: traffic psychology and behaviour 44, 42-52. https://doi.org/10.1016/j.trf.2016.10.013

Krueger, Richard A.; Casey, Mary A. (2014): Focus Groups: A Practical Guide for Applied Research (5 ed.). SAGE Publications.

Laird, James; Geurs, Karst; Nash, Chris (2009): Option and non-use values and rail project appraisal. In Transport Policy 16.4, 173-182. https://doi.org/10.1016/j.tranpol.2009.05.002

LaMondia, Jeffrey J.; Fagnant, Daniel J.; Qu, Hongyang; Barrett, Jackson; Kockelman, Kara (2016): Shifts in Long-Distance Travel Mode Due to Automated Vehicles: Statewide Mode-Shift Simulation Experiment and Travel Survey Analysis. In Transportation Research Record: Journal of the Transportation Research Board 2566, 1-11. https://doi.org/10.3141/2566-01

Le Vine, Scott; Zolfaghari, Alireza; Polak, John (2015): Autonomous cars: The tension between occupant experience and intersection capacity. In Transportation Research Part C: Emerging Technologies, 52, 1–14. https://doi.org/10.1016/j.trc.2015.01.002

Lyons, Glenn; Jain, Juliet; Holley, David (2007): The use of travel time by rail passengers in Great Britain. In Transportation Research Part A: Policy and Practice 41.1, 107-120. https://doi.org/10.1016/j.tra.2006.05.012

Lyons, Glenn; Urry, John (2005): Travel time use in the information age. In Transportation Research Part A: Policy and Practice 39, no. 2-3: 257-276. https://doi.org/10.1016/j.tra.2004.09.004

Maréchal, Séverine (2016): Modelling the aquisition of travel information and its influence on travel behaviour. PhD thesis, Imperial College London.

Marshall, Martin N. (1996): Sampling for qualitative research. In Family practice 13.6, 522-526. https://doi.org/10.1093/fampra/13.6.522

Meyer, Jonas; Becker, Henrik; Bösch, Patrick M.; Axhausen, Kay W. (2017): Autonomous vehicles: The next jump in accessibilities?. In Research in Transportation Economics 62, 80-91. https://doi.org/10.1016/j.retrec.2017.03.005

Milakis, Dimitris; Van Arem, Bart; Van Wee, Bert (2017): Policy and society related implications of automated driving: a review of literature and directions for future research. In Journal of Intelligent Transportation Systems 21.4, 324-348. https://doi.org/10.1080/15472450.2017.1291351

Milakis, Dimitris; Kroesen, Maarten; van Wee, Bert (2018): Implications of automated vehicles for accessibility and location choices: Evidence from an expert-based experiment. In Journal of Transport Geography, 68, 142-148. https://doi.org/10.1016/j.jtrangeo.2018.03.010

MIT Technology Review (2018): IKEA designs future autonomous cars that work as hotels, stores, and meeting rooms. Retrieved on 24.09.2018 from https://www.technologyreview.com/s/612125/ikea-designs-future-autonomous-cars-that-work-as-hotels-stores-and-meeting-rooms/

Mokhtarian, Patricia L.; Salomon, Ilan (2001): How derived is the demand for travel? Some conceptual and measurement considerations. In Transportation Research Part A: Policy and Practice 35(8), 695–719. https://doi.org/10.1016/s0965-8564(00)00013-6

Morgan, David L. (1996): Focus groups. In Annual Review Sociology 22, 120-152. https://doi.org/10.1146/annurev.soc.22.1.129

Nordhoff, Sina; de Winter, Joost; Kyriakidis, Miltos; van Arem, Bart; Happee, Riender (2018): Acceptance of Driverless Vehicles: Results from a Large Cross-National Questionnaire Study. In Journal of Advanced Transportation. https://doi.org/10.1155/2018/5382192

Onwuegbuzie, Anthony J.; Dickinson, Wendy B.; Leech, Nancy L.; Zoran, Annmarie G. (2009): A Qualitative Framework for Collecting and Analyzing Data in Focus Group Research. In International Journal of Qualitative Methods, 8(3) https://doi.org/10.1177/160940690900800301

Ory, David T.; Mokhtarian, Patricia L. (2005): When is getting there half the fun? Modeling the liking for travel. In Transportation Research Part A: Policy and Practice 39(2-3), 97–123. https://doi.org/10.1016/j.tra.2004.09.006

Paleti, Rajesh; Vovsha, Peter; Givon, Danny; Birotker, Yehoshua (2015): Impact of individual daily travel pattern on value of time. In Transportation 42, no. 6, 1003-1017. https://doi.org/10.1007/s11116-015-9654-6

Pawlak, Jacek; Polak, John W.; Sivakumar, Aruna (2015): Towards a microeconomic framework for modelling the joint choice of activity–travel behaviour and ICT use. In Transportation Research Part A: Policy and Practice 76, 92–112. https://doi.org/10.1016/j.tra.2014.10.013

Pawlak, Jacek; Polak, John W.; Sivakumar, Aruna (2017): A framework for joint modelling of activity choice, duration, and productivity while travelling. In Transportation Research Part B: Methodological 106, 153–172. https://doi.org/10.1016/j.trb.2017.10.010

Payre, William; Julien Cestac; Patricia Delhomme (2014): Intention to use a fully automated car: Attitudes and a priori acceptability. In Transportation Research Part F: Traffic Psychology and Behaviour 27, 252-263. https://doi.org/10.1016/j.trf.2014.04.009

[dataset] Pudāne, Baiba (2018): Transcripts of 5 focus groups discussing topic 'Possible impacts of automated vehicles on travel and daily life in the future'. In 4TU.Centre for Research Data. http://doi.org/10.4121/uuid:994f0ab2-0fa2-493f-88ad-fbf4eaaf470e .

Pudāne, Baiba; Molin, Eric J.E.; Arentze, Theo A.; Maknoon, Yousef; Chorus, Caspar G. (2018): A Time-use Model for the Automated Vehicle-era. In Transportation Research Part C: Emerging Technologies 93, 102-114. https://doi.org/10.1016/j.trc.2018.05.022

SAE International (2016): Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. SAE International, Warrendale, PA. https://doi.org/10.4271/j3016_201609

Singleton, Patrick A (2018): Discussing the “positive utilities” of autonomous vehicles: will travellers really use their time productively? In Transport Reviews, 1-16. https://doi.org/10.1080/01441647.2018.1470584

Silberg, Gary; Manassa, Mitch; Everhart, Kevin; Subramanian, Deepak; Corley, Michael; Fraser, Hugh; Sinha, Vivek (2013): Self-Driving Cars: Are We Ready?. KPMG LLP.

Steg, Linda (2005): Car use: Lust and must. Instrumental, symbolic and affective motives for car use. In Transportation Research Part A: Policy and Practice, 39(2), 147–162. https://doi.org/10.1016/j.tra.2004.07.001

Stewart, David W.; Shamdasani, Prem N. (2014): Focus groups: Theory and practice. Vol. 20. SAGE Publications.

te Brömmelstroet, Marco; Nikolaeva, Anna; Glaser, Meredith; Nicolaisen, Morten Skou; Chan, Carmen (2017): Travelling together alone and alone together: mobility and potential exposure to diversity. In Applied Mobilities 2, no. 1, 1-15. https://doi.org/10.1080/23800127.2017.1283122

Trommer, Stefan; Kolarova, Viktoriya; Fraedrich, Eva; Kröger, Lars; Kickhöfer, Benjamin; Kuhnimhof, Tobias; Lenz, Barbara; Phleps, Peter (2016): Autonomous Driving-The Impact of Vehicle Automation on Mobility Behaviour.

Wadud, Zia; MacKenzie, Don; Leiby, Paul (2016): Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. In Transportation Research Part A: Policy and Practice 86, 1-18. https://doi.org/10.1016/j.tra.2015.12.001

Wheatley, Daniel; Bickerton, Craig (2016): Time-use and well-being impacts of travel-to-work and travel-for-work. In New Technology, Work and Employment 31.3, 238-254. https://doi.org/10.1111/ntwe.12074

Yap, Menno D.; Correia, Gonçalo; Van Arem, Bart (2016): Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. In Transportation Research Part A: Policy and Practice 94, 1-16. https://doi.org/10.1016/j.tra.2016.09.003

Zmud, Johanna; Ipek N. Sener; Jason Wagner (2016): Self-Driving Vehicles: Determinants of Adoption and Conditions of Usage. In Transportation Research Record: Journal of the Transportation Research Board 2565, 57-64. https://doi.org/10.3141/2565-07

Appendix

Table 2-3 Details of the participants who are quoted in the paper

No	Name (replaced)	Age range	Gender	Profession	Dominating travel mode(s)	Commute time
1	André	20-29	M	Student	Bicycle, PT*	Short**
2	Bart	30-39	M	Researcher	PT	Short
3	Caroline	30-39	F	Researcher	Bicycle, PT	Short
4	Daniel	30-39	M	Researcher	PT	Short, sometimes long
5	Dennis	30-39	M	Researcher, consultant	Bicycle, PT	30 min
6	Elisabeth	40-49	F	Consultant	PT	40-75 min
7	Eric	30-39	M	Company owner	PT	30 min
8	Felix	30-39	M	Sales agent	Car, PT	20-40 min
9	Gabrielle	60-69	F	Teacher (recently retired)	Car	40 min
10	Jelmer	40-49	M	Contractor	Car	Travel throughout the day for work
11	Johanna	20-29	F	Catering assistant	Car	20 min
12	Laurens	40-49	M	Credit controller	Car, PT	30-60 min
13	Linda	40-49	F	Researcher	Bicycle, PT	60 min
14	Maarten	20-29	M	Software developer	Bicycle, car	25-45 min
15	Niek	30-39	M	Teacher and student	Bicycle, car	30 min
16	Nora	40-49	F	Customer service employee	Car	15 min
17	Norbert	30-39	M	Content manager	PT	45-60 min
18	Paulien	40-49	F	Pedicure specialist	Car	Travel throughout the day for work
19	Petra	20-29	F	Mortician	Car	20 min
20	Pieter	40-49	M	Sales agent	Car	30-45 min, sometimes 2h
21	Renate	40-49	F	Coordinator	Car	30 min

* public transport
** exact duration not specified

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

Pudāne, B., van Cranenburgh, S., & Chorus, C. G. (2021). A Day in the Life with an Automated Vehicle: Empirical Analysis of Data from an Interactive Stated Activity-Travel Survey. Journal of Choice Modelling, 39, 100286.

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.

3.1 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 & 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 & 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 impacts on travel episodes. Clearly, many impacts may originate there: taking away the driving task from travelling[7] 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 & 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.[8] 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,

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

[8] 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 & 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 & Bos, 2016; Le Vine et al, 2015).

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 & 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 & Jana, 2019; Varghese et al., 2020; Calastri et al., 2021).

The rest of the paper is organised as follows. Section 3.2 presents the interactive stated activity-travel survey and summarises the statistics of the sample. Section 3.3 presents the MDCEV model and the specifications for our study. Section 3.4 reports the modelling results for on-board and stationary activities in the pre- and post-AV schedules. Section 3.5 discusses potential links between on-board and stationary activity changes, as well as limitations of the study and avenues for further research. Section 3.6 concludes and discusses modelling implications.

3.2 Data collection

3.2.1 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.[9] 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, 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 3.2.2). 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 Figure 3-1), 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. Figure 3-1 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

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

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.’

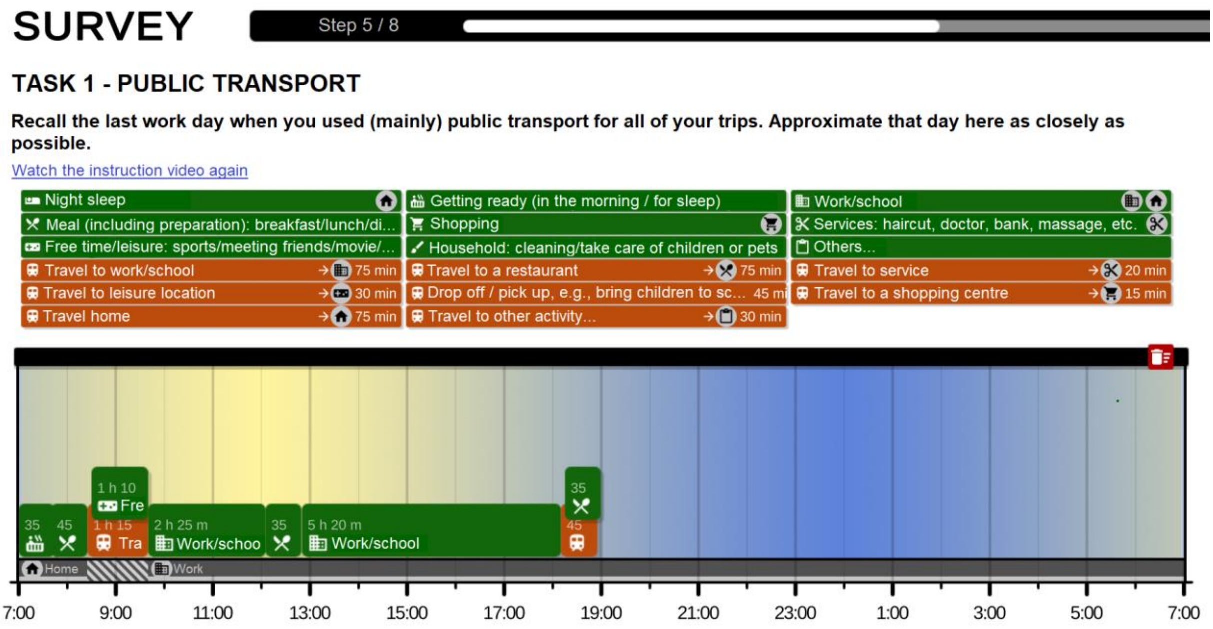


Figure 3-1 Survey screen – example of building a current schedule with public transport

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 Figure 3-1, 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).[10]

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

3.2.2 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.[11] 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 3-1 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.[12] 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.

Table 3-1 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%

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

[12] 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/

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%

3.2.3 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 (Figure 3-2 and Figure 3-3). Afterwards, we turn to correlations between AV-induced changes in activity durations (Figure 3-4), which will contribute to the later discussion of MDCEV results.

Figure 3-2 and Figure 3-3 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.[13] Given that only few respondents represented some transport modes (see Table 3-1), ‘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’.

Considering first the on-board activities (Figure 3-2), 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 & 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,

[13] 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.

indicating that participants did not consider motion sickness as an important determinant for their anticipated behaviours in the AV.

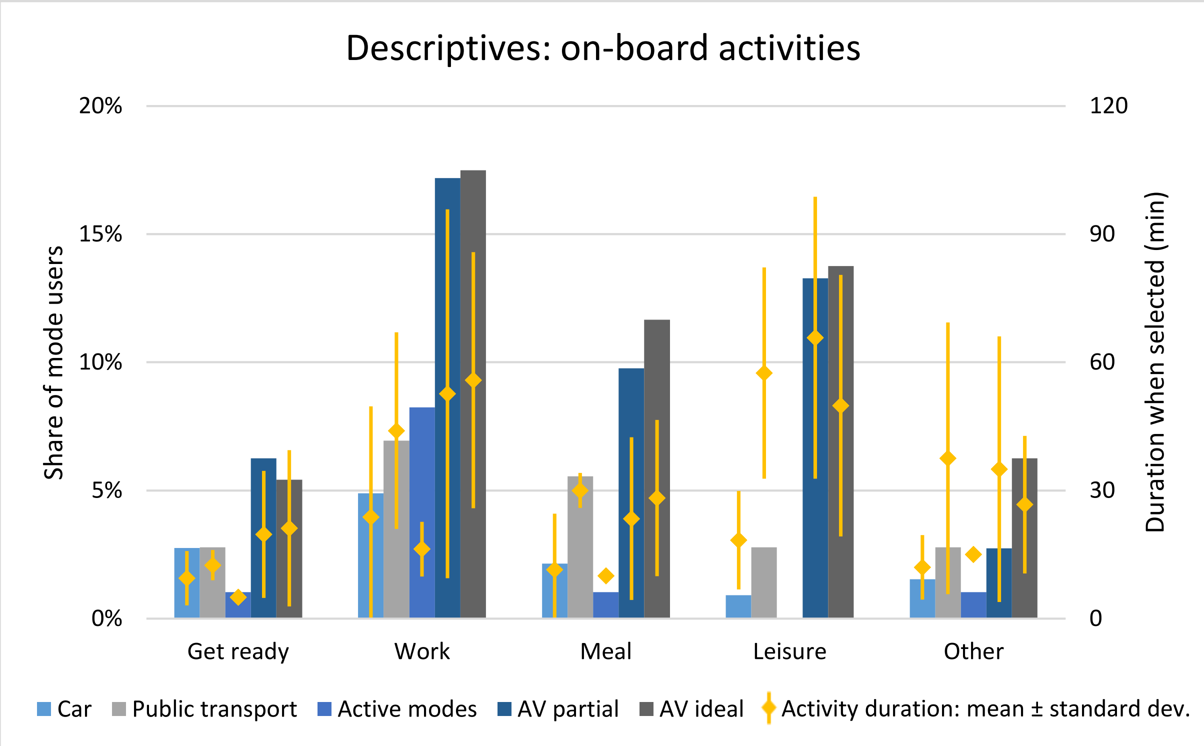


Figure 3-2 Descriptive statistics of on-board activities: selection and durations by travel mode

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 & 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 & 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 (Figure 3-3), 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 Figure 3-1). (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 3.2.1 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).

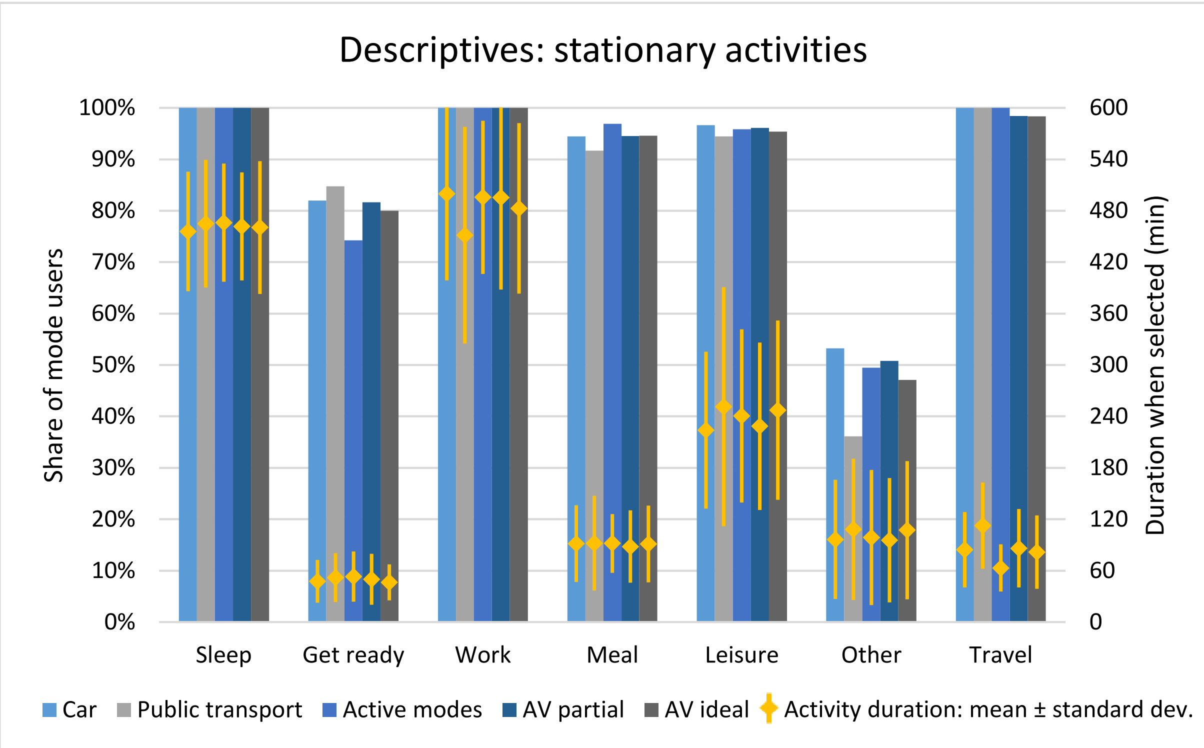


Figure 3-3 Descriptive statistics of stationary activities: selection and durations by travel mode

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. Figure 3-4 presents Pearson and Spearman rank correlations between the two activity categories. Since on-board activities mostly increased with AVs (see Figure 3-2), 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 ×. Spearman correlations are slightly stronger than Pearson correlations, which indicates a weak non-linear relation.

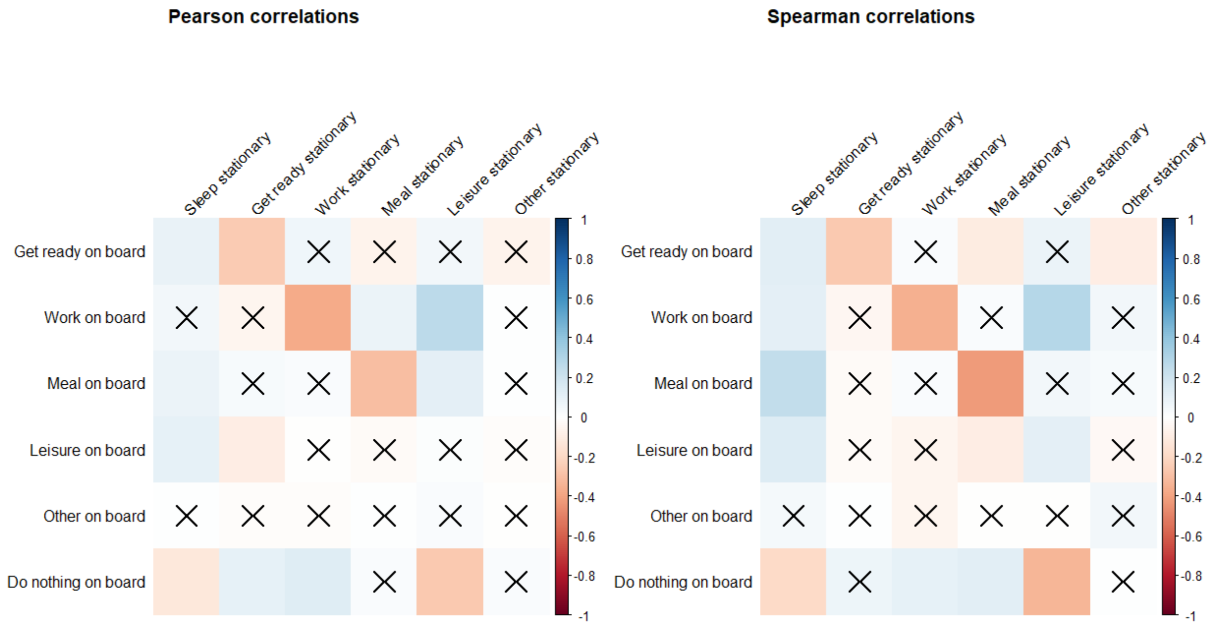


Figure 3-4 Pearson and Spearman rank correlations between on-board and stationary activity changes with AVs

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 Figure 3-3 (in comparison with Figure 3-2) 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 3.2.1.) 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.

3.3 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:

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

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^*, …, t_M^* is given by

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

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 3.4.1), 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 3.4.2), 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 3.2.3, travel time was not selected in few schedules, 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:

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

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.

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.

3.4 MDCEV model results

3.4.1 On-board activities

Table 3-2 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 Figure 3-2. 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 3-2 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[14] 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 3-2. The constants 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 3.4.2) 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

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

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, 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.

Table 3-2 Models for on-board activities: estimates (t-values)

	Constants-only model	Full model												
	Constant	**Constant**	**Female**	**Age 18-24**	**Age 55+**	**Young child**	**Student**	**Entrepreneur**	**Higher education**	**High income**	**PT user**	**Active mode user**	**Medium commute**	**Long commute**
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)						1.10 (2.77)	1.89 (3.94
Work	-2.18 (-17.59)	-3.74 (-13.19)				0.54 (2.39)						1.01 (2.25)		1.53 (5.09
Meal	-2.78 (-18.95)	-5.01 (-11.88)	0.92 (3.38)					1.30 (1.60)					0.63 (2.07)	1.13 (2.87
Leisure	-2.71 (-19.02)	-5.46 (-9.09)	0.54 (2.12)								1.35 (1.46)			
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)							1.30 (4.52)	0.50 (1.95)		-0.96 (-1.74)	0.83 (2.99)	
Meal		0.89 (1.89)						-1.38 (-1.41)	1.37 (3.66)	0.43 (1.43)				
Leisure		2.56 (4.01)							0.49 (1.75)		-1.89 (-1.86)		0.75 (2.54)	0.97 (2.08
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)									0.30 (1.45)		0.17 (1.35)	
Leisure	1.55 (3.67)	0.40 (1.19)											1.59 (1.49)	
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)								0.67 (1.59)				
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		$321.98 > 54.57 = \chi^2_{0.05;39}$												

3.4.2 Stationary activities

Table 3-3 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 Figure 3-3). 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 3-3 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 3-3. 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).

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

	Constants-only model	Full model														
	Constant	Constant	Female	Age 18-24	Age 35+	Age 45-54	Age 55+	Young child	Single	Student	Entrepre-neur	Higher education	High income	Active mode user	Medium commute	Long commute
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)		0.38 (3.51)						-1.42 (-15.15)	-2.29 (-11.54)
Meal	0.75 (9.3)	1.23 (9.86)	0.25 (1.72)					1.15 (4.44)						0.24 (2.32)	-1.59 (-17.04)	-2.78 (-18.79)
Leisure	0.64 (7.35)	2.11 (14.49)	-0.50 (-5.60)					-0.77 (-5.84)					-0.65 (-3.95)		-1.58 (-17.00)	-2.98 (-19.78)
BASELINE β_k: change with AVs																
Get ready		0.00 (0.03)										0.15 (1.13)				
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)		0.23 (1.56)							
SATIATION δ_k: base																
Sleep	4.68 (30.54)	8.28 (27.73)						-0.63 (-3.67)						0.39 (1.13)	-4.47 (-15.55)	-5.95 (-20.64)
Get ready	0.90 (21.13)	1.09 (12.85)					0.29 (2.19)			0.42 (2.63)		-0.14 (-1.86)				-0.29 (-2.68)
Work	4.87 (29.95)	8.83 (23.03)	-0.35 (-2.03)		0.39 (2.28)			-0.56 (-3.14)			-0.94 (-2.95)				-4.90 (-13.33)	-6.60 (-19.52)
Meal	0.90 (18.61)	1.28 (15.83)	-0.15 (-2.30)					-0.65 (-6.76)	-0.13 (-1.74)							
Leisure	2.51 (16.79)	2.57 (11.29)		1.23 (3.50)								-0.48 (-3.62)	1.03 (3.30)			
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		$857.56 > 67.50 = \chi^2_{0.05;50}$														

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 Figure 3-3). 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.

3.4.3 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 3-4 and Table 3-5, respectively. The duration predictions for the on-board activities in Table 3-4 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.

Table 3-4 Internal validity of model in 3.4.1: 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 3-5 Internal validity of model in 3.4.2: 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

3.5 Discussion

3.5.1 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 3-6 summarises the signs of our results from previous sections.

Table 3-6 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

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 Figure 3-4. 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 3-6 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 & 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.

3.5.2 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 Figure 3-3: 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 & 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.

3.6 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 & 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.

Acknowledgements

The work reported in this paper was funded by the Netherlands Organisation for Scientific Research (NWO) as part of the project ‘Spatial and Transport impacts of Automated Driving’ (STAD), project number 438-15-161. We thank two anonymous reviewers for their constructive comments that helped to improve this paper. Furthermore, we thank Tom van den Berg for translating the survey tool, José Ignacio Hernández for programming help and all the ESS colleagues who piloted and gave feedback on the survey.

References

Allard, M. D., & Janes, M. (2008). Time use of working parents: a visual essay. Monthly Lab. Rev., 131, 3.

Bernardo, C., Paleti, R., Hoklas, M., & Bhat, C. (2015). An empirical investigation into the time-use and activity patterns of dual-earner couples with and without young children. Transportation Research Part A: Policy and Practice, 76, 71-91. https://doi.org/10.1016/j.tra.2014.12.006

Bhat, C. R. (2005). A multiple discrete–continuous extreme value model: formulation and application to discretionary time-use decisions. Transportation Research Part B: Methodological, 39(8), 679-707. https://doi.org/10.1016/j.trb.2004.08.003

Bhat, C. R. (2008). The multiple discrete-continuous extreme value (MDCEV) model: role of utility function parameters, identification considerations, and model extensions. Transportation Research Part B: Methodological, 42(3), 274-303. https://doi.org/10.1016/j.trb.2007.06.002

Bhat, C. R. (2018). A new flexible multiple discrete–continuous extreme value (MDCEV) choice model. Transportation Research Part B: Methodological, 110, 261-279. https://doi.org/10.1016/j.trb.2018.02.011

Bhat, C. R., Goulias, K. G., Pendyala, R. M., Paleti, R., Sidharthan, R., Schmitt, L., & Hu, H. H. (2013). A household-level activity pattern generation model with an application for Southern California. Transportation, 40(5), 1063-1086. https://doi.org/10.1007/s11116-013-9452-y

Bhat, C. R., & Sen, S. (2006). Household vehicle type holdings and usage: an application of the multiple discrete-continuous extreme value (MDCEV) model. Transportation Research Part B: Methodological, 40(1), 35-53. https://doi.org/10.1016/j.trb.2005.01.003

Calastri, C., Hess, S., Daly, A., & Carrasco, J. A. (2017). Does the social context help with understanding and predicting the choice of activity type and duration? An application of the Multiple Discrete-Continuous Nested Extreme Value model to activity diary data. Transportation Research Part A: Policy and Practice, 104, 1-20. https://doi.org/10.1016/j.tra.2017.07.003

Calastri, C., Pawlak, J., & Batley, R. (2021). Participation in online activities while travelling: an application of the MDCEV model in the context of rail travel. Transportation, 1-27. https://doi.org/10.1007/s11116-021-10166-8

Childress, S., Nichols, B., Charlton, B., & Coe, S. (2015). Using an activity-based model to explore the potential impacts of automated vehicles. Transportation Research Record, 2493(1), 99-106. https://doi.org/10.3141/2493-11

Choi, S., & Mokhtarian, P. L. (2020). How attractive is it to use the internet while commuting? A work-attitude-based segmentation of Northern California commuters. Transportation Research Part A: Policy and Practice, 138, 37-50. https://doi.org/10.1016/j.tra.2020.05.007

Correia, G., Looff, E., van Cranenburgh, S., Snelder, M., & van Arem, B. (2019). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. Transportation Research Part A: Policy and Practice, 119, 359-382. https://doi.org/10.1016/j.tra.2018.11.016

Cyganski, R., Fraedrich, E., & Lenz, B. (2015). Travel-time valuation for automated driving: A use-case-driven study. In Proceedings of the 94th Annual Meeting of the TRB.

Diels, C., & Bos, J. E. (2016). Self-driving carsickness. Applied ergonomics, 53, 374-382. https://doi.org/10.1016/j.apergo.2015.09.009

Duarte, F., & Ratti, C. (2018). The impact of autonomous vehicles on cities: A review. Journal of Urban Technology, 25(4), 3-18. https://doi.org/10.1080/10630732.2018.1493883

Enam, A., Auld, J., Rashidi, T.H. (2019). Multitasking Time Allocation: Influence of Attitude towards Travel Mode. Under review.

Ettema, D., & Verschuren, L. (2007). Multitasking and value of travel time savings. Transportation Research Record, 2010(1), 19-25. https://doi.org/10.3141/2010-03

Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transportation Research Part A: Policy and Practice, 77, 167-181. https://doi.org/10.1016/j.tra.2015.04.003

Frei, C., Mahmassani, H. S., & Frei, A. (2015). Making time count: Traveler activity engagement on urban transit. Transportation Research Part A: Policy and Practice, 76, 58-70. https://doi.org/10.1016/j.tra.2014.12.007

Harb, M., Xiao, Y., Circella, G., Mokhtarian, P. L., Walker, J. L. (2018). Projecting travelers into a world of self-driving vehicles: estimating travel behavior implications via a naturalistic experiment. Transportation, 1-15. https://doi.org/10.1007/s11116-018-9937-9

Hess, S. & Palma, D. (2019), Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application, Journal of Choice Modelling, Volume 32, September 2019. https://doi.org/10.1016/j.jocm.2019.100170

Hess, S. & Palma, D. (2020), Apollo version 0.1.0, user manual, www.ApolloChoiceModelling.com, version from 25.04.2020.

Keseru, I., Bulckaen, J., Macharis, C., Minnen, J., Gloreiux, I., & van Tienoven, T. P. (2015). Is travel time wasted? Evidence from a time use survey in Flanders, Belgium. In 14th International Conference on Travel Behaviour Research, Old Windsor, UK.

Keseru, I., & Macharis, C. (2018). Travel-based multitasking: review of the empirical evidence. Transport reviews, 38(2), 162-183. https://doi.org/10.1080/01441647.2017.1317048

Kim, S. H., Mokhtarian, P. L., & Circella, G. (2020). How, and for whom, will activity patterns be modified by self-driving cars? Expectations from the state of Georgia. Transportation research part F: traffic psychology and behaviour, 70, 68-80. https://doi.org/10.1016/j.trf.2020.02.012

Krueger, R., Rashidi, T. H., & Auld, J. (2019). Preferences for travel-based multitasking: Evidence from a survey among public transit users in the Chicago metropolitan area. Transportation Research Part F: Traffic Psychology and Behaviour, 65, 334-343. https://doi.org/10.1016/j.trf.2019.08.004

Kyriakidis, M., Happee, R., & de Winter, J. C. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. Transportation research part F: traffic psychology and behaviour, 32, 127-140. https://doi.org/10.1016/j.trf.2015.04.014

Le Vine, S., Zolfaghari, A., & Polak, J. (2015). Autonomous cars: The tension between occupant experience and intersection capacity. Transportation Research Part C: Emerging Technologies, 52, 1-14. https://doi.org/10.1016/j.trc.2015.01.002

Lyons, G., Jain, J., & Holley, D. (2007). The use of travel time by rail passengers in Great Britain. Transportation Research Part A: Policy and Practice, 41(1), 107-120. https://doi.org/10.1016/j.tra.2006.05.012

Malokin, A., Circella, G., & Mokhtarian, P. L. (2019). How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios. Transportation Research Part A: Policy and Practice, 124, 82–114. https://doi.org/10.1016/j.tra.2018.12.015

Milakis, D., Kroesen, M., & van Wee, B. (2018). Implications of automated vehicles for accessibility and location choices: Evidence from an expert-based experiment. Journal of Transport Geography, 68, 142-148. https://doi.org/10.1016/j.jtrangeo.2018.03.010

Mokhtarian, P. L. (2018). The times they are a-changin': what do the expanding uses of travel time portend for policy, planning, and life? Transportation Research Record, 2672(47), 1-11. https://doi.org/10.1177/0361198118798602

Molin, E., Adjenughwure, K., de Bruyn, M., Cats, O., & Warffemius, P. (2020). Does conducting activities while traveling reduce the value of time? Evidence from a within-subjects choice experiment. Transportation Research Part A: Policy and Practice, 132, 18-29. https://doi.org/10.1016/j.tra.2019.10.017

Pawlak, J. (2020). Travel-based multitasking: review of the role of digital activities and connectivity. Transport Reviews, 1-28. https://doi.org/10.1080/01441647.2020.1728418

Pawlak, J., Polak, J. W., Sivakumar, A. (2015). Towards a microeconomic framework for modelling the joint choice of activity–travel behaviour and ICT use. Transportation Research Part A: Policy and Practice 76, pp. 92–112. https://doi.org/10.1016/j.tra.2014.10.013

Pawlak, J., Polak, J. W., Sivakumar, A. (2017): A framework for joint modelling of activity choice, duration, and productivity while travelling. Transportation Research Part B: Methodological 106, pp. 153–172. https://doi.org/10.1016/j.trb.2017.10.010

Pawlak, J., Circella, G., Mahmassani, H. S., & Mokhtarian, P. L. (2020): Information and Communication Technologies (ICT), Activity Decisions, and Travel Choices: 20 years into the Second Millennium and where do we go next?

Pfleging, B., Rang, M., & Broy, N. (2016). Investigating user needs for non-driving-related activities during automated driving. In Proceedings of the 15th international conference on mobile and ubiquitous multimedia (pp. 91-99). https://doi.org/10.1145/3012709.3012735

Pinjari, A. R., & Bhat, C. (2010a). A multiple discrete–continuous nested extreme value (MDCNEV) model: Formulation and application to non-worker activity time-use and timing behavior on weekdays. Transportation Research Part B: Methodological, 44(4), 562-583. https://doi.org/10.1016/j.trb.2009.08.001

Pinjari, A. R., Bhat, C. (2010b). An efficient forecasting procedure for Kuhn-Tucker consumer demand model systems: application to residential energy consumption analysis. Technical paper. Department of Civil and Environmental Engineering, University of South Florida

Pudāne, B. (2020). Departure time choice and bottleneck congestion with automated vehicles: Role of on-board activities. European Journal of Transport and Infrastructure Research, 20(4), 306-334. https://doi.org/10.18757/ejtir.2020.20.4.4801

Pudāne, B., Molin, E. J., Arentze, T. A., Maknoon, Y., & Chorus, C. G. (2018). A time-use model for the automated vehicle-era. Transportation Research Part C: Emerging Technologies, 93, 102-114. https://doi.org/10.1016/j.trc.2018.05.022

Pudāne, B., Rataj, M., Molin, E. J., Mouter, N., van Cranenburgh, S., & Chorus, C. G. (2019). How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands. Transportation Research Part D: Transport and Environment, 71, 222-235. https://doi.org/10.1016/j.trd.2018.11.014

Pudāne, B., van Cranenburgh, S., & Chorus, C. G. (2021). A Day in the Life with an Automated Vehicle: Supporting Data and Software. 4TU.ResearchData. https://doi.org/10.4121/14125880

Russell, M., Price, R., Signal, L., Stanley, J., Gerring, Z., & Cumming, J. (2011). What do passengers do during travel time? Structured observations on buses and trains. Journal of Public Transportation, 14(3), 7. https://doi.org/10.5038/2375-0901.14.3.7

SAE International (2016): Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. SAE International, Warrendale, PA. https://doi.org/10.4271/j3016_201609

Shaw, F. A., Malokin, A., Mokhtarian, P. L., & Circella, G. (2019). It's not all fun and games: an investigation of the reported benefits and disadvantages of conducting activities while commuting. Travel Behaviour and Society, 17, 8-25. https://doi.org/10.1016/j.tbs.2019.05.008

Singleton, P. A. (2019). Discussing the "positive utilities" of autonomous vehicles: will travellers really use their time productively? Transport reviews, 39(1), 50-65. https://doi.org/10.1080/01441647.2018.1470584

Sobhani, A., Eluru, N., & Faghih-Imani, A. (2013). A latent segmentation based multiple discrete continuous extreme value model. Transportation Research Part B: Methodological, 58, 154-169. https://doi.org/10.1016/j.trb.2013.07.009

Soteropoulos, A., Berger, M., & Ciari, F. (2019). Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies. Transport reviews, 39(1), 29-49. https://doi.org/10.1080/01441647.2018.1523253

Stern, R. E., Cui, S., Delle Monache, M. L., Bhadani, R., Bunting, M., Churchill, M., Hamilton, N., Haulcy, R., Pohlmann, H., Wu, F., Piccoli, B., Seibold, B., Sprinkle, J., & Work, D. B. (2018). Dissipation of stop-and-go waves via control of autonomous vehicles: Field experiments. Transportation Research Part C: Emerging Technologies, 89, 205-221. https://doi.org/10.1016/j.trc.2018.02.005

Susilo, Y. O., Lyons, G., Jain, J., & Atkins, S. (2012). Rail passengers' time use and utility assessment: 2010 findings from Great Britain with multivariate analysis. Transportation research record, 2323(1), 99-109. https://doi.org/10.3141/2323-12

Taiebat, M., Stolper, S., & Xu, M. (2019). Forecasting the impact of connected and automated vehicles on energy use: a microeconomic study of induced travel and energy rebound. Applied Energy, 247, 297-308. https://doi.org/10.1016/j.apenergy.2019.03.174

Tang, J., Zhen, F., Cao, J., & Mokhtarian, P. L. (2018). How do passengers use travel time? A case study of Shanghai–Nanjing high speed rail. Transportation, 45(2), 451-477. https://doi.org/10.1007/s11116-017-9824-9

Varghese, V., & Jana, A. (2019). Multitasking during Travel in Mumbai, India: Effect of Satiation in Heterogeneous Urban Settings. Journal of Urban Planning and Development, 145(2). https://doi.org/10.1016/j.tbs.2018.03.003

Varghese, V., Chikaraishi, M., & Kato, H. (2020). Analysis of Travel-Time Use in Crowded Trains using Discrete-Continuous Choices of Commuters in Tokyo, Japan. Transportation Research Record, 0361198120934794. https://doi.org/10.1177/0361198120934794

Wadud, Z., & Huda, F. Y. (2019). Fully automated vehicles: the use of travel time and its association with intention to use. In Proceedings of the Institution of Civil Engineers-Transport (pp. 1-15). Thomas Telford Ltd. https://doi.org/10.1680/jtran.18.00134

Wang, D., & Li, J. (2011). A two-level multiple discrete-continuous model of time allocation to virtual and physical activities. Transportmetrica, 7(6), 395-416. https://doi.org/10.1080/18128602.2010.520138

Xiao, J., Su, R., McBride, E. C., & Goulias, K. G. (2020). Exploring the correlations between spatiotemporal daily activity-travel patterns and stated interest and perception of risk with self-driving cars. AGILE: GIScience Series, 1, 1-15. https://doi.org/10.5194/agile-giss-1-22-2020

Yu, X., van den Berg, V. A., & Verhoef, E. (2019). Autonomous cars and dynamic bottleneck congestion revisited: how in-vehicle activities determine aggregate travel patterns. Tinbergen Institute Discussion Paper 2019-067/VIII. https://doi.org/10.2139/ssrn.3457298

4 A time-use model for the automated vehicle-era

Pudāne, B., Molin, E. J., Arentze, T. A., Maknoon, Y., & Chorus, C. G. (2018). A time-use model for the automated vehicle-era. Transportation Research Part C: Emerging Technologies, 93, 102-114.

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.

4.1 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 Vehicles[15] (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 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-minute 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 minutes of her journey she spends preparing and eating breakfast; the remaining 30 minutes 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

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

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 4.2 builds the time-use model. Section 4.3 illustrates the model’s working using minimalistic examples. Section 4.4 applies the model to an extended example. Section 4.5 reflects on the role and scope of our model and provides suggestions for calibrating, applying and extending our model. Section 4.6 concludes and discusses policy implications.

4.2 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 a 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_{il}^m for travel (dis)utility and H_{il}^m for travel time, both assuming that the entire trip is performed with mode m. The travel (dis)utility V_{il}^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_{il}^m and (dis)utilities V_{il}^m are assumed to be known and not dependent on other selected activities, nor their sequence.[16] 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_{il}^m to this stationary activity is zero.[17]

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 $y_i^l, y_{ijl}^m \in [0,1]$. 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_{ijl}^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

[16] 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).

[17] 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).

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 $y_{ijl}^m T_i^m$ 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_{ijl}^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 minutes and give a utility of size 2, or on the way home in mode m, which could take 60 minutes 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 $0.8 * 2 + 0.2 * 1 = 1.8$. The time spent reading the newspaper equals $0.8 * 30 + 0.2 * 60 = 36$ minutes.[18] 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).[19]

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

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

subject to:

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

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

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

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

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

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

[18] 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.

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

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

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

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

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

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 $\boldsymbol{r_i^l}$ and $\boldsymbol{s_{ijl}^m}$ 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)–(11) define the domain of variables. The resulting system (1)–(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.
4. We do not distinguish work activity from other activities. We implicitly assume that on most days the utility generated by, for example, 8 hours of work, far exceeds utility of 8 hours 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.
5. 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.

4.3 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 activities[20] into an activity wish-list and add hypothetical utilities and time requirements for all activities (see Table 4-1). 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.[21, 22] 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.

[20] The mid-day activity is assumed to be work, which is not modelled here (see the example in section 4.1).

[21] 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)).

[22] 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.

Table 4-1 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 hours for the morning activities and 3 hours for the evening activities.

Using these settings as an input for the model[23,24], we obtain the optimal activity schedule for Anne both before and after she switches to an AV, see Figure 4-1. The results correspond to the description in the introduction.

A clear pattern can be seen in Figure 4-1: 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.

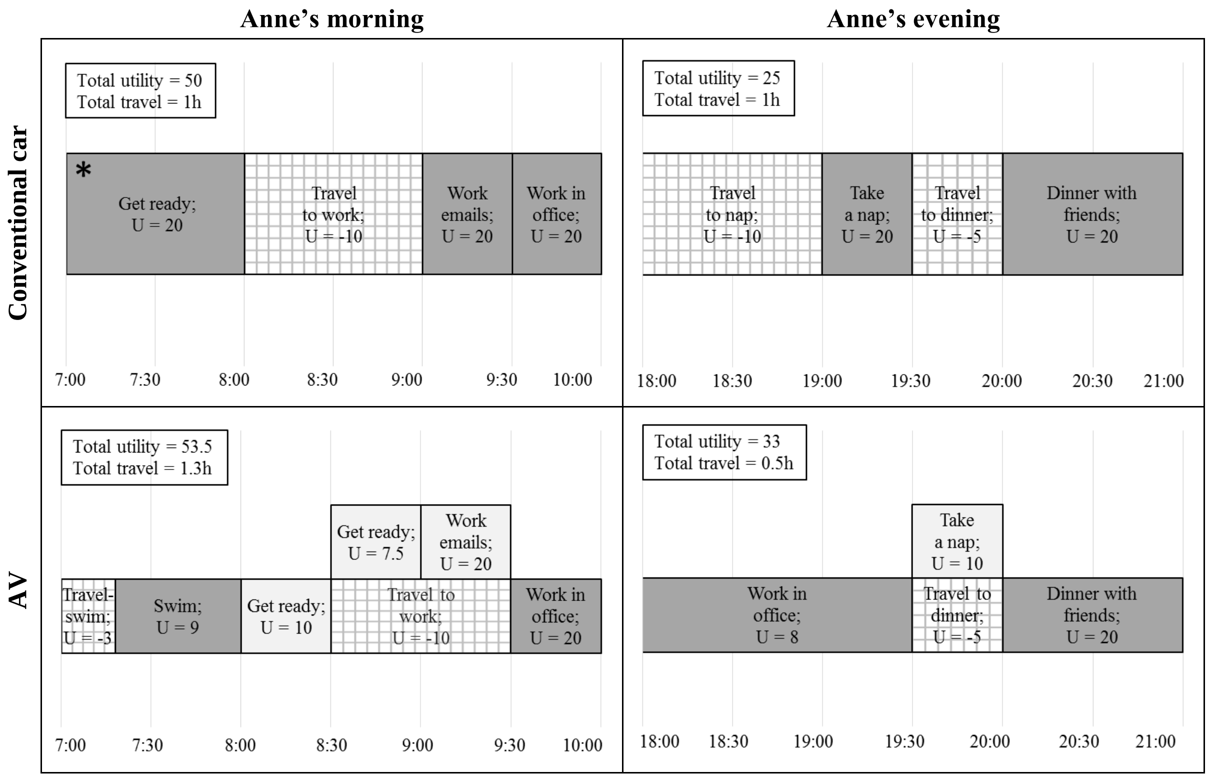
Furthermore, notice how the switch to an AV changes Anne's total utility and total travel time differently in the morning and evening activity plans. The total utility is always increased by adopting an AV, but in the morning this increase is smaller than in the evening. The total travel time is increased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

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.

---

23 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: $\sum_{i\in I} y_i^m T_i^m \leq \sum_{i\in I} z_i^m H_i^m$.

24 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.

Figure 4-1 Model predictions for the illustrative example

4.4 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 (subsection 4.4.1). Subsequently, we specify the traveller's activity wish-list as a combination of the activity types (subsection 4.4.2). Finally, we report and discuss the results of the extended example (subsection 4.4.3).

4.4.1 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 Figure 4-2. This classification relates to the insightful analysis of multitasking behaviour by Circella et al. (2012), who created a library of examples for primary and 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 Figure 4-2), whereas travel activities (or activities that involve travel, as in quadrants I and III) can hardly be secondary. In Figure 4-2, we illustrate the classification and provide an activity example for each quadrant, as well as a possible representation of it in model parameters.

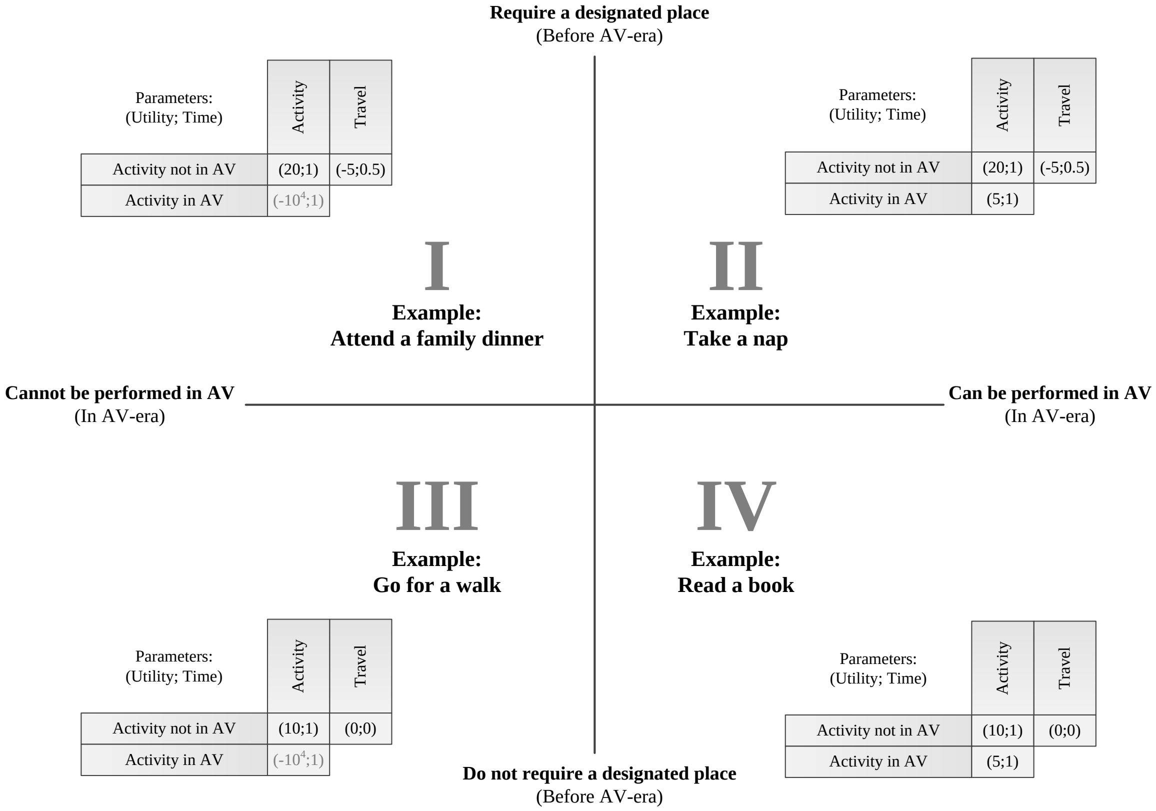


Figure 4-2 Activity types

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.

4.4.2 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 4-2, 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).

Table 4-2 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.

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.

According to these assumptions, we construct the extended activity wish-list, which displays the relative prevalence of activity types (see Table 4-3: quadrant I – 3 activities; quadrant II – 1 activity; quadrant III – 0 activities; quadrant IV – 2 activities).

Table 4-3 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	$-10^{4\,a}$/ 14^b/ 20^c	$1^{a,c}$/ 1.4^b	-5
IV	Watch a movie	10	1	0	0	$-10^{4\,a}$/ 7^b/ 10^c	$1^{a,c}$/ 1.4^b	-2
	Read a book	10	1	0	0	$-10^{4\,a}$/ 7^b/ 10^c	$1^{a,c}$/ 1.4^b	-1

Total time constraint: 5 hours.
a: no facilitation; b: partial facilitation; c: perfect facilitation.

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 (0.25h), 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 0.25h to 2h with a step of 0.25h. 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 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).

4.4.3 Model predictions

We use the constructed activity wish-list to find traveller's total utility and total travel time[25], 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 Figure 4-3 and Figure 4-4, respectively. The travel time scenarios are set on the x-axis. The facilitation level scenarios (no facilitation to perfect facilitation) correspond to different series.

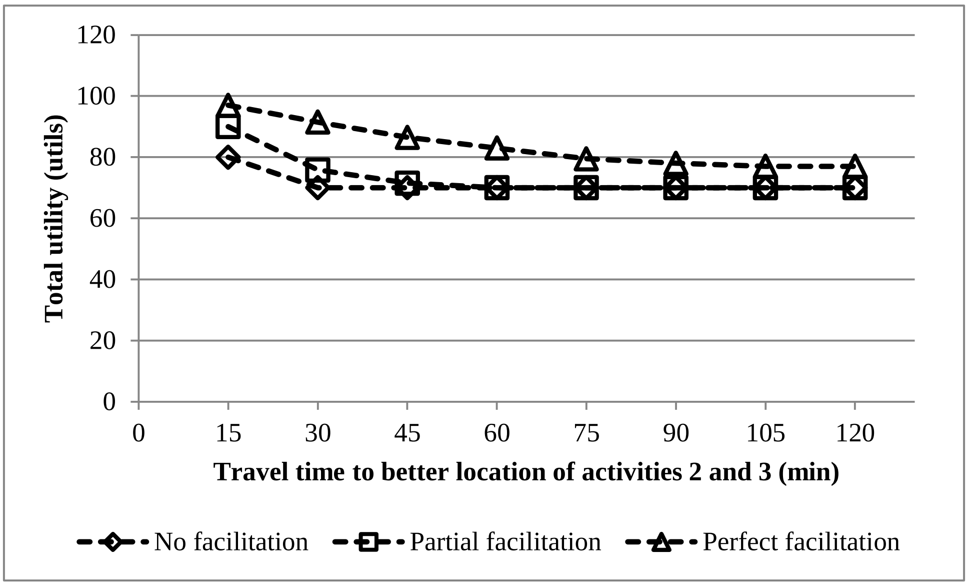


Figure 4-3 Total utility depending on travel time to better locations and facilitation scenario

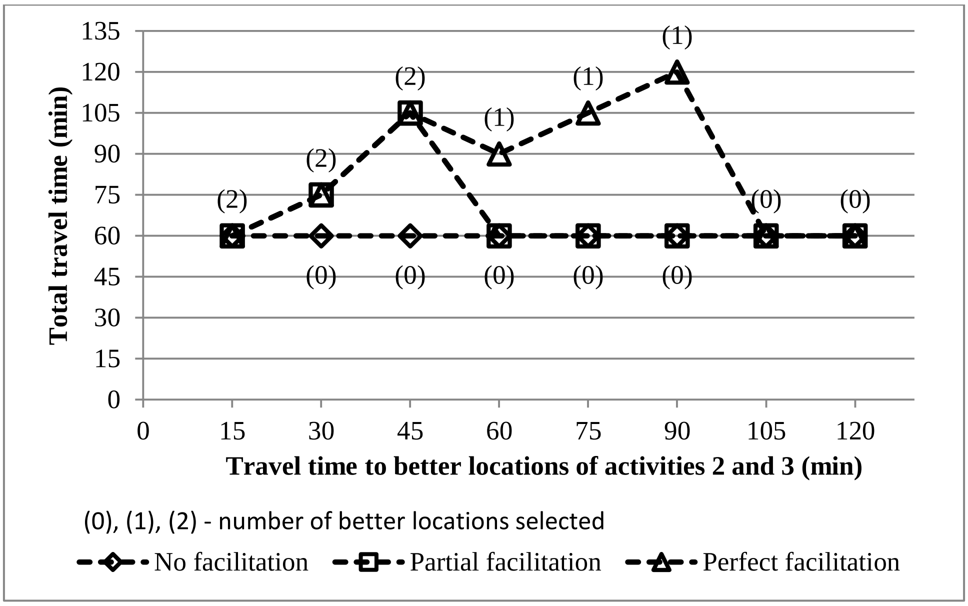


Figure 4-4 Total travel time depending on travel time to better locations and facilitation scenario

---

25 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).

In accordance with intuition, Figure 4-3 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.) Figure 4-4 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 minutes and partial activity facilitation. Figure 4-5 shows the selected activities (and their locations) as well as examples of schedules in 45- and 60-minute 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 minutes (top row of Figure 4-5, left) to 60 minutes (top row, right). In order to fit within the 5 hour 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 Figure 4-5). 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.

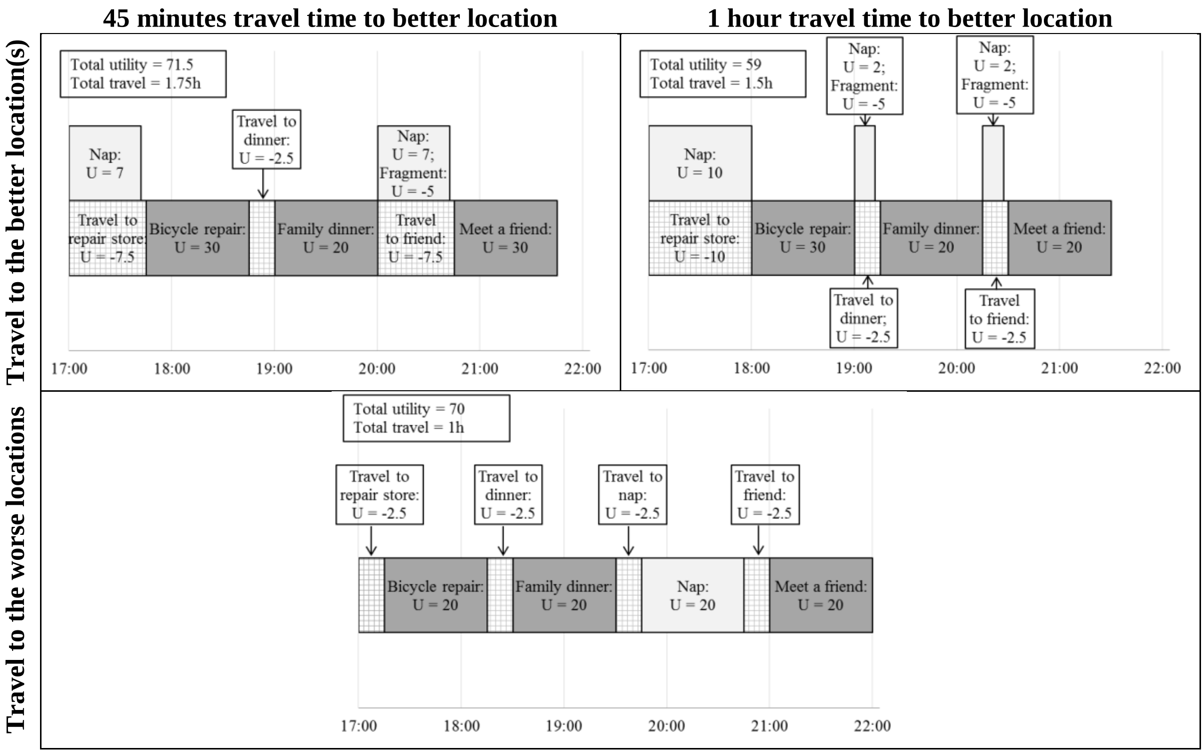


Figure 4-5 Schedule examples in partial facilitation scenario, travel times to the better locations: 45 min and 1 h

4.5 Reflections and suggestions for further research

4.5.1 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 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.

4.5.2 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 4.4.3), 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 4.4, 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 an 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.

4.5.3 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.

4.6 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 an 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.

Acknowledgment

The work reported in this paper was funded by the Netherlands Organisation for Scientific Research (NWO) as part of the project 'Spatial and Transport impacts of Automated Driving' (STAD), project number 438-15-161. We thank three reviewers for their insightful comments, which greatly helped to improve this paper. Discussions and advice from Sander van Cranenburgh has been a very valuable input for the paper.

References

Adjenughwure, Kingsley; Molin, Eric; de Bruyn, Menno; Cats, Oded; Warffemius, Pim; van der Waard, Jan; Chorus, Caspar (2018): The value of in-train activities and their impact on value of time. In 15th International Conference on Travel Behaviour Research

Arentze, Theo A.; Ettema, Dick; Timmermans, Harry J.P. (2010): Incorporating time and income constraints in dynamic agent-based models of activity generation and time use: Approach and illustration. In Transportation Research Part C: Emerging Technologies 18 (1), pp. 71–83. https://doi.org/10.1016/j.trc.2009.04.016

Banerjee, Ipsita; Kanafani, Adib (2008): The value of wireless internet connection on trains: Implications for mode-choice models. University of California Transportation Center.

Bansal, Prateek; Kockelman, Kara M.; Singh, Amit (2016): Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. In Transportation Research Part C: Emerging Technologies 67, pp. 1–14. https://doi.org/10.1016/j.trc.2016.01.019

Bates, J. J. (1987). Measuring travel time values with a discrete choice model: a note. In The Economic Journal 97(386), pp. 493-498. https://doi.org/10.2307/2232894

Becker, Gary S. (1965): A theory of the allocation of time. In The Economic Journal 75 (299), pp. 493–517. https://doi.org/10.2307/2228949

Bhat, Chandra R., Castro, Marisol, & Pinjari, Abdul Rawoof (2015). Allowing for complementarity and rich substitution patterns in multiple discrete–continuous models. Transportation Research Part B: Methodological, 81, pp. 59–77. https://doi.org/10.1016/j.trb.2015.08.009

Circella, Giovanni; Mokhtarian, Patricia L.; Poff, Laura K. (2012): A conceptual typology of multitasking behavior and polychronicity preferences. In Electronic International Journal of Time Use Research 9 (1), pp. 59–107. https://doi.org/10.13085/eijtur.9.1.59-107

Childress, Suzanne; Nichols, Brice; Charlton, Billy; Coe, Stefan (2015): Using an activity-based model to explore the potential impacts of automated vehicles. In Transportation Research Record: Journal of the Transportation Research Board 2493, pp. 99–106. https://doi.org/10.3141/2493-11

DeSerpa, Allan (1971): A theory of the economics of time. In The Economic Journal 81 (324), pp. 828–846. https://doi.org/10.2307/2230320

Ettema, Dick; Friman, Margareta; Gärling, Tommy; Olsson, Lars E.; Fujii, Satoshi (2012): How in-vehicle activities affect work commuters' satisfaction with public transport. In Journal of Transport Geography 24, pp. 215–222. https://doi.org/10.1016/j.jtrangeo.2012.02.007

Evans, Alan W. (1972): On the theory of the valuation and allocation of time. In Scottish Journal of Political Economy 19 (1), pp. 1–17. https://doi.org/10.1111/j.1467-9485.1972.tb00504.x

Fagnant, Daniel J.; Kockelman, Kara (2015): Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. In Transportation Research Part A: Policy and Practice 77, pp. 167–181. https://doi.org/10.1016/j.tra.2015.04.003

Frei, Charlotte; Mahmassani, Hani S.; Frei, Andreas (2015): Making time count: Traveler activity engagement on urban transit. In Transportation Research Part A: Policy and Practice 76, pp. 58–70. https://doi.org/10.1016/j.tra.2014.12.007

Gucwa, Michael (2014): Mobility and energy impacts of automated cars. In Proceedings of the Automated Vehicles Symposium, San Francisco.

Gustafson, Per (2012): Travel time and working time: What business travellers do when they travel, and why. In Time & Society 21(2), pp. 203–222. https://doi.org/10.1177/0961463X12444057

Heinrichs, Dirk (2016): Autonomous driving and urban land use. In Markus Maurer, J. Christian Gerdes, Barbara Lenz, Hermann Winner (Eds.): Autonomous driving: technical, legal and social aspects. https://doi.org/10.1007/978-3-662-48847-8_11

Hensher, D.A. (1977): Value of Business Travel Time. Pergamon Press, Oxford.

Jara-Díaz, Sergio R.; Munizaga, Marcela A.; Greeven, Paulina; Guerra, Reinaldo; Axhausen, Kay (2008): Estimating the value of leisure from a time allocation model. In Transportation Research Part B: Methodological 42 (10), pp. 946–957. https://doi.org/10.1016/j.trb.2008.03.001

Keseru, Imre; Macharis, Cathy (2017): Travel-based multitasking: Review of the empirical evidence. In Transport Reviews 133 (8), pp. 1–25. https://doi.org/10.1080/01441647.2017.1317048

Kitamura, Ryuichi; Fujii, Satoshi; Pas, Eric I. (1997): Time-use data, analysis and modeling: toward the next generation of transportation planning methodologies. In Transport Policy 4(4), pp. 225–235. https://doi.org/10.1016/S0967-070X(97)00018-8

Kono, Tatsuhito; Kishi, Akio; Seita, Emishi; Yokoi, Takahisa (2018): Limitations of using generalized transport costs to estimate changes in trip demand: A bias caused by the endogenous value of time. In Transportmetrica A: Transport Science, 14 (3), pp. 192-209. https://doi.org/10.1080/23249935.2017.1363316

Kyriakidis, Miltos; Happee, Riender; Winter, Joost C.F. de (2015): Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. In Transportation Research Part F: Traffic Psychology and Behaviour 32, pp. 127–140. https://doi.org/10.2139/ssrn.2506579

Lyons, Glenn; Jain, Juliet; Holley, David (2007): The use of travel time by rail passengers in Great Britain. In Transportation Research Part A: Policy and Practice 41 (1), pp. 107–120. https://doi.org/10.1016/j.tra.2006.05.012

Malokin, Alexander; Circella, Giovanni; Mokhtarian, Patricia L. (2016): How do activities conducted while commuting influence mode choice? Testing public transportation advantage and autonomous vehicle scenarios. In 94th Annual Meeting of the Transportation Research Board.

Milakis, Dimitris; van Arem, Bart; van Wee, Bert (2017): Policy and society related implications of automated driving: A review of literature and directions for future research. In Journal of Intelligent Transportation Systems. https://doi.org/10.1080/15472450.2017.1291351

Mokhtarian, Patricia L.; Salomon, Ilan (2001): How derived is the demand for travel? Some conceptual and measurement considerations. In Transportation research part A: Policy and practice 35(8), pp. 695–719. https://doi.org/10.1016/S0965-8564(00)00013-6

Ory, David T.; Mokhtarian, Patricia L. (2005): When is getting there half the fun? Modeling the liking for travel. In Transportation Research Part A: Policy and Practice 39(2-3), pp. 97–123. https://doi.org/10.1016/j.tra.2004.09.006

Ortúzar, Juan de Dios; Willumsen, Luis G. (2011): Modelling transport. John Wiley & Sons.

Pawlak, Jacek; Polak, John W.; Sivakumar, Aruna (2015): Towards a microeconomic framework for modelling the joint choice of activity–travel behaviour and ICT use. In Transportation Research Part A: Policy and Practice 76, pp. 92–112. https://doi.org/10.1016/j.tra.2014.10.013

Pawlak, Jacek; Polak, John W.; Sivakumar, Aruna (2017): A framework for joint modelling of activity choice, duration, and productivity while travelling. In Transportation Research Part B: Methodological 106, pp. 153–172. https://doi.org/10.1016/j.trb.2017.10.010

Sadat Lavasani Bozorg, Seyed Mohammad Ali (2016): Potential implication of automated vehicle technologies on travel behavior and system modeling. PhD thesis. Florida International University. https://doi.org/10.25148/etd.fidc001241

SAE International (2016): Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. SAE International, Warrendale, PA. https://doi.org/10.4271/j3016_201609

Sanchis, Raúl G. (2016). Economic Theories about the Allocation of Time: Review and an Extension for Multitasking. In The Economics of Multitasking, pp. 7–18. Palgrave Macmillan US. https://doi.org/10.1057/9781137381446_2

Wardman, M., Chintakayala, V. P. K., & de Jong, G. (2016). Values of travel time in Europe: Review and meta-analysis. In Transportation Research Part A: Policy and Practice, 94, pp. 93–111. https://doi.org/10.1016/j.tra.2016.08.019

Winston, Gordon C. (1982) The timing of economic activities: firms, households and markets in time-specific analysis. Cambridge University Press.

5 Departure time choice and bottleneck congestion with automated vehicles: Role of on-board activities

Pudāne, B. (2020). Departure time choice and bottleneck congestion with automated vehicles: Role of on-board activities. European Journal of Transport and Infrastructure Research, 20(4), 306-334.

Abstract

It is widely expected that automated vehicles (AVs) will revolutionise travel experience by better facilitating various on-board activities. While these activities could make travel more pleasant, as is often supposed, they could also affect daily schedules, the related travel choices, and finally, the aggregate travel patterns – possible influences that are still insufficiently studied. For example, a morning commuter deciding to perform some home or work activities during travel, instead of at home or work, could also reconsider his departure time to work. More such travellers together could reshape traffic congestion. This paper models exactly this scenario. It formulates new scheduling preferences, which account for home and/or work activities during morning commute, and uses these (1) to analyse the optimal departure times when there is no congestion, and (2) to obtain the equilibrium congestion patterns in a bottleneck setting. If there is no congestion, it is predicted that AV users would depart earlier (later), if the on-board environment supports their home (work) activities. If there is congestion, AV users that perform home (work) activities during travel skew the congestion to earlier (later) times, and AV users that perform both activities increase both early and late congestion. Engaging in any activity during travel worsens congestion, at least when assuming that AVs do not increase bottleneck capacity. If future AVs would be specialised to support only home, only work, or both home and work activities, and would do so to a similar extent, then 'Work AVs' would increase the congestion the least.

5.1 Introduction

Among the core expected benefits of automated vehicles[26] (AVs) is their promise to let their users perform new non-driving activities, or engage more efficiently in current non-driving activities, while being on the way. The literature (see Soteropoulos et al., 2019, for a recent review of modelling studies) commonly anticipates that this would make travel more pleasant, thus reducing the 'penalty' associated with travel time. This, the reasoning goes, may lead to acceptance of longer travel times, thereby increasing traffic congestion, which may be (partly) offset by shorter headways and increased throughput expected from AVs. The possible net congestion effects of AVs have been extensively modelled and discussed (e.g., van den Berg & Verhoef, 2016; Wadud et al., 2016; Auld et al., 2017; Milakis et al., 2017; Simoni et al., 2019).

However, a thought experiment can demonstrate that the substance of on-board activities may directly influence the timing preferences for a trip, and in so doing affect congestion patterns in ways that would not be predicted using travel time penalty. For example, an AV user may consider shifting or extending the pre- or post-travel activities into the trip. In the context of the morning commute, an individual may choose to perform in the AV 'home activities', such as getting ready, preparing and eating breakfast, getting a little more sleep, or 'work activities', such as replying to emails, planning the day, adjusting meeting schedule. This shift might reduce the aversion to longer travel and encourage AV users to depart at peak times. At the same time, it might result in a desire to depart from the origin earlier, while shifting origin-type activities to the trip, or to depart and arrive at the destination later, while shifting destination-type activities to the trip. That on-board activities may have varied influence on the preferred departure times, may also be expected knowing that various on-board activities differently influence the value of travel time or travel satisfaction (as found by Ettema & Verschuren, 2007; Susilo et al., 2012; Rasouli & Timmermans, 2014; Frei et al., 2015; Correia et al., 2019), as well as pre- and post-trip activities and daily time-use (Banerjee & Kanafani, 2008; Pawlak et al., 2015, 2017; Das et al., 2017; Krueger et al., 2019; Pudāne et al., 2018, 2019; Kim et al., 2020). Lastly, work or leisure during travel matters for the value of travel time savings, according to the time-use theory and the widely-used Hensher's equation (Hensher, 1977; Batley, 2015), and this link was recently examined by Pudāne and Correia (2020) in the AV context.

Yet, most current models that aim to predict mobility and congestion patterns in the AV era do not consider that various on-board activities may differently affect departure times (e.g., Correia & van Arem, 2016; Lamotte et al., 2017; Simoni et al., 2019; F. Zhang et al., 2020). The possibility to model multiple scenarios there is largely lost whenever the effects of a multitude of possible activities are condensed into a single travel time penalty (such as value of travel time). This treatment implies that the travel behaviour effects of various on-board activities are the same and indistinguishable from increased comfort of travel (such as more comfortable seats).

This study proposes a more flexible modelling approach, which lets to investigate, first, how various on-board activities may influence departure times of AV users and, second, how they may affect traffic congestion. It starts by formulating new scheduling preferences that let the analyst specify how suitable the travel environment is for home and work activities. After, it uses the new scheduling preferences to analyse the optimal departure times for users of different AVs. Finally, it obtains equilibrium congestion patterns in a minimalistic bottleneck setting, where a number of travellers with the same scheduling preferences move from a single origin to a single destination on a single route.

[26] This paper considers primarily the so-called level 5 or fully automated vehicles, according to SAE International (2016) standards.

Thereby, this study contributes to two streams of literature: first, to the study of the potential travel behaviour impacts of on-board activities (in AVs or other modes), especially those reaching beyond the effects on the value of travel time, and second, to the rich tradition of using the bottleneck model to analyse the impact of behaviour changes on congestion. With regard to the former, this study relates to the work of Pawlak et al. (2015, 2017), which uses a scenario with two out-of-vehicle activities connected by a trip, during which two in-vehicle activities may be performed. Pawlak et al. analysed a multidimensional choice in this setting: choice of activity types, departure times, duration and switching times between on-board activities, mode, route and use of ICT. Relatedly, Rasouli and Timmermans (2014) explored the impact of on-board activities on activities directly preceding or following the travel episode: interactions in what they named 'activity envelope'. More broadly, this work contributes to the literature that studies daily time-use effects of on-board activities (Banerjee & Kanafani, 2008; Pudāne et al., 2018; Kim et al., 2020).

With regard to the latter, this study provides an on-board time-use module to the classical bottleneck framework (conceived by Vickrey, 1969, and Arnott et al., 1990, 1993). The bottleneck model has been instrumental in investigating various factors influencing congestion (see the reviews by de Palma & Fosgerau, 2011, Small, 2015, and Li et al., 2020), and notably, it often allows to obtain analytic as opposed to simulated results. Related to the present work, time-use aspects were included in the bottleneck model by Gubins and Verhoef (2011), who studied the effects of teleworking on congestion, and by Xiaoning Zhang et al. (2005) and Li et al. (2014), who integrated bottleneck-based departure time choice in a whole-day activity pattern.

Moving forward, Li et al. (2020), in their review of the bottleneck model development over the past half a century, emphasise the need to include different properties of new transport technologies, such as automated vehicles, in the bottleneck model. This work contributes to this goal, along with other recent studies that have modelled congestion patterns when AVs and conventional vehicles use different roads (Lamotte et al., 2017), the congestion impacts of AVs being able to park themselves (Liu, 2018; Xiang Zhang et al., 2019; Tian et al., 2019), and the congestion patterns in the long run, when travellers can choose between conventional vehicles and AVs (F. Zhang et al., 2020). In particular, this work furthers the study of van den Berg and Verhoef (2016), who investigated the effects of AVs on congestion in a bottleneck, while assuming that any on-board activities contribute to a decreasing travel penalty. They concluded that AV users would concentrate in the middle of the peak congestion. The same conclusion was reached also by Fosgerau (2019) and F. Zhang et al. (2020). Finally, this study aligns with other ongoing work that looks into departure time effects of on-board activities in AVs: Yu et al. (2019) and Abegaz and Fosgerau (personal communication, September 2019). Yu et al. (2019) analyse congestion patterns given $\alpha - \beta - \gamma$ preferences[27], where an on-board activity simultaneously substitutes home and work activities to various degrees. They also derive market and AV-provision effects. Abegaz and Fosgerau model on-board activities as a separate class of mobile activities in a general scheduling preference framework and derive changes in value of time and reliability. The present work contributes to this ongoing research in two main directions. First, it shows how optimal departure times depend on the activities performed during travel – home-, work- or both home and work activities –, even if there is no congestion. Second, it provides a derivation of congestion patterns given a different (compared to Yu et al.) set-up within the $\alpha - \beta - \gamma$ preference framework, which also enables to capture a situation where traveller switches from performing home to work activities during travel.

The remainder of the paper is structured as follows. Section 5.2 introduces the scheduling preferences that capture the possibility to shift home or work activities to the trip. It

[27] The $\alpha - \beta - \gamma$ preferences, also called the step model, are the most commonly used scheduling preferences and are further explained in section 5.2.1.

also introduces three types of AVs that are used further in the paper. Section 5.3 analyses the departure times for a single traveller or multiple travellers that do not create congestion. Section 5.4 analyses congestion changes with AVs in bottleneck setting. Section 5.5 compares the current approach with travel time penalty method, discusses the assumption of $\alpha-\beta-\gamma$ scheduling preferences and other aspects of the model set-up, assesses the validity and applicability of the developed model to other transport modes, and recommends directions for further research. Section 5.6 concludes and discusses the implications of this study for AV-related transport policy.

5.2 Model set-up

5.2.1 Scheduling preferences considering on-board activities

A general form of scheduling functions (based on Vickrey, 1973) assumes that marginal home and work utilities $h[x]$ and $w[x]$ are positive and monotonously decreasing and increasing functions, respectively, of the clock-time x in a morning time interval $[0,\Omega]$. Conventionally, it is assumed that the individual cannot participate in any home or work activities during travel and therefore does not gain any home or work utility at that time. In the context of AVs however, I assume that individuals may continue with their home activities during travel or start to perform their work activities while on the way to work, but a specified share of the utility of these activities would be lost, reflecting some inconvenience of performing these activities in the vehicle. This loss is expressed using multiplicative efficiency factors $e_h, e_w \in [0,1]$ for home and work activities, respectively.[28]

Figure 5-1 illustrates the model set-up. It shows the marginal utilities of home and work activities (y-axis), which depend on time (x-axis) in a morning time interval. As can be seen from the distance between the solid and dashed lines, this figure illustrates a situation where home activities are better facilitated on board than work activities: $e_h > e_w$. Shaded areas represent the total utility gained from activities at home, at work and during travel.

The individual engages in home activity during travel at time x if $e_h h[x] > e_w w[x]$ (utility from on-board home activities is higher than utility of on-board work activities) and in work activity if $e_h h[x] < e_w w[x]$. Therefore, knowing that $e_h h[x]$ and $e_w w[x]$ are monotonously decreasing and increasing with $x \in [0,\Omega]$, respectively (due to the above assumptions), the optimal time for on-board home activity (if any) is at the start of the trip, and similarly the optimal time for the on-board work activity (if any) is at the end of the trip.

Furthermore, since marginal home and work utilities $h[x]$ and $w[x]$ are assumed to be positive for $x \in [0,\Omega]$, the individual would want to continually engage in on-board activities, if they are at least slightly facilitated (i.e., if $e_h, e_w > 0$, then utilities $e_h h[x], e_w w[x] > 0$). This setting yields a single optimal switching point between the home and work activities, which can be expressed as a share of the trip duration $k \in [0,1]$. Hence, a traveller that departs from home at time t and arrives at work at time $t + T[t]$ engages in home activity on board during the time interval $[t, t + kT[t]]$ and in work activity on board during the time interval $[t + kT[t], t + T[t]]$. Travel time $T[t]$ is assumed to depend on the departure time t, which enables to model the effects of congestion. The boundary cases, where $k = 0$ or $k = 1$, correspond to individual engaging only at work or home activity on board, respectively. If travel took no time at all (the individual would be able to 'teleport' from home to work), then the optimal switch time between home and work would be t^*.

[28] Alternatively, an additive efficiency factor would lead to a situation where higher utility of the activity is associated with a lower utility loss percentage-wise. See Yu et al. (2019) for the congestion derivations given this set-up. The assumption of multiplicative efficiency factors is further discussed in section 5.5.2.

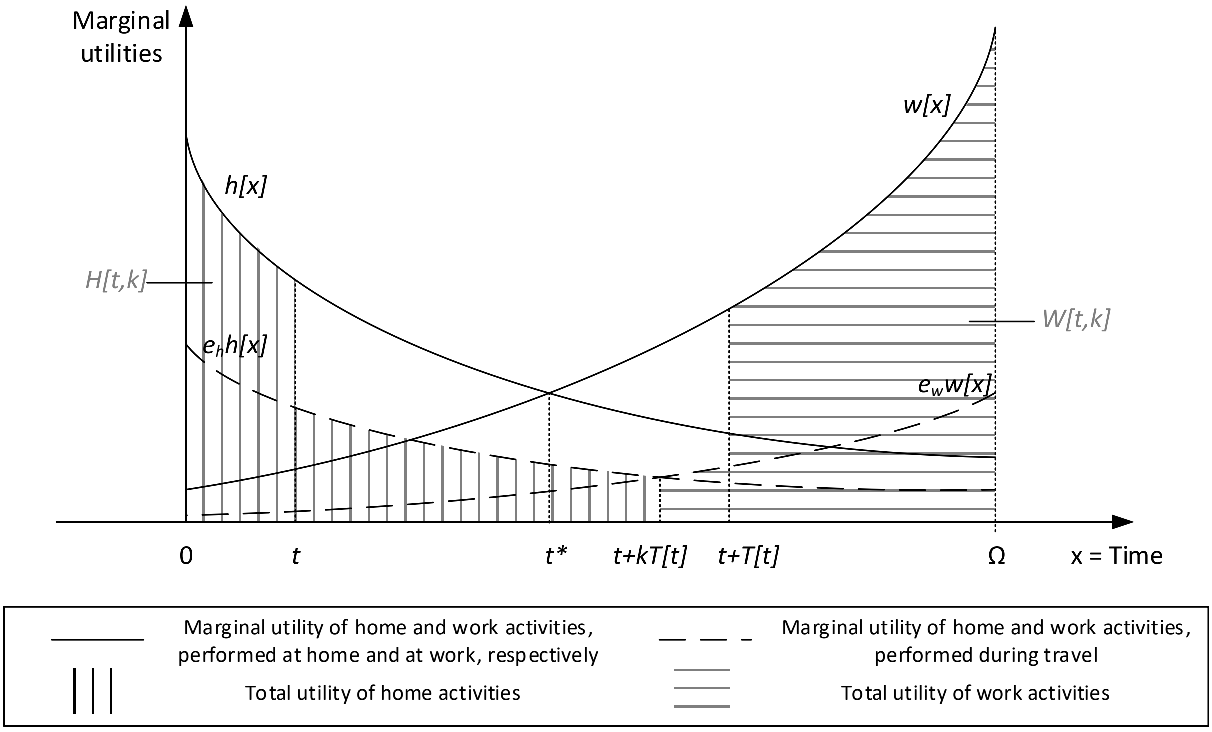


Figure 5-1 Scheduling preferences including the utility obtained from home and work activities on board: general scheduling preferences

Total home utility $H[t,k]$, total work utility $W[t,k]$ and total utility $V[t,k]$ are defined as follows:

$$H[t,k] = \int_0^t h[x]dx + e_h \int_t^{t+kT[t]} h[x]dx, \tag{1}$$

$$W[t,k] = \int_{t+T[t]}^{\Omega} w[x]dx + e_w \int_{t+kT[t]}^{t+T[t]} w[x]dx, \tag{2}$$

$$V[t,k] = H[t,k] + W[t,k]. \tag{3}$$

Every traveller tries to maximise the total utility $V[t,k]$ by choosing the departure time t and the switching point between the on-board activities k. This defines the scheduling preferences that determine the optimal departure times given a broad class of home and work marginal utility functions $h[x]$ and $w[x]$. From here on, I call these 'general scheduling preferences'. While it is possible to use them to analyse the optimal departure times in case of no congestion (section 5.3), the analysis of equilibrium congestion patterns (section 5.4) requires that specific forms of $h[x]$ and $w[x]$ are used. For this purpose, I select the most widely used scheduling preferences, the $\alpha - \beta - \gamma$ model[29] (Vickrey 1969; Small, 1982), which can be specified by inserting the following as the home and work utility functions in (1)-(3):

$$h[x] = \alpha, \tag{4}$$

[29] The advantages of the $\alpha - \beta - \gamma$ model in the present study are its elegant closed form flow rates (obtained by Arnott et al., 1990) and the conservative predictions for congestion changes with AVs. The drawbacks are the constant home utility assumption, which has been shown to have limited validity, and the restricted subset of e_h and e_w values, for which the flow rate computations apply. Section 5.5.2 further discusses these properties.

$$w[x] = \begin{cases} \alpha - \beta, if\ x \le t^* \\ \alpha + \gamma, if\ x > t^*, \end{cases} \tag{5}$$

where α, β, γ are positive constants, and α and β are assumed to have the relationship $\beta < \alpha$; t^* is the preferred arrival time at work. Parameter α is the utility of spending time at home; β and γ are the utility differences between home utility and work utility, if work is performed before or after the preferred arrival time, respectively. Figure 5-2 illustrates the model set-up, using the $\alpha - \beta - \gamma$ scheduling preferences. The illustrated efficiency factors e_h and e_w are such that until the time t^* it would be optimal for the individual to engage in home activities, but after time t^* it would be optimal to switch to performing work activities during travel: $e_h h[x] > e_w w[x]$ for $x \le t^*$ and $e_h h[x] < e_w w[x]$ for $x > t^*$.[30] The figure shows a situation where traveller arrives late at work ($t + T[t] > t^*$). As before, the shaded areas represent the total utility $V[t]$ gained from activities at home, at work and during travel. Note that these utilities no longer contain the switching point k as a decision variable: if the traveller switches between on-board home and on-board work activities, then he will do so necessarily at time t^* (see section 5.2.2 for further explanation).

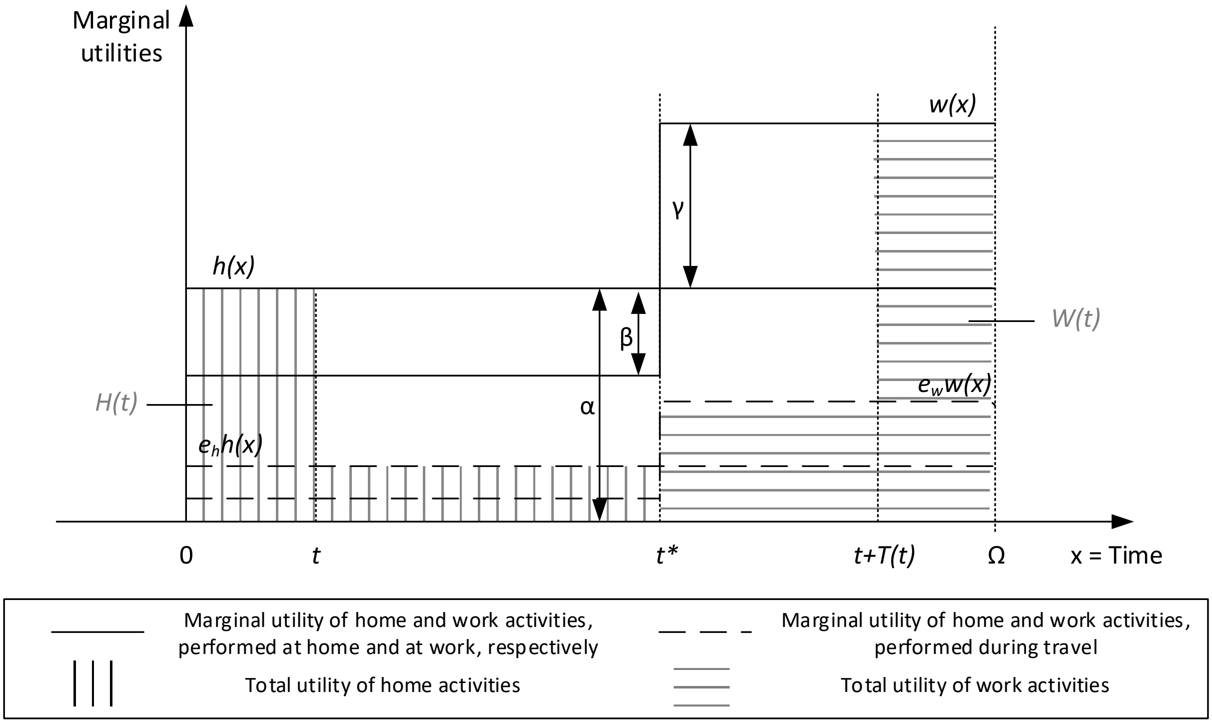


Figure 5-2 Scheduling preferences including the utility obtained from home and work activities on board: $\alpha - \beta - \gamma$ scheduling preferences

Finally, note that the $\alpha - \beta - \gamma$ model does not belong to the class of general scheduling preferences. For the general scheduling preferences, the home and work utility functions are strictly decreasing and increasing, respectively, but in the $\alpha - \beta - \gamma$ model they are constant and piecewise constant, respectively.

30 Note that the set-up (1)-(3) permits scenarios where the utility of on-board activity is higher than utility of home or work activities just before or after the trip. For example, in the context of $\alpha - \beta - \gamma$ preferences, home activity during travel may be more valuable than work activity before the preferred arrival time t^*: $e_h \alpha > \alpha - \beta$. In such cases, it is assumed that the individual would still leave the AV once it has arrived, rather than continuing with the home activity in a parked vehicle.

5.2.2 Three types of automated vehicles

The set-up introduced in section 5.2.1 allows us to imagine scenarios where AVs are specialised (e.g., via interior design and equipment) to suit the needs of (1) home activities, (2) work activities, or (3) both home and work activities. In the following sections, these AV-types are called ‘Home AV’, ‘Work AV’, and ‘Universal AV’, respectively. However, the precise classification differs between sections 5.3 and 5.4. In section 5.3 with general scheduling preferences (as in Figure 5-1), the three types are defined using only the efficiency factors: $e_h > e_w$ characterises the Home AV, $e_h < e_w$ represents the Work AV, and $e_h = e_w$ corresponds to the Universal AV.

In section 5.4, which uses the $\alpha - \beta - \gamma$ scheduling preferences (as in Figure 5-2), the definitions involve the parameters of the home and work utility functions (α, β, γ). The resulting definition of Universal AV is such that it would be optimal for the users of this AV to engage in home activities before time t^* and in work activities after t^* (as in Figure 5-2). The Home AV and Work AV facilitate one of the two activities much better than the other, such that, independently of the departure time t, it is optimal to engage in home activities in Home AV and work activities in Work AV during the entire trip. The parameter combinations that define each AV type in the context of $\alpha - \beta - \gamma$ preferences are shown in Figure 5-3. If, for example, αe_h (the utility of on-board home activity) is smaller than $(\alpha - \beta)e_w$ (the utility of on-board work activity before t^*), then these parameter values correspond to a Work AV.

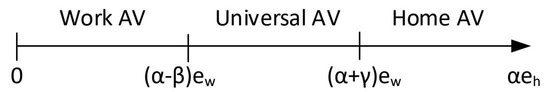


Figure 5-3 Definition of Home, Universal, Work AVs using $\alpha - \beta - \gamma$ scheduling preferences

In addition, it could be possible to distinguish a fourth type of AV that only increases the comfort of travel or facilitates such activities on board that do not substitute activities out-of-vehicle (e.g., on-board entertainment). Such an AV could be defined by replacing the home and work functions in the second integrals of equations (1) and (2) with constants (or other time-independent functions). This would define an AV that is modelled by reduced travel time penalty approach. This AV type is discussed as a point of reference in section 5.5.1.

5.3 Case of no congestion

5.3.1 Optimal departure times with general scheduling preferences

Having introduced the scheduling preferences, we can analyse the optimal departure time of a single traveller. The derivation would be the same in a hypothetical situation when multiple identical travellers do not create congestion, that is, when the bottleneck capacity exceeds the number of travellers who desire to depart in the given time unit. Formally, this situation can be represented as travel time being independent from the departure time and constant: $T[t] = T$. Using the general scheduling preferences, finding the optimal departure time is a 2-variable constrained optimisation problem: choose departure time t and switching point k between home- and work-type activities that maximises the total utility $V[t, k]$ from (3). The optimisation problem is constrained, because switching between activities needs to occur during the trip time ($0 \leq k \leq 1$).

These conditions result in the following model:

$$\max V[t,k], \tag{6}$$

subject to:

$$g_1[k] = -k \leq 0, \tag{7}$$

$$g_2[k] = k - 1 \leq 0. \tag{8}$$

Using the definition of $V[t,k]$ from (3), the Karush–Kuhn–Tucker conditions[31] for this problem are as follows:

$$\begin{aligned}\frac{\partial}{\partial t}\left(V[t,k] - \sum_{i=1,2} \lambda_i g_i[k]\right) \\ = h[t_0] + (h[t_0 + k_0 T] - h[t_0])e_h - w[t_0 + T] \\ + (w[t_0 + T] - w[t_0 + k_0 T])e_w = 0,\end{aligned} \tag{9}$$

$$\frac{\partial}{\partial k}\left(V[t,k] - \sum_{i=1,2} \lambda_i g_i[k]\right) = h[t_0 + k_0 T]e_h T - w[t_0 + k_0 T]e_w T + \lambda_1 - \lambda_2 = 0, \tag{10}$$

$$g_i[k_0] \leq 0 \qquad i = 1,2, \tag{11}$$

$$\lambda_i g_i[k_0] = 0 \qquad i = 1,2, \tag{12}$$

$$\lambda_i \geq 0 \qquad i = 1,2, \tag{13}$$

where the solution is denoted (t_0, k_0), and λ_i, $i = 1,2$ are the Karush–Kuhn–Tucker multipliers. The stationary points $(t_0; k_0)$ determined by (9)-(13) are the global maximum points of the utility $V[t,k]$, because the utility $V[t,k]$ is concave with respect to t and k, as shown next. The second order conditions are

$$\frac{\partial^2}{\partial t^2}V[t,k] = \frac{\partial}{\partial t}(h[t](1 - e_h) + h[t + kT]e_h - w[t + T](1 - e_w) - w[t + kT]e_w) < 0, \tag{14}$$

$$\frac{\partial^2}{\partial k^2}V[t,k] = \frac{\partial}{\partial k}(h[t + kT]e_h T - w[t + kT]e_w T) < 0, \tag{15}$$

and

$$\frac{\partial^2}{\partial t \partial k}V[t,k] = \frac{\partial}{\partial k}(h[t + kT]e_h - w[t + kT]e_w) < 0. \tag{16}$$

The negativity of the second order conditions can be confirmed by recalling that the marginal utilities $h[x]$ and $w[x]$ are monotonically decreasing and increasing, respectively. Therefore, $\partial/\partial x\, h[x] < 0$ and $\partial/\partial x\, w[x] > 0$. Further, parameters t and k enter the marginal utilities $h[x]$ and $w[x]$ in (14)-(16) positively, therefore the derivatives of $h[x]$ and $w[x]$ with respect to t and k maintain their signs. Finally, notice that $h[x]$ and $w[x]$ enter the second order conditions with positive and negative signs, respectively. From here follows that all additive terms in (14)-(16) are negative, making all second order derivatives negative. Hence, the utility is concave with respect to t and k.

Knowing that (9)-(13) yield the global maximum points, we can analyse the optimal departure times for Home, Universal, and Work AVs. Although these equations do not reveal

[31] The Karush-Kahn-Tucker conditions can be applied for this problem, because it fulfils the linear independence constraint qualification (Nocedal & Wright, 2006, p. 320). Since at most one of the constraints g_1 and g_2 is active for any k value, the independence is trivial.

the optimal points in a closed form, they are nevertheless sufficient to analyse their relationships. To proceed with that, we need to separately consider the non-binding and binding cases of constraints (11).

If (11) are non-binding, then $\lambda_1 = \lambda_2 = 0$ due to the complementary slackness conditions (12), and the traveller switches from performing home to work activities during the trip. Then (10) can be rewritten as

$$\frac{\partial}{\partial k}\left(V[t,k] - \sum_{i=1,2} \lambda_i g_i[k]\right) = h[t_0 + k_0 T]e_h T - w[t_0 + k_0 T]e_w T = 0. \tag{17}$$

Using this equality, we can simplify the first stationarity condition (9) for the non-binding case. Being an equation with a single unknown, (18) determines the optimal departure time in the non-binding case:

$$\frac{\partial}{\partial t}\left(V[t,k] - \sum_{i=1,2} \lambda_i g_i[k]\right) = h[t_0](1 - e_h) - w[t_0 + T](1 - e_w) = 0. \tag{18}$$

If one of the constraints (11) is binding, then the traveller spends the entire trip performing either home or work activity. Such a situation would arise, when one of the efficiency factors e_h and e_w is much higher than the other, as well as when only one of the factors equals zero or one. In the latter case, we can observe that the non-binding condition (17) would not yield a feasible solution if one of e_h or e_w equals zero, and the non-binding condition (18) would not yield a feasible solution if one of e_h or e_w equals one. The binding cases also necessarily correspond to Home AV ($k = 1$) or Work AV ($k = 0$), except when $e_h = e_w = 1$ (which would correspond to a Universal AV). We can derive the optimal departure times for the binding cases by inserting the binding k values in (9):

$$t_1, when\ k_0 = 1{:}\ h[t_1](1 - e_h) + h[t_1 + T]e_h = w[t_1 + T], \tag{19}$$

$$t_3, when\ k_0 = 0{:}\ h[t_3] = w[t_3]e_w + w[t_3 + T](1 - e_w). \tag{20}$$

Here and further the optimal departure times for Home, Universal, and Work AV users are denoted t_1, t_2, and t_3, respectively. We can use the obtained conditions (18)-(20) to analyse the relationship between these three departure times. The results are shown in Table 5-1. The rows in the table differentiate between scenarios where the maximum efficiency factor of 1 is or is not reached. The columns present results for the three AV types. Parameter t^* is defined such that $h[t^*] = w[t^*]$.

Table 5-1 Optimal departure times in case of no congestion

	t_1 – **Home AV** ($e_h > e_w$)	t_2 – **Universal AV** ($e_h = e_w$)	t_3 – **Work AV** ($e_h < e_w$)
$max(e_h, e_w) < 1$:	$t_1 > t^* - T$	$t_1 < t_2 < t_3$	$t_3 < t^*$
$max(e_h, e_w) = 1$:	$t_1 = t^* - T$	$t_2 \in [t^* - T; t^*]$	$t_3 = t^*$

The relationship between optimal departure times $t_1 < t_2 < t_3$ in the first line of Table 5-1 follows from the non-binding solution in equation (18) as well as from binding solutions (19) and (20). In the non-binding case, the definitions of the three AV types: $e_h > e_w$ for Home AVs, $e_h = e_w$ for Universal AVs, and $e_w < e_h$ for Work AVs should be inserted in (18). In the binding case, it can be noticed that both (19) and (20) contain weighted averages on one side of the equality.

The following (in-)equalities arise:

$$t_1 \; s.t. h[t_1] > w[t_1 + T], \tag{21}$$

$$t_2 \; s.t. h[t_2] = w[t_2 + T], \tag{22}$$

$$t_3 \; s.t. h[t_3] < w[t_3 + T]. \tag{23}$$

Recalling that home and work marginal utilities are decreasing and increasing, respectively, it follows that $t_1 < t_2 < t_3$. Note that equation (22) holds for any e_h and e_w values that are smaller than 1. Hence, they include the conventional vehicle, for which $e_h = e_w = 0$. This leads to the conclusion that the users of the Home AV would depart earlier and the users of the Work AV would depart later than the conventional vehicle users. The users of the Universal AV would depart at the same time as conventional vehicle users (given general scheduling preferences where $e_h = e_w < 1$).

The earliest and latest optimal departure times $t_1 = t^* - T$ and $t_3 = t^*$ for Home and Work AVs (in the second row of Table 5-1) follow from inserting $e_h = 1$ and $e_w = 1$ in the binding cases (19) and (20), respectively. It can be seen that for any efficiency factors lower than 1, these end-points are not reached, leading to the inequalities $t_1 > t^* - T$ and $t_3 < t^*$ in the first row of Table 5-1. Finally, if both home and work activities are perfectly facilitated in the AV ($e_h = e_w = 1$), then the traveller would experience zero disutility in such a Universal AV and would be indifferent between any departure times in the interval $[t^* - T, t^*]$, which is determined by conditions (17) and (18) and $0 \leq k \leq 1$ (constraints (11)).

Hereby, this section has obtained that, in case of general scheduling preferences, travellers whose home activities are better facilitated on board than work activities, would depart earlier than conventional vehicle users. Similarly, travellers whose work activities are better facilitated on board than home activities, would depart later than conventional vehicle users. This result holds even if there is no congestion. The implication of this finding is that a hypothetical traveller population with identical general scheduling preferences would, upon replacing their conventional vehicles with a mixture of Home, Universal and Work AVs, disperse with respect to their departure times. All departures would however still fit in the interval $[t^* - T, t^*]$.

5.3.2 Optimal departure times with $\alpha - \beta - \gamma$ scheduling preferences

It is useful to note that the departure time sequence $t_1 < t_2 < t_3$ does not hold for the $\alpha - \beta - \gamma$ scheduling preferences. Due to the discontinuity of $w[x]$, we cannot follow the same derivation as in the case of the general scheduling preferences. However, it is intuitive from Figure 5-2 that the optimal departure time generally equals $\tilde{t} = t^* - T$. Formally, it can be shown that only in two cases, the optimal departure time would be t^* instead of $\tilde{t}$: when $e_w > \gamma/(\beta + \gamma)$ for Work AV and when $(1 - e_h)/(1 - e_w) > 1 + \gamma/\alpha$ for Universal AV. Further, it can be demonstrated that optimal departure time is necessarily $\tilde{t}$, if it is (conservatively) assumed that e_w does not exceed 0.5 and that $\beta < \alpha < \gamma$ (as is conventional). The proofs of these results are in Appendix A.

The special case of optimal departure time being t^* rather than $\tilde{t}$ is intuitive for large e_w: excellent facilitation of work during travel should incentivise the traveller to travel when work, rather than home, activities are most valuable, which is the meaning of the preferred work start time t^*. However, one could argue that this special case also counters the common usage of the $\alpha - \beta - \gamma$ model: it is usually assumed that being late at work is worse than being early ($\gamma > \beta$). Therefore, the researcher may consider other scheduling preferences in such scenarios. Section 5.5.2 further discusses the choice of scheduling preferences.

5.4 Case of congestion

In order to analytically study the changes in congestion patterns, we need to assume that travellers have certain shape of departure time preferences. The previous section showed that, while general scheduling preferences lead to changing optimal departure times even if there is no congestion, the $\alpha - \beta - \gamma$ preferences lead to the same optimal departure time, unless work activity is very well facilitated on board. This makes the $\alpha - \beta - \gamma$ preferences an interesting case to be studied in the congestion setting: it would provide a conservative prediction for changes in congestion patterns, which can serve as a good starting point. Furthermore, $\alpha - \beta - \gamma$ preferences have a well-known closed form-solution for the equilibrium flow rate in a bottleneck setting – the number of travellers departing at every time moment, obtained by Arnott et al. (1990) –, which has contributed to their continuing popularity for congestion modelling. For these reasons, I adopt this form of scheduling preferences from now on. However, note that $\alpha - \beta - \gamma$ preferences in general and in the current application have some limitations; see section 5.5.2**.**

The following derivations assume the most minimalistic bottleneck setting, where a number of individuals with the same scheduling preferences travel from a single origin to a single destination on a single route. Free-flow travel time is assumed to be zero, such that the total travel time equals the queueing time at the bottleneck.[32]

5.4.1 Congestion with conventional vehicles

Before proceeding to compute the equilibrium congestion patterns for AVs, it is useful to recap how this is done for conventional vehicles (as per Arnott et al., 1990). As introduced in equations (4)-(5), the $\alpha - \beta - \gamma$ preferences contain a preferred arrival time t^*, when the individual starts to value being at work higher than being at home. Because everyone would like to arrive at work at exactly t^* (assuming homogeneous preferences), congestion arises – travel time is longer for trips that end around t^*. The departure time that leads to arrival at exactly t^* and is associated with the longest travel time is denoted $\tilde{t}$ and called the 'on-time departure time'. Eventually, it is assumed that the disutility caused by schedule delay and travel time at all departure times is perfectly balanced. This condition corresponds to the Nash equilibrium. In other words, as anyone would consider departing at another time, the gained and lost utility from so doing would cancel each other out.

Figure 5-4 illustrates a case where a traveller would consider postponing his departure by one time unit. The gained utility from home activity is α, whereas the lost utility from work activity is $\alpha - \beta$, if traveller arrives early, and $\alpha + \gamma$, if he arrives late. If we want to obtain the travel utility difference between these two hypothetical departure times, then the utility loss at the destination should be multiplied with the arrival time difference between the two considered departure times (because the travel times may differ at both considered departure times). This arrival time difference time is $1 + \dot{D}/s$, where $\dot{D}$ is the change in queue length at time t: $\dot{D} = r[t] - s$. Here, $r[t]$ is the number of individuals departing at time t, and s is the number of travellers that can pass through the bottleneck (i.e. the bottleneck capacity).

---

[32] It can be verified that this assumption does not limit the generality of the results: the equilibrium flow rates follow from the travel time changes due to queuing (see the derivations in the next sections 5.4.1 and 5.4.2); start and end times of congestion, as well as the on-time departure time would be shifted earlier by a positive free-flow time (due to condition 3 in Appendix B).

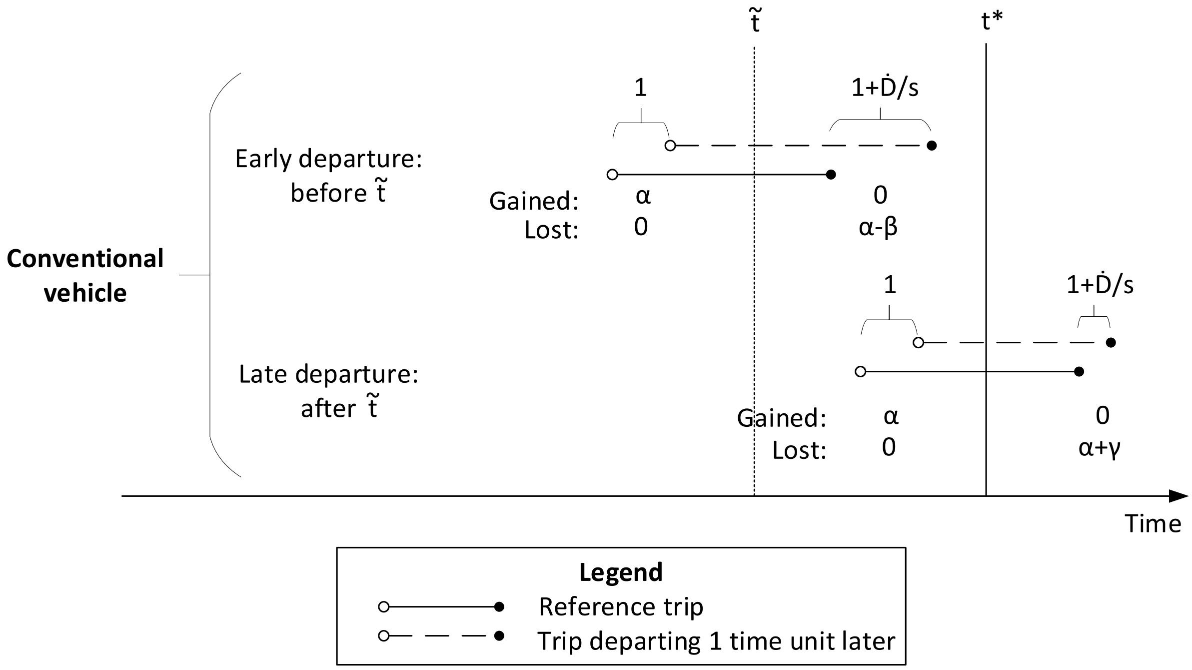


Figure 5-4 Utility components for computing equilibrium flow rate with conventional vehicles (CV)

By equalling the gained and lost utilities (as illustrated in Figure 5-4), we can obtain the flow rate $r[t]$:

$$r[t] = \begin{cases} \dfrac{\alpha s}{\alpha - \beta}, if\ t \in [t_q, \tilde{t}) \\ \dfrac{\alpha s}{\alpha + \gamma}, if\ t \in (\tilde{t}, t_{q'}], \end{cases} \tag{24}$$

where t_q and $t_{q'}$ are times at which congestion begins and ends. At these end-points of the congestion, the travel (or queueing) times are zero, but the earliness or lateness (respectively) is at its maximum. Conversely, as explained before, queueing time is longest at the on-time departure time $\tilde{t}$. Using an equation system, Arnott et al. (1990) further derived these three times:

$$t_q = t^* - \frac{\gamma}{\beta + \gamma}\frac{N}{s}, \tag{25}$$

$$t_{q'} = t^* + \frac{\beta}{\beta + \gamma}\frac{N}{s}, \tag{26}$$

$$\tilde{t} = t^* - \frac{\beta\gamma}{\alpha(\beta + \gamma)}\frac{N}{s}, \tag{27}$$

where N is the number of travellers. Equations (24)-(27) fully describe the congestion pattern with conventional vehicles.

5.4.2 Congestion with automated vehicles

Moving on to AVs, it has so far been established that the scheduling preferences of AV users would differ from those of the conventional vehicle users and depend on the activity performed during travel (see section 5.2). This section analyses the changes in congestion that stem from such scheduling preferences of AV users. Note that this section does not consider the other major source of potentially changed congestion patterns with AVs: their ability to drive closer to each other and thereby increase road capacity, especially in high penetration scenarios (e.g., Wadud et al., 2016). This simplification is made for two reasons. First, omitting the capacity changes allows to isolate the effect of various on-board activities on congestion. Second, the relative magnitude of capacity increase to the changes in scheduling parameters is rather unclear: see van den Berg and Verhoef (2016) for how net congestion patterns (assuming a generic on-board activity) depend strongly on these relative magnitudes.

The most intuitive approach, when studying how changes in scheduling preferences may affect the congestion, is to consider, whether the changes can be expressed as a transformation of the parameters α, β, γ. If such transformation could be found, we could use the results (24)-(27), while only modifying the parameters therein. For the Home AV such a transformation is intuitive. Replacing α with $\alpha(1-e_h)$ leads to the desired result (and replicates the result of van den Berg & Verhoef, 2016). In case of Universal and Work AVs however, it is not immediately clear what transformation of the α, β, γ parameters would capture the AV impact on travel costs (see Figure 5-2).[33] Therefore, it is necessary to follow the path of Arnott et al. (1990) to obtain the equilibrium flow rates for these AVs. As the on-board activities lead to more complex forms for the equilibrium flow rates, Figure 5-5 is helpful in the derivations. Similarly to Figure 5-4 for conventional vehicles, Figure 5-5 shows all the utility components needed to compute the flow rates for AVs. Compared to the Home AV, it can be seen that the Universal and Work AV results contain an additional line for computing the equilibrium flow rate. This is needed because the utility of time spent in the AV changes depending on the clock time. Before t^*, the utility during travel is obtained from home activity carried out in a Universal AV or early work activity carried out in a Work AV. After t^*, the utility is obtained from late work activity carried out in either the Universal or Work AV.

Table 5-2 shows the results: the parameters needed to fully describe congestion patterns with AVs. The equilibrium flow rates are derived from Figure 5-5 by balancing the utility components in each line. The congestion start, end and on-time departure times are derived in Appendix B. It is found that the start and end times of congestion are the same for conventional vehicles and all AVs, while the on-time departure time is earlier for all AV-types than for the conventional vehicles, and even earlier, if the AV facilitates home activities. The last row in Table 5-2 indicates that the results are valid only for the specified relationships between efficiency factors e_h, e_w and the parameters α, β, and γ. These conditions follow from the definitions of the three AV types and from a requirement that the flow rates are positive. It can be shown that these conditions are stronger than the sufficient condition for the optimal departure time to be $\tilde{t}$ in the no-congestion case (i.e., $e_w < 0.5$, as derived in Appendix A). As an example, for common values in the literature $\alpha = 2, \beta = 1, \gamma = 4$ (Small, 1982, 2015), the highest possible e_h that satisfies the conditions in Table 5-2 would be 0.5, and the highest possible e_w would be 0.33. The values of Small and efficiency factors of 0.3 (for home and/or work activities, depending on AV type) are used for the following illustrations of the congestion patterns.[34]

[33] Note that such transformation can be derived for Home and Work AVs if the utility of stationary and on-board activities is assumed to always differ by a fixed amount – the additive set-up developed in Yu et al. (2019).

[34] The efficiency of 0.3 may appear low at first, considering that Wardman and Lyons (2016) summarised several studies that found comparable productivity of work during travel and outside of it: i.e., $q \approx 1$ in Hensher (1977) equation. Note, however, that this productivity applies only to the 0-50% of travel time that is used for work in different modes (parameter p in Hensher's equation). If the remaining travel time would be characterised by lower productivity (hence, the travellers not using it for work), then an average factor of 0.3 does not seem entirely unrealistic. Nonetheless, clearly, much future work is needed to calibrate these parameters, considering also AV and commute trip contexts; see more discussion in sections 5.5.2 and 5.5.3.

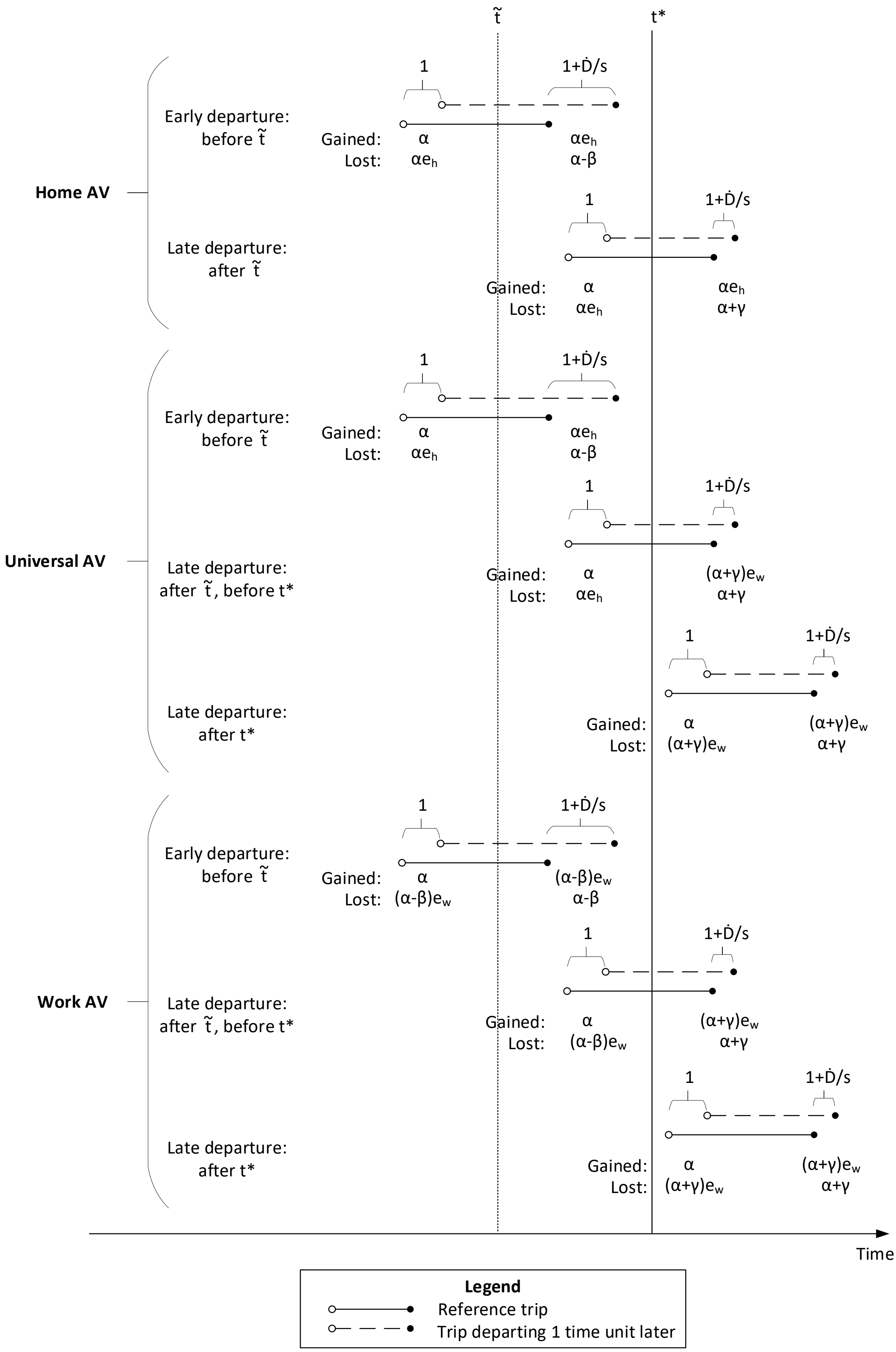


Figure 5-5 Utility components for computing equilibrium flow rates with AVs

Table 5-2 Flow rates, congestion start, end times, on-time departure times for homogeneous AV population

	Home AV	Universal AV	Work AV
Optimal on-board activity before t^*	Home	Home	Work
Optimal on-board activity after t^*	Home	Work	Work
Equilibrium flow rate $r[t]$	In departure time interval $t \in [t_q, \tilde{t}]$:		
	$\frac{\alpha(1-e_h)}{\alpha(1-e_h)-\beta}s$	$\frac{\alpha(1-e_h)}{\alpha(1-e_h)-\beta}s$	$\frac{\alpha-(\alpha-\beta)e_w}{\alpha-(\alpha-\beta)e_w-\beta}s$
	In departure time interval $t \in [\tilde{t}, t^*]$:		
	$\frac{\alpha(1-e_h)}{\alpha(1-e_h)+\gamma}s$	$\frac{\alpha(1-e_h)}{\alpha-(\alpha+\gamma)e_w+\gamma}s$	$\frac{\alpha-(\alpha-\beta)e_w}{\alpha-(\alpha+\gamma)e_w+\gamma}s$
	In departure time interval $t \in [t^*, t_{q'}]$:		
	$\frac{\alpha(1-e_h)}{\alpha(1-e_h)+\gamma}s$	$\frac{\alpha-(\alpha+\gamma)e_w}{\alpha-(\alpha+\gamma)e_w+\gamma}s$	$\frac{\alpha-(\alpha+\gamma)e_w}{\alpha-(\alpha+\gamma)e_w+\gamma}s$
Congestion start time t_q	$t^* - \frac{\gamma}{\beta+\gamma}\frac{N}{s}$	‘’	‘’
On-time departure time $\tilde{t}$	$t^* - \frac{\beta\gamma}{\alpha(1-e_h)(\beta+\gamma)}\frac{N}{s}$	$t^* - \frac{\beta\gamma}{\alpha(1-e_h)(\beta+\gamma)}\frac{N}{s}$	$t^* - \frac{\beta\gamma}{(\alpha-(\alpha-\beta)e_w)(\beta+\gamma)}\frac{N}{s}$
Congestion end time $t_{q'}$	$t^* + \frac{\beta}{\beta+\gamma}\frac{N}{s}$	‘’	‘’
Conditions	$e_h < \frac{\alpha-\beta}{\alpha}$ $e_w < \frac{\alpha}{\alpha+\gamma}e_h$	$\frac{\alpha-\beta}{\alpha}e_w < e_h < \frac{\alpha-\beta}{\alpha}$ $\frac{\alpha}{\alpha+\gamma}e_h < e_w < \frac{\alpha}{\alpha+\gamma}$	$e_h < \frac{\alpha-\beta}{\alpha}e_w$ $e_w < \frac{\alpha}{\alpha+\gamma}$

The resulting congestion shapes for all AV-types and the base conventional vehicle are illustrated in Figure 5-6. This and later figures use queueing time as an indicator for the severity of the congestion. The queueing time $T[t]$ is a function of the departure rate $r[u]$:

$$T[t] = \int_0^t \frac{r[u]-s}{s}\,du. \tag{28}$$

Four properties of AV congestion can be observed from Figure 5-6. First, congestion is more severe with AVs compared to conventional vehicles (at least while not considering any potential capacity effects of AVs)**.** This result is intuitive – performing any activity during travel leads to less negative experience of travel, and consequently, lower aversion to the most congested and longest travel times**.** And this result aligns with previous works that do not differentiate between on-board activities (and specifically, with van den Berg & Verhoef, 2016, who use bottleneck models). Second, congestion is more skewed to earlier times for the Home AVs and to later times for Work AVs. This finding aligns with Yu et al. (2019) who found that when an on-board activity closer resembles home- (work-) activity (defined differently than here), then the AV users will travel in the beginning (end) of the peak. Universal AVs (in Figure 5-6) partially overlap with both Home and Work AV graphs, thereby increasing both early and late congestion. It is noteworthy that these results of skewed congestion follow from the $\alpha - \beta - \gamma$ preferences, which do not lead to any changes in optimal departure times in the no congestion case (see section 5.3.2). Intuitively, an even stronger skew in congestion could be expected, if general scheduling preferences were used. Third, Home and Universal AVs lead to longer maximum queueing times than Work AVs. It can be shown that this property holds when

$\alpha e_h^H > (\alpha - \beta) e_w^W$, where e_h^H is the efficiency of home activities in the Home or Universal AV, and e_w^W is the efficiency of work activities in the Work AV. This condition determines that the Home AV is not inferior to Work AV in terms of the on-board activity facilitation. In the converse scenario, the queueing times of Home AVs would be shorter than of Work AVs at all departure times. Fourth, congestion starts and ends at the same time for all vehicles. This leads to the conclusion that, although congestion levels are increasing, the experienced costs of congestion do not change. The proofs of these four properties are in Appendix C.

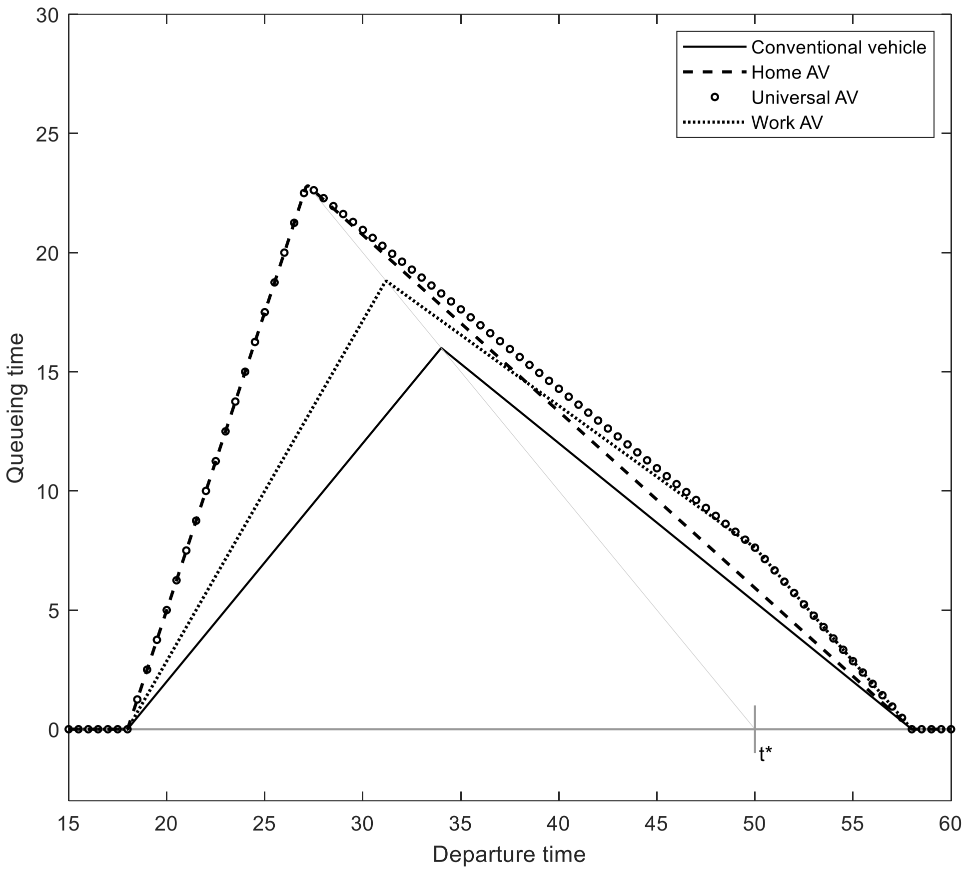


Figure 5-6 Development of queueing times for conventional vehicles and AVs. $N = 200$, $s = 5$, $(\alpha, \beta, \gamma) = (2, 1, 4)$, $t^* = 50$, $(e_h; e_w) = (0.3; 0)$ for Home AVs, $(e_h; e_w) = (0.3; 0.3)$ for Universal AVs, $(e_h; e_w) = (0; 0.3)$ for Work AVs.

5.4.3 Congestion with mixed vehicles

Given that all AV types intensify the congestion, but possibly in different directions, it is useful to see the net congestion effect of having different AVs in the population. Arnott et al. (1994) demonstrated how this can be done using the so-called Travel Equilibrium Frontier (TEF). The idea of the TEF is that the travellers are indifferent between departing at any moment $t \in [t_q, t_{q'}]$, given that the queueing times are as depicted in Figure 5-6 (for their vehicle type). They would therefore not use any departure times when the queueing times are longer – which is whenever a graph of other traveller group lies above theirs. Furthermore, note that decreasing or increasing the number of travellers N adjusts the graph proportionally 'down or up' (the duration of congestion is always N/s). Similarly, to obtain the TEF with a specified number of travellers using each vehicle, the graphs need to be 'scaled down or up', such that all travellers of each group depart during the time intervals, when their graph lies above other graphs.

Three combinations of vehicles are used to demonstrate the congestion patterns in Figure 5-7: Home AVs and conventional vehicles (top left of Figure 5-7)**,** Work AVs and conventional vehicles (top right)**,** and Home and Work AVs (bottom).[35] For every pair, Figure 5-7 shows scenarios with 25%, 50%, 75% of travellers using each vehicle, as well as the corresponding homogeneous cases from Figure 5-6. The different shades of grey represent the scenarios with various vehicle shares; lane types (solid, dashed, dotted) represent vehicle types departing at every moment during the congestion. Note that a part of the graph stays unchanged for every mixture – this part overlaps with the congestion graph of the vehicle with lower peak (e.g., the graph of conventional vehicles on the top left of Figure 5-7). Considering any type of AV, the graphs demonstrate, in line with van den Berg and Verhoef (2016) and F. Zhang et al. (2020), that having a mixture of AVs and conventional vehicles leads to the AVs occupying the central departure time interval, and the conventional vehicles departing as the first and last in the congestion. Furthermore, higher share of AVs in the mixture leads to more severe congestion. This is intuitive: being able to perform any on-board activity reduces the travel time costs and makes AV users less averse to long travel times. However, note once again that higher AV shares do not lead to increased bottleneck capacity in the present model.

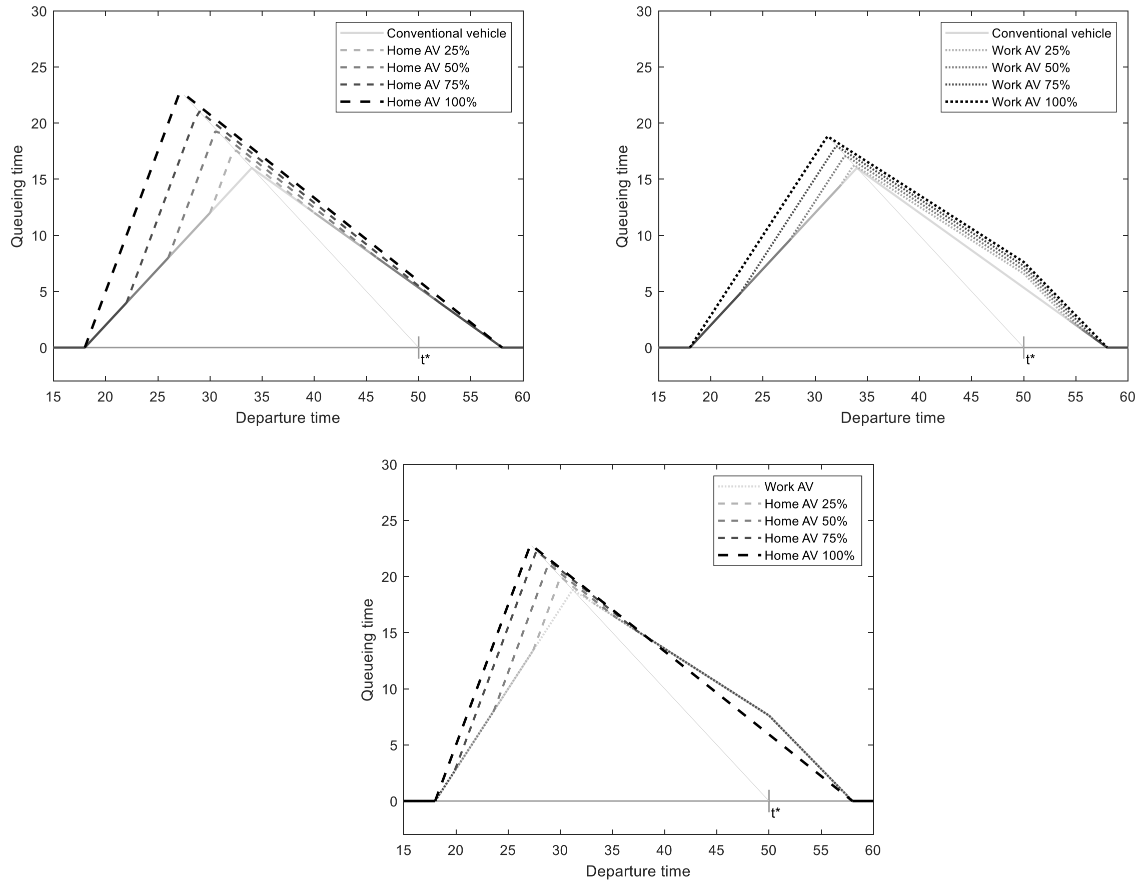


Figure 5-7 Development of queueing times with mixture of conventional vehicles and Home AVs (top left), conventional vehicles and Work AVs (top right), Home AVs and Work AVs (bottom). $\boldsymbol{N = 200}$**,** $\boldsymbol{s = 5}$**,** $\boldsymbol{(\alpha, \beta, \gamma) = (2, 1, 4), t^* = 50, (e_h; e_w) = (0.3; 0)}$ **for Home AVs,** $\boldsymbol{(e_h; e_w) = (0; 0.3)}$ **for Work AVs.**

Considering the congestion effects of different AVs, Work AVs depart later than Home AVs and conventional vehicles (top right and bottom of Figure 5-7). Given a mixture of Home

[35] The MATLAB code used to create figures can be found in Pudāne (2020), https://doi.org/10.4121/13247633.

and Work AVs (bottom of Figure 5-7), Work AVs reduce congestion, unless Home AVs are inferior to Work AVs in terms of the on-board activity experience (in a sense explained at the end of section 5.4.2: the third congestion property). However, if Home AVs are inferior, the converse is true and they reduce the congestion; the effect then resembles the combination of Work AVs and conventional vehicles (top right of Figure 5-7). In general, the higher the efficiency of on-board activities in AVs, the more likely are the AV users to cause severe congestion, and the more likely they are to benefit from sharing a road with travellers whose activities are less well facilitated on board (their graphs are 'scaled down'). See van den Berg and Verhoef (2016) and Yu et al. (2019) for an in-depth discussion of how, in terms of congestion benefits or costs, the AV introduction affects their users and the users of conventional vehicles.

Hereby, this section has demonstrated that, given the $\alpha - \beta - \gamma$ scheduling preferences and bottleneck setting, travellers whose home activities are better facilitated on board than work activities, would prefer to depart earlier than conventional vehicle users and increase the severity of congestion in its early to middle part. Similarly, travellers whose work activities are better facilitated on board than home activities, would prefer to depart later than conventional vehicle users and increase the congestion mostly in its middle to late part. Given similar levels of activity facilitation on board, the increase in queueing times due to Work AVs is smaller than due to Home AVs. Thereby, Work AVs have a moderating effect on the increasing congestion levels.

5.5 Discussion and suggestions for further research

5.5.1 Comparison with the travel time penalty approach

This work started from a proposition that it is important to differentiate among on-board activities when modelling departure time choice and congestion patterns. It was assumed that, similarly to out-of-vehicle activities, the utility of different on-board activities varies with clock-time. In contrast, the travel time penalty approach assumes that the utility of on-board activities is time-independent. Now we are in a position to ask: has the approach taken in this paper yielded qualitatively different results than the travel time penalty approach would have?

In the case of no congestion and general scheduling preferences, the answer is 'yes'. If the utility of on-board activities did not vary with time, the on-board activities would not influence the departure time preference, and the optimal departure time of conventional vehicles would be maintained. Formally, the second integrals of the total home and work utility functions (1) and (2) would not depend on t, and hence would disappear when the total utility (3) is differentiated with respect to t. However, clearly, the conclusion of section 5.3 was that the optimal departure times depend on the activities performed during travel – or on the use of various AV types that facilitate various activities to different extents.

In the case of congestion and the $\alpha - \beta - \gamma$ preferences, the answer is 'yes, but with an exception'. Different congestion patterns were obtained for Home-, Work-, and Universal AVs. However, because the $\alpha - \beta - \gamma$ preferences assume constant home utility, the results of Home AV exactly replicate the travel time penalty approach (as derived in van den Berg & Verhoef, 2016). Since it is furthermore known that a constant home utility is a rough approximation (Tseng & Verhoef, 2008), this correspondence is not desirable. A way to avoid this situation would be to adapt other scheduling preferences where both home and work activity utility varies with clock-time. The following section further discusses this possibility.

5.5.2 Beyond $\alpha - \beta - \gamma$ scheduling preferences and multiplicative efficiency factors

As just mentioned, adopting the $\alpha - \beta - \gamma$ scheduling preferences has some potential drawbacks. First, it means that the scenario, where the traveller engages in home activities, is constrained to be equivalent to the scenario where AVs generally provide better travel experience (e.g., less stressful, smoother drive), which is embedded in the travel time penalty concept. Second, the assumption of constant home utility has been challenged before (Tseng & Verhoef, 2008). Finally, using the $\alpha - \beta - \gamma$ preferences allows the researcher to arrive at closed-form departure rates only for low to medium e_h and e_w values (see 'Conditions' in Table 5-2). For these reasons, exploring the effects of other scheduling functions on the congestion changes with AVs, while differentiating between home and work activities performed on board, is a highly recommended direction for further research. The literature offers good alternatives for this endeavour: the so-called slope model (Fosgerau and Engelson, 2011), where the marginal utilities of out-of-vehicle activities are linear functions of time, or exponential scheduling preferences (Hjorth et al., 2015). A closed-form departure rate function for the slope model has recently been derived (Xiao et al., 2017) and would be useful for such study.

It can be expected that replacing the $\alpha - \beta - \gamma$ model with any type of general scheduling preferences (such as slope model or exponential preferences) would lead to larger congestion differences between conventional vehicles and AVs and among different AVs. Because of this consequence however, the weakness of the $\alpha - \beta - \gamma$ model is also its strength: the current approach provides conservative results – a lower bound of the possible influence of on-board activities on congestion patterns, which would apply even in contexts with a strong preference for a single work-start time.

Another feature of the current model set-up that deserves further discussion is the assumption of multiplicative efficiency factors. This assumption implies that the utility of on-board home and work activities depends on the clock-time in a similar way as the utility of stationary activities. Considering stationary activities, Fosgerau and Small (2017) discuss how their time-dependent utilities emerge from the benefits of agglomeration in time. That is, it is often important to synchronise the working hours within companies and industries (e.g., teamwork, work with clients), as well as to synchronise them with supporting services (e.g., childcare). Similarly, many leisure or home activities require the members of a household or social circle to be simultaneously available, as well as some leisure activities (e.g., theatre, TV programs, opening hours of bars) are scheduled considering such typical available times. To some extent, this clock-time dependence could be assumed to translate to on-board activities. However, unlike for stationary activities, the utility variations of on-board activities are not influenced by availability of physical spaces (such as opening hours of shops) or presence of other people, unless remote communication with them is sufficient. Hence, future work should further explore whether this utility reduction is, first, proportional, and second, whether it depends only on the utilities of stationary activities. As for the first, other functional forms could be used. For example, Yu et al. (2019) penalise the on-board activities with an additive factor. Other forms could reflect, for example, that some travellers may not be able to work on board after the preferred arrival time, but they may engage in preparatory work tasks during travel. Ultimately, the functional form should be determined empirically. As for the second assumption, it is evident that the utility of on-board activities could depend also on travel-specific conditions that vary within a trip: winding road or congestion may obstruct or ease activities for only some portions of the trip. Furthermore, travellers may choose to switch between home and work activities multiple times during the journey (as was observed by, e.g., Pawlak et al., 2017), especially if both activities are well facilitated on board. Incorporating such dependencies and multiple switches in a bottleneck model would be challenging, and would likely require a simulation approach.

5.5.3 Validity and applicability to public transport and shared automated vehicles

As with all travel behaviour models, an important aspect is their validation and estimation. While there are not yet sufficient number of AVs on the roads, studies have occasionally turned to public transport to gain insights into possible effects of on-board activities (e.g., Pawlak et al., 2015; Malokin et al., 2019). Hence, a relevant question to the present study is: would the devised models apply and could they be validated using public transport data? Unfortunately, there are several important obstacles to such an application. First, future AVs could be expected to perform significantly better in facilitating on-board activities compared to current public transport. The difference may be even larger when considering on-board activities that substitute out-of-vehicle activities: recall the examples of morning home activities - getting ready, preparing and eating breakfast, getting a little more sleep - or work activities - replying to emails, planning the day, adjusting meeting schedule. Several of these may require privacy, space, silence, continuity (absence of transfers), comfort and facilities that may be available in AVs, but not in public transport. On the flipside, public transport may outperform AVs with regard to proneness to motion sickness. (See Pudāne et al., 2019, for a qualitative discussion of the potential advantages and disadvantages of AVs for on-board activities.) Second, trade-offs involved in departure time choices are fundamentally different for car and public transport users: while car drivers trade off on-time arrival with travel time, public transport users balance on-time arrival with crowding levels and to a lesser extent, travel time and reliability. Third, public transport users face constraints (which the car drivers do not) when choosing departure time: they must choose from a set of scheduled departure times or predicted departure times according to public transport frequency. These characteristics would make the departure time choice model for a public transport user, who is able to engage in on-board activities during travel, fundamentally different from the model presented in this paper. Therefore, other sources of travel behaviour and departure time data could be more useful for estimation and validation of the current models: naturalistic experiments (Harb et al., 2018) or surveys (for example, stated choice experiments), which have been shown to provide trustworthy results in AV contexts (Wadud & Huda, 2019). This is an important direction for further research.

Nevertheless, even before having access to data supporting the current models, it is possible to argue for their face-validity. The current work builds on established microeconomic models of scheduling preferences (Vickrey, 1969, 1973; Small, 1982), which have stood the test of time to predict departure time choice and resulting congestion patterns in a variety of contexts. Furthermore, the analytical results correspond to intuition: the possibility to substitute home or work activities with their on-board counterparts leads to departure time adjustments towards the most desirable time for these activities.

Another often asked and important question is: how would travel experience and behaviour differ between users of privately owned and shared AVs (including both car sharing and ride sharing), and would the same models be valid for these modes? Considering the current departure time choice model, two differences could be anticipated. First, the on-board activities may be facilitated to a different extent in shared AVs. The activities may be impaired by the reduced privacy, storage and personalisation possibilities, which would be available in privately owned AVs. At the same time, the facilitation may be increased, if fleet owners customise the AVs to suit various on-board activity needs. For example, some cars may be equipped with business and conference facilities, while others may be suited for resting and leisure. The net effect of sharing on the efficiency of on-board activities is an interesting question for future research. Second, clients of car and ride sharing may have less flexibility of choosing their departure time as compared to owners of vehicles: they may need to book the car in advance or coordinate with other users. Hence, the departure time choice and congestion models for future AV owners and users of shared AVs may differ somewhat; yet, the present model can provide a good starting point for modelling these scenarios.

5.5.4 Suggestions for further research

This work has presented the first steps in a detailed analysis of the impact of different on-board activities on congestion patterns. Nevertheless, and as importantly, it opens up a new field of study into the AV-effect on future mobility – and invites further work to investigate whether the proposed peak-skewing, increasing and moderating effects are also observed in more complex contexts. Previous sections mentioned the need to explore other scheduling preferences and specifications of on-board activity utility (section 5.5.2), as well as to obtain data to estimate and validate the current models (section 5.5.3). Following are few other suggestions for further research.

1. A natural extension of the present work would be to simulate the effects of the proposed scheduling preferences in artificial and real city networks, as done by Correia and van Arem (2016), while incorporating heterogeneity in scheduling parameters. An extended simulation would also include other types of choices, such as mode- and route-choices, trip making and destination choice, to balance the effects of departure time changes with other anticipated AV effects, such as induced travel. Potentially increased road capacity in high AV penetration scenarios would also need to be considered.
2. An important extension would be to account for various on-board activities when modelling the full day of a commuter and account for the flexibility of work hours, as is done in the activity-based bottleneck analyses (Xiaoning Zhang et al., 2005; Li et al., 2014; Xiang Zhang et al., 2019) and studies of departure time choice (e.g., Thorhauge et al., 2016). Some flexibility in activity schedules in general and work start times in particular is a prerequisite for the congestion shifting and moderating effects observed in this work.
3. Empirical work should continue in assessing the sources of decreasing travel time disutility in AVs. Note that the peak-mitigating effect would come into play only if on-board activities constitute a significant portion of the AV-benefits. If instead the travellers mainly appreciate the reduced burden and increased comfort when using AVs (as argued by Singleton, 2019) or even experience some disadvantages of converting resting time into busy activity time (Shaw et al., 2019; Pudāne et al., 2019), they would constitute a more homogeneous group, and hence, be more prone to intense congestion.
4. Finally, it would be important to incorporate potential endogeneity effects in the model. Travellers whose work or home activities can be performed on board may self-select to obtain access to certain type of AVs. The approach here could follow F. Zhang et al. (2020), who included a choice between conventional vehicles and (a generic type of) AVs into bottleneck congestion analysis.

5.6 Conclusions and policy implications

The arrival of automated vehicles (AVs) is expected to increase the feasibility and role of on-board activities in people's daily schedules. This paper argued that the current ways of modelling the departure time choice and congestion impacts of the improved on-board activities, based mostly on the idea of a reduced travel time penalty, are not sufficient. While travel time penalty condenses effects of all on-board activities into a single indicator, different activities may in reality have varied impacts on travel behaviour. This intuition was supported in the present paper. A classical microeconomic approach – modelling departure time choices and their congestion impacts using scheduling functions – was extended to consider effects of different on-board activities in AVs. It was obtained that, if travellers are able to perform home activities on board (in Home AVs), they prefer to depart earlier than if they are able to perform work activities (in Work AVs), even if there is no congestion. If there is congestion, results obtained in a minimalistic bottleneck setting indicate that congestion would increase due to on-board activities in AVs, – doing something during travel decreases people's aversion to longer travel times, thereby prioritising on-time arrival and concentrating travellers in the middle of the peak. However, if several AV types are available that facilitate home and/or work activities to a similar extent, then Work AVs increase the congestion levels the least.

The model developed and results obtained in this paper can provide input for one of the key AV-related policy questions: will AVs lead to higher congestion levels and, if yes, how to avoid or mitigate that effect? While congestion can be expected to increase, at least while assuming no increases in road capacity due to AVs, travellers who are able to work during travel seem to mitigate that effect. This offers a valuable tool for policy makers: although some work tasks may be easily transferred to AVs, the mobile work possibilities could be further encouraged by allowing flexible working hours and, perhaps even, making work-equipped AVs available for a broader range of professions. Such measures should be further tested using models that account for possibly diverging effects of different on-board activities (such as the one presented in this paper, but also by Yu et al., 2019), while accounting for the model limitations outlined earlier. If their effects are positive, these measures could help to ensure that the celebrated benefits of AVs – such as allowing individuals to re-allocate their travel time for other activities – are maintained, while their potential downsides are reduced.

Acknowledgement

This work is funded by the Netherlands Organisation for Scientific Research (NWO) as part of the project 'Spatial and Transport impacts of Automated Driving' (STAD), project number 438-15-161. I would like to thank Caspar Chorus and Sander van Cranenburgh for the valuable discussions and support throughout this research. Furthermore, I am grateful to Mogens Fosgerau and Yousef Maknoon for the keen advice and feedback on different parts of this work, and to Erik Verhoef, Dereje Fentie Abegaz, Katrine Hjorth, Xiaojuan Yu and Vincent van den Berg for the helpful discussions during the hEART 2019 conference and/or thereafter. All responsibility remains with the author.

References

Arnott, R., De Palma, A., & Lindsey, R. (1990). Economics of a bottleneck. Journal of urban economics, 27(1), 111-130.

Arnott, R., De Palma, A., & Lindsey, R. (1993). A structural model of peak-period congestion: A traffic bottleneck with elastic demand. The American Economic Review, 161-179.

Arnott, R., De Palma, A., & Lindsey, R. (1994). The welfare effects of congestion tolls with heterogeneous commuters. Journal of Transport Economics and Policy, 139-161.

Auld, J., Sokolov, V., & Stephens, T. S. (2017). Analysis of the effects of connected–automated vehicle technologies on travel demand. Transportation Research Record, 2625(1), 1-8.

Banerjee, I., & Kanafani, A. (2008). The value of wireless internet connection on trains: Implications for mode-choice models. University of California Transportation Center.

Batley, R. (2015). The Hensher equation: derivation, interpretation and implications for practical implementation. Transportation, 42(2), 257-275. https://doi.org/10.1007/s11116-014-9536-3 de Almeida Correia, G. H., Looff, E., van Cranenburgh, S., Snelder, M., & van Arem, B. (2019). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. Transportation Research Part A: Policy and Practice, 119, 359-382. https://doi.org/10.1016/j.tra.2018.11.016

de Almeida Correia, G. H., & van Arem, B. (2016). Solving the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility. Transportation Research Part B: Methodological, 87, 64-88. https://doi.org/10.1016/j.trb.2016.03.002

Das, S., Sekar, A., Chen, R., Kim, H. C., Wallington, T. J., & Williams, E. (2017). Impacts of autonomous vehicles on consumers time-use patterns. Challenges, 8(2), 32. https://doi.org/10.3390/challe8020032

de Palma, A., & Fosgerau, M. (2011). Dynamic traffic modeling. In A handbook of transport economics. Edward Elgar Publishing, 188-212. https://doi.org/10.4337/9780857930873

Ettema, D., & Verschuren, L. (2007). Multitasking and value of travel time savings. Transportation Research Record, 2010(1), 19-25. https://doi.org/10.3141/2010-03

Fosgerau, M. (2019). Automation and the value of time in passenger transport. In International Transport Forum Discussion Papers (No. 2019/10). OECD Publishing. https://doi.org/10.1787/6efb6342-en

Fosgerau, M., & Engelson, L. (2011). The value of travel time variance. Transportation Research Part B: Methodological, 45(1), 1-8. https://doi.org/10.1016/j.trb.2010.06.001

Fosgerau, M., & Small, K. (2017). Endogenous scheduling preferences and congestion. International Economic Review, 58(2), 585-615. https://doi.org/10.1111/iere.12228

Frei, C., Mahmassani, H. S., & Frei, A. (2015). Making time count: Traveler activity engagement on urban transit. Transportation Research Part A: Policy and Practice, 76, 58-70. https://doi.org/10.1016/j.tra.2014.12.007

Gubins, S., & Verhoef, E. T. (2011). Teleworking and congestion: A dynamic bottleneck analysis. Tinbergen Institute Discussion Paper, 2011-096/3. https://doi.org/10.2139/ssrn.1888241

Harb, M., Xiao, Y., Circella, G., Mokhtarian, P. L., & Walker, J. L. (2018). Projecting travelers into a world of self-driving vehicles: estimating travel behavior implications via a naturalistic experiment. Transportation, 45(6), 1671-1685. https://doi.org/10.1007/s11116-018-9937-9

Hensher, David A.: The Value of Business Travel Time. Pergamon Press, Oxford (1977)

Hjorth, K., Börjesson, M., Engelson, L., & Fosgerau, M. (2015). Estimating exponential scheduling preferences. Transportation Research Part B: Methodological, 81, 230-251. https://doi.org/10.1016/j.trb.2015.03.014

Kim, S. H., Mokhtarian, P. L., & Circella, G. (2020). How, and for whom, will activity patterns be modified by self-driving cars? Expectations from the state of Georgia. Transportation research part F: traffic psychology and behaviour, 70, 68-80. https://doi.org/10.1016/j.trf.2020.02.012

Krueger, R., Rashidi, T. H., & Auld, J. (2019). Preferences for travel-based multitasking: Evidence from a survey among public transit users in the Chicago metropolitan area. Transportation Research Part F: Traffic Psychology and Behaviour, 65, 334-343. https://doi.org/10.1016/j.trf.2019.08.004

Lamotte, R., De Palma, A., & Geroliminis, N. (2017). On the use of reservation-based autonomous vehicles for demand management. Transportation Research Part B: Methodological, 99, 205-227. https://doi.org/10.1016/j.trb.2017.01.003

Li, Z. C., Huang, H. J., & Yang, H. (2020). Fifty years of the bottleneck model: A bibliometric review and future research directions. Transportation research part B: methodological, 139, 311-342. https://doi.org/10.1016/j.trb.2020.06.009

Li, Z. C., Lam, W. H., & Wong, S. C. (2014). Bottleneck model revisited: An activity-based perspective. Transportation research part B: methodological, 68, 262-287. https://doi.org/10.1016/j.trb.2014.06.013

Liu, W. (2018). An equilibrium analysis of commuter parking in the era of autonomous vehicles. Transportation Research Part C: Emerging Technologies, 92, 191-207. https://doi.org/10.1016/j.trc.2018.04.024

Malokin, A., Circella, G., & Mokhtarian, P. L. (2019). How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios. Transportation Research Part A: Policy and Practice, 124, 82-114. https://doi.org/10.1016/j.tra.2018.12.015

Milakis, D., Snelder, M., van Arem, B., van Wee, B., & de Almeida Correia, G. H. (2017). Development and transport implications of automated vehicles in the Netherlands: scenarios for 2030 and 2050. European Journal of Transport and Infrastructure Research, 17(1). https://doi.org/10.18757/ejtir.2017.17.1.3180

Nocedal, J., & Wright, S. (2006). Numerical optimization. Springer Science & Business Media. https://doi.org/10.1007/978-0-387-40065-5

Pawlak, J., Polak, J. W., & Sivakumar, A. (2015). Towards a microeconomic framework for modelling the joint choice of activity–travel behaviour and ICT use. Transportation Research Part A: Policy and Practice, 76, 92-112. https://doi.org/10.1016/j.tra.2014.10.013

Pawlak, J., Polak, J. W., & Sivakumar, A. (2017). A framework for joint modelling of activity choice, duration, and productivity while travelling. Transportation Research Part B: Methodological, 106, 153-172. https://doi.org/10.1016/j.trb.2017.10.010

Pudāne, Baiba (2020): Queueing Times of Automated Vehicles in a Bottleneck: MATLAB Code. 4TU.ResearchData. https://doi.org/10.4121/13247633

Pudāne, B., & Correia, G. (2020). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey–A comment. Transportation Research Part A: Policy and Practice, 132, 324-328. https://doi.org/10.1016/j.tra.2019.11.019

Pudāne, B., Molin, E. J., Arentze, T. A., Maknoon, Y., & Chorus, C. G. (2018). A time-use model for the automated vehicle-era. Transportation Research Part C: Emerging Technologies, 93, 102-114. https://doi.org/10.1016/j.trc.2018.05.022

Pudāne, B., Rataj, M., Molin, E. J., Mouter, N., van Cranenburgh, S., & Chorus, C. G. (2019). How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands. Transportation Research Part D: Transport and Environment, 71, 222-235. https://doi.org/10.1016/j.trd.2018.11.014

Rasouli, S., & Timmermans, H. (2014). Judgments of travel experiences, activity envelopes, trip features and multi-tasking: A panel effects regression model specification. Transportation Research Part A: Policy and Practice, 63, 67-75. https://doi.org/10.1016/j.tra.2014.02.012

SAE International, 2016. Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. SAE International, Warrendale, PA. https://doi.org/10.4271/j3016_201609

Shaw, F. A., Malokin, A., Mokhtarian, P. L., & Circella, G. (2019). It's not all fun and games: an investigation of the reported benefits and disadvantages of conducting activities while commuting. Travel Behaviour and Society, 17, 8-25. https://doi.org/10.1016/j.tbs.2019.05.008

Simoni, M. D., Kockelman, K. M., Gurumurthy, K. M., & Bischoff, J. (2019). Congestion pricing in a world of self-driving vehicles: An analysis of different strategies in alternative future scenarios. Transportation Research Part C: Emerging Technologies, 98, 167-185. https://doi.org/10.1016/j.trc.2018.11.002

Singleton, P. A. (2019). Discussing the "positive utilities" of autonomous vehicles: will travellers really use their time productively?. Transport reviews, 39(1), 50-65. https://doi.org/10.1080/01441647.2018.1470584

Small, K. A. (1982). The scheduling of consumer activities: work trips. The American Economic Review, 72(3), 467-479.

Small, K. A. (2015). The bottleneck model: An assessment and interpretation. Economics of Transportation, 4(1-2), 110-117. https://doi.org/10.1016/j.ecotra.2015.01.001

Soteropoulos, A., Berger, M., & Ciari, F. (2019). Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies. Transport reviews, 39(1), 29-49. https://doi.org/10.1080/01441647.2018.1523253

Susilo, Y. O., Lyons, G., Jain, J., & Atkins, S. (2012). Rail passengers' time use and utility assessment: 2010 findings from Great Britain with multivariate analysis. Transportation research record, 2323(1), 99-109. https://doi.org/10.3141/2323-12

Thorhauge, M., Cherchi, E., & Rich, J. (2016). How flexible is flexible? Accounting for the effect of rescheduling possibilities in choice of departure time for work trips. Transportation Research Part A: Policy and Practice, 86, 177-193. https://doi.org/10.1016/j.tra.2016.02.006

Tian, L. J., Sheu, J. B., & Huang, H. J. (2019). The morning commute problem with endogenous shared autonomous vehicle penetration and parking space constraint. Transportation Research Part B: Methodological, 123, 258-278. https://doi.org/10.1016/j.trb.2019.04.001

Tseng, Y. Y., & Verhoef, E. T. (2008). Value of time by time of day: A stated-preference study. Transportation Research Part B: Methodological, 42(7-8), 607-618. https://doi.org/10.1016/j.trb.2007.12.001

van den Berg, V. A., & Verhoef, E. T. (2016). Autonomous cars and dynamic bottleneck congestion: The effects on capacity, value of time and preference heterogeneity. Transportation Research Part B: Methodological, 94, 43-60. https://doi.org/10.1016/j.trb.2016.08.018

Vickrey, W. S. (1969). Congestion theory and transport investment. The American Economic Review, 59(2), 251-260.

Vickrey, W. (1973). Pricing, metering, and efficiently using urban transportation facilities (No. 476).

Wadud, Z., & Huda, F. Y. (2019, March). Fully automated vehicles: the use of travel time and its association with intention to use. In Proceedings of the Institution of Civil Engineers-Transport (pp. 1-15). Thomas Telford Ltd. https://doi.org/10.1680/jtran.18.00134

Wadud, Z., MacKenzie, D., & Leiby, P. (2016). Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transportation Research Part A: Policy and Practice, 86, 1-18. https://doi.org/10.1016/j.tra.2015.12.001

Wardman, M., & Lyons, G. (2016). The digital revolution and worthwhile use of travel time: implications for appraisal and forecasting. Transportation, 43(3), 507-530. https://doi.org/10.1007/s11116-015-9587-0

Xiao, Y., Coulombel, N., & De Palma, A. (2017). The valuation of travel time reliability: does congestion matter?. Transportation Research Part B: Methodological, 97, 113-141. https://doi.org/10.1016/j.trb.2016.12.003

Yu, X., van den Berg, V. A., & Verhoef, E. (2019). Autonomous cars and dynamic bottleneck congestion revisited: how in-vehicle activities determine aggregate travel patterns. Tinbergen discussion paper, no. 19-067/VIII https://doi.org/10.2139/ssrn.3457298

Zhang, F., Liu, W., Lodewijks, G., & Travis Waller, S. (2020). The short-run and long-run equilibria for commuting with autonomous vehicles. Transportmetrica B: Transport Dynamics, 1-28. https://doi.org/10.1080/21680566.2020.1779146

Zhang, X., Liu, W., Waller, S. T., & Yin, Y. (2019). Modelling and managing the integrated morning-evening commuting and parking patterns under the fully autonomous vehicle environment. Transportation Research Part B: Methodological, 128, 380-407. https://doi.org/10.1016/j.trb.2019.08.010

Zhang, X., Yang, H., Huang, H. J., & Zhang, H. M. (2005). Integrated scheduling of daily work activities and morning–evening commutes with bottleneck congestion. Transportation Research Part A: Policy and Practice, 39(1), 41-60. https://doi.org/10.1016/j.tra.2004.04.005

Appendix A. Proofs of the optimal departure times with $\boldsymbol{\alpha - \beta - \gamma}$ scheduling preferences in case of no congestion

Proposition A1. If the optimal departure time without congestion using $\alpha - \beta - \gamma$ preferences is not $\tilde{t} = t^* - T$, then it must be t^*.

Proof.

Departure time $\tilde{t}$ is better than any departure time $t < \tilde{t}$. The earlier departure times t would incur the same costs during travel as departing at $\tilde{t}$ (being the lost utility due to on-board activity being less efficient than home activity). However, the early departure would also incur costs due to arriving early.

Departure time t^* is better than any departure time $t > t^*$. The later departure times t would incur the same costs during travel as departing at t^* (being the lost utility due to on-board activity being less efficient than work activity). However, the later departure would also incur costs due to performing home instead of work activity after t^*.

Departure times between $\tilde{t}$ and t^* have either monotonously increasing or decreasing utility, which depends on whether a travel time unit costs more before or after t^*, see Figure 5-2. Therefore, the optimal departure time is either $\tilde{t}$ or t^*.

Proposition A2. Optimal departure time is t^* in two cases only: when $e_w > \gamma/(\beta + \gamma)$ for Work AV or when $(1 - e_h)/(1 - e_w) > 1 + \gamma/\alpha$.

Proof.

The necessary and sufficient condition for t^* to be the optimal departure time is that unit costs of travel before t^* is higher than after t^*.

For Home AVs, the condition equals $\alpha(1-e_h) > \alpha(1-e_h)+\gamma$, which is never true.

For Universal AVs, the condition leads to $(1-e_h)/(1-e_w) > 1+\gamma/\alpha$.

For Work AVs, the condition leads to $e_w > \gamma/(\beta+\gamma)$.

Proposition A3. Optimal departure time is never t^* if $e_w < 0.5$ and $\beta < \alpha < \gamma$.

Proof.

For Universal AVs, the condition from Proposition 2 requires that $(1-e_h)/(1-e_w) > 1+\gamma/\alpha$. Since it is assumed that $\gamma > \alpha$, then the strongest form of the condition is $(1-e_h)/(1-e_w) > 2$. If $e_w < 0.5$, then that will never occur, and optimal departure time for Universal AVs will never be t^*.

For Work AVs, the condition from Proposition 2 requires that $e_w > \gamma/(\beta+\gamma)$. Since it is assumed that $\gamma > \beta$, then the strongest form of the condition is $e_w > 0.5$. Hence, if $e_w < 0.5$, then optimal departure time for Work AVs is never t^*.

Appendix B. Start, end and on-time departure times of AV congestion

Three conditions determine the start, end and on-time departure times of congestion:

1. Total number of travellers departing equals N;
2. Duration of the congestion is $\frac{N}{s}$, where s is the bottleneck capacity;
3. Departing at the on-time departure time leads to the arrival at the preferred arrival time t^*.

Derivation for Universal AVs

Conditions 1 and 2:

$$\frac{\alpha(1-e_h)}{\alpha(1-e_h)-\beta}s(\tilde{t}-t_q)+\frac{\alpha(1-e_h)}{\alpha-(\alpha+\gamma)e_w+\gamma}s(t^*-\tilde{t})+\frac{\alpha-(\alpha+\gamma)e_w}{\alpha-(\alpha+\gamma)e_w+\gamma}s(t_{q'}-t^*)=N \quad \text{(B1)}$$

$$t_{q'}-t_q=\frac{N}{s} \quad \text{(B2)}$$

Insert condition 2 into condition 1, and obtain t_q as a function of $\tilde{t}$:

$$t_q=\frac{\frac{\gamma\frac{N}{s}-t^*((\alpha+\gamma)e_w-\alpha e_h)}{\alpha-(\alpha+\gamma)e_w+\gamma}-\left(\frac{\alpha(1-e_h)}{\alpha(1-e_h)-\beta}-\frac{\alpha(1-e_h)}{\alpha-(\alpha+\gamma)e_w+\gamma}\right)\tilde{t}}{\frac{\alpha-(\alpha+\gamma)e_w}{\alpha-(\alpha+\gamma)e_w+\gamma}-\frac{\alpha(1-e_h)}{\alpha(1-e_h)-\beta}}. \quad \text{(B3)}$$

Condition 3:

$$\tilde{t}=t^*-\frac{D(\tilde{t})}{s}=t^*-\frac{\int_{t_q}^{\tilde{t}}r(u)du-s(\tilde{t}-t_q)}{s}=t^*-\frac{\beta}{\alpha(1-e_h)-\beta}(\tilde{t}-t_q) \quad \text{(B4)}$$

Obtain $\tilde{t}$ as a function of t_q from condition 3:

$$\tilde{t}=\frac{(\alpha(1-e_h)-\beta)t^*+\beta t_q}{\alpha(1-e_h)}. \quad \text{(B5)}$$

Insert (B5) into (B3) to obtain t_q, which, after simplification, coincides with the t_q for the conventional vehicle case:

$$t_q = t^* - \frac{\gamma}{\beta + \gamma}\frac{N}{s}. \tag{B6}$$

Using (B2), the end of congestion $t_{q'}$ is

$$t_{q'} = t^* + \frac{\gamma}{\beta + \gamma}\frac{N}{s}. \tag{B7}$$

Inserting (B6) into (B5), we can obtain the on-time departure time:

$$\tilde{t} = t^* - \frac{\beta\gamma}{\alpha(1 - e_h)(\beta + \gamma)}\frac{N}{s}. \tag{B8}$$

Derivation for Work AVs

Conditions 1 and 2:

$$\frac{\alpha - (\alpha - \beta)e_w}{\alpha - (\alpha - \beta)e_w - \beta} s\left(\tilde{t} - t_q\right) + \frac{\alpha - (\alpha - \beta)e_w}{\alpha - (\alpha + \gamma)e_w + \gamma} s(t^* - \tilde{t}) + \frac{\alpha - (\alpha + \gamma)e_w}{\alpha - (\alpha + \gamma)e_w + \gamma} s\left(t_{q'} - t^*\right) = N \tag{B9}$$

$$t_{q'} - t_q = \frac{N}{s} \tag{B10}$$

Insert condition 2 into condition 1, and obtain t_q as a function of $\tilde{t}$:

$$t_q = \frac{\frac{\gamma\frac{N}{s} - t^*(\beta+\gamma)e_w}{\alpha-(\alpha+\gamma)e_w+\gamma} - \left(\frac{\alpha-(\alpha-\beta)e_w}{\alpha-(\alpha-\beta)e_w-\beta} - \frac{\alpha-(\alpha-\beta)e_w}{\alpha-(\alpha+\gamma)e_w+\gamma}\right)\tilde{t}}{\frac{\alpha-(\alpha+\gamma)e_w}{\alpha-(\alpha+\gamma)e_w+\gamma} - \frac{\alpha-(\alpha-\beta)e_w}{\alpha-(\alpha-\beta)e_w-\beta}}. \tag{B11}$$

Condition 3:

$$\tilde{t} = t^* - \frac{\beta}{\alpha - (\alpha - \beta)e_w - \beta}\left(\tilde{t} - t_q\right) \tag{B12}$$

Obtain $\tilde{t}$ as a function of t_q from condition 3:

$$\tilde{t} = \frac{(\alpha - (\alpha - \beta)e_w - \beta)t^* + \beta t_q}{\alpha - (\alpha - \beta)e_w}. \tag{B13}$$

Insert (B13) into (B11) to obtain t_q. Congestion start and end times turn out to be the same for all vehicles. Insert t_q into (B13) to obtain the on-time departure time for Work AV:

$$\tilde{t} = t^* - \frac{\beta\gamma}{(\alpha - (\alpha - \beta)e_w)(\beta + \gamma)}\frac{N}{s}. \tag{B14}$$

Appendix C. Proofs of the congestion properties given single AV type and $\alpha - \beta - \gamma$ scheduling preferences

Proposition C1. The queueing times are longer with AVs compared to conventional vehicles.

Proof.

It is sufficient to show that the inflection points of AV graphs at $\tilde{t}$ are higher and lie earlier for the AV graphs than the inflection point of the conventional vehicle graph, and that the inflection point at t^* for Universal and Work AVs also lies above the conventional vehicle graph.

The highest peak at $\tilde{t}$ is as high as it is far from the preferred arrival time t^*. This follows from the definition of $\tilde{t}$ as the departure time that leads to on-time arrival. Knowing this, it can be seen from Table 5-2 that $t^* - \tilde{t}$ increases with e_h and e_w for all AV types. Therefore, the inflection point at $\tilde{t}$ is higher and earlier for the AV graphs than for the conventional vehicle graph, for which $e_h = e_w = 0$.

The peak at t^* for Universal and Work AVs lies above the conventional vehicle graph, because the Work AV graph in segment $[\tilde{t}, t^*]$ is flatter than the conventional vehicle graph. This is because the departure rate (from Table 5-2) is higher for Work AV in that interval: it can be verified that $(\alpha - (\alpha - \beta)e_w)/(\alpha - (\alpha + \gamma)e_w + \gamma)\, s > \alpha/(\alpha + \gamma)$ is always true. Since Work and Universal AV graphs overlap from t^* onward, the inflection point of Universal AVs is also necessarily above the conventional vehicle graph.

Proposition C2. Congestion is more skewed to earlier times for the Home AVs and to later times for Work AVs. Congestion with Universal AVs is skewed in both directions.

Proof.

To prove this property, we need to select an indicator that describes the skew well. I propose the following indicator, which captures the difference between the relative increase of congestion at times $\tilde{t}$ and t^*, while taking the congestion with conventional vehicles as a reference point:

$$S^{AV} = \frac{Q_{\tilde{t}}^{AV}}{Q_{\tilde{t}}^{CV}} - \frac{Q_{t^*}^{AV}}{Q_{t^*}^{CV}}, \tag{C1}$$

where $Q_{\tilde{t}}^{AV}$ and $Q_{\tilde{t}}^{CV}$ are queuing times at the on-time departure time $\tilde{t}$ with AV and conventional vehicle (CV), respectively; $Q_{t^*}^{AV}$ and $Q_{t^*}^{CV}$ are the corresponding queueing times at t^*. If S^{AV} is positive, then the congestion is skewed towards earlier times as compared to the congestion with conventional vehicles; if it is negative, then congestion is skewed to later times.

The skew indicators for the Home AV (S^{AV_1}), Universal AV (S^{AV_2}) and Work AV (S^{AV_3}) are the following:

$$S^{AV_1} = \frac{1}{1 - e_h} - \frac{\alpha + \gamma}{\alpha(1 - e_h) + \gamma} = \frac{\gamma e_h}{(\alpha(1 - e_h) + \gamma)(1 - e_h)} > 0, \tag{C2}$$

$$S^{AV_2} = \frac{1}{1 - e_h} - \frac{1}{1 - e_w}, \tag{C3}$$

$$S^{AV_3} = \frac{\alpha}{\alpha - (\alpha - \beta)e_w} - \frac{1}{1 - e_w} = -\frac{\beta e_w}{(\alpha - (\alpha - \beta)e_w)(1 - e_w)} < 0. \tag{C4}$$

This indicator shows that, indeed, Home AVs skew the congestion to earlier times; Work AVs skew it to later times. The indicator is zero for Universal AVs, if $e_h = e_w = 0$, and positive (negative), if e_h is larger (smaller) than e_w.

Proposition C3. Longer queueing times are reached with Home and Universal AVs compared to Work AVs.

Proof.

Having congestion with any vehicle, the longest queueing time occurs at the on-time departure time $\tilde{t}$. Following the definition of $\tilde{t}$, this queueing time equals $t^* - \tilde{t}$. Comparing the distance $t^* - \tilde{t}$ for Home (or Universal), and Work AVs, it can be obtained that $t^* - \tilde{t}$ is larger for Home and Universal AVs, whenever $\alpha e_h^H > (\alpha - \beta) e_w^W$, where e_h^H is the efficiency of home activities in the Home and Universal AV, and e_w^W is the efficiency of work activities in the Work AV. This condition determines that home activities would yield higher utility in Home AV than early work activities (before t^*) yield in Work AV. If this condition is not fulfilled, then Home AVs are inferior to Work AVs in terms of the quality of on-board activities, and Home AVs would lead to shorter queueing times than Work AVs (the congestion pattern would be only slightly altered from the conventional vehicle case).

However, if AVs are specialised to support only home, only work, or both home and work activities, and do so to a similar extent (such that none of AVs is inferior to another at all clock-times), then Work AVs would result in a smaller congestion increase than other AV types.

Proposition C4. Congestion costs with AVs are the same as with conventional vehicles.

Proof.

The start and end times of congestion are the same for conventional vehicles (25) and (26) and AVs (Table 5-2). At these times, the travel time is zero, and the individual experiences only the costs of being at work too early or too late. Since these costs are not influenced by AVs, the equilibrium costs of all congestion patterns in Figure 5-6 are the same and equal $(\beta\gamma/(\beta + \gamma)) * (N/s))$.

Appendix D. Code used to create Figures 6 and 7

Code can be found in Pudāne (2020), https://doi.org/10.4121/13247633. Code was created in MATLAB R2018b.

6 On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey – A Comment

Pudāne, B., & Correia, G. (2020). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey–A comment. Transportation Research Part A: Policy and Practice, 132, 324-328.

Abstract

This note revises the theoretical insights concerning the Value of Travel Time for automated vehicles as derived in a recent paper in this journal (Correia et al., 2019). That paper concluded that Value of Travel Time in an automated vehicle should be lower than in a conventional vehicle by salary rate, if the traveller works during the trip, and unchanged compared to conventional vehicles, if the traveller engages in leisure activities while travelling. However, these conclusions have limited validity, because the models, upon which they are based, contain a term whose interpretation differs across the models. This note clarifies this interpretation and offers an alternative extended model, which allows comparison across models. The alternative model provides an intuitive result: the facilitation-level of on-board activities determines the reduction of the Value of Travel Time in the automated vehicle. If automated vehicles provide identical work or leisure experience to out-of-vehicle locations, then the opportunity costs of travel time are erased and the Value of Travel Time equals the intrinsic costs of travel, which is strictly smaller than the Value of Travel Time in a conventional vehicle.

6.1 Clarifying the theoretical insights in Correia et al. (2019)

The recent paper by Correia et al. (2019) set on an important mission to theoretically derive the Value of Travel Time (VoTT) for the Automated Vehicle (AV) era and to compare the theoretical insights with empirical results. The theoretical part of the work was based on the classical microeconomic time-use framework. In order to incorporate the possibility of future AV-users to perform activities during the trip, the authors altered the constraints of the time-use model and, after derivations, obtained the VoTT in a work- and leisure-equipped AV:

$$VoTT_{AV-work} = \frac{\frac{\partial U}{\partial W}}{\frac{\partial U}{\partial G} - \alpha\theta} - \frac{\frac{\partial U}{\partial t_i}}{\frac{\partial U}{\partial G} - \alpha\theta} \tag{C 13[36]}$$

and

$$VoTT_{AV-leisure} = \frac{\frac{\partial U}{\partial L}}{\frac{\partial U}{\partial G} - \alpha\theta} - \frac{\frac{\partial U}{\partial t_i}}{\frac{\partial U}{\partial G} - \alpha\theta}. \tag{C 18}$$

The notation in the equations is as follows:

U – overall utility obtained from engaging in activities and consuming goods in some time period;

G – purchased goods (in monetary terms);

L – time spent in leisure;

W – time spent working;

t_i – travel time (in mode i);

w – salary rate per time unit (e.g., an hour);

α – leisure time needed to consume one (monetary) unit of purchased goods;

θ – Lagrange multiplier of the technical constraint (see Correia et al., 2019 or Jara-Díaz, 2008 for details).

Having obtained results (C 13) and (C 18), the authors correctly interpreted that the VoTT in a work-equipped AV equals the utility difference between working outside the vehicle (first term of C 13) and working inside the vehicle (last term of C 13). Likewise, the VoTT in a leisure equipped vehicle could be interpreted as the utility difference between having leisure inside the vehicle, instead of outside it (C 18).

Further however, the authors deduced that (C 18) could be rewritten as (C 19):

$$VoTT_{AV-leisure} = w + \frac{\frac{\partial U}{\partial W}}{\frac{\partial U}{\partial G} - \alpha\theta} - \frac{\frac{\partial U}{\partial t_i}}{\frac{\partial U}{\partial G} - \alpha\theta}. \tag{C 19}$$

This led to the conclusion that the VoTT in a leisure-equipped AV (C 19) is identical to the VoTT in a conventional vehicle (CV) (Jara-Díaz, 2008):

$$VoTT_{CV} = w + \frac{\frac{\partial U}{\partial W}}{\frac{\partial U}{\partial G} - \alpha\theta} - \frac{\frac{\partial U}{\partial t_i}}{\frac{\partial U}{\partial G} - \alpha\theta}. \tag{C 8}$$

[36] Equations that are copied from Correia et al. (2019) preserve the original numbering from their paper, but are marked with a preceding 'C'. Equations that are original in the present note are numbered as conventional.

Similarly, it was obtained that the VoTT in a work-equipped AV should be less than the VoTT in a CV exactly by the salary rate w (by comparing equations (C 13) and (C 8)) (see p. 362, 375-376).

However, there are two reasons why the above conclusions have limited validity. The first of these lies in the transition from (C 18) to (C 19), which affects the comparison between VoTT in CVs and leisure-equipped AVs. This transition assumes that terms $(\partial U/\partial L)/(\partial U/\partial G-\alpha\theta)$ and $w+(\partial U/\partial W)/(\partial U/\partial G-\alpha\theta)$ are equal – but they are in general not so for the present model. The correct relationship between the two terms follows from the first order condition of the model, which can be obtained from equations (C 6) and (C 7) of Correia et al. (not repeated here):

$$\frac{\partial U}{\partial G}w-\frac{\partial U}{\partial L}+\frac{\partial U}{\partial W}-\theta(1+\alpha w)=0. \tag{1}$$

Re-arranging the terms in (1), we can obtain

$$\frac{\frac{\partial U}{\partial L}}{\frac{\partial U}{\partial G}-\alpha\theta}=w+\frac{\frac{\partial U}{\partial W}}{\frac{\partial U}{\partial G}-\alpha\theta}-\frac{\theta}{\frac{\partial U}{\partial G}-\alpha\theta}. \tag{2}$$

Having (2), we can see that (C 18) is equal to (C 19) only when $\theta=0$, that is, when the technical constraint connecting leisure time and consumed goods is not binding.[37] However, the VoTT is derived for the binding case $\theta>0$ and, due to being more general, it also applies to the non-binding case. Therefore, to incorporate all cases to which the VoTT applies, equation (C 19) should be corrected as follows:

$$VoTT_{AV-leisure}=w+\frac{\frac{\partial U}{\partial W}}{\frac{\partial U}{\partial G}-\alpha\theta}-\frac{\frac{\partial U}{\partial t_i}}{\frac{\partial U}{\partial G}-\alpha\theta}-\frac{\theta}{\frac{\partial U}{\partial G}-\alpha\theta}. \tag{3}$$

Consequently, the conclusion of unchanged VoTT in leisure-equipped AVs (as compared to CVs) has limited validity. If the comparison is performed (while accounting also for the second reason, explained below), then it should be based on equations (C 8) and (3), which differ by the last term $\theta/(\partial U/\partial G-\alpha\theta)$ in (3). This means that the VoTT in AVs with leisure activities would be smaller than the VoTT in CVs, if consumption is limited by the leisure time, and equal to the VoTT in CVs, if the leisure time exceeds the time needed to consume purchased goods. Note that the former case – consumption being limited by the leisure time – can be expected to be rather rare; it would imply that individuals are earning money faster than they are able to spend it, which would hold presumably only for a small share of very high-income individuals (Evans, 1972). Therefore, empirically, the first limitation of the comparison is less severe than the second one.

The second and most important reason, which limits the comparison of VoTT between CVs and both AVs, lies in the term $\partial U/\partial t_i$, defined in the paper as the utility of 'spending time inside a car' (p. 362). This utility can be expected to be influenced by the activities performed inside the car – none in the CV and work or leisure in the AV. Therefore, the term $\partial U/\partial t_i$ has different interpretations in the three equations used for comparison: (C 8), (C 13) and (C 18).

[37] The general inequality of these terms, given the present model specification, is discussed by Jara-Díaz (2008) on p. 372: 'If consumption is limited by time (...), the marginal utility of leisure is smaller than the total value of work given by the wage rate plus work itself.' The equality holds for the non-binding case as well as for other model specifications, where no constraint connects the goods consumption and leisure time (see, e.g., the first model presented by Jara-Díaz, 2008 on p. 365).

A direct comparison across the VoTT results is possible only by assuming that the utility differences are negligible, which is limiting.[38]

In addition to the so-far outlined concerns, we would like to highlight two other details that might cause confusion for the readers of the original paper.

1. The unchanged VoTT for leisure-equipped AV (as compared to CV) is explained as follows (p. 362): 'It seems that consumption G yielded from the salary is constraining the leisure time formed by the normal leisure (L) and the travel time in mode i which is also counting as leisure in this scenario. A person will not be able to consume while traveling if the income is not enough.'
   This analysis suggests that insufficient income limits the time which an individual can spend in leisure activities during travel, and therefore the VoTT for leisure-equipped vehicle does not change. However, this reason does not fit with the time-use model for leisure-equipped AVs: leisure is performed during travel by construction. Furthermore, the time-use model assumes that leisure is possible 'for free': you do not need income or goods in order to engage in leisure. What could be said instead, is – if goods consumption is not bound by the leisure time in the CV case, then the individual does not gain any benefit from having extra leisure time during travel for goods consumption. This corresponds to the non-binding case ($\theta = 0$), for which the equations of VoTT in AV and CV models are the same. (Though, as discussed before, even if equations are the same, the interpretation of terms and hence the values of VoTT differ in both models.)
2. There is an inconsequential error in (C A6). The last term should have '+', not '-' in front.

6.2 An extended time-use model and VoTT for automated vehicles

Having outlined the difficulty in comparing the VoTT results of AVs and CVs in the original work, we propose an alternative extended model that permits such a comparison. The key differences between the new and the old model are two: first, the utility of on-board activities is made explicit rather than being part of $\partial U/(\partial t_i)$; second, the utility of on-board activities accounts for the quality of activity-facilitation on board. Both are achieved by including travel time in the objective function also as work or leisure time: $U(G, L, W + \beta t_i, t_i)$ and $U(G, L + \zeta t_i, W, t_i)$ for work- and leisure-equipped AVs, respectively.[39] The parameters $\beta, \zeta \in [0,1]$ represent the facilitation levels of activities in AV: the share of the work- or leisure-utility that the traveller gains while performing activities during travel.[40] Note that in practice this facilitation level is determined by the vehicle and by the activities that the traveller performs on board: reading a book would likely be associated with a much higher ζ than doing sports.

The time-use model for work-equipped vehicles becomes as follows (bold parts highlight the differences with the models in the original paper):

$$MaxU(G, L, W + \beta t_i, t_i), \tag{4}$$

subject to:

---

[38] To highlight that $\partial U/\partial t_i$ differs in these vehicles, we could replace the term t_i with t_i^w in (C 13), with t_i^l in (C 19), and with t_i^n in (C 8), where indexes w, l, n would stand for work, leisure, and no-activity, respectively.

[39] The double-counting of travel time in this approach reflects the idea that activities during travel is a type of multitasking (as opposed to the complete experience being regarded as modified travel or modified activities). This classification can be supported by observing that both travel and on-board activities typically require some mental and/or physical resources (Circella et al., 2012).

[40] Taken plainly, utility of $W + \beta t_i$ would be interpreted as utility obtained while working longer by share β of travel time, while work yields its full utility on board. However, we suggest that utility in such case is equivalent to the utility obtained while working the entire t_i, but in imperfect conditions represented by β.

$$G + c_i = wW + \gamma w t_i, \tag{5}$$

$$L + W + t_i = \tau, \tag{C 11}$$

$$L \geq \alpha G. \tag{C 12}$$

In addition to the notation presented earlier, c_i are travel costs and τ is the total available time. Parameter $\gamma \in [0,1]$ specifies the salary-share obtained from work during travel. The salary could be lower during travel than at the work place, if, for example, per-piece work of an individual is slowed down due to any disturbances during travel.

Similarly, the time-use model for leisure-equipped vehicles is as follows:

$$MaxU(G, L + \boldsymbol{\zeta t_i}, W, t_i), \tag{6}$$

subject to:

$$G + c_i = wW, \tag{C 15}$$

$$L + W + t_i = \tau, \tag{C 16}$$

$$L + \eta t_i \geq \alpha G. \tag{7}$$

Parameter η corrects the rate, in which the individual can consume the purchased goods during travel. For example, it may take longer to read a book in the car, if the motion of the car interrupts the reading at times. Performing the same steps as Correia et al. (2019) and Jara-Díaz (2008), we can derive the VoTT for work- and leisure-equipped vehicles:

$$VOTT_{AV-work} = w(1-\gamma) + \frac{\frac{\partial U}{\partial W}}{\frac{\partial U}{\partial G} - \alpha\theta}(1-\beta) - \frac{\frac{\partial U}{\partial t_i}}{\frac{\partial U}{\partial G} - \alpha\theta} \tag{8}$$

and

$$VOTT_{AV-leisure} = \frac{\frac{\partial U}{\partial L}}{\frac{\partial U}{\partial G} - \alpha\theta}(1-\zeta) + \frac{\theta}{\frac{\partial U}{\partial G} - \alpha\theta}(1-\eta) - \frac{\frac{\partial U}{\partial t_i}}{\frac{\partial U}{\partial G} - \alpha\theta}. \tag{9}$$

As could be expected, the different facilitation levels are attached to the corresponding terms. Share $1-\gamma$ of the salary and share $1-\beta$ of the work utility is lost when working in AV as compared to the work place. Share $1-\zeta$ of the leisure utility is lost due to it being performed in the AV and not at another (stationary) place; factor $1-\eta$ determines the lost value due to potentially lower rate of goods consumption during leisure on board (if the goods consumption is bound by the leisure time: $\theta > 0$). At an extreme, if work or leisure experience during travel is identical to work or leisure experience at their stationary locations $\beta = \gamma = \zeta = \eta = 1$, then VoTT is as follows:

$$VOTT_{AV-work} = VOTT_{AV-leisure} = -\frac{\frac{\partial U}{\partial t_i}}{\frac{\partial U}{\partial G} - \alpha\theta}. \tag{10}$$

This is an intuitive result. It expresses that the opportunity costs (the first two terms in (8) and (9)) would be eliminated given an 'ideal' AVs and only intrinsic costs of travel would enter the VoTT.[41]

[41] Note that the interpretation of $\partial U/(\partial t_i)$ differs here from the original work: it represents the intrinsic utility here, but joint utility from spending time in the vehicle in Correia et al. (2019).

Hereby, we have introduced a way to explicitly model the utility obtained from performing activities during travel. Note that much work can still be done to improve the new model. Among the first priorities could be modelling the possibility to engage in both work and leisure activities during travel, as well as accounting for different types of work and leisure activities. The latter would require that parameters $\beta, \gamma, \zeta, \eta$ are treated as endogenous.

6.3 Conclusions

This note highlights a subtlety, which however has crucial importance, in the interpretation of the theoretical VoTT results for the AV era, as obtained by Correia et al. (2019). This subtlety relates to the fact that one term – the utility of spending time in the vehicle – has different interpretations in the separate models in this paper, which limits the validity of a direct comparison between the derived VoTT for conventional and automated vehicles. In addition, this note reports few other (less crucial) oversights in the derivations and interpretations. Nevertheless, it should be emphasised that the theoretical revisions do not challenge the empirical results of Correia et al. (2019). Rather, the extended model provides more flexibility that could help in understanding these and other empirical results.

The second half of this note presents a new, extended model, which circumvents the interpretation difficulty in the original work. The VoTT results obtained from the new model will likely confirm some intuitions that have been often verbally expressed when discussing the benefits of AVs: future AVs are expected to provide an opportunity to use travel time for various activities and thereby to reduce or even eliminate the opportunity costs of travel. In a nutshell, AVs may ‘give back’ the travel time to the travellers.

Acknowledgement

The work reported in this note was funded by the Netherlands Organisation for Scientific Research (NWO) as part of the project ‘Spatial and Transport impacts of Automated Driving’ (STAD), project number 438-15-161. We thank three anonymous reviewers for their constructive comments that helped to improve the note, as well as Sergio Jara-Díaz for the valuable feedback on the models. The first author would like to thank Caspar Chorus and Sander van Cranenburgh for support and discussions. Finally, thanks go to Bart van Arem for the comments on an earlier version of this note.

References

Circella, Giovanni; Mokhtarian, Patricia L.; Poff, Laura K (2012): A conceptual typology of multitasking behavior and polychronicity preferences. Electronic International Journal of Time Use Research 9, no. 1.

Correia, Gonçalo; Looff, Erwin; van Cranenburgh, Sander; Snelder, Maaike; van Arem, Bart (2019): On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. Transportation Research Part A: Policy and Practice, 119, 359-382. https://doi.org/10.1016/j.tra.2018.11.016

Evans, Alan W., 1972. On the theory of the valuation and allocation of time. Scottish J. Polit. Econ. 19 (1), 1–17. http://dx.doi.org/10.1111/j.1467-9485.1972.tb00504.x.

Jara-Díaz, Sergio R. (2008): Allocation and valuation of travel time savings. Handbook of Transport Modelling, second edition, Emerald Group Publishing Limited, 363-379.

7 Conclusions and reflection

This thesis has looked at the time-use and travel-behaviour effects of automated vehicles (AVs): how time-use inside a vehicle can impact the time use outside of it, including the associated travel behaviour choices. It has investigated this theme empirically and modelled it, as well as has cast a first view on the aggregate travel patterns resulting from various on-board time-uses. Now I would like to summarise the main lessons from this work, and discuss some broader implications and questions for future research that have emerged from it.

The first three sections of this chapter follow the three aims that were outlined in the introduction. Namely, section 7.1 summarises the qualitative and quantitative empirical insights that call for updating time-use and travel behaviour models for the AV era. Section 7.2 reviews the new and updated time-use and travel behaviour models. Section 7.3 reflects on the results regarding changes in aggregate travel patterns with AVs. Since the larger part of this thesis has argued for new and updated models, it is useful to discuss the opposite: when would the current modelling tools be accurate for AV applications? The following two sections summarise the assumptions about behaviour (changes) with AVs that underlie the travel time penalty (section 7.4) and the value of travel time (section 7.5).[42] The next section 7.6 proposes some avenues for future research that emerge from this thesis. Finally, sections 7.7 and 7.8 discuss methodological and substantive implications for policy.

7.1 Empirical basis for new time-use and travel behaviour models

This thesis started with two empirical studies – the first being based on focus group interviews, and the second using a novel interactive stated activity-travel survey. The aim was to survey

[42] The terminology here distinguishes the travel time penalty and value of travel time as tools used for activity-travel prediction and transport project appraisal, respectively. Literature often refers to the value of travel time also in the prediction context, but, strictly speaking, this usage is not accurate: it does not align with the definition of value of travel time in the microeconomic time-use framework.

travellers' current expectations about their time use and travel behaviour in the future with AVs, and to do so both in depth and in breadth.

The qualitative focus group (chapter 2) study revealed that the travellers imagine a variety of ways how they could use their time inside AVs. The variety of mentioned activities was structured along two axes: their novelty (i.e., whether the participant performs the activity during travel in their current modes) and importance (i.e., high-importance versus optional activities, following the participants' own judgment). Participants expected changes in their daily schedules from performing new and important activities during travel (especially work during travel made some participants reconsider their commute departure times) or letting the car perform such important tasks (such as sending and picking up people). Several participants reflected on how these changes would save time in the day. An interesting discussion emerged in several groups about whether saving time and making days more efficient is desirable, or will that induce even more pressure to be productive at all times. Questioned about their expected daily travel amount with AVs, some thought that they would travel more, while others did not expect any change. Changes in daily schedules did not always include more travel. Reflecting on non-daily long-distance travel, participants were more united in their desire for more leisure travel thanks to the higher comfort of AVs and also new available activities (such as sleep during a night ride).

The quantitative study (chapter 3) analysed data from an interactive stated activity-travel survey using the MDCEV. Two models were estimated: the first considered the time use during travel, and the second analysed time use at stationary locations. This approach lets us discover, whether there are aggregate trends in on-board and stationary time use, which may be triggered by AVs. The results indicate a clear increase in on-board activities with AVs, with the most popular activities for the entire sample being leisure and getting ready (i.e., in the morning or before sleep). The remaining two analysed activities – work and meals during travel – were popular among the highly educated and high income respondents. The analysis of the stationary activities did not reveal any change in time use that would have been made by the entire sample. But respondents in some socio-demographic groups were united in their schedule changes. The higher educated segment was the only one that indicated changes in stationary activities (more likely to indicate 'getting ready' activity) together with above-average changes also in on-board activities (more likely to work, have meals and leisure during travel) with AVs.

Overall, our empirical studies indicate need for new models that would capture the link between on-board and stationary time use. The focus group participants expected varied schedule changes due to the possibility to perform new activities during travel. Although our quantitative study did not reveal any stationary schedule changes in the aggregate, changes appeared within some socio-demographic groups. Finally, neither of our datasets indicate induced daily travel due to AVs, although such a development should be expected, if the travel time penalty was a good descriptor of the expected schedule changes. These results indicate that the current assumptions underlying travel behaviour and transport models may need to be revised.

7.2 New time-use and travel behaviour models

This thesis proposed three new or updated models. The first (chapter 4) is a time-use model. Building on the classical works of Becker (1965), deSerpa (1971) and Evans (1972), we added on-board activities in the daily time-use optimisation problem. To accommodate this addition, we linked all activities with travel times and added a second time constraint, which limits the on-board activity time to these travel times. Worked-out examples show how transitioning to AVs can lead to replacement of stationary activities with their on-board counterparts, which results in the 'saved time effect' – freed up time for more activities during the day. We also provided an example, where the replacement of a stationary activity with its on-board variant leads to reduction of daily travel time. Thus, this model demonstrates that an opposite travel adjustment to the travel time penalty assumption could, given certain activity schedules and wish-lists, be entirely rational in a microeconomic utility-maximising sense.

The second model (chapter 5) is a scheduling model (based on Vickrey, 1973, and Small, 1982), which is used to analyse optimal departure times and congestion forming with AVs. In the classical transport economics' set-up, travellers are assumed to choose their departure time from home to work (the morning commute is the most common application), while minimising the utility that would be lost from being at home and at work. This chapter added to this set-up a condition that home- and work-type activities are facilitated to a specified extent also during travel. The closed-form results of this chapter show that in most cases AV users would have different optimal departure times than conventional vehicle users, even if there is no congestion. If the AV facilitates home-type activities better than work, then its users would depart earlier than conventional vehicle users. The converse holds true for AVs that support work activities better. If, like in most literature to date, models do not distinguish among various activities during travel, then AVs do not lead to dispersion in departure times in uncongested traffic.

The third modelling contribution (chapter 6) of this thesis is an update to a time-use model underlying the theoretical value of travel time (VoTT) derivation for AVs. Correia et al. (2019) theoretically derived VoTT for AVs that facilitate home or leisure activities, as well as reported results from a stated choice survey estimating the VoTT for both AV types. The interpretation of their theoretical results needed to be clarified, which was the first goal of this note. Afterwards, it derived a more general version of the model, in which home or leisure activities are facilitated imperfectly (which is specified with an efficiency factor). This extended model shows how one of the two components of the VoTT, namely the opportunity costs, is reduced (or eliminated) by AVs, corresponding to the facilitation levels of activities on board.

Although the three developed models belong to different disciplines, they have some common features. First, all modelling exercises aimed to distinguish among different on-board activities. Whereas most literature to date summarises the effects of any on-board activity into a single (reduced) travel time penalty, this thesis has shown how differentiating among various activities can lead to different, but intuitive predictions. Second, a common aspect of these new predictions is the possible substitution and saved-time effect of on-board activities: if an activity can be performed during travel, then it may be eliminated or shortened outside of it, giving space to other activities. Third, the first two of the above models share an optimistic message that individual travel amount (ch. 3) and congestion (ch. 4) with AVs need not increase as much as previously thought, since also other schedule changes are possible.

7.3 First insights in aggregate travel patterns

This thesis only briefly touched on the question of how the above-described schedule rearrangements could reshape the aggregate travel patterns, and it did so in the second half of chapter 5. The developed scheduling model was applied in a bottleneck setting (Arnott et al., 1990) to analyse the shape and severity of congestion with AVs that facilitate home and work activities to various extents. Results show that congestion in this setting is always increased with AVs, at least when not considering any capacity changes. To the extent that AVs support home activities, they increase congestion early in the peak. The opposite holds for AVs that support work activities. Congestion of work-type AVs was found to be less severe.

An additional aspect of aggregate travel patterns is discussed in the epilogue of this thesis (in particular, section 8.3): the aggregate vehicle kilometres travelled. The chapter focusses on the individual travel amount and mode choice as the main determinants of vehicle kilometres. The discussion of the latter includes a conceptual map that illustrates how the substitution of current travel modes with their closest AV counterparts could lead to more vehicle kilometres. This could be expected even if the amount of person-kilometres (the former determinant) does not change. The chapter proceeds to discuss health and well-being implications of the individual travel behaviour developments and their aggregate impacts.

7.4 Travel time penalty (TTP): when does it accurately predict behaviour in AV era?

What we learned from all modelling exercises, is that various rearrangements in schedules can stem from various available and performed activities in AVs. If this substance of on-board activities is not represented in models (such that the activities are ‘anonymous’, as they are in the TTP approach), then only a single rearrangement follows from any on-board activity. Now, it might be useful to summarise and state explicitly, under what conditions would the TTP be accurate? In other words, what potential time-use and travel behaviour changes in the AV era are compatible with the TTP, and what are conflicting? This is done in Table 7-1. Clearly, if the analyst has direct or at least indirect evidence that only ‘compatible’ changes are expected, then TTP is not only justified, but being a simple approach, it should, in fact, be the preferred tool in modelling this behaviour.

Table 7-1 Behavioural assumptions behind the TTP

When new or enhanced activities are available during travel, the traveller may…		
Behaviour compatible with the TTP	change nothing in her schedule OR spend more time travelling, and shorten / rearrange other activities to accommodate the longer travel	
Behaviour conflicting with the TTP	add or eliminate stationary activities OR change durations of stationary activities OR change departure times OR change the sequence of stationary activities	… all while not prolonging travel

As summarised in section 7.1, our data indicate some of the ‘conflicting’ changes of Table 7-1 (e.g., changed commute departure times). Also other studies have found small but not negligible shares of travellers that consider such non-TTP daily schedule changes. For example, Kim et al. (2020) found some support for specific proposed changes in stationary activity durations. In sum, it could be that the applicability of the TTP varies by travel type (e.g., daily versus holiday travel) and region. This is certainly an area that is certainly worth exploring further. Nonetheless, it is clear that TTP should not be the only considered option without extensive or case-specific evidence.

7.5 Value of travel time (VoTT): when does it accurately measure project benefits in AV era?

The Value of Travel Time (VoTT) and the Travel Time Penalty (TTP) are, in some sense, two sides of the same coin: both convey that travel is something that individuals would rather reduce, and measures that inconvenience per time unit. It can therefore be compelling to conclude that the VoTT is subject to the same difficulties, when applied for project assessment in the AV era, as is the TTP when predicting the resulting travel behaviour from these projects. That is not exactly true.

As was summarised in the previous section, using TTP presupposes a certain type of change in activity-travel behaviour. However, conducting a discrete choice experiment to find out the VoTT, the analyst does not seek to know the exact change in activity-travel behaviour, but the travellers' valuation (in monetary terms) of it. Obtaining the latter without the former is possible in the discrete choice setting thanks to the underlying time-use theory (Jara-Díaz, 2007). This theory postulates that the respondents, when confronted with travel time and cost combinations (the classical choice task used to obtain the VoTT), consider their optimal time and resource allocation conditionally on the presented combinations, and chooses the option with the highest (daily) utility. This highest utility can be derived analytically. From here, the analyst needs to assume that this highest utility is a well-behaved function with respect to travel time and costs (a linear form is often used), in order to take derivatives with respect to both, and eventually obtain the VoTT.

Now, we are in a position to ask – under what conditions would the VoTT, which is obtained from a discrete choice task as described above, accurately measure the value of saving travel time in AVs? Two points can be made here. First, if the AV impacts on time-use can be represented in the time-use model that underlies the VoTT derivation, and if a single theoretical VoTT can be obtained from it, then the empirical methods devised for the non-AV case will likely preserve their accuracy with AVs. In this regard, chapter 6 of this thesis has shown one such derivation of a theoretical VoTT for AVs. It assumed that the travel time doubles as either work or leisure time, depending on the AV type. Resulting from this specification is a property that better facilitation of on-board work or leisure activities leads to a larger reduction in stationary work or leisure activities, respectively. The VoTT is shown to be necessarily lower than the VoTT in conventional cars. The reduction is due to the opportunity costs' component of VoTT, and it is proportional to the specified facilitation levels of on-board activities, in terms of their utility, salary rate of on-board work, and speed of goods consumption while engaging in leisure in AV. All of these facilitation levels are assumed to be constant – that is, independent of the travel or on-board activity duration. Note that this framework also allows scenarios, whereby the on-board activities reduce utility, but do not affect the time allocation to stationary activities – that is, they only add to the schedule.

Second, if the AV impacts cannot be summarised in a time-use model, or if no single VoTT can be derived from it, then that case needs to be further examined. To name a few such instances, on-board activities may have specified ideal durations, there may be cost of splitting them in fragments, and on-board activities may substitute stationary activities that would otherwise require a trip (these being the conditions modelled in chapter 4). Lyons (2019) adds more items to this list: travel time being used for multiple (productive, unproductive, work-related, leisure-related) activities, the difficulty to measure productivity of a knowledge worker (being it stationary or during travel), etc. Under such circumstances, it will be difficult to formulate a time-use model that allows to derive an analytical, closed-form VoTT for any individual. However, and this is the part that requires further examination, the VoTT may still be an adequate measure at the population level – which is of highest policy relevance. Fowkes (1996), as cited in Mackie et al. (2001), discusses the issue of small travel time savings, where the distinction between the individual and population matters as well. An individual may not be able to make use (opportunity costs) of small travel time savings – say, a minute – if the minimum duration of all of his activities is five minutes. However, because population of such individuals would be bound to have some unused time between zero and five minutes, a subset of this population will be able to perform the five minute activity, given the small travel time saving. Yet, there is a difference between this discussion about the value of small travel time savings, which could still in principle be thought of as savings, and, say, the value of reducing travel time that is used for productive (or otherwise meaningful and important) activity (e.g., Jain & Lyons, 2008; Gripsrud & Hjorthol, 2012). In an extreme but not entirely unrealistic case especially for future AV users, travel time reduction may be experienced as intrusion in their private space – almost as if travellers would be forced to leave their (mobile-) home in the middle of their breakfast. Perhaps a middle ground between these two perspectives is the idea of ideal travel time (Redmond & Mokhtarian, 2001) – to be saved, if it is too much, and enjoyed, if it is not.

To conclude, my thesis has not given a definite answer as to when the VoTT will preserve its accuracy in measuring travel time benefits with AVs. It is clear that the VoTT is far more robust for various time-use scenarios than its prediction counterpart – the TTP. Furthermore, it was shown that under some conditions, the multitasking capability can be represented in VoTT, leading to necessarily lower VoTT than in a conventional vehicle. Under these conditions, the value of infrastructure investments that reduce travel times will be smaller in AV future. Yet, the qualifications for this conclusion remain an important question for further research, which may contribute to the long-standing debate of 'how derived is the demand for travel' (Mokhtarian & Salomon, 2001).

7.6 Some directions for future research

As this thesis has modelled and analysed the impacts of AVs on daily time-use and schedules, a natural direction for further study is to continue empirically exploring such impacts. In particular, future studies could explore other data collection methods to observe stated changes in activity schedules. The interactive stated activity-travel survey proposed in this thesis (chapter 3) served well to collect detailed daily time-use information under somewhat constrained conditions (such as fixed travel times and a single travel mode per schedule). In contrast, Kim et al. (2020) – the only other study, known to the author, that explored hypothetical schedule changes with AVs – used respondents' ratings of statements describing various types of schedule changes. This approach gives the analyst full freedom to specify various scenarios, including non-daily changes, which can be represented by 'more often' statements. However, the magnitude of the changes (e.g., how much further would the respondents travel with an AV) is hard to observe using this approach. As a future research direction, it seems that a hybrid option with statements and visual representations of customised schedule changes could be explored. Such approach could also let the analyst to 'zoom in' to specific changes of interest, for example, departure time adjustments in morning peak (such as modelled in chapter 5), or other empirically-determined common rearrangements in the schedules.

Beyond the estimation of models describing schedule changes, numerous other questions are currently not sufficiently explored. In the context of AVs, studies are needed regarding the fit between activity wishes and their feasibility in future AVs. Motion sickness is likely the most important potential obstacle to performing various activities in AVs (Iskander et al., 2019). However, also smoothness of the ride and the equipment, which may be necessary for some activities, play a role (Roeckle et al., 2018). Coupled with hypothetical data, such as collected in this thesis, this information could give a good proxy for what on-board activities and schedule changes could be expected in the AV future. Furthermore, real-life observations or experiments in contexts that resemble AVs (such as chauffeur data by Harb et al., 2018, and Wadud & Huda, 2019) can provide more reliable data about how travellers may use their time in AVs and possibly adjust their daily schedules as a result.

More generally, it is informative to observe daily schedule changes as response to other global developments, such as the continuous expansion of ICT services. Since activity schedules vary greatly among individuals, studies based on panel data would be most suited for this purpose (Hoogendoorn-Lanser et al., 2015). It would be interesting to complement such panel studies (which contain daily activity diaries) with queries about unfulfilled activity needs and wishes. Then, as the respondents adopt any efficiency-enhancing technology (e.g., an ICT service, and later also the AV), the relationship between the former activity wish-list and schedule change can be determined. A further way to learn from the studies that explore the impacts of ICT and other innovations on daily schedules, is to expand the model repertoire to represent various observed schedule changes. Specifically, the introduction and development of ICT spurred much curiosity regarding the role of the newly available tele-activities in daily schedules. The initial expectation that there would be many substitution effects (and hence reduction in travel), was soon replaced with evidence of complementarity (e.g., online shopping spurred more in-person shopping) and modification (Pawlak et al., 2020). In this vein, although this thesis has just contributed models describing mostly substitution between on-board and stationary activities, it would be wise to look ahead and consider ways to model other roles of on-board activities in daily schedules.

To add to the complexity, the roles of on-board activities likely differ across population. Beyond the 'usual suspects' (such as demographic and economic variables) that are used to explain heterogeneity in tastes and decision rules, it is possible that the heterogeneity of on-board activity roles relates to various time-styles of individuals. Here, Cotte et al. (2004) discuss the determinants that make up the time-style of an individual – past-present-future orientation, tendency for planning versus impulsiveness, priority for self-time versus time for others, and the monochronic versus polychronic orientation. It seems plausible that the time-saving or, equivalently, activity substitution effects modelled in this thesis describe future-oriented, planning, polychronic individuals the best. In addition to the heterogeneity among AV users, it could well be that the role of on-board time evolves for every individual. New AV users may replace some stationary activities with on-board ones, since total activity needs and wishes may be constant in the short term (and these are the scenarios modelled in this thesis). But, in longer term, the availability of new and enhanced on-board activities may alter their needs and wishes, resulting in more complex developments in daily schedules (as also briefly discussed in chapter 2 of this thesis). Exploring these heterogeneities and evolutions are exciting directions for future research.

As a final suggestion in this clearly non-exhaustive list, I propose that boundedly-rational behaviour in time use should be further explored. There are several reasons, why some non-utility-maximising aspects should be expected. First, the planning of daily activities is a necessarily complex task, resulting in a limited ability (and need) of individuals to optimise their days fully. Second, the role of habit could be particularly strong when dealing with activity patterns – there is a large benefit in keeping to a daily rhythm. Third, new technology in general, and AVs may be no exception, often caters to our limitations as decision makers. Just like travel information reduced the need to optimise all journeys in advance, mobile phones reduced the need to schedule the joint activities to a minute detail, so the newly available time inside AVs may reduce the need to schedule daily activities in great detail. The savings in the planning cost could be larger than the reduction in the schedule optimality due to spontaneous decision making. Fourth, as covered in chapter 2, the ability to increase the productivity of daily schedules with AVs may be valued negatively by some individuals, resulting in an aversion to AVs – a counterintuitive result, if viewed from conventional activity utility-maximising (and, hence, productivity-maximising) perspective, but a well understandable one considering multiple competing goals in activity planning (Dellaert et al., 2018).

7.7 Policy implications: data and methods

As the policy makers seek to prepare for the introduction of (highly) automated vehicles, they first need to prepare the tools that should help them prepare. While travel behaviour and transport tools are reasonably well suited for the present travel modes, many questions remain regarding how to represent the novel AV mode in them. For example, how will AV usage impact departure times and congestion? How will time spent in AV influence other daily activities and the associated travel patterns? How the afore-mentioned new travel patterns will influence long-term decisions of vehicle ownership and residential location? This thesis has, for the most part, challenged a common modelling tool used to answer these questions – the travel time penalty (TTP). It has offered intuitive arguments and first empirical evidence in favour of a more detailed approach, which considers the substance of on-board activities when predicting their activity-travel impacts. Specifically, it proposed two models for behaviour prediction, in which on-board activities can impact the entire (daily) time use (chapter 4) or only the preceding and succeeding activities, resulting in departure time adjustments (chapter 5).

At this point, the policy makers may like to ask – should the on-board activities be differentiated also in the models used for AV policy analysis? If yes, when and how to adapt the models to achieve that? If no, what to do with the knowledge that the theoretical exercises provide? In what follows, I will reflect on these questions, while considering the two afore-mentioned prediction models[43] as examples of models that differentiate among on-board activities. I devise four criteria to assess the suitability of the proposed models for quantitative policy analysis: contribution to policy-relevant variables, gain in soundness and accuracy, effort of implementation and use, and other external criteria.

Contribution to policy-relevant variables

The first criterion to assess the policy need of updating a model is, quite expectedly, the relevance of the update for specific policy questions. Below I list some policy questions for which my models (as updates on large-scale transport models) could be particularly valuable.

Daily time-use model:

- What will be the amount of person-kilometres travelled by AV users?
- What will be the traffic volumes in business, leisure and residential land-use areas in various parts of the day and week?
- What will be the demand for AVs that support different activities on board?
- What will be the demand for private versus shared and pooled AVs at various times of the day and week?
- What will be the demand for housing in various parts of the country, and will AVs lead to sprawling of cities, if unregulated?

Departure time choice and congestion model:

- What will be the congestion pattern of morning commuters?
- What congestion pricing scheme to implement?
- What is the benefit of flexible working hours?
- What share of the value of travel time savings accrue to the employees and employers?
- How could the changing congestion patterns and enhanced routing capabilities of AVs impact route choice (e.g., cut-through traffic) and the resulting vehicle-kilometres travelled?

[43] Note that I focus here on travel behaviour prediction and not project assessment, since there lay the most challenges with the currently used tools (see sections 7.4-7.5).

These questions likely have different priorities at different life-cycle stages of AVs. For example, the potential attractiveness of AV fleets is an interesting question before a wide-scale uptake of privately-owned AVs – thus, in the initial stages of AV deployment. In contrast, the congestion developments with increasing AV market share, and the efficacy of various policy instruments in regulating it (such as flexible working hours or congestion pricing) are important considerations given a critical mass of AV users. Hence, the relevance of specific model updates varies during the planning and implementation process of the AV. These aspects can be considered together with the next category – the gain in soundness, which also depends on the stage of the AV introduction.

Gain in soundness and accuracy

Two good guiding principles in model development in general are theoretical soundness, which is in the centre of theory-driven approaches, and model flexibility, which is exhibited most strongly in data-driven approaches. The view of the author is that the models presented in this thesis contribute strongly to the soundness criterion, if compared to the TTP approach. That is, they are based on established microeconomic theories, as well as suggest an explicit treatment of on-board activities, which aligns with the (equally established) activity-based principles. It could also be said that, in some sense, the models are more flexible, since TTP is a special case of both models.[44] As always, this flexibility comes at the expense of more model parameters. Whether this increase is justified is, of course, up to an empirical investigation.

Given that the presented models are more theoretically sound, it would be expected that the practical (read: policy) gain of using them would be more accurate predictions. Nevertheless, the accuracy benefit of the sounder models diminishes, as their application cases move further in the future. This is so, because the application relies on data collected at present, which may become outdated quite quickly. Among the reasons is the fact that people's lifestyles, daily activities, and activity planning styles are changing over the years (due to, for example, ICT developments). In addition, the vision of AVs becomes progressively more clear (e.g., what on-board activities they will support; whether they will be available for private or shared use). Furthermore, more individuals will have tried AVs in the future, which will shape their ideas about how to use them. Given that wide-scale AV uptake will take at least few more decades according to average forecasts, it may even be that the travel decisions are made by a different generation than the one answering survey questions at present. What I have described so far, is the so-called temporal transferability problem of model estimates. Literature has observed that even for relatively standard present-day choice situations, model estimates are not well transferable over time (see Fox and Hess, 2010, for a review). This problem is exacerbated for such detailed and flexible activity-travel models as this thesis proposes. The more heterogeneity among individuals is modelled – the larger the concern about the transferability (Chorus, 2020).

As a side note for the accuracy discussion, it should be mentioned that the state-of-the-art approach to achieve highest prediction accuracy is to use machine learning models. Without imposing any theoretical constraints and with ability to draw upon multiple categories of data, these models have the highest flexibility and potential to deliver the most accurate predictions. However, recent discussion papers – Aboutaleb et al. (2021), van Cranenburgh et al. (2021) – caution that, because these data-driven models have no means to distinguish between causation and correlation, they should be used for prediction only on the support of the data. This immediately precludes long-term forecasting, such as prediction of travel behaviour in the (likely rather distant) AV future. In addition, and quite clearly, data-driven models should use reliable sources of data, since that is their only base for predictions. The above discussed

[44] In case of the departure time choice model, only the variant using $\alpha - \beta - \gamma$ preferences contains TTP as a special case.

limitations of the currently available data of travel behaviour with AVs inhibit the use of machine learning models even stronger.

To sum up the discussion on soundness and accuracy, it may be prudent to wait with implementing (theory-driven) updates in the models, until more reliable data become available. Of course, policy makers need to balance this decision with the policy need for more accurate predictions at various times (see above) and other criteria (see below – and I do not aim to be exhaustive in listing them). With regard to the data limitations, researchers and decision makers could explore alternative sources of data to the classical survey approaches employed most widely for AV travel behaviour research. Harb et al. (2021) suggest that approximations of AVs as chauffeur-driven cars (as in Harb et al., 2018; Wadud & Huda, 2019) do not suffer from many limitations of hypothetical survey settings, such as the varied interpretation of written descriptions and videos of AVs by the respondents. They suggest that an even better approximation of future travel behaviour could be observed, if the technical AV testing could be coupled with travel behaviour data collection, which would require cooperation between governments and industry (Harb et al., 2021).

Effort of implementation and use

A further criterion in considering the decision and timing of model updating is the necessary effort to do so. This 'cost' part of transitioning to a new model depends, of course, on how far the new model departs from the base. Hence, it depends on the model currently used for policy assessments. Considering the national transport models as an important category of models, the main types are the four- (or sometimes five-) step models, tour-based models (including the Dutch national transport model), and activity-based models. Clearly, the time-use model of this thesis is a small departure from an activity-based model, whereas it is, in fact, incompatible with (or would require major adjustments to be reconciled with) the other models. The departure time choice model seems to be compatible with all three national model schemes, and it was implemented in a regional four/five-step model by Hooft (2020). Furthermore, the effort to use any model includes the need to periodically collect data and re-estimate its parameters. Again, the daily time-use model weighs heavier here, since it requires an entire daily activity diaries, as well as a wish-list of activities that the individual would want to perform. Finally, intangible cost components are the simplicity of the models and the continuity in the modelling practice. There is a case for simple models in policy applications – they can be easily understood, explained, and presented. Similarly, preserving the continuity in modelling practice means that it is not necessary to communicate and justify the model change to all involved parties. These intangible costs are higher with models that depart more from the base. Hence, a model that has a smaller degree of innovation compared to the base model is probably preferred from the costs' perspective.

External criteria

Besides the considerations of policy-relevance, gains in soundness and accuracy, and effort, there may be external criteria that support or oppose certain models due to their contents or implementation procedure. Two such criteria come to mind when considering the models proposed in this thesis. First, more complex models often use a large amount of individual-specific information. For a daily time-use model, it would be a complete daily schedule, as well as a list of unfulfilled activity wishes by each individual. As the society (rightly) becomes more mindful of protecting individuals' privacy (consider, for example, the relatively recent GDPR regulations), it may become unacceptable that such amount of personal information is collected and used for policy purposes. Second, the detachment between and new couplings of activities and locations (such as on board a vehicle) is a current development not only due to AVs. The ICT has long served to detach activities, such as work and leisure, from their traditional locations (e.g., Vilhelmson & Thulin, 2001; Mokhtarian et al., 2006). Furthermore, writing this recommendation at the start of 2021, it seems impossible to talk about the future of travel behaviour and mobility, while disregarding the effects of the COVID-19 pandemic. Some newest surveys indicate that the remote participation in work and shopping activities (from home) will have a lasting impact – people expect to continue with some activities remotely even after the pandemic (de Haas et al., 2020; Shamshiripour et al., 2020). This suggests that travellers may be more flexible with their daily activities not only due to opportunities offered by AVs, but also due to the experiences gathered in the present time. These concurrent trends support the need for updating models to reflect this multifunctional use of locations in more depth and detail. The models developed in this thesis could be viewed as examples of such more comprehensive model building.

Conclusion

Summing up the preceding discussion, there are arguments in favour of implementing more theoretically sound models as well as waiting with or even avoiding complex updates altogether. If the resources allow it, then perhaps even different versions of large scale transport models could be developed – just like the Dutch national transport model has a regret-based twin (van Cranenburgh & Chorus, 2018). Whatever the decision, it is the view of the author that the development of sounder travel behaviour models for the AV era is important for policy for at least two reasons. First, even if the data reliability or other considerations do not (yet) justify their large-scale implementation, theoretically grounded models can be valuable for furthering the policy discussion or be used in qualitative scenario building (a recommended approach in transport futures research – e.g., Marchau et al., 2013). Applied for such purposes, the models can use smaller samples and regional settings or even (well-reasoned) synthetic data and theoretical settings to communicate an expected effect about the future, which is uncertain also in many other ways. Second, even within such a clearly applied field as transport and travel behaviour, there is need for basic research. Due to multiple trends, including automation, but also ICT developments, sharing economy, and the most recent pandemic, people's perceptions, planning styles, and roles of travel in their everyday lives are changing (Mokhtarian, 2018). Travel behaviour models need to adapt to these trends in order to stay truthful to such fast-evolving reality and, through that, relevant for future policy applications.

7.8 Policy implications: substantive

When it comes to substantive policy questions and concerns of AVs, the following narrative often occupies a central space in the public discussion:

> *'Automated vehicles will reduce the value of travel time, thanks to the travellers' ability to use travel time more productively. This will greatly increase personal travel, vehicle kilometres travelled, traffic congestion, and urban sprawl. Hence, although automated vehicles promise some advances in safety and accessibility, they can greatly compromise the environmental goals.'*

What I would like to do here, is to discuss, while drawing on the results of this thesis as well as literature, these four 'common concerns' of AVs: increased personal travel, vehicle kilometres travelled, traffic congestion, and urban sprawl. What will be seen, is that the behavioural and transport systems' mechanisms that are behind these four expectations are different. Hence, the introduction of AVs may cause some of the effects and not others, or at least – their magnitudes may differ greatly. After this discussion, I would like to end this thesis with a brief discussion of some 'uncommon concerns'. This is to emphasise that – while many of the classical models and discussion themes apply to the AVs, there are also plenty of other possibilities for indirect and, at first, surprising ways how AVs may impact our transport systems.

Increased personal travel

The expectation of increased personal travel (e.g., choosing to participate in activities further away or to make trips more often) demand rests mainly on the following assumed effects of AVs: first, AVs will better facilitate on-board activities and therefore make travel more pleasant, and second, AVs will increase the network capacity. Starting with the first, this thesis has shown, that this expectation is strongly linked with the use of the travel time penalty (TTP) in simulation studies. However, intuition and data suggest that this modelling tool may not be adequate for behaviour prediction in the AV era (especially not for daily travel): on-board activities may result in various re-arrangements in schedules that do not necessarily involve more travel. This is not to say that on-board activities will lead to less travel demand in the population, or no changes in it, but rather that there is much more uncertainty and context-dependency surrounding their impact on total travel demand. This uncertainty is reflected also in the recent review of Harb et al. (2021): considering 25 studies that simulated vehicle-kilometres travelled with AVs, the observed increase ranges from 1% to 90% (most of the studies used the TTP approach).

The second assumed effect of AVs – increasing network capacity – may occur for several reasons. The reason that is mentioned most often is the ability of AVs to drive closer to each other due to shorter reaction times compared to human driving. However, this benefit may be reserved for complete or very high penetration scenarios. A sooner impact – occurring even in moderate AV penetration scenarios – could be thanks to AVs' ability to relieve the shockwave formation and propagation (Talebpour & Mahmassani, 2016). This would lessen congestion and travel times, as well as make travel times more reliable – factors that would likely create some rebound effect: encourage the travellers to accept further travel distances or to get on the road more often.

Overall, this reflection suggests that a moderate increase in travel demand can be expected with AVs due to its' physical properties (i.e., reaction time), while the behavioural effect is more uncertain than currently thought. More research is clearly needed on the impacts of AVs on the daily personal travel amount (due to changes in activity-travel patterns). If, what seems more likely according to author's opinion, the travel demand increase is currently overestimated, this can cause unnecessary delay with the introduction of AVs, and any positive impacts that they may bring (e.g., for safety, accessibility, well-being).

Increased vehicle kilometres travelled

The expectation of more vehicle kilometres with AVs rests mainly on the following assumed effects of AVs: increased personal travel and modal shifts. The preceding discussion arrived at a conclusion that the first effect, increased personal travel, is more uncertain and possibly more modest than currently thought. The second effect – modal shifts – is an interesting one to discuss. A conventional idea has been that modal shifts towards private AVs are worse than shifts towards shared or pooled AV services: reduction in car ownership should discourage car use, and travelling together should generate less kilometres than travelling alone. Therefore, a common policy recommendation has been to discourage private use of AVs, and instead support AV use in fleets – car-sharing and/or ride-sharing. However, such a policy can come with its own challenges, as explained next.

First, it is not clear that car-sharing without ride-sharing would reduce the vehicle kilometres travelled. On the one hand, users of shared services, who do not have an AV parked in garage at all times, may habitually consider a broader set of travel modes than owners. On the other hand, vehicle travel might even increase as compared to the privately-owned AV scenario, because AVs would probably (depending on the regulations) relocate to their consumers while being empty. For the present car sharing companies that rebalance their fleets with employed drivers, the rebalancing / relocating would become cheaper due to savings in wages. For the sharing companies that do not rebalance their fleets and offer primarily round-trip rental, they would be able to tap into new demand. Second, supporting car-sharing and/or ride-sharing might actually be counterproductive to decreasing the vehicle kilometres. By bringing down the costs of these travel modes (and they are already cheaper than privately-owned AVs due to being shared), they would more strongly compete with public transport for ridership (Bösch et al., 2018). In addition, various forms of sharing may be more attractive to current public transport users also for other reasons. The epilogue of this thesis compares (using a diagram) current modes and future AV configurations with respect to a range of commonly-used attributes: travel time, presence of access trip and transfers, cost, privacy, ability to use travel time productively, storage and personalisation possibilities, etc. It becomes clear that the current and future modes can be 'matched' based on their similarity, resulting in the following pairs: private car and private AV, rented car / taxi and shared AV, public transport and pooled AV. If pooled AVs are also subsidised or otherwise supported by the government, then the similarity with public transport becomes even greater (also with respect to 'soft attributes', such as image). Hence, it should be no surprise, if the pooled AVs draw their customers from higher capacity public transport, resulting in more vehicle kilometres travelled. Tirachini et al. (2020) provide supporting empirical evidence to this argument by surveying current ride-sharing service users about their alternative travel options (which they would chose if the ride-sharing platform was not available). They conclude that most ride-sharing modes have increased vehicle kilometres travelled.

The above discussion has considered shared and pooled AVs as an additional mode in the transport system. To complete the picture, however, it is important to mention an alternative policy approach where pooled AVs replace public transport. Fielbaum (2019) and Tirachini and Antoniou (2020) demonstrate analytically that, transitioning to automated driving, public transport *should* transition to smaller and more frequent services (i.e., pooled AVs), in order to save costs and increase service quality (this would also allow to reduce the subsidies to public transport). Quite intuitively, if drivers' costs are eliminated, then more and smaller vehicles become financially viable. With more vehicles, the headway is reduced and the service level improves, which in turn attracts even more travellers to the service, initiating a 'virtuous cycle'. Reducing the vehicle kilometres is, however, not the objective in these models. Hence, it seems that the optimal AV system design depends on the trade-off among policy goals – service quality and system costs versus its environmental impacts. Clearly, the environmental impacts of the increasing vehicle kilometres travelled would be much reduced, if the AVs are electric. However, extensive use of electric AVs would still have liveability and safety externalities.

Increased congestion

The expectation of increased congestion rests, once again, on two assumed effects of AVs: increased vehicle kilometres travelled and shifts in departure times toward the peaks. The previous paragraphs discussed the possibility of increased vehicle kilometres travelled. Overall, it seems that the vehicle kilometres will be increased in the future with AVs, but the amount depends on the policy choices regarding public transport and shared services. However, congestion is determined not only by the amount of cars, but strongly – also by their distribution in time, or, in other words, the departure time choices of travellers. The contribution of this thesis in modelling the latter was discussed before. Overall, it can be concluded that the long-standing policies of congestion charging and flexible working hours will continue to be important in the AV era. A potential new policy tool, which should be further investigated, is the distribution of various AV types (e.g., such that support primarily home or work activities, and therefore incentivise different departure times in commute peaks).

Increased urban sprawl

The expectation of further urban sprawl in the cities is similar to the expectation of more personal travel, since relocating further would involve more travel. But, in other ways, the relocation choice is also very different: unlike adjusting daily travel choices, changing a residence involves a large transaction cost. Hence, it is no surprise that roughly 80% respondents in several surveys (Harb et al., 2021) indicated that they would not change home location 'for a car'. In addition, several other studies suggest that residences closer to the city centres may become more attractive thanks to the availability of AV fleets (e.g., Gelauff et al., 2019). At the same time, the availability will be less attractive, if AV fleets overcrowd the streets – which may happen if they decide to wait for the next customer while slowly cruising around (Millard-Ball, 2019). Overall, it seems likely that residential neighbourhoods and land-use will change, but the direction of change is unclear.

Uncommon concerns

While AVs will certainly impact the classical transport indicators (such as person- and vehicle-kilometres travelled, congestion severity), it is important to remember that, in its nature, AVs are not simply better cars, but a radical innovation, which in its societal impact has often been compared to the invention of the car itself. Few questions can illustrate some less expected concerns.

- Will workday congestion be overshadowed by an acute influx of AVs to popular tourist destinations during holidays (e.g., Dannemiller et al., 2020)?
- Will excessive vehicle sizes and weights of 'mobile homes' become the main environmental and liveability concern of AVs (Harb et al., 2021)?
- Will corporately-owned AVs (subtly) optimise their routes to pass by sponsored billboards (Ferdman, 2020)?
- Will the night-time highways turn from being occupied mostly by heavy-goods vehicles on long-haul journeys to being flooded by slow-moving pods with sleeping occupants? What will this mean for night-time road repairs and roadside motel industry (Cohen & Hopkins, 2019)?

The AV revolution may well make us reconsider what falls under the category of 'common concerns' and what – under 'concerns of the past'.

References

Aboutaleb, Y. M., Danaf, M., Xie, Y., & Ben-Akiva, M. (2021). Discrete Choice Analysis with Machine Learning Capabilities. arXiv preprint arXiv:2101.10261.

Arnott, R., De Palma, A., & Lindsey, R. (1990). Economics of a bottleneck. Journal of urban economics, 27(1), 111-130. https://doi.org/10.1016/0094-1190(90)90028-l

Becker, Gary S., 1965. A theory of the allocation of time. Econ. J. 75 (299), 493–517. http://dx.doi.org/10.2307/2228949.

Bösch, P. M., Becker, F., Becker, H., & Axhausen, K. W. (2018). Cost-based analysis of autonomous mobility services. Transport Policy, 64, 76-91. https://doi.org/10.1016/j.tranpol.2017.09.005

Chorus, Caspar (2020). Essay over de rol in modellen van attitudes, differentiatie en heterogeniteit in mobiliteitsmodellen en -beleid. Essay written for Rijkswaterstaat.

Cohen, S. A., & Hopkins, D. (2019). Autonomous vehicles and the future of urban tourism. Annals of Tourism Research, 74, 33-42. https://doi.org/10.1016/j.annals.2018.10.009

Correia, Gonçalo, Looff, Erwin, van Cranenburgh, Sander, Snelder, Maaike, van Arem, Bart, 2019. On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: theoretical insights and results from a stated preference survey. Transp. Res. Part A: Policy Pract. 119, 359–382. https://doi.org/10.1016/j.tra.2018.11.016.

Cotte, J., Ratneshwar, S., & Mick, D. G. (2004). The times of their lives: Phenomenological and metaphorical characteristics of consumer timestyles. Journal of consumer research, 31(2), 333-345. https://doi.org/10.1086/422112

Dannemiller, K. A., Mondal, A., Asmussen, K. E., & Bhat, C. R. (2020) Investigating Autonomous Vehicle Impacts on Individual Activity-Travel Behavior. Technical paper, Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin.

de Haas, M., Faber, R., & Hamersma, M. (2020). How COVID-19 and the Dutch 'intelligent lockdown'change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. Transportation Research Interdisciplinary Perspectives, 6, 100150. https://doi.org/10.1016/j.trip.2020.100150

Dellaert, B.G., Swait, J., Adamowicz, W.L.V., Arentze, T.A., Bruch, E.E., Cherchi, E., Chorus, C., Donkers, B., Feinberg, F.M. and Marley, A.A., 2018. Individuals' decisions in the presence of multiple goals. Customer Needs and Solutions, 5(1), pp.51-64. https://doi.org/10.1007/s40547-017-0071-1

DeSerpa, Allan, 1971. A theory of the economics of time. Econ. J. 81 (324), 828–846. http://dx.doi.org/10.2307/2230320.

Evans, Alan W., 1972. On the theory of the valuation and allocation of time. Scottish J. Polit. Econ. 19 (1), 1–17. http://dx.doi.org/10.1111/j.1467-9485.1972.tb00504.x.

Ferdman, A. (2020). Corporate ownership of automated vehicles: discussing potential negative externalities. Transport Reviews, 40(1), 95-113. https://doi.org/10.1080/01441647.2019.1687606

Fielbaum, A. (2019). Strategic public transport design using autonomous vehicles and other new technologies. International Journal of Intelligent Transportation Systems Research, 1-9. https://doi.org/10.1007/s13177-019-00190-5

Fowkes, T. (1996). Issues in evaluation: A justification for awarding all time savings and losses, both small and large, equal unit value in scheme evaluation. In Proceedings of the Value of Time seminar, held 29-30 October 1996. Session 8.

Fox, J., & Hess, S. (2010). Review of evidence for temporal transferability of mode-destination models. Transportation Research Record, 2175(1), 74-83. https://doi.org/10.3141/2175-09

Gelauff, G., Ossokina, I., & Teulings, C. (2019). Spatial and welfare effects of automated driving: Will cities grow, decline or both?. Transportation research part A: policy and practice, 121, 277-294. https://doi.org/10.1016/j.tra.2019.01.013

Gripsrud, M., & Hjorthol, R. (2012). Working on the train: from 'dead time'to productive and vital time. Transportation, 39(5), 941-956. https://doi.org/10.1007/s11116-012-9396-7

Harb, M., Stathopoulos, A., Shiftan, Y., & Walker, J. L. (2021). What do we (Not) know about our future with automated vehicles?. Transportation Research Part C: Emerging Technologies, 123, 102948. https://doi.org/10.1016/j.trc.2020.102948

Harb, M., Xiao, Y., Circella, G., Mokhtarian, P. L., Walker, J. L. (2018). Projecting travelers into a world of self-driving vehicles: estimating travel behavior implications via a naturalistic experiment. Transportation, 1-15. https://doi.org/10.1007/s11116-018-9937-9

Hooft, F. (2020). Network effects of activity based departure time choice with automated vehicles: A case study in the'Haaglanden'region. MSc thesis. Delft University of Technology.

Hoogendoorn-Lanser, S., Schaap, N. T., & OldeKalter, M. J. (2015). The Netherlands Mobility Panel: An innovative design approach for web-based longitudinal travel data collection. Transportation Research Procedia, 11, 311-329. https://doi.org/10.1016/j.trpro.2015.12.027

Iskander, J., Attia, M., Saleh, K., Nahavandi, D., Abobakr, A., Mohamed, S., ... & Hossny, M. (2019). From car sickness to autonomous car sickness: A review. Transportation research part F: traffic psychology and behaviour, 62, 716-726. https://doi.org/10.1016/j.trf.2019.02.020

Jain, J., & Lyons, G. (2008). The gift of travel time. Journal of transport geography, 16(2), 81-89. https://doi.org/10.1016/j.jtrangeo.2007.05.001

Jara-Díaz, S. R. (2007). Allocation and valuation of travel-time savings. In Handbook of transport modelling. Emerald Group Publishing Limited. https://doi.org/10.1108/9780857245670-018

Kim, S. H., Mokhtarian, P. L., & Circella, G. (2020). How, and for whom, will activity patterns be modified by self-driving cars? Expectations from the state of Georgia. Transportation research part F: traffic psychology and behaviour, 70, 68-80. https://doi.org/10.1016/j.trf.2020.02.012

Lyons, G. (2019). The wicked problem of travel time use and the effects of ICTs. In Advances in Transport Policy and Planning (Vol. 3, pp. 145-170). Academic Press. https://doi.org/10.1016/bs.atpp.2019.04.001

Mackie, P. J., Jara-Díaz, S., & Fowkes, A. S. (2001). The value of travel time savings in evaluation. Transportation Research Part E: Logistics and Transportation Review, 37(2-3), 91-106. https://doi.org/10.1016/S1366-5545(00)00013-2

Marchau, V. A. W. J., Annema, J. A., Walker, W., & van der Waard, J. (2013). Transport futures research. The Transport System and Transport Policy: An Introduction, 305-328.

Millard-Ball, A. (2019). The autonomous vehicle parking problem. Transport Policy, 75, 99-108. https://doi.org/10.1016/j.tranpol.2019.01.003

Mokhtarian, P. L. (2018). The times they are a-changin': what do the expanding uses of travel time portend for policy, planning, and life?. Transportation Research Record, 2672(47), 1-11. https://doi.org/10.1177/0361198118798602

Mokhtarian, P. L., & Salomon, I. (2001). How derived is the demand for travel? Some conceptual and measurement considerations. Transportation research part A: Policy and practice, 35(8), 695-719. https://doi.org/10.1016/S0965-8564(00)00013-6

Mokhtarian, P. L., Salomon, I., & Handy, S. L. (2006). The impacts of ICT on leisure activities and travel: a conceptual exploration. Transportation, 33(3), 263-289. https://doi.org/10.1007/s11116-005-2305-6

Pawlak, J., Circella, G., Mahmassani, H., & Mokhtarian, P. (2020). Information and Communication Technologies (ICT), Activity Decisions, and Travel Choices: 20 years into the Second Millennium and where do we go next?. http://hdl.handle.net/10044/1/79466

Redmond, L. S., & Mokhtarian, P. L. (2001). The positive utility of the commute: modeling ideal commute time and relative desired commute amount. Transportation, 28(2), 179-205. https://doi.org/10.1023/A:1010366321778

Roeckle, F., Hahn, R., Stegmueller, S., & Herrmann, F. (2018). Features of future autonomous cars: beyond interior design. In Conference on Future Automotive Technology.

Shamshiripour, A., Rahimi, E., Shabanpour, R., & Mohammadian, A. K. (2020). How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago. Transportation Research Interdisciplinary Perspectives, 7, 100216. https://doi.org/10.1016/j.trip.2020.100216

Small, K. A. (1982). The scheduling of consumer activities: work trips. The American Economic Review, 72(3), 467-479.

Talebpour, A., & Mahmassani, H. S. (2016). Influence of connected and autonomous vehicles on traffic flow stability and throughput. Transportation Research Part C: Emerging Technologies, 71, 143-163. https://doi.org/10.1016/j.trc.2016.07.007

Tirachini, A., & Antoniou, C. (2020). The economics of automated public transport: Effects on operator cost, travel time, fare and subsidy. Economics of Transportation, 21, 100151. https://doi.org/10.1016/j.ecotra.2019.100151

Tirachini, A., Chaniotakis, E., Abouelela, M., & Antoniou, C. (2020). The sustainability of shared mobility: Can a platform for shared rides reduce motorized traffic in cities?. Transportation Research Part C: Emerging Technologies, 117, 102707. https://doi.org/10.1016/j.trc.2020.102707

van Cranenburgh, S., & Chorus, C. G. (2018). Does the decision rule matter for large-scale transport models?. Transportation Research Part A: Policy and Practice, 114, 338-353. https://doi.org/10.1016/j.tra.2018.01.035

van Cranenburgh, S., Wang, S., Vij, A., Pereira, F., & Walker, J. (2021). Choice modelling in the age of machine learning. arXiv preprint arXiv:2101.11948.

Vickrey, W. (1973). Pricing, metering, and efficiently using urban transportation facilities (No. 476).

Vilhelmson, B., & Thulin, E. (2001). Is regular work at fixed places fading away? The development of ICT-based and travel-based modes of work in Sweden. Environment and planning A, 33(6), 1015-1029. https://doi.org/10.1068/a33207

Wadud, Z., & Huda, F. Y. (2019). Fully automated vehicles: the use of travel time and its association with intention to use. In Proceedings of the Institution of Civil Engineers-Transport (pp. 1-15). Thomas Telford Ltd. https://doi.org/10.1680/jtran.18.00134

8 Epilogue: Potential health and well-being implications of autonomous vehicles

Singleton, P. A., De Vos, J., Heinen, E., & Pudāne, B. (2020). Potential health and well-being implications of autonomous vehicles. In Milakis, D., Thomopoulos, N., & van Wee, B. (Eds.), Policy implications of Autonomous Vehicles, 5 (pp. 163-190). Academic Press.

Abstract

Transportation's effects on health and well-being are widely recognized. In the near future, autonomous vehicles (AVs) are expected to revolutionize transportation options and ways of travel. Consequently, the effect of AVs on population health and well-being is a crucial topic of interest for transportation policymaking, one that has received comparatively little attention. This chapter discusses (and anticipates) potential AV impacts on health and well-being. First, we summarize knowledge surrounding effects of transportation on physical health (traffic safety, air and noise pollution, and physical activity) and well-being (travel satisfaction, access to activities, etc.). We then discuss how AVs may affect traveler behaviors, focusing on mode shifts towards private, shared, and/or pooled AVs, and how these shifts may lead to an overall increase in automobile travel, even if not necessarily in person-travel. Finally, we interpret the previous two sections to deduce potential positive, negative, and uncertain health/well-being effects of AVs. We expect benefits from improved safety, well-being, and access to opportunities; disadvantages from reduced physical activity; and uncertain impacts around land use changes and emissions. We conclude by discussing policy implications and research paths forward.

8.1 Introduction

The transportation sector is currently undergoing a rapid transformation, in large part due to new mobility options and services made possible by technological developments. The emergence of "micro-mobility" modes, transportation network companies, mobility-as-a-service, vehicle-to-vehicle/infrastructure communications, and other changes will likely disrupt how people get around, how communities plan for future transportation needs, and how policymakers deal with (positive and negative) impacts of a complex transportation system. Adding on to these, autonomous vehicles (AVs), or self-driving cars (and trucks), if and when they become wide-spread in the future, may generate huge shifts in mobility patterns and behaviors. Therefore, policymakers and scholars are already actively investigating the many policy implications of ubiquitous automated driving. Much research currently addresses the impacts of AVs on vehicle ownership and use, energy consumption, and location choices, yet the area of health and well-being has received comparatively less attention, according to a recent review (Milakis et al., 2017). A possible reason for this knowledge gap is the uncertainty regarding how AVs may affect travel behavior (Soteropoulos et al., 2019), including AV ownership and use models (private, shared, and/or pooled), which have important implications for health and well-being analyses. Nevertheless, research in the area of AVs and health is increasing, with recent publications by Richland et al. (2016), Crayton and Meier (2017), and Curl et al. (2018), and even two articles (Dean et al., 2019; Sohrabi et al., 2020) available since our work on this chapter commenced in mid-2019.

In this chapter, we discuss the potential implications of AVs for health (both physical and mental health) and well-being (happiness, satisfaction, and fulfillment). Given the relative lack of empirical evidence on this topic, we employ a deductive approach rather than a systematic review of the literature. First, we review the major pathways by which the transportation system affects multiple dimensions of health and well-being. Given the importance of travel choices in these pathways, we then summarize some of the most relevant ways in which AVs may change travel behaviors. Finally, we combine these insights to deduce potential positive, negative, and unknown effects of AVs on health/well-being, leading to a discussion of policy implications and a prospective research agenda (a similar deductive approach was also used by Curl et al. (2018) and Sohrabi et al. (2020)). Although we cannot offer definitive conclusions because the exact technology and future use of AVs is still unknown, we aim to initiate a broader conversation among planners and industry leaders about potential health and well-being impacts of AVs. This is a crucial conversation for the present time, because AV use is not yet ingrained in travelers' daily lives and policies can still play a major role in helping lead the automated driving transition towards healthier outcomes.

8.2 How transportation influences health and well-being

Transportation is linked to various health and well-being outcomes. In recent decades, this linkage has been increasingly recognized among academics and practitioners (De Vos, 2018b; Malekafzali, 2009; van Wee and Ettema, 2016), resulting in new interdisciplinary collaborations, journals (the *Journal of Transport & Health*), and conferences (e.g., the International Conference on Transport & Health). There are various ways to discuss the health and well-being impacts of transport, although it is beyond the scope of this chapter to discuss this in detail (see e.g. Giles-Corti et al. (2016) for a conceptualization). In this section, we first discuss relationships between transportation and physical health, followed by an overview of intersections with well-being. Our aim is not to conduct a systematic review, but rather to provide an overview of existing (systematic) reviews or, in the absence of such studies, key policy and empirical papers. We conclude by summarizing these impacts in a conceptual framework.

8.2.1 Physical health

The four main pathways through which travel affects physical health are the following: (i) traffic safety, (ii) air pollution, (iii) physical activity, and (iv) noise. This selection of impacts is based on the current list of the health risks of transportation acknowledged by the World Health Organization (WHO, 2019a), although we excluded climate change in our discussion. These impacts correspond with the main risk exposures listed by Giles-Corti et al (2016).

Traffic injuries and deaths

Poor traffic safety has long been recognized as a detriment to individual and public health. According to the WHO, road traffic crashes are one of the top ten causes of death worldwide and the leading cause of death for children and young adults (WHO, 2018a). Several developed countries have successfully reduced the number of deaths and relative deaths by inhabitants and distances-traveled (OECD, 2019). Nevertheless, the absolute number of deaths globally due to road traffic has continued to climb in recent years, reaching 1.35 million people in 2016; however, relative to the size of the world's population, it has stabilized. Between 2013 and 2016, there were no reductions in road traffic deaths in any low-income country (WHO, 2018a).

The distributions of traffic casualties and serious injuries, as well as the risk of serious injury or death from traffic, is unequally distributed and depends on location and travel mode. Controlling for the number of inhabitants, the risk is three times higher in developing countries compared to developed countries (27.5 versus 8.3 deaths per 100,000 population) (WHO, 2018a). In the EU, the majority of traffic fatalities occur on urban (38%) or rural roads (53%); few take place on motorways (9%) (Eurostat, 2017). Globally, pedestrian and cyclists constitute a quarter of all fatalities, motorized two-wheelers comprise another quarter, and car occupants 29% (WHO, 2018a). This distribution varies by location. Most deaths in Africa are of pedestrians and cyclists, whereas in south-east Asia, deaths occur primarily for motorized two-wheelers. In Europe and the US, car occupants constitute the highest number of deaths, but non-occupants are overrepresented among deaths and serious injuries (USDOT, 2019). Driver errors cause more than 90% of traffic collisions (USDOT, 2015).

Air pollution

In addition to contributing to climate change, the transportation sector is responsible for a large proportion of urban air pollution, including particulate matter, CO_2, and NO_x. In the EU, transportation contributes a quarter of direct greenhouse gas emissions and a fifth of CO_2 emissions (EEA, 2018a). Although many sectors have successfully reduced their emissions in recent decades, transportation emissions are stable in the UK and EU (DfT, 2018; EEA, 2018b). Transportation is thus not only a major contributor, but its relative contribution is growing. Road travel is estimated to be responsible for up to 30% of particulate emissions in European cities and up to 50% in OECD countries, mostly due to diesel traffic, though the exact amount varies widely between locations (WHO, 2019b). Moreover, air travel (a heavily polluting mode) continues to grow.

The WHO estimates that 4.2 million annual deaths result from exposure to ambient (outdoor) air pollution, and 91% of the global population lives in areas exceeding WHO exposure guidance levels. Health consequences of ambient air pollution include lung cancer, acute lower respiratory tract infection, stroke, ischemic heart disease, and chronic obstructive pulmonary disease (WHO, 2018b).

Differences exist in exposure to air pollution and the inhaled dose by mode of travel. Most studies report that car commuters have the highest cumulative exposure levels (Cepeda et al., 2017). However, due to the active nature of walking and cycling and resulting higher respiratory rates, active commuters have higher inhalation doses than do commuters using motorized modes.

Physical activity

The lack of physical activity is a major cause of morbidity and mortality (Lee et al., 2012). The WHO (2010) recommends spending at least 150 minutes of moderate-intensity aerobic activity—or at least 75 min of vigorous-intensity aerobic activity (or an equivalent combination)—a week. Annually, two million deaths can be attributed to a lack of physical activity. A lack of physical activity is a leading risk factor for obesity and cardiovascular disease, type 2 diabetes, and some types of cancer. Independent of the level of physical activity, sedentary behavior (total sitting and TV-viewing time) is associated with greater risks for several major chronic diseases (Patterson et al., 2018).

Levels of engagement in physical activity differ by location and socio-economic characteristics. Globally, 25% of adults are insufficiently active (WHO, 2018c). Women are more likely to be insufficiently active than men, and a higher gross domestic product is often associated with lower physical activity levels (WHO, 2018c).

The decrease in physical activity over time has coincided with an increase in motorization, including motorized transportation. Walking, cycling, and other forms of active travel provide a sufficient level of physical activity to improve health and well-being (Chief Medical Officers, 2011). For example, a cycling level corresponding to WHO recommendations results in a 10% reduction in the risk of all-cause mortality (Kelly et al., 2014). Walking and cycling levels sharply differ between locations, and the social and spatial context has a strong influence (Heinen et al., 2010).

Noise

Despite receiving less attention than the previous three topics, noise is increasingly acknowledged to have negative health impacts. Noise can affect the auditory system and result in hearing loss and tinnitus. Moreover, noise (especially following long-term exposure) has additional adverse health effects resulting from psychological and physiological distress, homeostasis disturbance, and increasing allostatic load (Basner et al., 2014, in WHO, 2018d). Exposure to noise can disturb sleep, cause cardiovascular and psychophysiological effects, reduce performance, and provoke annoyance responses and changes in social behavior (WHO, 2018d).

Road traffic is the largest contributor to noise pollution in urban areas and is the most important source of noise annoyance. Over 70 million Europeans are assumed to have a day–evening–night noise level greater than 55 dB as a result of road traffic noise (EEA, 2014, 2018c). In addition, noise from air transportation can be high in specific areas. Noise levels increase with higher traffic volumes and speeds, but urban design, road surfaces, and weather conditions influence noise levels as well.

8.2.2 Well-being

In recent decades, interest in linkages between travel and well-being has rapidly increased (De Vos et al., 2013; Mokhtarian, 2019). In this section, we consider three main effects of transportation on mental health and well-being: (i) travel satisfaction, (ii) access to activities, and (iii) spill-over effects on the activity at the destination.

Travel satisfaction

Travel satisfaction refers to the emotions people experience during trips and how they evaluate these trips (De Vos and Witlox, 2017). After the development of a reliable tool to measure travel satisfaction—the Satisfaction with Travel Scale (Ettema et al., 2011)—multiple studies (from different geographical contexts) have analyzed determinants of travel satisfaction. The chosen travel mode has an important influence on how people perceive their trips: specifically, active travel mostly results in the highest levels of travel satisfaction, while public transit (bus in particular) is perceived least positively (De Vos et al., 2016; Singleton, 2019b; Ye and Titheridge, 2017). Most studies also find a negative effect of trip duration on travel satisfaction (Higgins et al., 2018; Morris and Guerra, 2015), since long trips might be a mental and physical burden. Positive (or negative) attitudes towards the chosen travel mode positively (or negatively) impact satisfaction with the trip made (De Vos, 2018a; St-Louis et al., 2014), while traveling alone has a negative effect on satisfaction levels (De Vos, 2019; Zhu and Fan, 2018). The effects of the built environment and travel distance on travel satisfaction remain unclear so far (De Vos et al., 2016; Ye and Titheridge, 2017). Finally, satisfaction can be influenced by the activities people undertake while traveling. For public transit users, productive activities and talking to other passengers are found to positively affect satisfaction levels, while entertaining and relaxing activities seem to negatively influence travel satisfaction (Ettema et al., 2012; Lyons et al., 2007); perhaps they are done to cope with a burdensome trip. Since experiencing positive emotions can improve people's life satisfaction (by stimulating original thinking, fostering skills, liking of self and others, etc. (Lyubomirsky et al., 2005)), travel satisfaction can directly influence well-being and mental health.

Access to activities

Transportation also affects well-being by providing access to activities at different locations (accessibility additionally influences physical health through access to health care, healthy food, and recreational opportunities). Elements such as life satisfaction, personal growth, and realization of the best in oneself are significantly influenced by the participation in (and performance of) out-of-home activities enabled by travel (Ettema et al., 2010; Morris, 2015). Even the potential to travel ("motility")—having access to transportation options (e.g., living close to public transport, owning a car) and the knowledge and skills to use them (Kaufmann et al., 2004)—can generate feelings of freedom, competence, and belonging.

Not being able to reach rewarding out-of-home activities due to limited travel options can consequently affect quality of life in a negative way (Delbosc and Currie, 2011; Lucas, 2012). Especially low-income groups and individuals with limitations on physical or cognitive functioning (e.g., older adults) might suffer from transportation disadvantage and social isolation. Travel might also restrict the execution of certain rewarding activities, as time spent traveling cannot be used for other activities (disregarding activities during travel). For instance, Stutzer and Frey (2008) found that long commute trips resulted in low levels of subjective well-being, partly due to limited time for family activities. On the other hand, examining relationships between commute duration and life satisfaction is complicated (Clark et al., 2019; Morris and Zhou, 2018), since long commutes are often linked to (financially) rewarding jobs, owning a house, and being married, which positively impact life satisfaction.

Spill-over effects on the activity at the destination

Not only does transportation provide access to out-of-home activities, but the performance of (and satisfaction with) that activity can be influenced by perceptions of the preceding travel episode. In fact, travel satisfaction might mainly influence life satisfaction indirectly (De Vos, 2019), i.e., through satisfaction with destination activities. Morris and Zhou (2018) associated longer commute durations with lower positive emotions at work. Friman et al. (2017) found that satisfaction with the trip to work influenced the mood directly after the commute trip but not later in the day. Studies focusing on children found active travel to be associated with a positive mood after arriving at school or during the first school lesson (Stark et al., 2018; Westman et al., 2017). In addition to satisfaction with the destination activity, travel may also affect the performance of that activity. Stress experienced during the commute can negatively affect job performance (Legrain et al., 2015); while Loong et al. (2017) found that cyclists felt most energized at work, drivers were least energized. On the other hand, travel time can also be used to mentally prepare for the activity ahead, potentially improving the performance of that activity (Jain and Lyons, 2008).

8.2.3 Conceptual framework

So far, we have discussed health and well-being impacts as a consequence of transportation. However, in order to fully understand the impacts of changes in transportation supply—such as the introduction of AVs—it is crucial to recognize that such changes first influence individuals' travel choices (which are also partly affected by the acceptance levels of AVs; see, e.g., Becker and Axhausen (2017) for a review on acceptance of AVs), which subsequently affect health and well-being. Handy (2014) explains how choices of travel amount, travel mode, and other dimensions (e.g., time-of-day, driving speed and style, physical and mental condition) impact individual and population health. Figure 8-1 translates her discussion into a conceptual diagram and supplements it with well-being impacts. It also relates to other conceptualizations of health–transportation relationships (e.g., van Wee and Ettema, 2016).

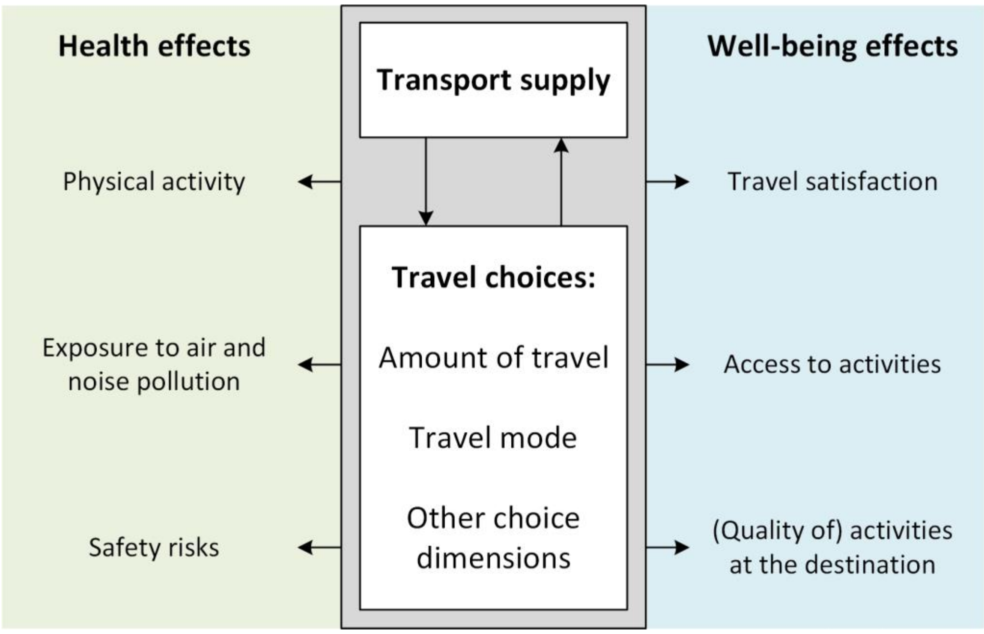


Figure 8-1 Conceptual framework of individual health and well-being impacts of travel choices.

Figure 8-1 demonstrates not only how the characteristics of the transportation supply (e.g., AVs) directly impact health and well-being, but also how supply interacts with demand – the various dimensions of travel choices. Therefore, these two should be examined jointly when studying AV effects on health and well-being. Although we focus on individual effects in the following sections, the population effects of AVs can be thought of as the sum of individual impacts and any higher-order influences due to aggregation (e.g., access to activities leads to land-use changes, which again influences the access to activities).

8.3 Expected effects of autonomous vehicles on travel behavior

The major anticipated benefits of AVs are that they would make “driving” safer and reduce negative emotions (e.g., stress) often linked with navigating a car through traffic. By reducing the burdens of driving and navigating, AVs could allow travelers to use travel time for other purposes: working, reading, entertainment, or rest (Pfleging et al., 2016; Singleton, 2019a). According to Figure 8-1, this change in transportation supply would influence travel choices, which would further affect individual and population health and well-being. In particular, the amount of individual travel together with travel mode choice (including the various proposed forms of AV-sharing) influences vehicle-distances traveled, which carries health and well-being impacts. These two travel behavior dimensions are discussed in the following sections.

8.3.1 Amount of individual travel

Literature suggests that the introduction of AVs will prompt people to travel longer distances for their daily activities (choosing further destinations and/or traveling more frequently); supporting results have been obtained from activity-based modeling studies (Auld et al., 2017; Childress et al., 2015). However, it is worth noting that these studies assume that improved travel experiences—commonly formalized as reduced values of travel time—will make people accept longer in-vehicle travel times. Although this may occur in aggregate, two individual-level considerations warrant discussion. First, new activities performed during travel could interact with other daily activities and lead to a variety of total travel time developments, including a possibility of reduced daily travel time (Mokhtarian, 2018; Pudāne et al., 2018).[45] Second, increased travel time means less time for other activities, possibly altering travelers' daily activity schedules. Changing daily routines to accommodate more travel is not easy or desired by all (Zmud et al., 2016). Alternatively, increased travel for holidays seems a more likely consequence of AVs, since that does not require systematic changes in daily activity schedules (LaMondia et al., 2016).

The other proposed source of increasing individual travel amounts comes from longer-term changes to home and/or work locations, resulting (as before) from the reductions in travel disutility. This would lead to an unwelcome effect of urban sprawl (Heinrichs, 2016; Zakharenko, 2016). However, the implications of accepting longer commute durations (and possible counter-arguments for doing so) should also be considered carefully, e.g., in the context of travelers' daily activity schedules. Furthermore, if value of time is used as the main predictor of travel behavior changes, then it should preferably be obtained from stated choice studies using a trip-making or residential location (as opposed to mode-choice) context. Adopting the latter, Krueger et al. (2019) did not observe significant changes in the value of travel time.

8.3.2 Travel mode choice

That AVs could lead to a higher mode share for (private) cars is just as widely expected as the potentially increasing travel distances (e.g., Soteropoulos et al., 2019). To reduce the negative effects of such modal shifts, shared and pooled AVs are often suggested as more sustainable future modes. Therefore, the question of shared-AV acceptance and success has been among the top priorities in AV-research in the last few years (Haboucha et al., 2017; Krueger et al., 2016; Lavieri and Bhat, 2019; Nazari et al., 2018; Stoiber et al., 2019). Although most studies

[45] An example in Pudāne et al. (2018) shows how a traveler, who is able to rest in an AV, may eliminate a detour to home after work and go straight to an evening activity, thereby reducing the total travel time. Such activity rearrangement is fully rational and in line with microeconomic theory, given a certain activity wish list. Although such instances may occur less often than activity rearrangements that result in more travel, the possibility of less individual travel cannot be excluded *a priori*.

find increased acceptance of car-sharing as compared to the low present levels (Conway et al., 2018), the travelers most interested in shared AV systems are current public transit, car-sharing, or active mode users, not private car users (Haboucha et al., 2017; Krueger et al., 2016; Nazari et al., 2018). Relatedly, shared/pooled-AV acceptance is high in places where travelers are accustomed to attractive public transit options (Stoiber et al., 2019). Finally, and even among current non-automated modes, car-sharing has been shown to be a weak substitute to private car travel and tends to replace public transit and bicycle modes instead (Carrone et al., 2019; Gehrke et al., 2018).

These empirical studies support an intuitive idea that travelers prefer the mode most similar to their current choice: the travel option that is the best substitute for their current ways of travel (van Wee et al., 2019). We represent this concept in Figure 8-2, which shows characteristics of current and future AV modes and expected modal shifts. Even though this comparison does not include all relevant travel characteristics and is qualitative—the exact values and relative importance of attributes could magnify or reduce the impact of various characteristics—it provides a framework to discuss potential modal shifts in an AV future. Overall, we expect modal shifts towards private, shared, and pooled AV modes. However, changes to distances traveled are determined not only by the relative preferences for new AV modes, but also by the shifts away from current modes.

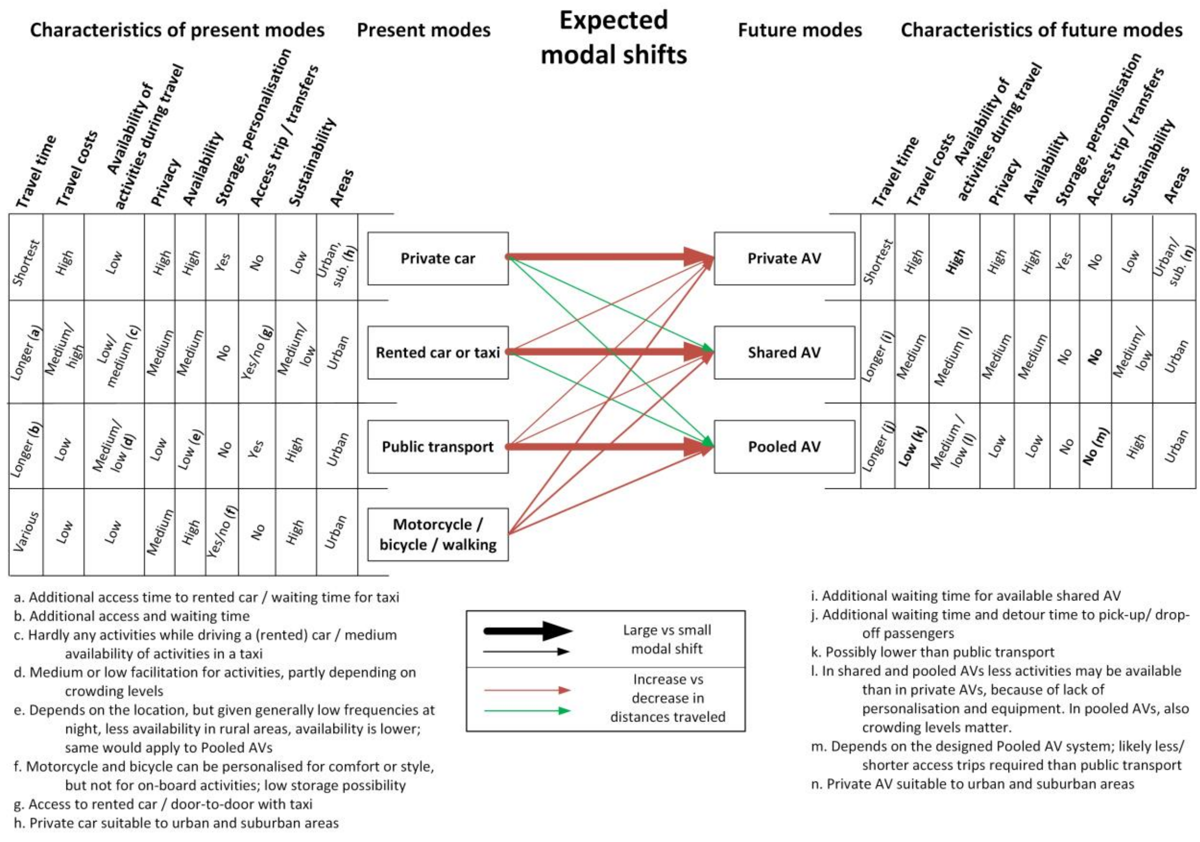


Figure 8-2 Comparison of present and future transportation modes and expected modal shifts.

Although, at first glance, shared or pooled AVs could seem to be a close substitute to private cars, Figure 8-2 shows that, with respect to many attributes, they resemble—and hence could substitute—current car-sharing, taxis, and, most importantly, public transit.[46] Furthermore, it can be argued that the new AV modes improve upon their current mode "counterparts" (highlighted bold on the right side of Figure 8-2). For today's private car users, private AVs offer much greater possibility to engage in new non-driving activities during travel. Shared AVs would provide present rental car and car-sharing users a comparable level of multitasking facilities, plus reduced access times and improved door-to-door and one-way services (Krueger et al., 2016). For public transit riders, pooled AVs would likely pick up and drop off closer to the destination and might even be cheaper than public transit thanks to the savings of driver costs (Bösch et al., 2018), especially outside of dense urban areas.[47] These benefits will likely motivate the users of the current modes to shift to the most similar automated modes. Results of Pakusch et al. (2018) empirically support these trends, although they also argue that the current modes will most likely remain popular in the near future.

The preceding discussion on the shifts from current modes to their AV "counterparts" is crucial, because we expect that this shift would result in increased vehicle use and distances traveled (the thick red arrows in Figure 8-2), due to three potential reasons. First, if travelers experience the new mode as superior to the present mode, they (in aggregate) might use it more—for longer and/or more frequent travel (however, see the previous section on "Amount of individual travel" for points of caution). Ferdman (2019) even warns that corporations, who may own the future shared or pooled AV fleets, will have an interest in prolonging trips to maximize exposure to in-vehicle advertising. Second, the nature of shared/pooled AVs is such that greater vehicle-distances will be traveled to satisfy the same number of person-trips, compared to the most similar non-automated mode. Shared AVs would travel further distances to provide door-to-door travel, instead of requiring drivers to pick-up and drop-off vehicles at designated locations. The same is true for pooled AVs, which would (additionally) generate greater travel distances than public transit because they have a lower capacity/occupancy. Third, all automated modes might involve empty travel: to access the next customer for a shared AV or to share a private vehicle among household members; to perform pick-up or drop-off tasks independently (reducing some trip chaining behavior); or to access cheaper parking.

To summarize, this section has argued that AVs may change travel choices in a way that would lead to more automobile travel, even if not necessarily to more person-travel. In particular, this increase could be most strongly determined by modal shifts away from current modes to their more attractive (but also more travel-distance-intensive) AV counterparts.

8.4 Potential effects of autonomous vehicles on health and well-being

We now turn our attention to outlining potential effects that AVs could have on health and well-being. It should be noted that these impacts are speculative, deduced in part from our discussions in earlier sections—about the more general health/well-being impacts of the current transportation system and how/why AVs might affect traveler behaviors within that system. Rather than conducting a systematic review ourselves, we also rely in part upon summaries of the literature identified in a recent scoping review (Dean et al., 2019). Recent work by Richland

---

[46] There may be exceptions to this correspondence, as shown by the thin arrows in Figure 8-2. For example, public transit passengers who currently like the ability to be productive while traveling may be attracted to the activity facilitation made possible by shared or even private AVs. In the opposite direction, current car drivers who choose to own because they value or require door-to-door service and departure time flexibility may find some value in shared or even pooled AVs, if the lower costs and multitaskability outweigh the loss of privacy and personalization.

[47] Some have noted that AVs might even attract a portion of active mode users (cyclists and pedestrians) because of the much greater convenience to use AVs for short trips (e.g., it would not be necessary to look for a parking spot); however, Figure 8-2 hypothesizes that this shift would not be great due to dissimilarity of active modes and AVs in other aspects.

et al. (2016), Crayton and Meier (2017), Curl et al. (2018), and Sohrabi et al. (2020) is also particularly informative.

We organize this section around the central transportation – health/well-being linkages we identified earlier: safety, travel satisfaction, access to activities, physical activity, air pollution and noise. Within each topic, we discuss the variety of possible benefits and adverse effects of AVs that we and others have considered. Despite the potential varied effects, based on our exploration we suggest that AVs are likely to have overall positive impacts on some health and well-being aspects (safety, travel satisfaction, access to activities) and overall negative impacts on others (physical activity), while effects are more uncertain for other topics (urban built environments, air and noise pollution).

8.4.1 Overall positive effects

Improved safety

The most consistently cited health benefit of AVs is the reduction of injuries and deaths from traffic collisions (Dean et al., 2019; Pettigrew et al., 2018). AVs will be (ostensibly) safer than current vehicles because they will be driven by computers rather than people, thus removing the human element—the cause of the majority of traffic crashes (USDOT, 2015). The computer vision systems of fully-automated vehicles are expected to improve collision avoidance, lane keeping, and other driving tasks, while connected vehicles/infrastructure will allow for sharing vehicle trajectories and improving safety in high-crash-risk situations (e.g., queues, intersections) (Milakis et al., 2017). Crashes could be reduced by 40% or more (Fagnant & Kockelman, 2015).

Nevertheless, such safety benefits may be modest until AV penetration rates are high and AVs can operate without any human intervention; also, aggregate safety gains would be reduced if AVs lead to more car travel. Safety could actually decrease for AVs in which humans are required to monitor and take over driving under certain conditions (Strand et al., 2014). Recent fatalities involving such vehicles highlight these and other questions regarding the safety performance of AVs in challenging (low light, poor weather) conditions and in complex or unique traffic situations. Cyberattacks may also be a threat (Petit and Shladover, 2014). Finally, there are ethical and legal issues remaining to be resolved over how AVs should act in situations where a collision is unavoidable (Bonnefon et al., 2016): Does the computer prioritize protecting the vehicle occupants over non-occupants (including vulnerable road users)? The way in which this issue is resolved could exacerbate existing inequalities in safety between motorized and non-motorized users. Nevertheless, we expect overall positive health benefits from improved safety.

Improved travel satisfaction and spill-over effects

AVs will likely improve travel experiences of "driving" that affect mental health and well-being. By removing the need to operate a vehicle when traveling alone, AVs may reduce many of the stresses associated with navigating urban traffic and congestion (Curl et al., 2018; Crayton & Meier, 2017; Dean et al., 2019; Richland et al., 2016), thus improving mental well-being and physical health. By providing opportunities to do other, more productive/rewarding things while traveling by car, AVs may also improve enjoyment and happiness with travel (and satisfaction with the destination activity). Although these well-being effects may be substantial, they should not be overestimated (Singleton, 2019a).

There could also be some negative impacts to well-being as a result of AVs. Some studies find that the increased possibility to use travel time productively creates psychological pressure to do so and may actually decrease travel satisfaction and well-being (Shaw et al., 2019; Pudāne et al., 2019). Furthermore, sharing and especially pooling AVs reduces one of its core benefits: the improved travel experience and the multitasking possibility during travel. This is also reflected in stated choice studies that find the value of travel time to be lower for shared (exclusive use) AVs than pooled AVs (e.g., Krueger et al., 2016). Finally, some people enjoy the act of driving and gain status from owning a specific vehicle; these intrinsic experiences related to driving might be diminished when (especially shared) AVs dominate (Curl et al., 2018).

Greater access to activities

We and others expect that AVs will likely improve access to activity opportunities, for a couple of reasons. First, distant activities—which may have been too time-consuming to reach with conventional cars—might become accessible if people do not "lose" time and can perform certain activities (e.g., working, studying, etc.) during AV travel (Meyer et al., 2017). More generally, formerly outside-the-trip activities can be brought into the trip, thereby freeing time for new or expanded out-of-trip activities (Mokhtarian, 2018; Pudāne et al., 2018). Even if travelers do not (frequently) make use of the enhanced accessibility, there is an "option-value" from having greater activity opportunities (Laird et al., 2009).

Second, AVs can increase accessibility for people with mobility limitations (Curl et al., 2018; Dean et al., 2019; Pettigrew, 2017; Richland et al., 2016). A large minority of the population cannot (easily) transport themselves to/from daily activities: young children, older adults, and people with certain physical and intellectual disabilities (Bennett et al., 2019; Pettigrew et al., 2018). By eliminating the need to rely on others for travel, AVs will likely improve access to health care, grocery stores, jobs, education, etc. for these people. These user groups are expected to be among the main drivers of increased AV travel demand (Harper et al., 2016). Improved mobility may also help people living in rural areas to access hospitals and other services. Additionally, by facilitating independent mobility and access to opportunities, including social activities and connections with family and friends, AVs may indirectly reduce social isolation, increase social inclusion/connectivity, and improve mental health and quality of life (Curl et al., 2018; Pettigrew, 2017; Richland et al., 2016).

At the same time, AVs have the potential to widen existing disparities in transportation access, depending on how they are implemented and managed and how much they cost to use. Private AV ownership models may exacerbate inequalities by increasing financial barriers to accessing driver-less mobility, especially for low-income and aging populations (Curl et al., 2018; Dean et al., 2019; Pettigrew et al., 2019). Historically-disadvantaged communities (including low income, people of color, and immigrant communities) already face financial, technological, and social barriers to accessing electric and shared mobility, issues unlikely to be addressed simply through the addition of AVs (Cohen & Shirazi, 2017). Finally, there are concerns that increasing suburban sprawl and mode shifts towards AVs may reduce funding and political support for public transportation, thus exacerbating access for transit-dependent populations (Cohen & Shirazi, 2017; Fleetwood, 2017).

8.4.2 Overall negative effects

Reduced transport-related physical activity

Due to some of the positive well-being effects anticipated (see above) and other improvements to the existing suite of transportation options (see Figure 8-2), we and others expect AVs to reduce transport-related physical activity by taking some mode share away from walking, bicycling, public transit, and other forms of active transportation (Crayton & Meier, 2017; Curl et al., 2018; Milakis et al., 2017; Sohrabi et al., 2020; Soteropoulos et al., 2019). Such modal shifts away from these active modes pose a high health risk, because—as Handy (2014) notes—trips with active modes are more beneficial if they replace sedentary passive travel in a car (as opposed to being newly-generated leisure trips). Similarly, replacement of active mode trips with less active AV travel is likely more harmful for the individual (per distance traveled) than current car trips becoming longer or more frequent in AVs. Less physically active transportation and more sitting (in AVs) is likely to increase risks of obesity and non-communicable diseases (Crayton & Meier, 2017).

Although the exact impacts are difficult to predict, AVs may offer some pathways to increase overall physical activity. Being productive in AVs may free up time for other physically-active non-travel activities, or compensating behavior may increase leisure-time physical activity, and it is possible (though not highly likely) that AVs could be equipped with exercise machines (Crayton & Meier, 2017; Curl et al., 2018). Road capacity might increase with connected AVs, and some suggest that this (plus a reduction in demand for on-street parking) might open up road space for non-motorized infrastructure (Milakis et al., 2017; Soteropoulos et al., 2019). Yet, these opportunities seem unlikely to outweigh negatives from mode shifts. Overall, we expect physical activity obtained through personal transportation to decrease.

8.4.3 Uncertain effects

Changes to urban built environments

Two main perspectives have been articulated regarding how AVs might change built environments. The "hopeful view" for health (Richland et al., 2016) is that AVs will lead to denser urban developments and reallocation of road space (Crayton & Meier, 2017; Curl et al., 2018; Dean et al., 2018; Milakis et al., 2017). In dense urban areas, land is valuable and in high demand. According to Fraedrich et al. (2019), widespread AV adoption is expected to reduce the need for parking in dense urban centers as AVs, after dropping off passengers, can drive themselves to a remote (cheaper) location to wait for their next trip (shared and pooled AVs might furthermore reduce the total number of vehicles, thus also reducing parking demands). As previously mentioned, road space may be able to be reallocated towards transit and/or walk/bicycle infrastructure. Altogether, this may open up land for more development as well as public space, which has the opportunity to make for more attractive, walkable urban environments, thus facilitating greater physical activity. Also, people interested in using AVs might be inclined to move to cities if AVs are introduced there first.

The pessimistic view is that AVs will increase urban sprawl and lead to more land dedicated to transportation and parking (Crayton & Meier, 2017; Curl et al., 2018; Richland et al., 2016). This view presumes that the reduced disutility of travel would lead to a willingness to live further from work and therefore increased levels of urban sprawl and automobile dependence (Mokhtarian, 2018; Soteropoulos et al., 2019). However, this link is complex (see discussion in the section "Expected effects of autonomous vehicles on travel behavior"), and a recent study shows that travel disutility is not reduced in the context of residential location (Krueger et al., 2019). Nevertheless, even if AVs do not lead to increased person-travel (and thereby urban sprawl), the increases in vehicle-travel (see the section "Travel mode choice") could further strain crowded and congested urban street networks, forcing more traffic onto local streets and making them less conducive for walking and cycling. At the same time, other parts of urban/suburban locations (especially those in close proximity to urban centers) may experience an influx of parked or circling (empty) AVs (Ostermeijer et al., 2019). Land area dedicated to cars would increase, thus deteriorating walkable environments, discouraging physical activity, and further exacerbating geospatial inequities in healthy travel behaviors.

Because these land use and built environment changes are likely to occur over a long period of time, we are uncertain about whether they will be positive or negative, overall.

Air pollution and noise

Overall impacts of AVs on air pollution and noise are similarly uncertain (Crayton & Meier, 2017; Dean et al., 2019; Sohrabi et al., 2020). There are likely to be benefits since many experts expect AVs to be battery-electric powered (Pettigrew, 2017). Even without electrification, more smooth driving operations, improved navigation, and fewer cold starts (especially for shared/pooled AVs) could lower tailpipe emissions of air pollutants such as NO_x, CO, and CO_2 (Milakis et al., 2017). In the long run, heavy safety equipment may not be as necessary, thus reducing vehicle weights and emissions (Richland et al., 2016). Reduced vehicle emissions would yield public health benefits in population centers, but the overall emission (including GhG) impacts of increased electric energy demand depend upon the portfolio of energy generation methods in different regions. Areas with less renewable and more polluting electric energy sources would see less health benefits.

On the other hand, the impact of more trips and longer vehicle-distances traveled by AVs could work against some of these emissions reductions (Richland et al., 2016; Wang et al., 2018). While electric vehicle engines operate more quietly, the majority of road noise comes from tire/pavement interactions (Rochat and Reiter, 2016) that would be only modestly decreased (if at all) and potentially counteracted by increased traffic volumes and faster speeds (Sohrabi et al., 2020). The impacts of AVs on air pollution will likely depend greatly upon changes in travel demand as well as the degree to which AVs are also EVs (Crayton & Meier, 2017).

Other

These discussions do not include other secondary and tertiary impacts of AVs on people's lives that may have implications for health, well-being, and equity, but that may act outside of the transportation system or in transport-adjacent ways. Positively, affordable shared/pooled AVs could help economically disadvantaged households free themselves from the burden of auto ownership and spend more money on health care and healthy food. AVs could also reshape the last mile of shipping and shopping, allowing people (especially those with mobility limitations) cheaper, quicker, and easier ordering and delivery of groceries, prescriptions, and other consumer goods. Negatively, improved traffic safety may reduce organ transplant availability (Pettigrew, 2017). Replacing drivers with computers could eliminate hundreds of thousands of transportation industry jobs (Crayton & Meier, 2017; Fagnant & Kockelman, 2015; Sohrabi et al., 2020), and increased independent mobility for seniors could reduce employment in home care (Pettigrew et al., 2019). Nevertheless, Clements and Kockelman (2017) offer a comprehensive analysis of AV effects on different industries, including also job and efficiency gains in different sectors. They conclude that AVs will bring a net gain for the economy. Overall, consideration of the multitude of potential impacts of AVs on health and well-being, some of which may not be apparent today, requires an evolving systems approach.

8.5 Conclusions

In this chapter, we have aimed to fill a gap in the literature discussing potential health and well-being implications of AVs. Given the scarcity of empirical work on this topic, our perspectives are based on merging understanding of current transportation–health relationships with discussion on potential travel behavior changes in an AV-era. As our discussion of the positive, negative, and uncertain effects of AVs on health and well-being makes clear, there appear to be likely benefits (improved safety, satisfaction, and access) as well as disadvantages (reduced physical activity), but much about these and other impacts remains unknown. It is our hope that this chapter: (1) increases awareness of the importance of considering health/well-being impacts of AVs; (2) encourages policymakers to consider how best to facilitate health benefits and mitigate disadvantages of AVs; and (3) inspires researchers to study these relationships and impacts in more detail. Towards these latter two aims, we close this chapter by discussing potential policy implications and research programs.

8.5.1 Policy implications

Policy measures should try to limit the possible negative effects of AVs on health and well-being, such as reduced physically-active travel and increased vehicle-distances traveled and urban sprawl. Spatial planning policies creating compact and mixed-use neighborhoods and restricting new suburban neighborhoods located far away from city centers (i.e., urban sprawl) therefore remain important. Improved infrastructure for cyclists and pedestrians (e.g., separated bike lanes, broad sidewalks with safe crossings) could mitigate the active travel-reducing effect of AVs, especially if road space can be re-allocated from automobile parking and travel lanes. Care should be taken to avoid further legal restrictions on how, where, and when pedestrians can access and cross streets, as conflicts with automatically-yielding vehicles may become a point of contention.

The types of AVs people use may have an impact on the severity of health impacts (Fitt et al., 2018; Dean et al., 2019). Private AVs could have more negative effects, such as additional and longer car trips (especially for holiday purposes) but also equity issues due to the large up-front costs. However, shared and pooled AVs may also be associated with increased distances traveled due to their lower capacity (compared to public transport), door-to-door service policy, and empty trips. Therefore, we would recommend that policymakers seeking to prioritize health and well-being should focus on provisions for active travel rather than placing high hopes on shared AVs.

Attention should also be paid to facilitating a more widespread and equitable distribution of the health and well-being benefits of AVs in the areas of safety, travel satisfaction, and access to activities. Zoning and other urban development policies should ensure that disadvantaged communities do not end up on the receiving end of large AV parking and circulation zones. Pricing or other policies could discourage AVs in places where they might compete with more healthy modes (like public transportation, walking, and bicycling in dense urban areas) and encourage AVs in more exurban and rural areas where they might improve access the most. The safety of non-occupants and vulnerable road users should be considered when developing collision avoidance and decision algorithms, as there are ethical issues involved in forced choice situations in which a collision is unavoidable (Bonnefon et al., 2016; Fleetwood, 2017; Goodall, 2017). Financial incentives and subsidies, as well as programs to develop technological skills, may be warranted to help people in poverty, older adults, or rural residents to use AVs to access healthy opportunities and experience improved independent mobility and well-being. Other policy and planning strategies for AVs (not necessarily focused on health/well-being) are described in Zmud et al. (2017).

8.5.2 Research agenda

The difficulty with analyzing the effects of AVs on health and well-being is that AVs are currently very niche. As a result, it is hard to measure how people will change their travel behavior and how this will affect health and well-being. Ideally, one would measure individual and/or population health outcomes or risk factors before and after the introduction of AVs, compared to a control group. While difficult to conduct, such experimental or quasiexperimental designs may start to be possible as AV technology advances and AV testbeds expand. In the meantime, various other research approaches are possible.

Stated choice experiments are a common way to study options or attributes that are rare or non-existent. Among stated choice approaches, most attention has been devoted to willingness-to-pay for AVs and choice of privately-owned versus shared/pooled AVs (Gkartzonikas and Gkritza, 2019). However, other choices—e.g., activity generation and scheduling, location choices—are also outcomes of interest. To estimate some of these effects, more stated choice experiments should be directed towards destination choice (including residential location choice, as in Krueger et al., 2019) and trip-making choice in the AV-era. Changes to daily activity schedules should also be considered (Pudāne et al., 2019).

This relates to a widely-known limitation of all stated choice studies: respondents' answers might differ from their real reaction to AVs in the future, partly because their knowledge of different types of AVs may be limited and partly because the options provided by the researchers may condition their answers. An alternative approach is to simulate AV trips in the real-world. A privately-owned self-driving vehicle could be mimicked by providing respondents a free chauffeur service for a certain period of time (see, for instance, Harb et al., 2018). Of course, the high expense associated with these types of experiments makes it difficult to obtain large sample sizes, negatively affecting representativeness. Another promising approach is to research travel behavior in locations where chauffeur-driven cars are commonplace (Wadud and Huda, 2019). As analog for shared/pooled AVs, the impacts of ride-hailing services on travel behaviors and mode shifts could be studied (e.g., Alemi et al., 2018; Clewlow and Mishra, 2017). In all cases, the presence of a human driver likely affects user trust of the service and, possibly, the availability of some activities during travel, therefore challenging the transferability of knowledge to a driverless situation.

A different way to simulate AVs and their health/well-being effects is to develop scenarios and model the impacts. Recent tools—e.g., the Integrated Transport and Health Impact Modelling Tool, based in epidemiological evidence—can model the health impacts (due to traffic injuries, air pollution, and physical activity) of various transportation scenarios. These health impact modeling tools could conceivably be used to examine the impacts of various AV adoption or policy scenarios (Pourrahmani et al., 2020). This information would be particularly useful to gain a better understanding of the relative magnitude of the tradeoffs between the positive effects of improved safety and the negative effects of reduced physical activity. Recent studies have found that the physical activity benefits of scenarios or interventions with even modest increases in active travel far outweigh the elevated safety risks and pollution exposure (Mueller et al., 2015); although, those studies did not consider AV scenarios.

No matter what method is used, there are key research questions that could illuminate potential health and well-being impacts as AVs become more widely used. The degree to which people are willing to use (and pay for) the experiential and productivity benefits of AVs is a critical travel behavioral factor—affecting mode choices, travel amounts, and location choices—and should be further investigated. Similarly important is the value travelers assign to the privacy and personal attributes of private AVs over shared/pooled AVs, given their differing societal impacts. Across all areas, research should also pay more attention to equity considerations and the distribution of the benefits and costs of AVs.

Overall, the existing state of the knowledge suggests that the effects of AVs on health and well-being are still uncertain and require continued attention. Great benefits are expected from this innovation—such as improvements in traffic safety—but the ripples from AV introduction will likely spread beyond the most obvious gains and have more varied (and potentially negative) impacts on health and well-being. We hope that this chapter has shed light on these future possibilities and opened gateways for further research and discussion.

References

Alemi, F., Circella, G., Handy, S., Mokhtarian, P.L., 2018. What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. Travel Behaviour and Society 13, 88–104.

Auld, J., Sokolov, V., Stephens, T.S., 2017. Analysis of the effects of connected–automated vehicle technologies on travel demand. Transportation Research Record 2625, 1–8.

Basner, M., Babisch, W., Davis, A., Brink, M., Clark, C., Janssen, S., Stansfeld, S., 2014. Auditory and nonauditory effects of noise on health. The Lancet 383, 1325–1332.

Becker, F., Axhausen, K.W., 2017. Literature review on surveys investigating the acceptance of automated vehicles. Transportation 44 (6), 1293–1306.

Bennett, R., Vijaygopal, R., Kottasz, R., 2019. Willingness of people with mental health disabilities to travel in driverless vehicles. Journal of Transport & Health 12, 1–12.

Bonnefon, J.F., Shariff, A. Rahwan, I., 2016. The social dilemma of autonomous vehicles. Science 352, 1573–1576.

Bösch, P.M., Becker, F., Becker, H. Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. Transport Policy 64, 76–91.

Carrone, A.P., Hoening, V.M., Jensen, A.F., Mabit, S.E., Rich, J., 2019. Car sharing preferences and mode substitution: A stated choice experiment. Presented at the World Conference on Transport Research, Mumbai.

Cepeda, M., Schoufour, J., Freak-Poli, R., Koolhaas, C.M., Dhana, K., Bramer, W.M. Franco, O.H., 2017. Levels of ambient air pollution according to mode of transport: a systematic review. The Lancet Public Health 2, e23–e34.

Chief Medical Officers, 2011. Start active, stay active: A report on physical activity from the four home countries'. Department of Health, Physical Activity, Health Improvement and Protection, London.

Childress, S., Nichols, B., Charlton, B., Coe, S., 2015. Using an activity-based model to explore the potential impacts of automated vehicles. Transportation Research Record 2493, 99–106.

Clark, B., Chatterjee, K., Martin, A., Davis, A., 2019. How commuting affects subjective wellbeing. Transportation, 1–29.

Clements, L.M., Kockelman, K.M., 2017. Economic effects of automated vehicles. Transportation Research Record 2606, 106–114.

Clewlow, R.R., Mishra, G.S., 2017. Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States. Research Report – UCD-ITS-RR-17-07. Institute of Transportation Studies, University of California, Davis.

Cohen, S., Shirazi, S., 2017. Can we advance social equity with shared, autonomous and electric vehicles? Institute of Transportation Studies at the University of California, Davis.

Conway, M., Salon, D. King, D., 2018. Trends in taxi use and the advent of ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. Urban Science 2, 79.

Crayton, T.J., Meier, B.M., 2017. Autonomous vehicles: Developing a public health research agenda to frame the future of transportation policy. Journal of Transport & Health 6, 245–252.

Curl, A., Fitt, H., Dionisio-McHugh, R., Ahuriri-Driscoll, A., Fletcher, A., Slaughter, H., 2018. Autonomous vehicles and future urban environments: Exploring changing travel behaviours, built environments, and implications for wellbeing in an ageing society. Christchurch, NZ: National Science Challenge 11: Building Better Homes, Towns and Cities.

Dean, J., Wray, A.J., Braun, L., Casello, J.M., McCallum, L., Gower, S., 2019. Holding the keys to health? A scoping study of the population health impacts of automated vehicles. BMC Public Health 19, 1258.

Delbosc, A., Currie, G., 2011. Exploring the relative influences of transport disadvantage and social exclusion on well-being. Transport Policy 18, 555–562.

Department for Transport (DfT), 2018. Transport Statistics Great Britain. https://www.gov.uk/government/collections/transport-statistics-great-britain#about-the-transport-statistics-great-britain-data-and-reports (accessed 20 December 2018)

De Vos, J., 2018a. Do people travel with their preferred travel mode? Analysing the extent of travel mode dissonance and its effect on travel satisfaction. Transportation Research Part A 117, 261–274.

De Vos, J., 2018b. Towards happy and healthy travelers: A research agenda. Journal of Transport & Health 11, 80–85.

De Vos, J., 2019. Analysing the effect of trip satisfaction on satisfaction with the leisure activity at the destination of the trip, in relationship with life satisfaction. Transportation 46, 623–645.

De Vos, J., Mokhtarian, P.L., Schwanen, T., Van Acker, V., Witlox, F., 2016. Travel mode choice and travel satisfaction: bridging the gap between decision utility and experienced utility. Transportation 43, 771–796.

De Vos, J., Schwanen, T., Van Acker, V., Witlox, F., 2013. Travel and subjective well-being: A focus on findings, methods and future research needs. Transport Reviews 33, 421–442.

De Vos, J., Witlox, F., 2017. Travel satisfaction revisited. On the pivotal role of travel satisfaction in conceptualising a travel behaviour process. Transportation Research Part A 106, 364–373.

Ettema, D., Friman, M., Gärling, T., Olsson, L.E., Fujii, S., 2012. How in-vehicle activities affect work commuters' satisfaction with public transport. Journal of Transport Geography 24, 215–222.

Ettema, D., Gärling, T., Eriksson, L., Friman, M., Olsson, L.E., Fujii, S., 2011. Satisfaction with travel and subjective well-being: development and test of a measurement tool. Transportation Research Part F 14, 167–175.

Ettema, D., Gärling, T., Olsson, L.E., Friman, M., 2010. Out-of-home activities, daily travel, and subjective well-being. Transportation Research Part A 44, 723–732.

European Environment Agency (EEA), 2014. Noise in Europe 2014. EEA, Luxemburg.

EEA, 2018a. Greenhouse gas emissions from transport. https://www.eea.europa.eu/data-and-maps/indicators/transport-emissions-of-greenhouse-gases/transport-emissions-of-greenhouse-gases-11 (accessed 13 July 2019)

EEA, 2018b. Transport emissions. https://ec.europa.eu/clima/policies/transport_en (accessed 12 September 2018)

EEA, 2018c. Environmental noise, briefing. https://www.eea.europa.eu/airs/2018/environment-and-health/environmental-noise (accessed 13 July 2019)

Eurostat, 2017. Transport accident statistics. https://ec.europa.eu/eurostat/statistics-explained/pdfscache/7375.pdf (accessed 13 July 2019)

Fagnant, D. J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transportation Research Part A 77, 167–181.

Ferdman, A., 2019. Corporate ownership of automated vehicles: discussing potential negative externalities. Transport Reviews, 1–19.

Fitt, H., Curl, A., Dionisio-McHugh, R., Fletcher, A., Frame, B., Ahuriri-Driscoll, A., 2018. Think piece: Autonomous vehicles and future urban environments: Exploring implications for wellbeing in an ageing society (2nd ed.). Christchurch, NZ: National Science Challenge 11: Building Better Homes, Towns and Cities.

Fleetwood, J., 2017. Public Health, Ethics, and Autonomous Vehicles. American Journal of Public Health 107, 532–537.

Fraedrich, E., Heinrichs, D., Bahamonde-Birke, F.J., Cyganski, R., 2019. Autonomous driving, the built environment and policy implications. Transportation Research Part A 122, 162–172.

Friman M., Olsson, L.E., Ståhl, M., Ettema, D., Gärling, T., 2017. Travel and residual emotional wellbeing. Transportation Research Part F 49, 159–176.

Gehrke, S., Felix, A. Reardon, T., 2018. Fare choices: A survey of ride-hailing passengers in metro Boston. Metropolitan Area Planning Council, Boston.

Giles-Corti, B., Vernez-Moudon, A., Reis, R., Turrell, G., Dannenberg, A. L., Badland, H., ... & Owen, N., 2016. City planning and population health: A global challenge. The Lancet, 388, 2912–2924.

Gkartzonikas, C. Gkritza, K., 2019. What have we learned? A review of stated preference and choice studies on autonomous vehicles. Transportation Research Part C 98, 323–337.

Goodall, N.J., 2017. From trolleys to risk: Models for ethical autonomous driving. American Journal of Public Health 107, 496.

Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. Transportation Research Part C 78, 37–49.

Handy S., 2014. Health and travel, in: Gärling T., Ettema D., Friman M. (Eds.), Handbook of Sustainable Travel. Springer, Dordrecht, pp. 199–214.

Harb, M., Xiao, Y., Circella, G., Mokhtarian, P.L., Walker, J.L., 2018. Projecting travelers into a world of self-driving vehicles: Estimating travel behavior implications via a naturalistic experiment. Transportation 45, 1671–1685.

Harper, C.D., Hendrickson, C.T., Mangones, S. Samaras, C., 2016. Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. Transportation Research Part C 72, 1–9.

Heinen E., van Wee B., Maat K., 2010. Commuting by bicycle: An overview of the literature. Transport Reviews 30, 59–96.

Heinrichs, D., 2016. Autonomous driving and urban land use, in: Maurer, M., Gerdes, J.C., Lenz, B., Winner, H. (Eds.), Autonomous driving: Technical, legal and social aspects. Springer Nature, pp. 213–231.

Higgins, C.D., Sweet, M.N., Kanaroglou, P.S., 2018. All minutes are not equal: Travel time and the effects of congestion on commute satisfaction in Canadian cities. Transportation 45, 1249–1268.

Jain, J., Lyons, G., 2008. The gift of travel time. Journal of Transport Geography 16, 81–89.

Kaufmann, V., Bergman, M.M., Joye, D., 2004. Motility: Mobility as capital. International Journal of Urban and Regional Research 28, 745–756.

Kelly P., Kahlmeier S., Götschi T., Orsini, N., Richards, J., Roberts, N., Scarborough, P., Foster, C., 2014. Systematic review and meta-analysis of reduction in all-cause mortality from walking and cycling and shape of dose response relationship. International Journal of Behavioural Nutrition and Physical Activity, 11, 132.

Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transportation Research Part C 69, 343–355.

Krueger, R., Rashidi, T.H., Dixit, V.V., 2019. Autonomous driving and residential location preferences: Evidence from a stated choice survey. arXiv preprint arXiv:1905.11486.

Laird, J., Geurs, K., Nash, C., 2009. Option and non-use values and rail project appraisal. Transport Policy 16, 173–182.

LaMondia, J.J., Fagnant, D.J., Qu, H., Barrett, J. Kockelman, K., 2016. Shifts in long-distance travel mode due to automated vehicles: Statewide mode-shift simulation experiment and travel survey analysis. Transportation Research Record 2566, 1–11.

Lavieri, P.S., Bhat, C.R., 2019. Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future. Transportation Research Part A 124, 242–261.

Lee, I.M., Shiroma E.J., Lobelo F., Puska P., Blair S.N., Katzmarzyk P.T., 2012. Effect of physical inactivity on major non-communicable diseases worldwide: An analysis of burden of disease and life expectancy. The Lancet 380, 219–229.

Legrain, A., Eluru, N., El-Geneidy, A., 2015. Am stressed, must travel: The relationship between mode choice and commuting stress. Transportation Research Part F 34, 141–151.

Loong, C., van Lierop, D., El-Geneidy, A., 2017. On time and ready to go: An analysis of commuters' punctuality and energy levels at work or school. Transportation Research Part F 45, 1–13.

Lucas, K., 2012. Transport and social exclusion: Where are we now? Transport Policy 20, 105–113.

Lyons, G., Jain, J., Holley, D., 2007. The use of travel time by rail passengers in Great Britain. Transportation Research Part A 41, 107–120.

Lyubomirsky, S., King, L., Diener, E., 2005. The benefits of frequent positive affect: Does happiness lead to success? Psychological Bulletin 131, 803–855.

Malekafzali, S., 2009. Healthy, equitable transportation policy: recommendations and research. PolicyLink, Oakland.

Meyer, J., Becker, H., Bösch, P. M., Axhausen, K. W., 2017. Autonomous vehicles: The next jump in accessibilities?. Research in Transportation Economics 62, 80–91.

Milakis, D., Van Arem, B. Van Wee, B., 2017. Policy and society related implications of automated driving: A review of literature and directions for future research. Journal of Intelligent Transportation Systems 21, 324–348.

Mokhtarian, P.L., 2018. The times they are a-changin': What do the expanding uses of travel time portend for policy, planning, and life? Transportation Research Record 2672, 1–11.

Mokhtarian, P.L., 2019. Subjective well-being and travel: Retrospect and prospect. Transportation 46, 493–513.

Morris, E.A., 2015. Should we all just stay home? Travel, out-of-home activities, and life satisfaction. Transportation Research Part A 78, 519–536.

Morris, E.A., Guerra, E., 2015. Are we there yet? Trip duration and mood during travel. Transportation Research Part F 33, 38–47.

Morris, E.A., Zhou, Y., 2018. Are long commutes short on benefits? Commute duration and various manifestations of well-being. Travel Behaviour and Society 11, 101–110.

Mueller, N., Rojas-Rueda, D., Cole-Hunter, T., de Nazelle, A., Dons, E., Gerike, R., Goetschi, T., Panis, L.I., Kahlmeier, S. Nieuwenhuijsen, M., 2015. Health impact assessment of active transportation: A systematic review. Preventive Medicine, 76, 103–114.

Nazari, F., Noruzoliaee, M., Mohammadian, A.K., 2018. Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes. Transportation Research Part C 97, 456–477.

OECD, 2019. Road accidents. https://data.oecd.org/transport/road-accidents.htm. (accessed 13 July 2019)

Ostermeijer, F., Koster, H.R., van Ommeren, J., 2019. Residential parking costs and car ownership: Implications for parking policy and automated vehicles. Regional Science and Urban Economics 77, 276–288.

Pakusch, C., Stevens, G., Boden, A. Bossauer, P., 2018. Unintended effects of autonomous driving: A study on mobility preferences in the future. Sustainability 10, 2404.

Patterson, R., McNamara, E., Tainio, M., de Sá, T.H., Smith, A.D., Sharp, S.J., Edwards, P., Woodcock, J.. Brage, S., Wijndaele, K., 2018. Sedentary behaviour and risk of all-cause, cardiovascular and cancer mortality, and incident type 2 diabetes: A systematic review and dose response meta-analysis. European Journal of Epidemiology 33, 811–829.

Petit, J. Shladover, S.E., 2014. Potential cyberattacks on automated vehicles. IEEE Transactions on Intelligent Transportation Systems 16, 546–556.

Pettigrew, S., 2017. Why public health should embrace the autonomous car. Australian and New Zealand Journal of Public Health 41, 1–3.

Pettigrew, S., Talati, Z., Norman, R., 2018. The health benefits of autonomous vehicles: Public awareness and receptivity in Australia. Australian and New Zealand Journal of Public Health 42, 480–483.

Pfleging, B., Rang, M., Broy, N., 2016. Investigating user needs for non-driving-related activities during automated driving. Proceedings of the 15th international conference on mobile and ubiquitous multimedia (pp. 91–99). ACM.

Pourrahmani, E., Jaller, M., Maizlish, N., Rodier, C., 2020. Health impact assessment of autonomous vehicles in San Francisco, Bay Area using the Integrated Transport and Health Impacts Model (ITHIM). Presented at the 99th Annual Meeting of the Transportation Research Board, Washington, DC.

Pudāne, B., Molin, E.J., Arentze, T.A., Maknoon, Y., Chorus, C.G., 2018. A time-use model for the automated vehicle-era. Transportation Research Part C 93, 102–114.

Pudāne, B., Rataj, M., Molin, E.J., Mouter, N., van Cranenburgh, S., Chorus, C.G., 2019. How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands. Transportation Research Part D 71, 222–235.

Richland, J., Lee, J., Butto, E.D., 2016. Steering autonomous vehicle policy: The role of public health. Washington, DC: Altarum Institute.

Rochat, J.L. Reiter, D., 2016. Highway traffic noise. Acoustics Today 12, 38–47.

Shaw, F.A., Malokin, A., Mokhtarian, P.L., Circella, G., 2019. It's not all fun and games: An investigation of the reported benefits and disadvantages of conducting activities while commuting. Travel Behaviour and Society 17, 8–25.

Singleton, P.A., 2019a. Discussing the "positive utilities" of autonomous vehicles: Will travelers really use their time productively? Transport Reviews 39, 50–65.

Singleton, P.A., 2019b. Walking (and cycling) to well-being: Modal and other determinants of subjective well-being during the commute. Travel Behaviour and Society 16, 249–261.

Sohrabi, S., Khreis, H. Lord, D., 2020. Autonomous vehicles and public health: A conceptual model and policy recommendation. Presented at the 99th Annual Meeting of the Transportation Research Board, Washington, DC. https://ceprofs.civil.tamu.edu/dlord/Papers/Sohrabi_et_al_AV_Health_TRB.pdf (accessed 1 December 2019)

Soteropoulos, A., Berger, M., Ciari, F., 2019. Impacts of automated vehicles on travel behavior and land use: an international review of modelling studies. Transport Reviews 39, 29–49.

Stark, J., Meschik, M., Singleton, P.A., Schützhofer, B., 2018. Active school travel, attitudes and psychological well-being of children. Transportation Research Part F 56, 453–465.

St-Louis, E., Manaugh, K., van Lierop, D., El-Geneidy, A., 2014. The happy commuter: A comparison of commuter satisfaction across modes. Transportation Research Part F 26, 160–170.

Stoiber, T., Schubert, I., Hoerler, R., Burger, P., 2019. Will consumers prefer shared and pooled-use autonomous vehicles? A stated choice experiment with Swiss households. Transportation Research Part D 71, 265–282.

Strand, N., Nilsson, J., Karlsson, I.M. and Nilsson, L., 2014. Semi-automated versus highly automated driving in critical situations caused by automation failures. Transportation Research Part F 27, 218–228.

Stutzer, A., Frey, B.S., 2008. Stress that doesn't pay: The commuting paradox. Scandinavian Journal of Economics 110, 339–366.

U.S. Department of Transportation (USDOT), 2015. Critical reasons for crashes investigated in the National Motor Vehicle Crash Causation Survey. USDOT, Washington.

USDOT, 2019. Traffic facts annual reports tables. https://cdan.nhtsa.gov/tsftables/tsfar.htm (accessed 1 July 2019)

van Wee, B., & Ettema, D., 2016). Travel behaviour and health: A conceptual model and research agenda. Journal of Transport & Health 3, 240–248.

van Wee, B., van Cranenburgh, S., Maat, K., 2019. Substitutability as a spatial concept to evaluate travel alternatives. Journal of Transport Geography 79, 102469.

Wadud, Z., Huda, F.Y., 2019. Fully automated vehicles: The use of travel time and its association with intention to use. Proceedings of the Institution of Civil Engineers: Transport, 1–15.

Wang, A., Stogios, C., Gai, Y., Vaughan, J., Ozonder, G., Lee, S., ... Hatzopoulou, M., 2018. Automated, electric, or both? Investigating the effects of transportation and technology scenarios on metropolitan greenhouse gas emissions. Sustainable Cities and Society 40, 524–533.

Westman, J., Olsson, L.E., Gärling, T., Friman, M., 2017. Children's travel to school: Satisfaction, current mood, and cognitive performance. Transportation 44, 1365–1382.

World Health Organization (WHO), 2010. Global recommendations on physical activity for health. WHO, Geneva.

WHO, 2018a. Global status report on road safety 2018. WHO, Geneva.

WHO, 2018b. Ambient (outdoor) air quality and health. https://www.who.int/en/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health (accessed 13 July 2019)

WHO, 2018c. Physical activity. https://www.who.int/news-room/fact-sheets/detail/physical-activity (accessed 13 July 2019)

WHO, 2018d. Environmental noise guidelines for the European Region. WHO, Copenhagen.

WHO, 2019a. Transport and health risks. https://www.who.int/sustainable-development/transport/health-risks/en/ (accessed 11 November 2019)

WHO, 2019b. Air pollution. https://www.who.int/sustainable-development/transport/health-risks/air-pollution/en/ (accessed 13 July 2019)

Ye, R., Titheridge, H., 2017. Satisfaction with the commute: The role of travel mode choice, built environment and attitudes. Transportation Research Part D 52B, 535–547.

Zakharenko, R., 2016. Self-driving cars will change cities. Regional Science and Urban Economics 61, 26–37.

Zhu, J., Fan, Y., 2018. Daily travel behavior and emotional well-being: Effects of trip mode, duration, purpose, and companionship. Transportation Research Part A 118, 360–373.

Zmud, J., Sener, I.N., Wagner, J., 2016. Self-driving vehicles: Determinants of adoption and conditions of usage. Transportation Research Record 2565, 57–64.

Zmud, J., Goodin, G., Moran, M., Kalra, N., & Thorn, E., 2017. Advancing automated and connected vehicles: Policy and planning strategies for state and local transportation agencies. National Cooperative Highway Research Program, Washington.

Summary

Background

Automated vehicles (AVs) have been a dream for a long time. From science fiction in the 1930s to countless prototypes, extensive road testing, and first use cases at present, the technology has clearly come a long way. So too has the vision of practitioners and academics matured to recognise the various potential benefits (e.g., accessibility, traffic safety, productivity, well-being) as well as threats (e.g., safety and security risks, induced travel demand, urban sprawl) of automation. The task at hand is to comprehensively assess these impacts in preparation for the AV future. How will the modal split between AVs and other modes unravel? In what forms and services would automation be most beneficial? What developments in travel demand and congestion patterns can be expected?

While there are still many uncertainties regarding the technological development, just as crucial and unknown in the assessment of AV impacts is the travel behaviour of the future AV users. Letting go of the steering wheel may mean more than making travel more pleasant for some travellers (or perhaps less so for others who prefer to stay in control). For current car drivers, this may mean gained time and energy in a day that could let them re-optimise their activity schedule. For instance, they may choose to perform work tasks during commute, and spend less time at work as a result. That would let them increase the time spent – and potentially, trips made – for leisure. In other instances, a traveller may be able to skip a detour to home, if a certain activity (such as getting ready, preparing a simple meal, etc.) is possible during travel. In short: new activities during travel may directly influence the activities outside of it. In addition, a major change for current drivers could be the possibility to let AVs park themselves (e.g., outside of the city centre): parking availability may no longer discourage from visiting busy destinations. The list of possible changes for current car drivers does not end here. Nonetheless, the list may be even longer for those who may become new car users with the introduction of AVs.

It is evident from the above description that such individual-level transitions can aggregate to complex and significant trends in the transport system. Person- and vehicle-kilometres, as well as the modal split will likely change. But also, the spatial and temporal distribution of travel demand could be altered. Perhaps sleeping AV users will increase the night-time traffic, and AV personal robots will run errands in the mid-day? Perhaps some areas may receive more such personal robots thanks to the presence of an AV-friendly facility (such as an automated gas or charging station)? In the long term, perhaps changed schedules will result in altered preferences for home and work locations, resulting in different land-use patterns?

How can the policy makers anticipate such complex developments? The answer to such queries has, for a long time, been provided by the coupling of travel behaviour and (large-scale) transport models. However, these models have so far been developed, successfully applied and fine-tuned for predicting travel patterns with the current, non-AV travel modes. The question that needs to be answered before using them to predict transport system developments with AVs is evident: can they reliably describe the travel behaviour of AVs? This PhD is, for the largest part, inspired by my conviction that the answer to this question is 'no'.

In particular, I argue that the time-use dimension of travel demand models – that is, the effects of time-use in AVs on daily time-use – has not been sufficiently developed. Even state-of-the-art models commonly assume that on-board activities in AVs will lower the so-called travel time penalty or the value of travel time (depending on whether the model is used for prediction or evaluation). In the prediction context, this inevitably leads to a prediction of more person- (and vehicle-) travel, but otherwise limited changes in daily schedules. Clearly, this approach misses a layer of important details, such as the possibility that the new activities during travel directly affect the activities outside of it. In the evaluation context, this approach gives an illusion that the benefits from travel time savings will accrue gradually and not step-wise, due to, for example, discrete schedule re-arrangements. While the gradual approach has been an accepted simplification for the present modes, the issue may become more pressing with AVs, since it is possible to both win and lose when shortening the time allocated to travel and on-board activities. This leads to two problem statements.

- **Scientific problem.** The current travel behaviour and transport models assume identical time-use implications of varied on-board activities. This could lead to biased travel behaviour predictions and estimates of AV benefits.
- **Policy problem.** With the current modelling tools being potentially misaligned with future travel behaviour, the policy makers are left with unreliable tools for predicting transport system performance and assessing transport investments for the AV era. This could lead to poor transport policy decisions, wasteful investments, and detrimental impacts to society.

Contents of this thesis

This thesis aims to reduce this potential misalignment between the conceivable behaviour of future AV users and its representation in travel behaviour and time-use models. Specifically, the three main goals of this thesis are the following:

- to obtain and analyse data on the travellers' expectations of their future time use and travel behaviour with AVs, and to identify aspects that are not well represented in the current time-use and travel behaviour models;
- to use the insights from the analysis to build and update models describing time use and travel behaviour in the AV era;
- to use the updated models to obtain first insights into aggregate travel patterns.

Chapters 2 and 3 contribute primarily to the first aim, chapters 4, 5, and 6 to the second, and chapter 5 and the epilogue to the third. The main findings of the chapters are summarised below.

Chapter 2 uses focus group interviews to explore the terrain of the travel behaviour and daily activity effects of AVs. It reports how the participants reacted differently to the possibility to perform new activities in AVs. Some said that they would change their current on-board activities, while others would not. Some would engage in substantial high-priority activities, while others would rather perform optional or background-type activities, such as leisure and relaxing. Consequently, AVs made some reconsider their daily schedules, while others did not expect to change their schedules much. The prospect of increasing daily travel received mixed reactions as well. In contrast, participants were rather united in expecting more long-distance and holiday travel. Interesting discussions unfolded regarding the impacts of AVs on daily time pressure. Several participants expected that the initial time savings may be more than compensated by increased activity needs, especially due to social pressure to work during travel.

Chapter 3 develops and uses an interactive stated activity-travel survey to quantitatively analyse changes in daily time use with AVs. A medium-large online sample of commuters (n = 509) designed their current and future daily schedules (with AVs), while paying special attention to the potential overlap of travel and activities. The AV impacts on on-board and stationary activities are analysed using the multiple discrete-continuous extreme value framework. Results show that AVs lead to significantly more and longer on-board activities. The overall impacts on stationary activities are negligible, although present in few socio-demographic groups (e.g., the higher educated and high-income respondents). Nonetheless, even if the aggregate changes are small, they are correlated with on-board activity changes in intuitive ways. The chapter concludes that at least some demographic groups may experience time-saving or other schedule effects due to AVs, and that more schedule effects may be discovered in future studies with larger samples.

Chapter 4 formalises the described time-saving effects from on-board activities. Building upon the classical time-use framework, it adds elements that are needed to capture varied on-board activities. Applied to a series of examples, the model shows how AVs lead to time savings and allow their users to perform more activities during a day. It also shows that on-board activities can lead to more or less daily travel in different scenarios. Thereby, this chapter provides an alternative to the pervasive travel time penalty approach, which predicts only such changes in daily time-use that result from further destinations or more frequent trips becoming more attractive with AVs. With these results, this chapter demonstrates that schedule changes are not only peculiar to the data described in previous chapters, but could in fact be expected from economic agents.

Chapter 5 formalises time-saving and schedule change effects in the context of (morning) commute. It demonstrates, first, how on-board activities can influence departure time choice: performing home-type activities during travel would lead rational individuals to depart to work earlier, while work-type activities would make later departures more attractive. Second, it uses a minimalistic bottleneck setting to analyse changes in congestion patterns that result from these on-board activities. It becomes clear that the enhanced activities in automated vehicles lead to more intense congestion; however, the shape of congestion is influenced by the type of on-board activities, of which work activities lead to the least dramatic increase.

Chapter 6 considers the time-use effects in the evaluation context. Based on a re-interpretation of a recently presented model, it theoretically derives the value of travel time from an extended classical microeconomic framework. The extension allows to specify the extent to which on-board environments support work and leisure activities. It concludes that, as the value of travel time is classically split into, first, an intrinsic liking or disliking of travel and, second, the loss of time that could be used for other activities, the automated vehicles can be expected to reduce (or, in an extreme case, eliminate) the latter for future travellers.

The epilogue of this thesis discusses health and well-being effects of AVs. In this relation, the author contributed to this chapter a discussion on the individual travel amount and mode choice – aspects of travel behaviour that may particularly strongly impact the health and well-being of AV users and non-users alike. With regard to the individual travel amount, the chapter concludes that various developments are possible; thus, not only an increase, as is usually assumed. This argument aligns with the other discussions in this thesis. With regard to the mode choice, it argues that shared and pooled AVs may draw their users from (relatively) sustainable travel modes, such as public transport, active modes, and conventional car sharing. This idea is grounded in literature and in the concept of substitutability among travel options, and it is captured in a conceptual map. The consequence of such modal shifts would be more vehicle-travel, even assuming the same amount of person-travel – an outcome that is relevant not only in the health and well-being discussion, but also in the general debate about the societal implications of AVs.

In conclusion

This thesis aimed to narrow the gap between the expected travel and time-use behaviour of AV users and the models that describe it. Throughout the chapters, it has, first, provided intuition that such gap indeed exists. Second, it has analysed empirical evidence that partially supports this intuition. Third, it developed three time-use and travel behaviour models that incorporate some of the missing behavioural elements. Lastly, this thesis has provided first insights into how these model updates make a difference for the predictions of aggregate travel patterns – a crucial input for transport policy making for the AV era.

Samenvatting

Achtergrond

Geautomatiseerde voertuigen (GV's) zijn al heel lang een droom. Van sciencefiction in de jaren 1930 tot talloze prototypes, uitgebreide tests op de weg en de eerste gebruikssituaties op dit moment, heeft de technologie duidelijk een lange weg afgelegd. Ook de visie van mensen uit de praktijk en academici heeft zich ontwikkeld en kent verschillende potentiële voordelen van automatisering (bv. bereikbaarheid, verkeersveiligheid, productiviteit, welzijn) en bedreigingen (bv. veiligheids- en beveiligingsrisico's, een te grote vraag naar vervoer, stedelijke wildgroei). Het is nu zaak deze effecten uitvoerig te beoordelen ter voorbereiding op de toekomst van GV. Hoe zal de modal split tussen GV's en andere vervoerswijzen zich ontwikkelen? In welke vormen en diensten zal de automatisering het meeste voordeel opleveren? Welke ontwikkelingen in de reisvraag en congestiepatronen kunnen worden verwacht?

Hoewel er nog veel onzekerheden zijn over de technologische ontwikkeling, is het reisgedrag van de toekomstige GV-gebruikers net zo belangrijk en onbekend in de beoordeling van GV effecten. Het stuur loslaten kan meer betekenen dan het reizen aangenamer maken voor sommige reizigers (of misschien minder aangenaam voor anderen die liever de controle behouden). Voor huidige autobestuurders kan dit betekenen dat ze tijd en energie winnen op een dag, waardoor ze hun dagelijkse activiteitenpatronen kunnen heroptimaliseren. Zij kunnen er bijvoorbeeld voor kiezen om tijdens het reizen werktaken uit te voeren waardoor er minder tijd op het werk doorgebracht hoeft te worden. Daardoor kunnen ze meer tijd besteden aan vrije tijd (en mogelijk ook meer reizen). In andere gevallen kan een reiziger een omweg naar huis overslaan, als een bepaalde activiteit (zoals zichzelf opmaken, een eenvoudige maaltijd bereiden, enz.) mogelijk is tijdens de reis. Kortom: nieuwe activiteiten tijdens de reis kunnen de activiteiten daarbuiten rechtstreeks beïnvloeden. Bovendien zou een belangrijke verandering voor de huidige bestuurders de mogelijkheid kunnen zijn om GV's zelf te laten parkeren (bijv. buiten het stadscentrum): de beschikbaarheid van parkeergelegenheid mag niet langer ontmoedigend werken om drukke bestemmingen te bezoeken. De lijst van mogelijke veranderingen voor de huidige autobestuurders houdt hier niet op. De lijst kan echter nog langer zijn voor degenen die mogelijk nieuwe autogebruikers worden door de introductie van GV's.

Uit de bovenstaande beschrijving blijkt dat dergelijke overgangen op individueel niveau kunnen leiden tot complexe en significante trends in het vervoerssysteem. Het aantal persoons- en voertuigkilometers en de modal split zullen waarschijnlijk veranderen. Maar ook de ruimtelijke en temporele spreiding van de reisvraag kan veranderen. Misschien zullen slapende GV-gebruikers het nachtelijke verkeer doen toenemen, en zullen GV-persoonlijke robots boodschappen doen in het midden van de dag? Misschien zullen sommige gebieden meer van dergelijke persoonlijke robots ontvangen dankzij de aanwezigheid van een GV-vriendelijke voorziening (zoals een geautomatiseerd tank- of oplaadstation)? Op lange termijn zullen veranderde dagelijkse activiteitenpatronen misschien resulteren in gewijzigde voorkeuren voor woon- en werklocaties, met andere ruimtelijke ordeningspatronen tot gevolg?

Hoe kunnen de beleidsmakers op dergelijke complexe ontwikkelingen anticiperen? Het antwoord op dergelijke vragen wordt al geruime tijd gegeven door de koppeling van reisgedrag- en (grootschalige) transportmodellen. Deze modellen zijn tot dusver echter ontwikkeld, met succes toegepast en verfijnd voor het voorspellen van reispatronen met de huidige, niet-GV-reiswijzen. De vraag die beantwoord moet worden voordat ze gebruikt kunnen worden voor het voorspellen van transportsysteemontwikkelingen met GVs is duidelijk: kunnen ze het reisgedrag van GV's betrouwbaar beschrijven? Dit doctoraat is grotendeels geïnspireerd door mijn overtuiging dat het antwoord op deze vraag ‘nee’ is.

Ik argumenteer in het bijzonder dat de tijdsgebruik-dimensie van reisvraagmodellen - d.w.z. de effecten van het tijdsgebruik in GV's op het dagelijkse tijdsgebruik - niet voldoende ontwikkeld is. Zelfs de meest recente modellen gaan er gewoonlijk van uit dat activiteiten aan boord van GV's de zogenaamde reistijdboete of de waarde van reistijd zullen verlagen (afhankelijk van het feit of het model wordt gebruikt voor voorspelling of evaluatie). In de voorspellingscontext leidt dit onvermijdelijk tot een voorspelling van meer persoons- (en voertuig-) verplaatsingen, maar daarentegen beperkte veranderingen in de dagelijkse activiteitenpatronen. Het is duidelijk dat deze benadering een aantal belangrijke details mist, zoals de mogelijkheid dat de nieuwe activiteiten tijdens de reis rechtstreeks van invloed zijn op de activiteiten daarbuiten. In de evaluatiecontext wekt deze benadering de illusie dat de voordelen van reistijdbesparingen geleidelijk en niet stapsgewijs zullen toenemen, bijvoorbeeld als gevolg van discrete herschikkingen van activiteiten. Hoewel de geleidelijke aanpak een aanvaarde vereenvoudiging is voor de huidige vervoerswijzen, kan de kwestie urgenter worden met GV's, aangezien het mogelijk is zowel te winnen als te verliezen bij het inkorten van de tijd die aan reizen en activiteiten aan boord wordt besteed. Dit leidt tot twee probleemstellingen.

- **Wetenschappelijk probleem**. De huidige reisgedrag- en vervoersmodellen gaan uit van identieke tijdsbestedingsimplicaties van uiteenlopende activiteiten aan boord. Dit kan leiden tot vertekende voorspellingen van reisgedrag en schattingen van GV-voordelen.
- **Beleidsprobleem.** Omdat de huidige modelleringsinstrumenten mogelijk niet zijn afgestemd op het toekomstige reisgedrag, blijven de beleidsmakers zitten met onbetrouwbare instrumenten voor het voorspellen van de prestaties van transportsystemen en het beoordelen van transportinvesteringen voor het GV-tijdperk. Dit kan leiden tot slechte beleidsbeslissingen op vervoersgebied, verkwistende investeringen, en nadelige gevolgen voor de maatschappij.

Inhoud van dit proefschrift

Dit proefschrift heeft tot doel deze potentiële wanverhouding tussen het denkbare gedrag van toekomstige GV-gebruikers en de vertegenwoordiging ervan in reisgedrag- en tijdgebruikmodellen te verminderen. Meer specifiek, de drie hoofddoelen van dit proefschrift zijn de volgende:

- het verkrijgen en analyseren van gegevens over de verwachtingen van reizigers over hun toekomstige tijdsbesteding en reisgedrag met GV's, en het identificeren van aspecten die niet goed worden gerepresenteerd in de huidige modellen voor tijdsbesteding en reisgedrag;
- de inzichten uit de analyse te gebruiken om modellen op te stellen en te actualiseren die de tijdsbesteding en het reisgedrag in het GV-tijdperk beschrijven
- de geactualiseerde modellen te gebruiken om eerste inzichten te verwerven in geaggregeerde reispatronen.

De hoofdstukken 2 en 3 dragen in de eerste plaats bij tot het eerste doel; de hoofdstukken 4, 5 en 6 - tot het tweede doel; hoofdstuk 5 en de epiloog - tot het derde doel. De belangrijkste bevindingen van de hoofdstukken worden hieronder samengevat.

Hoofdstuk 2 gebruikt focusgroep-interviews om het terrein van het reisgedrag en de dagelijkse activiteitseffecten van GV's te verkennen. Het beschrijft hoe de deelnemers verschillend reageerden op de mogelijkheid om nieuwe activiteiten uit te voeren in GV's. Sommigen zeiden dat ze hun huidige activiteiten aan boord zouden veranderen, terwijl anderen dat niet zouden doen. Sommigen zouden substantiële activiteiten met een hoge prioriteit uitvoeren, terwijl anderen eerder optionele of achtergrondachtige activiteiten zouden uitvoeren, zoals ontspanning. Vervolgens deden GV's sommigen hun dagelijkse planning’s heroverwegen, terwijl anderen niet verwachtten hun planning's veel te zullen veranderen. Het vooruitzicht van meer dagelijkse verplaatsingen leverde eveneens gemengde reacties op. Daarentegen waren de deelnemers eerder eensgezind in hun verwachting van meer langeafstands- en vakantiereizen. Er ontspon zich interessante discussies over de effecten van GV's op de dagelijkse tijdsdruk. Meerdere deelnemers verwachtten dat de initiële tijdwinst meer dan gecompenseerd zou worden door de toegenomen behoefte aan activiteit, vooral door de sociale druk om te werken tijdens het reizen.

Hoofdstuk 3 ontwikkelt en gebruikt een interactieve enquête over activiteit en verplaatsing om de veranderingen in de dagelijkse tijdsbesteding met GV's kwantitatief te analyseren. Een middelgrote online steekproef van forensen ($n = 509$) stelde hun huidige en toekomstige dagelijkse activiteitenpatronen (met GV's) op, met speciale aandacht voor de mogelijke overlapping van reizen en activiteiten. De GV-effecten op de activiteiten aan boord en op de stationaire activiteiten worden geanalyseerd met behulp van het meervoudig discreet-continu extreme-waarde raamwerk. Uit de resultaten blijkt dat GV's leiden tot aanzienlijk meer en langere activiteiten aan boord. De algemene gevolgen voor stationaire activiteiten zijn verwaarloosbaar, hoewel ze in enkele sociaal-demografische groepen aanwezig zijn (bv. hoger opgeleiden en respondenten met een hoog inkomen). Niettemin zijn de totale veranderingen weliswaar gering, maar zij zijn op intuïtieve wijze gecorreleerd met veranderingen in de activiteiten aan boord. Het hoofdstuk concludeert dat ten minste sommige demografische groepen tijdbesparende of andere planningseffecten kunnen ondervinden als gevolg van GV's, en dat in toekomstige studies met grotere steekproeven meer planningseffecten kunnen worden ontdekt.

Hoofdstuk 4 formaliseert de beschreven tijdbesparende effecten van activiteiten aan boord. Voortbouwend op het klassieke tijdsbestedingskader voegt het elementen toe die nodig zijn voor verschillende activiteiten aan boord. Toegepast op een reeks voorbeelden toont het model aan hoe GV's tot tijdwinst leiden en hun gebruikers in staat stellen meer activiteiten uit te voeren gedurende een dag. Het toont ook aan dat activiteiten aan boord in verschillende scenario's kunnen leiden tot meer of minder verplaatsingen per dag. Daarmee biedt dit hoofdstuk een alternatief voor de alomtegenwoordige reistijdboetebenadering, die alleen die veranderingen in de dagelijkse tijdsbesteding voorspelt die het gevolg zijn van het feit dat verdere bestemmingen of frequentere verplaatsingen aantrekkelijker worden met GV's. Met deze resultaten toont dit hoofdstuk aan dat veranderingen van dagelijkse activiteitenpatronen niet alleen kenmerken zijn van de gegevens beschreven in de vorige hoofdstukken, maar in feite ook kunnen worden verwacht van economische agenten.

Hoofdstuk 5 formaliseert tijdsbesparing en planning-wijzigingseffecten in de context van het (ochtend)woon-werkverkeer. Ten eerste wordt aangetoond hoe activiteiten aan boord de keuze van de vertrektijd kunnen beïnvloeden: als rationele individuen tijdens de reis activiteiten uitvoeren die ze anders thuis zouden uitvoeren, vertrekken ze vroeger naar hun werk, terwijl werktaken tijdens de reis later vertrekken aantrekkelijker maken. Ten tweede wordt een minimalistische bottleneck-setting gebruikt om veranderingen in de congestiepatronen als gevolg van deze activiteiten aan boord te analyseren. Het wordt duidelijk dat de toegenomen activiteiten in geautomatiseerde voertuigen tot intensievere congestie leiden; de vorm van de congestie wordt echter beïnvloed door het soort activiteiten aan boord, waarvan de werkactiviteiten tot de minst dramatische toename leiden.

In hoofdstuk 6 worden de tijd-gebruik effecten in de evaluatiecontext bekeken. Op basis van een herinterpretatie van een recent gepresenteerd model, wordt de waarde van reistijd theoretisch afgeleid uit een uitgebreid klassiek micro-economisch kader. De uitbreiding maakt het mogelijk te specificeren in welke mate de omgeving aan boord werk en vrijetijdsbesteding ondersteunt. Er wordt geconcludeerd dat, aangezien de waarde van reistijd klassiek wordt opgesplitst in, ten eerste, een intrinsieke voorkeur of afkeer van reizen en, ten tweede, het verlies van tijd die voor andere activiteiten zou kunnen worden gebruikt, van de geautomatiseerde voertuigen kan worden verwacht dat zij dit laatste voor toekomstige reizigers zullen verminderen (of, in een extreem geval, elimineren).

De epiloog van dit proefschrift bespreekt de gezondheids- en welzijnseffecten van GVs. De auteur heeft het epiloog van een discussie voorzien over een bespreking van de individuele verplaatsingsomvang en de moduskeuze - aspecten van verplaatsingsgedrag die een bijzonder sterke impact kunnen hebben op de gezondheid en het welzijn van zowel GV-gebruikers als niet-gebruikers. Wat de individuele verplaatsingsomvang betreft, concludeert het hoofdstuk dat verschillende ontwikkelingen mogelijk zijn; dus niet alleen een toename, zoals meestal wordt aangenomen. Dit argument sluit aan bij de andere discussies in dit proefschrift. Met betrekking tot de moduskeuze wordt betoogd dat gedeelde en gepoolde GV's hun gebruikers kunnen onttrekken aan (relatief) duurzame reiswijzen, zoals openbaar vervoer, actieve vervoerswijzen en conventioneel autodelen. Dit idee is gebaseerd op de literatuur en op het concept van substitueerbaarheid tussen reismogelijkheden, en het is vastgelegd in een conceptuele kaart. Het gevolg van dergelijke modale verschuivingen zou een toename van het aantal voertuigverplaatsingen zijn, zelfs bij een gelijkblijvend aantal persoonsverplaatsingen - een resultaat dat niet alleen relevant is in de gezondheids- en welzijnsdiscussie, maar ook in het algemene debat over de maatschappelijke implicaties van GV's.

Tot slot

Dit proefschrift heeft tot doel de kloof te dichten tussen het verwachte reis- en tijdsbestedingsgedrag van GV-gebruikers en de modellen die het beschrijven. Door de hoofdstukken heen werd eerst verondersteld dat een dergelijke kloof inderdaad bestaat. Ten tweede werd empirisch bewijs geanalyseerd dat deze veronderstelling gedeeltelijk ondersteunt. Ten derde werden drie tijd-gebruik en reisgedrag modellen ontwikkeld die een aantal van de ontbrekende gedragselementen bevatten. Ten laatste heeft dit proefschrift de eerste inzichten verschaft in hoe deze modelupdates een verschil maken voor de voorspellingen van geaggregeerde reispatronen - een cruciale input voor het maken van vervoersbeleid in het GV-tijdperk.

About the author

Baiba Pudāne was born on the 10th of August 1988, in Ogre, Latvia. She studied Transport and Logistics in TUM Asia, Singapore (2012-2014) and Mathematics and Statistics in University of Latvia (2007-2012). Between her study periods, she worked for the research institute TUM CREATE in Singapore and the Latvian national airline, airBaltic. In 2016, she joined the Transport and Logistics group of TU Delft to conduct her PhD research on time use and travel behaviour of future automated vehicle users, as part of the project Spatial and Transport impacts of Automated Driving (STAD). In the following four and a half years, Baiba presented her research in numerous international and national conferences, as well as in industry and government agencies and professional events. She supervised three master students and a group of five bachelor students. She developed interest in open science and became one of TU Delft's data champions. In January 2021, Baiba started her tenure track as an Assistant Professor in the Transport and Logistics group, TU Delft. Her research interests are automated vehicles and other transport innovations, travel and time-use behaviour, transport economics, choice modelling, and bounded rationality.

Publications

Journal publications

- Pudāne, B., van Cranenburgh, S., & Chorus, C. G. (2021). A Day in the Life with an Automated Vehicle: Empirical Analysis of Data from an Interactive Stated Activity-Travel Survey. Journal of Choice Modelling, 39, 100286. https://doi.org/10.1016/j.jocm.2021.100286
- Pudāne, B. (2020). Departure Time Choice and Bottleneck Congestion with Automated Vehicles: Role of On-board Activities. European Journal of Transport and Infrastructure Research, 20(4), 306-334. https://doi.org/10.18757/ejtir.2020.20.4.4801
- Pudāne, B., & Correia, G. (2020). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey–A comment. Transportation Research Part A: Policy and Practice, 132, 324-328. https://doi.org/10.1016/j.tra.2019.11.019
- Pudāne, B., Rataj, M., Molin, E. J., Mouter, N., van Cranenburgh, S., & Chorus, C. G. (2019). How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands. Transportation Research Part D: Transport and Environment, 71, 222-235. https://doi.org/10.1016/j.trd.2018.11.014
- Pudāne, B., Molin, E. J., Arentze, T. A., Maknoon, Y., & Chorus, C. G. (2018). A Time-use Model for the Automated Vehicle-era. Transportation Research Part C: Emerging Technologies, 93, 102-114. https://doi.org/10.1016/j.trc.2018.05.022
- Chorus, C. G., Pudāne, B., Mouter, N., & Campbell, D. (2018). Taboo trade-off aversion: a discrete choice model and empirical analysis. Journal of choice modelling, 27, 37-49. https://doi.org/10.1016/j.jocm.2017.09.002

Book chapter

- Singleton, P. A., De Vos, J., Heinen, E., & Pudāne, B. (2020). Potential health and well-being implications of autonomous vehicles. In Milakis, D., Thomopoulos, N., & van Wee, B. (Eds.), Policy implications of Autonomous Vehicles, 5 (pp. 163-190). Academic Press. https://doi.org/10.1016/bs.atpp.2020.02.002

International conference presentations

- Pudāne, B., van Cranenburgh, S., & Chorus, C. G. (2019). A time-use model for the automated vehicle–era: Extension and validation with interactive stated activity-travel survey. ICMC 2019: International Conference Modelling Conference, Kobe, 19-21 Aug 2019.
- Pudāne, B. (2019). Departure time choices and peak congestion with automated vehicles. hEART 2019: 8th symposium by European Association for Research in Transportation, Budapest, 4-6 Sep 2019.
- Pudāne, B., Rataj, M., Molin, E. J., Mouter, N., Asghari H., van Cranenburgh, S., & Chorus, C. G. (2018). Daily Activity Schedules in the Automated Vehicle-era: A Focus Group Study. Automated Vehicle Symposium, San Francisco, 9-12 Jul, 2018.
- Pudāne, B., Molin, E. J., van Cranenburgh, S., Arentze T., Maknoon Y., Rataj, M., Mouter, N., Asghari H., & Chorus, C. G. (2018). Activity-travel Behaviour in the Automated Vehicle-era: A Focus Group Study and a Time-use Model. Poster in Automated Vehicle Symposium, San Francisco, 9-12 Jul, 2018.
- Pudāne, B., Molin, E. J., Arentze T., Maknoon Y., van Cranenburgh, S., & Chorus, C. G. (2018). A Time-use Model for the Automated Vehicle-era. IATBR, Santa Barbara, 15-20 Jul, 2018.
- Pudāne, B., Rataj, M., Molin, E. J., Mouter, N., van Cranenburgh, S., Asghari H., & Chorus, C. G. (2018). Time-use in Automated Vehicles and Daily Activity Schedules:

A Focus Group Study. hEART – 7th Symposium of the European Association for Research in Transportation, Athens, 5-7 Sep 2018.
- Pudāne, B., Maknoon Y., van Cranenburgh, S., & Chorus, C. G. (2018). Activity-travel Behaviour in the Automated Vehicle–era: A Mixed Integer Linear Model and Its Estimation with Discrete Choice Techniques. OR 2018: International Conference on Operations Research, Brussels, 12-14 Sep 2018.
- Pudāne, B., van Cranenburgh, S., Chorus, C. G. (2016). Scheduling preferences and optimal departure times for regret minimisers. hEART 2016: 5th Symposium by European Association for Research in Transportation.
- Pudāne, B., Rau, A. (2015). Step versus slope model for valuing waiting time unreliability. hEART 2015: 4th Symposium of the European Association for Research in Transportation, Copenhagen, 9-11 Sep 2015.

Publications in professional journals
- Baiba Pudāne interviewed by Ymkje de Boer. Automatisch rijden leidt tot andere dagindeling. Published in Verkeerskunde, 4 Mar 2021. https://www.verkeerskunde.nl/artikel/automatisch-rijden-leidt-tot-andere-dagindeling
- Pudāne, B. (2019). De waarde van reistijd in een zelfrijdende auto. Published in Verkeerskunde, 18 Dec 2019. https://www.verkeerskunde.nl/artikel/de-waarde-van-reistijd-in-een-zelfrijdende-auto
- Pudāne, B., Molin, E. J., Arentze, T. A., Maknoon, Y., & Chorus, C. G.. Activiteitenpatronen in zelfrijdende auto: Model leert effecten zelfrijdende auto's te begrijpen. Published in Verkeerskunde, 13 Sep 2018. https://www.verkeerskunde.nl/artikel/activiteitenpatronen-in-zelfrijdende-auto
- Baiba Pudāne interviewed by Leonie Walta. Hoe neemt de zelfrijdende auto risico's? Published in Verkeerskunde, 20 Dec 2018. https://www.verkeerskunde.nl/artikel/baiba-pudane-hoe-neemt-de-zelfrijdende-auto-risicos

Data sets
- Pudāne, B.; van Cranenburgh, S.; Chorus, C. (2021). A Day in the Life with an Automated Vehicle: Supporting Data and Software. 4TU.ResearchData. Dataset. https://doi.org/10.4121/14125880.v1
- Pudāne, B. (2020). Queueing Times of Automated Vehicles in a Bottleneck: MATLAB Code. 4TU.ResearchData. Software. https://doi.org/10.4121/13247633.v1
- Pudāne, B. (2018). Transcripts of 5 focus groups discussing topic 'Possible impacts of automated vehicles on travel and daily life in the future'. 4TU.ResearchData. Dataset. https://doi.org/10.4121/uuid:994f0ab2-0fa2-493f-88ad-fbf4eaaf470e

TRAIL Thesis Series

The following list contains the most recent dissertations in the TRAIL Thesis Series. For a complete overview of more than 275 titles see the TRAIL website: www.rsTRAIL.nl.

The TRAIL Thesis Series is a series of the Netherlands TRAIL Research School on transport, infrastructure and logistics.

Pudāne, B., Time Use and Travel Behaviour with Automated Vehicles, T2021/21, July 2021, TRAIL Thesis Series, the Netherlands

Gent, P. van, Your Car Knows Best, T2021/20, July 2021, TRAIL Thesis Series, the Netherlands

Wang, Y., Modeling Human Spatial Behavior through Big Mobility Data, T2021/19, June 2021, TRAIL Thesis Series, the Netherlands

Coevering, P. van de, The Interplay between Land Use, Travel Behaviour and Attitudes: a quest for causality, T2021/18, June 2021, TRAIL Thesis Series, the Netherlands

Landman, R., Operational Control Solutions for Traffic Management on a Network Level, T2021/17, June 2021, TRAIL Thesis Series, the Netherlands

Zomer, L.-B., Unravelling Urban Wayfinding: Studies on the development of spatial knowledge, activity patterns, and route dynamics of cyclists, T2021/16, May 2021, TRAIL Thesis Series, the Netherlands

Núñez Velasco, J.P., Should I Stop or Should I Cross? Interactions between vulnerable road users and automated vehicles, T2021/15, May 2021, TRAIL Thesis Series, the Netherlands

Duivenvoorden, K., Speed Up to Safe Interactions: The effects of intersection design and road users' behaviour on the interaction between cyclists and car drivers, T2021/14, April 2021, TRAIL Thesis Series, the Netherlands

Nagalur Subraveti, H.H.S., Lane-Specific Traffic Flow Control, T2021/13, March 2021, TRAIL Thesis Series, the Netherlands

Beirigo, B.A., Dynamic Fleet Management for Autonomous Vehicles: Learning- and optimization-based strategies, T2021/12, March 2021, TRAIL Thesis Series, the Netherlands

Zhang, B., Taking Back the Wheel: Transition of control from automated cars and trucks to manual driving, T2021/11, February 2021, TRAIL Thesis Series, the Netherlands

Boelhouwer, A., Exploring, Developing and Evaluating In-Car HMI to Support Appropriate use of Automated Cars, T2021/10, January 2021, TRAIL Thesis Series, the Netherlands

Li, X., Development of an Integrity Analytical Model to Predict the Wet Collapse Pressure of Flexible Risers, T2021/9, February 2021, TRAIL Thesis Series, the Netherlands

Li, Z., Surface Crack Growth in Metallic Pipes Reinforced with Composite Repair System, T2021/8, January 2021, TRAIL Thesis Series, the Netherlands

Gavriilidou, A., Cyclists in Motion: From data collection to behavioural models, T2021/7, February 2021, TRAIL Thesis Series, the Netherlands

Methorst, R., Exploring the Pedestrians Realm: An overview of insights needed for developing a generative system approach to walkability, T2021/6, February 2021, TRAIL Thesis Series, the Netherlands

Walker, F., To Trust or Not to Trust? Assessment and calibration of driver trust in automated vehicles, T2021/5, February 2021, TRAIL Thesis Series, the Netherlands

Schneider, F., Spatial Activity-travel Patterns of Cyclists, T2021/4, February 2021, TRAIL Thesis Series, the Netherlands

Madadi, B., Design and Optimization of Road Networks for Automated Vehicles, T2021/3, January 2021, TRAIL Thesis Series, the Netherlands

Krabbenborg, L.D.M., Tradable Credits for Congestion Management: support/reject?, T2021/2, January 2021, TRAIL Thesis Series, the Netherlands

Castelein, B., Accommodating Cold Logistics Chains in Seaport Clusters: The development of the reefer container market and its implications for logistics and policy, T2021/1, January 2021, TRAIL Thesis Series, the Netherlands

Huang, B., The Influence of Positive Interventions on Cycling, T2020/20, December 2020, TRAIL Thesis Series, the Netherlands

Xiao, L., Cooperative Adaptive Cruise Control Vehicles on Highways: Modelling and Traffic Flow Characteristics, T2020/19, December 2020, TRAIL Thesis Series, the Netherlands

Polinder, G.J., New Models and Applications for Railway Timetabling, T2020/18, December 2020, TRAIL Thesis Series, the Netherlands

Scharpff, J.C.D., Collective Decision Making trough Self-regulation, T2020/17, November 2020, TRAIL Thesis Series, the Netherlands

Guo, W. Optimization of Synchromodal Matching Platforms under Uncertainties, T2020/16, November 2020, TRAIL Thesis Series, the Netherlands

Narayan, J., Design and Analysis of On-Demand Mobility Systems, T2020/15, October 2020, TRAIL Thesis Series, the Netherlands

Gong, X., Using Social Media to Characterise Crowds in City Events for Crowd Management, T2020/14, September 2020, TRAIL Thesis Series, the Netherlands

Rijal, A., Managing External Temporal Constraints in Manual Warehouses, T2020/13, September 2020, TRAIL Thesis Series, the Netherlands

Summary

It is widely expected that travellers will enjoy an unprecedented selection of on-board activities in future automated vehicles. This thesis investigates how this new availability may affect travellers' daily time use and travel behaviour. It analyses qualitative and quantitative data, and develops microeconomic models. The models include on-board activities in daily time-use planning, in departure time choice and congestion prediction, and in theoretical analysis of the value of travel time.

About the Author

Baiba Pudāne is a researcher of transport innovations, time use, travel behaviour and transport systems. She conducted her PhD research in Transport and Logistics group of TU Delft. She holds degrees in Transport and Logistics and in Mathematics and Statistics.

TRAIL Research School ISBN 978-90-5584-296-4

Erasmus University Rotterdam
Radboud University
rijksuniversiteit groningen
TU Delft Delft University of Technology
UNIVERSITY OF TWENTE.
TU/e Technische Universiteit Eindhoven University of Technology